INCORPORATING UNCERTAINTIES INTO POLICYMAKING PROCESS FOR AIDING A BALANCED REGIONAL ECONOMIC DEVELOPMENT: A FUZZY INVESTMENT RISK ASSESSMENT OF THE DELAWARE BROWNFIELDS

by

Ali Abedini

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Ali Abedini

Approved: ______________________________
Maria P. Aristigueta, D.P.A.
Director of the School of Public Policy and Administration

Approved: ______________________________
George H. Watson, Ph.D.
Dean of the College of Arts and Sciences

Approved: ______________________________
Ann L. Ardis, Ph.D.
Senior Vice Provost for Graduate and Professional Education

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

Edward C. Ratledge, M.S.
Professor in charge of dissertation

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

Daniel Rich, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

William W. Boyer, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

Steven Peuquet, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ______________________________

William R. Latham III, Ph.D.
Member of dissertation committee

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ABSTRACT

This study develops a new solution to the problem of uncertainties into the policymaking process. As an applied research, this study introduces a new policy framework called “Vectorial Policy Process” through which to understand and incorporate them into it. In light of Fuzzy Set Theory, and with the help of Analytic Hierarchy Process (AHP) and Empirical Bayesian Kriging (EBK), this study develops a framework to help explore, recognize, and structure various kinds of uncertainties that are associated with economic development and policymaking at the regional level. Selecting the Delaware Brownfields Program (DBP) as a case study, this research employs an exclusive in-depth, market-driven data analysis, which is dominantly used by the banking, financial, and insurance industries, to conduct an investment-based risk assessment of brownfield sites. This helps public funds target those sites in a positively discriminatory way to achieve a more balanced regional economic development.

This study develops a composite fuzzy membership function which defines the transition from Investment Risk Set to Investment Safety Set. All Delaware brownfield sites are assessed based on their degree of membership to each of the two fuzzy sets. By employing this framework, policymakers can see how safe or risky is each site from the investors’ lens, with respect to their surrounding communities. This incorporates uncertainty into the policymaking process by viewing the brownfield development inequality problem from the perspectives of investors and the private sector, rather than that of public entities. This facilitates transferring more ‘unknown-knowns' to 'known-knowns' in shaping brownfield policies. Through a data-driven approach, this study recognizes and classifies 62 different sources of uncertainty that may be considered as deterrents to new investment in communities affected by the presence of brownfields. By employing the AHP method as a fuzzy membership function, these uncertainty sources (risk factors) are structured in a risk hierarchy and grouped into five main categories, as follows: (1) Socioeconomic Risk; (2) Demographic Risk; (3) Infrastructure Risk; (4) Spatial (Proximity) Risk; and (5) Financial Demand Risk. More importantly, this research employs EBK to estimate the spatial variability of these factors. This is a procedure for quantifying proximity risk when data becomes available from the area of interest. In EBK, interpolation is carried out by means of a Bayesian form of Kriging through Geographical Information Systems (GIS).

The structure presented in this study is completely flexible, and may be modified and adapted to fit policymakers' needs in the future. The research outcome is an effective policy support system for aiding in policymaking under uncertainty, which can be utilized by decision-makers under the regional scale.

Key Words: Uncertainty, Policymaking Process, Investment Risk Assessment, Vectorial Policy Process (VPP), Analytical Hierarchy Process (AHP), Empirical Bayesian Kriging (EBK), Brownfield, Regional Economic Development

Chapter 1

INTRODUCTION

1.1 Statement of Research Question

The policy research process has been widely perceived as doing something such as observing people, using equipment, or analyzing data. However, the most critical parts of the process are those which are associated with thinking, not doing. The first step in a policy research process is to identify a problem and develop an empirical research question. This stage is the most crucial part of policy research. If one is not exactly clear about what one is studying, then the results of that research may be just as unclear as the research study. Contrary to common perceptions, many policy research studies are unclear and ill-conceived, due to careless thinking at the early stage of the process. It starts with a research question that states clearly what the study will investigate and the issue it will then attempt to address. It is a rational, coherent statement that progress from what is known, or believed to be true, to that which is unknown and therefore requires validation.

Most of today's research questions can be classified into three categories of "what," "why," and "how." It is not so unlikely that most applied research questions fall into the category of "how" – especially when it comes to policymaking – since the agenda is to change the world, rather than interpret it. As applied research, this study starts with a "how" kind of question, to address a current, real-world problem in the policymaking process. The research question goes along with the so-called dialectic of subjective-versus-objective methodologies. Some researchers, including Shackle

(1972) and Friedman (1953), start with the comparison and evaluation of "prediction" of the future and "explanation" of the past, using examples of economic development. Prediction endows economics with preciseness and accuracy, but also lets it lose some of the truth. There is a balance between preciseness and truth in economic development. As Shackle (1972) comments, the difference between "prediction" and "explanation" is that, in the task of explanation, the known sequel is available as a guide to assist in selecting among the antecedent circumstances, whereas the selection of antecedent circumstances for prediction has to be based on some other criteria. Designing and formulating a policy or program is more like a prediction task than one of explanation.

Model supporters might say that a theoretically exact description is not possible because simplification and abstractness are necessary components. This is true. However, it still cannot prove the properness of neglecting the reality. On the contrary, we should strive for some methodology in theory to solve such a contradiction. Chaos is continuously aroused by the problem: real economy is constructed by human beings and enslaved to an open system with forever-outside impacts, while the model economics used to make predictions about it represent a closed system. The facts of economics are not akin to movements of machines, which therefore determine they cannot be accurately predicted. Models for the economic affairs of actual societies do not have the capacity to engage social and human changes, and they are built on previous and current knowledge. So, such models cannot manage creativity or predict the future therein.

Along with the subjectivity and objectivity dialectic, throughout my career as an urban and regional planner, a challenging question has gradually been shaped in the

Cartesian part of my mind. Throughout many working group discussions and professional meetings over urban and regional problems, with planners, managers, and policymakers, I came to understand that we had been talking about something which is not actually clear to us. In so many ways, there are uncertainties embedded therein, of which we are not even aware of. In such non-Euclidian uncertain situations, most of the time however, we made Euclidian policies and decisions without any skepticism about the realization of their predicted outcomes. Sometimes we tried to recognize and examine those uncertainties, yet we could not design or develop an effective model to incorporate them into policymaking processes.

Knight (2012) suggests that our main concern should be about the possibility of classifying the “state of nature.” That is to say, “When our ignorance of the future is only partial ignorance, incomplete knowledge and imperfect inference," he says, "it becomes impossible to classify instances objectively” (Knight, 2012, p.259). The point is not so much that we do not know probabilities, as that we are not aware of the classification of outcomes. Thus, he concludes, uncertainty arises from the impossibility of an exhaustive classification of states (Langlois & Cosgel, 1993).

On the other hand, Tenembaum (2012) suggests that we can identify risk much like we can recognize a distant train coming towards us. The train might change its course before reaching us; it may slow down, or ultimately stop. The risk itself is not the train that has hit us. That does not constitute a risk. Instead, the danger assumed to be looming – whether far away or close by – represents the risk. The danger and threat, once realized, is no longer a risk. Uncertainty, on the other hand, has too many unknown variables, much the same as our not being aware of whether the train has left the station or not; and, if it has, whether or not it would be traveling along tracks that would lead it to us; and, if we are aware that it has used the tracks leading to us and has left the station, whether we are sure that it finally will hit us, or not; or, maybe someone whom we are not aware of just pushes us away from the track before the train actually hits us. Uncertainty would be much like knowing there is a dog somewhere in the neighborhood, yet without us knowing whether or not it might head towards us. It may not bark at us at all. Thus, the difference between a risk and uncertainty may be a matter of perception. All of this is a matter of perspective. The distinction between risk and uncertainty can be defined objectively, but when it comes to the shaping of public policy, it is often just a matter of perception as to whether an event or a process is seen as risky or uncertain; states which provide different thresholds.

Most policymaking factors and their interactions are associated with uncertainties and complexities that are difficult for policymakers to handle without considerable expertise. I'd always thought about the necessity for developing a sort of comprehensive policy support system that would enable us to incorporate all possible uncertainties into the policymaking process, systematically. The big question still left unanswered, however, is: "How?"

A core aim of many policies and programs around the world today, meanwhile, is sustainable and balanced economic development. As an important global agenda, the need for a greater level of sustainable development in all countries was discussed for the first time in 1987 (WCED, 1987). This has arisen alongside the increase in environmental problems as a result of the most rapid economic development in the world since the Industrial Revolution. Many of the planet's ecosystems have been degraded and species have been threatened, while global warming has become increasingly apparent. To slow the damage caused by human development, it is essential that our actions become more sustainable.

As Wheeler (2004) indicates, the concept of “sustainable development” has been employed to denote alternatives to traditional patterns of physical, social, and economic development, in both developed and developing countries. These alternatives can help avoid or at least minimize problems such as pollution, exhaustion of natural resources, overpopulation, loss of species, destruction of ecosystems, and the degradation of human living conditions. Growth management and sustainable development are widely considered essential to maintaining the quality of life on this planet. However, the task of determining which policies, decisions, and actions can guarantee “sustainable development,” and just how they will do so, is complicated and needs to deal with the fuzzy world of uncertainties.

Sustainability can be studied and managed over many scales of time and space and in many contexts of environmental, social, and economic organization. The focus ranges from the total carrying capacity (sustainability) of planet Earth to the sustainability of economic sectors, ecosystems, countries, states, metropolitan areas, municipalities, neighborhoods, home gardens, individual lives, individual goods and services, occupations, lifestyles, behavior patterns, and so on. In short, it can entail the full compass of biological and human activity, or any part of it (Conceptual Framework Working Group of The Millennium Ecosystem Assessment, 2003). As Daniel Botkin has stated: “We see a landscape that is always in flux, changing over many scales of time and space” (Botkin, 1990, p.84). Wheeler (2009) believes that region is a significant scale for sustainability planning. He reiterates that regions can be a source of great dynamism and initiative, but also that their growth is problematic for sustainable development, in some ways that differ from similar growth contained within more localized communities.

One of the main goals in planning for sustainable development is to identify and choose the most sustainable scenario and policy from among multiple alternatives. Facilitating and resolving such difficult decision situations can be complex. Moreover, large-scale policy and planning interventions, populations, and environments share several general features: complexity, dynamics, and uncertainty. Standard analytical methods go a long way toward adequately modeling complexity and dynamics, but incorporating uncertainty presents additional difficulties. Missing or inaccurate information, errors in forecasting future data, and external uncontrollable occurrences all introduce uncertainty. Ignoring uncertainty (and its potential costs) can prove perilous and so, to make decision models effective, policymakers must actively consider them. Thus, additional research is needed to acquire further knowledge and understanding of its different types (e.g., knowledge, variability, decision, and linguistic uncertainty) inherent in policymaking for economic development, and how these areas affect the quality of policies rendered.

To sum up briefly, this study, as an applied interdisciplinary research, begins with this specific question:

> *"How can various kinds of uncertainties in the policymaking process be recognized, classified, and structured?" and "How can they be systematically incorporated into the process in a comprehensive way, to aid regional economic development?*

From what it has inferred from the question, this study adopts a deductive, rather inductive, analytical approach in order to begin the research journey to answer this specific, focused question. The “How” nature of it directs the journey through an applied means of scientific exploration. In other words, this research ends up with effective tools and models for aiding in regional policymaking under uncertainty. To conceptualize and structure the question, we should investigate three important aspects:

- Uncertainty
- Recognition
- Incorporation

Emphasizing the existence of uncertainty in the policymaking process itself is a matter of importance, no matter how it is dealt with. Policymaking under uncertainty is a disciplined, methodical approach to public policy, with uncertainty analysis at the heart of its logical reasoning. Most important regional policies involve many known and unknown stakeholders who often have differing perspectives. The important policies are often complex in nature, have a high degree of uncertainty, and can become sources of internal tension due to differences in priorities and objectives. Recognizing those uncertainties, however, is quite a difficult job since getting to know the unknown seems as though it can be impossible. Although many sources of uncertainty are recognized, there is still a lack of information and agreement on their characteristics and relative magnitudes, as well as available means for dealing with them. In addition, “many typologies have been developed for different purposes [for] which there are neither a commonly shared terminology nor agreement on a generic typology of uncertainties” (Walker et al., 2003, p.8). Regarding incorporation, which is the most important part of the question, some major approaches can be examined and developed to address uncertainties in regional policymaking, including the "Bayesian approach" (Ascough, Maier, Ravalico, & Strudley, 2008).

When it comes to data and information for extending our knowledge of this research topic, the first step undertaken involves the investigation of decision-making context and documenting issues surrounding uncertainty and policymaking. A literature search of policymaking at the regional level, as well as one on uncertainty analysis methods, seem to be necessary. This should focus on critical success factors and impediments to incorporating uncertainties into the planning and policymaking process.

Two types of data will be used in this study: non-spatial and spatial. The term "spatial data" hereafter refers to Geographical Information Systems (GIS) data, or geo-referenced data; i.e. the attributes of all information as defined at unique locations in space. Also known as geospatial data or geographic information, it identifies the geographic location of features and boundaries on Earth, such as natural or constructed features, and more. Non-spatial data are needed to address the objective regarding uncertainty analysis of planning for economic development. A set of variables concerning costs and benefits involved in planning and policymaking systems needs to be identified. The relationships among these variables should then be defined to simulate different scenarios of policies and planning interventions.

1.2 Significance of The Research

The consequence of ignoring the uncertainty in future regional development is to expose environment and society to an extensive variety of social, economic, and environmental issues, wherein choices are made that are unsuitable for both society and the environment. This can refer to expensive, wasted investments and also unnecessary, possibly irreversible, harm to people and ecosystems. It is an example of under-adaptation, wherein there is either no action at all or adjustments go just far enough to cope with any unforeseen changes that occur.

We, as policymakers and planners, advocate economic development at the regional level. However, by relying on current approaches and concepts only, we will not succeed in overcoming this global challenge. We need innovative solutions from policymakers and planners in order to make the impacts of economic development manageable. Innovation and research are needed more than ever to identify new policy approaches. Above all, holistic concepts are required, which can take into account ecological, economical, and socially relevant issues. The scope of this approach could be a regional influence on policymaking processes as public and policymakers interact in their dealings with spatial policies on brownfields, land use, transportation, housing, and natural resources. This is significant to a broad range of policymakers concerned about sustainability and economic development, and makes clear the need for a new policymaking approach to the uncertain nature of spatial policies at regional, national, and global levels.

At the same time, increasing concern has been recognized in the scientific community regarding whether the variety of current approaches to sustainable economic development are really comprehensive, and therefore able to judge in a robust and reliable way whether or not new developments meet the needs of the present, without compromising the ability of future generations to meet their own needs (EPA, 2016a). Concerns are mainly related to an inherent vagueness of the sustainability concept itself, and to its capability of addressing environmental, economic, and social problems and their interactions with robust and meaningful measures. Policymakers and planners struggle with the need to make decisions that can and do have far-reaching, often irreversible impacts on both society and the environment, with sparse and imprecise information being the source of their uncertainty. Regardless of which phases of the policymaking process are considered, various sources of uncertainty need to be dealt with explicitly, to enable decisions to be made with confidence or, at minimum, some known level of certainty. So as to manage them, it is important to determine an appropriate conceptual framework to guide policymakers, through which to expand their capacity to comprehend the primary drivers of their analyses. Only in this way will they be able to quantify the robustness of the results of any policy or program. The issue is that uncertainties behind the comprehension of our reality are most likely too high to allow us assuming to provide clear and certain answers on what is a good balanced economic development and what is not. All we can do now – hence, the significance of this study – is to attempt to recognize the primary sources of uncertainty and to manage them accordingly.

1.3 Conceptual Framework of The Research

A conceptual framework is the logical structure over which a research theory and its scientific approach are developed. It promotes interpretation and integration and makes the theories applicable to the focused and specific research project. It helps clarify and focus what to study, what to expect from analysis, and to determine which derived data to use. Without a conceptual framework, theories remain ad hoc, incomplete, and biased by the particular expertise and research interest of the authors; excessively dense in some areas, while sparse or even empty in other important ones.

Due to its cross-disciplinary nature, this research demands a theory synthesis, in three specific areas: policy/decision making framework, uncertainty analysis, and economic development. It addresses the issue of uncertainty in policymaking, in the form of an applied research that aims to develop a new solution to the specific problem of uncertainties embedded in policymaking, at the regional level. This study develops a new policy framework called "Vectorial Policy Process," in order to first understand, then incorporate uncertainties into the policymaking process. With the help of Analytic Hierarchy Process (AHP) and Empirical Bayesian Kriging (EBK), it develops a framework to help explore, recognize, and structure all kinds of uncertainties associated with economic development and policymaking processes at the regional scale.

Thus, this should not be considered as a conventional or basic study, merely trying to test a hypotheses or proposition. Rather, it is applied research seeking recommendations and solutions to the specific problem of uncertainties, as well as the complexities associated with economic development in policymaking process at the regional scale. Adopting a deductive analytical approach, this research develops an effective tool and model for aiding in policymaking under uncertainty, which can be used by decision makers at the regional scale.

1.4 Methodological Approach

There is a broad range of literature on research methodology, in which a continuous discussion about the relative benefits of quantitative and qualitative research methods exists. Researchers contend that both have their respective advantages and drawbacks. For instance, one cannot describe the intricacies of economic development, or those of policymaking, only through survey research.

Mixed-method research (qualitative and quantitative) is likely to provide superior research findings and outcomes (Johnson, Onwuegbuzie, & Turner, 2007). Most quantitative research methods provide good ways to gather basic data and to find out what the major concerns are.

There is a view propounded by a few researchers that qualitative and quantitative methods ought to never again be viewed as exclusive to their conventional methodological 'clubs,' and that it is possible for a single examination to utilize both methods (e.g. Howe, 1988). As Miles and Hubermann (1994) acknowledge, "in epistemological debates it is tempting to operate at the poles. But in the actual practice of empirical research, we believe that all of us … are closer to the centre with multiple overlaps … an increasing number of researchers now see the world with more pragmatic, ecumenical eyes."(page 4). Other researchers (Strauss & Corbin, 1990) indicate that distinctions between the two conventional approaches are not as exact as was previously believed, and so it is no longer uncommon for researchers to utilize a plurality of methods.

Taking that into account, the nature of this research topic promotes the adoption of a combination approach, utilizing both quantitative and qualitative techniques, to study uncertainties in the policymaking process.

1.5 Research Design Framework

As discussed above, this study adopts a two-step, mixed-method approach. The first involves investigating policy/decision-making context and documenting issues, surrounding uncertainty and economic development, and includes a well-covered literature review. There are many different approaches as to how to organize the such a review, depending on what the literature looks like. This study takes a combination of the three approaches when it explores the concepts of economic development, uncertainty, and policy/decision-making framework: chronological, major theories, and broad-to-specific.

In the second phase, a comprehensive synthesis is done, based on what has been extracted through a literature review in order to feed a deductive analytical method. The study expands and augments the framework, synthesized through the review, for characterizing the geographic (spatial) dimensions of information in policymaking. It uses these synthesized concepts to: (1) inform the methodological structure of the policymaking process; (2) explore how the policy/decision scenarios for economic development under uncertainty respond and can better address these issues; and, (3) make connections between theoretical issues developed in the literature and practical applications to current policy/decision-making scenarios.

It then develops a logical structure for the policy support systems by drawing upon three principal areas of research: policymaking frameworks, uncertainty analysis, and geographic information systems (GIS). Uncertainty analysis investigates the uncertainty of variables of policy/decision-making problems, in which observations and models represent the knowledge base. In other words, it aims to make a technical contribution to policy/decision-making through the quantification of uncertainties in the relevant variables. It develops a multi-objective, quantitative model with which to frame the policymaking/planning process, within the context of long-term goals for economic development. Development of the quantitative formulation draws primarily from uncertainty analysis models provided in the operations research and the systems modeling literature. The model is then integrated with GIS to store geo-reference data and information.

Finally, the study applies its proposed framework and model in an actual public policy: the Delaware Brownfields Program. This case study reflects a range of uncertainty and policy/decision-making characteristics. The overall goal of the research design framework is to better assist this study in exploring the uncertainties of policies/decisions at hand, and to analyze the trade-offs between the competing criteria (i.e., the degrees to which the policy/planning alternatives meet the predefined objectives, based on the selected indicators).

In summary, this study develops a general conceptual framework for understanding the impact of uncertainty in the process of policymaking and implementation: Vectorial Policy Process (VPP). It then introduces a 'Fuzzy Approach' to deal with uncertainty, through conducting an investment-based risk assessment of brownfield sites for a balanced regional economic development, by employing a decision support tool (Analytical Hierarchy Process) and a Bayesian geostatistical analysis method (Empirical Bayesian Kriging).

1.6 Data Identification

Regarding data identification, there are two types of data which will be used in this study: non-spatial and spatial. The term "spatial data" refers to GIS or geo-referenced data (also known as geospatial data or geographic information), i.e. the attributes of all information as defined at unique locations in space. It comprises information or data that identifies the geographic locations of boundaries and features on Earth; for example, constructed or natural elements, and more. Spatial data is typically stored as topology, by coordinates that can be mapped. It is commonly accessed, analyzed, and manipulated through Geographic Information Systems. On the other hand, non-spatial data are collected primarily through scientific literature, survey, documents, and scholarly articles.

A substantial amount of pre-processing is demanded to format all data, which are often specifically formatted for and stored on transportable media such as ASCII flat files. Analysts and researchers often utilize spatial data as input for statistical software that requires a specific file format, which can require a lot of money and time to re-format from their original versions. This reformatted data can be utilized in several distinct ways: as input to analysis modules; to build a computerized database; and for constructing presentation graphics such as charts, maps, and tables.

In this study, the non-spatial data is collected mainly through a literature review of related scholarly and professional articles. The spatial data is collected from these three sources: the Delaware Department of Natural Resources & Environmental Control (DNREC), S & P Global Market Intelligence (S&P Capital IQ and SNL Financial), and The Federal Deposit Insurance Corporation (FDIC). The DNREC database is used for information related to brownfield sites, such as geographical locations, cleanup expenses, lot size, etc.. Demographic, socioeconomic and consumer financial demand data, meanwhile, are pulled from S&P Global Market Intelligence (www.SNL.com) across the entire state of Delaware, at the census tract level. The SNL platform is sourced from The Nielsen Company©, which bases its data on the U.S. Census and the annual American Community Survey, along with many other current sources such as the Bureau of Economic Analysis (BEA), the Internal Revenue Service (IRS), the Bureau of Labor Statistics, USPS, new construction data, as well as from many other data providers that offer real-time insight on the national population. The Estimated Annual Sale of all businesses in Delaware is also retrieved through the

SNL Financials website, which collects this data from a third party provider (DatabaseUSA, which has developed a proprietary model that estimates the sales volume for each business.) Data from the Department of Commerce (representing the economic wealth factor, based on geographic location in conjunction with the results from employment acquired above) are all synthesized in order to create an estimated annual sales volume for each business location. Where companies publish actual revenue figures, DatabaseUSA uses the published values to represent revenue, accordingly. Sales volume is not estimated for some lines of business however, such as educational institutions, government offices, associations, and organizations because such entities within those industries generally do not generate sales. The data are compiled and updated monthly from among hundreds of public and proprietary sources, including the U.S. government, market data, utility data, phone validation, directories, and other proprietary sources.

Deposit balances of all Delaware financial institutions and their 5-year deposit growth rate (2010-2015) extracted from FDIC public database. The Federal Deposit Insurance Corporation (FDIC) is a United States government corporation that provides insurance to depositors in US banks on their deposits therein. The FDIC Summary of Deposits (SOD) is the annual survey of branch office deposits for all FDIC-insured institutions, including insured U.S. branches of foreign banks.

1.7 Research Process

This research starts with defining and elaborating the research question, which is rooted in the researcher’s expertise, empirical reality, and scientific literature review. From what is inferred from the review, a non-elaborated proposition is developed deductively. Then, it is fostered and grounded with the results of the collected data. The results comprise an incipient theory of policymaking under uncertainty, which provides a scientific foundation for developing further research toward a conceptual model of uncertainty analysis. There is a case study for applying the conceptual model in real world as well, which helps the theory to be grounded and tested empirically. The Delaware Brownfield Development Program is selected as a real public policy case study, which addresses a legitimate contemporary policy issue within which the current policy is clearly discernible.

By the 1980s, deteriorating hulks of abandoned factories and overgrown vacant lots in many American cities served as notable symbols of urban decline. These sites earned the label of "brownfields," which the U.S. Environmental Protection Agency (EPA) defines as “abandoned, idled, or under-used industrial and commercial facilities, where expansion or redevelopment is complicated by real or perceived environmental contamination” (EPA, 2016a). In 2004, the Delaware Brownfield Development Program was signed into law. DBDP encourages the cleanup and redevelopment of vacant, abandoned, or underutilized properties which may be contaminated, and welcomes applications for brownfield certification. A party seeking to develop such a property negotiates with Site Investigation & Restoration Section (SIRS) for a Brownfield Development Agreement (BDA) to perform an investigation and, if necessary, a remedial action or remedy to address the risks posed by past releases of hazardous substances at these sites (Delaware Department of Natural Resources and Environmental Control, 2013). This voluntary cleanup program then continues for site owners, and financial assistance is available to eligible parties in the form of Brownfield Grants, funded by the Hazardous Substance Cleanup Act (HSCA) and the Brownfield Revolving Loan Fund. Both help eligible borrowers to pay for the cleanup of brownfields (DNREC, 2013). The Department has sought to give preference to such projects offering a clear public benefit, such as affordable housing (e.g. for low-to-middle income buyers), LEED Certified Green Buildings, and development consistent with smart growth principles, including Delaware Strategies for State Policies and Spending (DNREC, 2013).

The next steps of the research process include designing, then applying a policymaking model of uncertainty for the Delaware Brownfield Development Policy issue. These steps help to modify as well as to elaborate the initial model and review of the preliminary assumptions. Generalization of the outcomes and suggestions for further research are the last steps. The proposed policymaking model is comprised of an Uncertainty-Incorporated Policy Support System, which systematically incorporates uncertainties into the policymaking process.

1.8 Chapter Outlines

Chapter 1: Introduction. This chapter describes the research question with regard to policymaking under uncertainty, and lays out the reasoning behind it; a theoretical argument. It justifies the study, in terms of how it fills a real need for this information, and how it will provide this, in order to develop a theory to best understand, explain, and further describe the necessity of incorporating uncertainty into the policymaking process. This chapter starts with a general description of policymaking under uncertainty, and the significance of the research problem, followed by an analysis of the theoretical basis of this study.

Chapter 2: Literature Review. This chapter reviews what has already been written in the field on the topic of the study: policy/decision-making, economic development, and uncertainty. The literature supports the theoretical argument being made by demonstrating the major ideas and findings that pertain to the topic.

Chapter 3: Conceptual Framework. This chapter summarizes, then synthesizes what has been inferred from the literature review section, in order to reach a conceptual framework for conducting the research. This section is reflective of deductive reasoning, starting broadly and then narrowing the focus. As Shields and Rangarajan (2013) suggest, a conceptual framework is the way ideas are organized in order to achieve a research project's purpose.

Chapter 4: Introduction to the Case Study. This chapter introduces the Delaware Brownfield Development Program (DBDP), providing some background for it and for the overall U.S. brownfield policy as well. This includes an overview of DBDP, its funding mechanisms, challenges it faces, and policy solutions.

Chapter 5: Method, Data, and Analysis. This chapter presents, with sufficient detail, the methodology that is used in the study, so that it can be replicated. It also tries to ground the research's conceptual framework through applying the theoretical model into a real policy context: DBDP which, in turn, helps the theory to be grounded and tested empirically.

Chapter 6: Conclusion and Discussion for Future Research. This chapter presents the summary of the research and its findings. It also evaluates the strengths and weaknesses of the proposed approach. The research model is interpreted in light of the research questions and is discussed in conjunction with other relevant literature. Limitations of interpretation and the implications thereof for further research will be presented here.

Chapter 2

LITERATURE REVIEW

There are a wide range of ways to organize a literature review, depending on what the given literature looks like. This study takes a combination of three major approaches when exploring the concept of policymaking under uncertainty, from an economic development approach: chronological, major theories, and broad-to-specific.

The chronological approach is a primary approach, particularly for topics that have been discussed for a long time and have changed throughout their history, and is applicable specifically for studying the concept of economic development. I have organized it in stages of how the topic has changed over time: the first definition(s) of it, the major time periods of change as researchers discussed it, then how it is thought about today.

When it comes to policy/decision-making and uncertainty, there are multiple models and prominent theories; it is a good idea to outline those that are applied the most in scholarly articles. Accordingly, I have grouped the models by the theoretical framework that each prefers, in order to provide a good overview of the prominent approaches to the concept of uncertainty analysis and policymaking. Then, a broad-to-specific approach is taken, starting with a section on the general issue of policymaking under uncertainty, then narrowing it down to specific topics in the literature that are most specifically similar to the present research question and statement. This seems to be a good way to introduce many backgrounds and related facets of the topic. Taking into account that there is not much published directly on these specific topics, I have tied together many related, broader studies from the published literature. Although not covering these topics and their related areas in their entirety, the purpose of this review is to, briefly, provide background material essential to understanding where this particular work begins and what it is trying to accomplish. Thus, it excludes most theories and frameworks I studied for this section, including only those which are empirically employed by this research.

2.1 Decision-Making Theories

Decision-making is at the heart of policymaking. In each phase of policymaking, decisions are made and executed by responsible parties. The study of this overlaps the domains of multiple academic disciplines: psychology, sociology, economics, political science, mathematics, and statistics. Philosophers contemplate what our decisions say about ourselves and our values, while historians analyze the decisions leaders make at critical points in time. Research into risk springs from a more practical desire to help decision-makers achieve better outcomes. Moreover, while a decent choice does not guarantee a good outcome, such pragmatism has historically paid off. Developing complexity while managing risk, along with a nuanced comprehension of human behavior and advances in technological innovations that support and copy cognitive processes, have enhanced decision-making in many situations.

In decision research, we observe a progression of paradigms, from normative models based on mathematical equations to psychological models aimed at explaining actual behavior. Faced with the imperfectability of decision-making, theorists have sought ways to achieve, if not optimal outcomes, at least acceptable ones. Gigerenzer and Todd (1999) urge us to make a virtue of our limited time and knowledge by mastering simple heuristics; an approach they call "fast and frugal" reasoning. Etzioni (2001) proposes "humble decision-making"; an assortment of non-heroic tactics that include tentativeness, delay, and hedging.

In a word, since policymaking comprises decisions made by responsible parties, an overview of the decision-related frameworks and theories is presented in the following sections, in order to supplement, theoretically, the part of the literature review related to policymaking practice.

This section reviews, very briefly, ten important approaches in modern decision theory that have been developed since the middle of the twentieth century, through contributions from several academic disciplines (for further information on these theories, you are referred to the references section):

1. The rational-comprehensive model assumes a rational and completely informed decision-maker who has vast amounts of information and ability to predict future consequences of decisions made. This process of rational decision-making comprises a number of steps: intelligence gathering, design, choice, and review (Simon, 1977; von Neumann & Morgenstern, 1947; Kreitner & Kinicki, 2001).
2. The bounded rationality model is a procedural decision-making framework which pursues not the best option available, but one that is 'good enough,' through the process of editing and evaluation, in the direction of maximization without ever having it as a deliberate goal (Simon, 1955,1957, 1978, 1995; Lindblom's, 1959; Kahneman & Tversky's, 1982, 1986).

3. Incremental decision-making is a step-by-step evolutionary process in which decision-makers compare among the current state of affairs and develop small adjustments that are completely manageable (Lindblom, 1959; Carayannis & Stokes, 2000).
4. Organizational decision-making is the process by which decisions are influenced by the organization's values, hierarchies, structures, procedural rules, communications, authority, and cultures (March & Simon 1958; March, 1978; Krabuanrat & Phelps, 1998).
5. Mixed-scanning strategy includes elements of both rationalistic and incrementalist approaches. It suggests that organizations plan on two different levels: tactical (detail) and strategic (broad). This means, essentially, scanning the environment on multiple levels and then choosing different strategies and tactics to address what is found there (Etzioni, 1967, 1968, 1986, 2001; Goldberg, 1975).
6. The garbage can model is a decision process that is not a sequence of steps which starts with an issue and concludes with a solution. Rather, solutions are proposed even when issues do not exist; decisions are made without taking care of issues; issues may persevere without being solved; or, just a few issues are solved (Cohen, March, & Olsen, 1972).
7. The individual differences perspective focuses attention on the problem-solving behavior of individuals, as influenced by each individual’s decision-making style, background, and personality. It tries to explain how various individuals might use different methods from one another, or come to different conclusions because of differing

personalities (Mischel, 1968, 2004; Keen & Morton, 1978; Weber, 2001).

8. Naturalistic decision-making (NDM) is a blend of intuition and analysis. Decision-makers generate a single option or course of action and then modify it to meet the demands of the situation. NDM deals with changing conditions and ambiguous information, versus stable conditions and information within the decision event. It may include the need for extensive experience among decision-makers (Klein, 1989, 1999, 2008; Donaldson & Lorsch, 1983; Beach & Lipshitz, 1993).
9. In the Multiple Perspective Approach, technical, organizational, and personal perspectives come together to form a superior basis for decision-making than that of the technical point of view, alone. The choice of perspectives requires judgment, as perspectives are dynamic and change over time. A technical point of view usually dominates in the planning phase; organizational and personal views dominate in the decision and implementation phases. However, there is no guarantee that all relevant perspectives have been included (Mitroff & Linstone, 1993; Linstone, 2003; Turpin & Marais, 2006).
10. Context-dependent rationality model denies the existence of pure rationality in decision-making, within the public domain. It is based on the notion that power defines reality, presenting it as context-dependent wherein the context of rationality is power. That is to say, rationalization presented as rationality is a principal strategy in the exercise of power. In open confrontation, rationality yields to power. In

> other words, interactions between rationality and power tend to stabilize power relations and often even constitute them (Flyvbjerg, 1998).

Although it is now clearly an academic subject in its own right, decision theory is typically pursued by researchers from a number of disciplines, including those who identify themselves as economists, statisticians, psychologists, political and social scientists, as well as philosophers. A political scientist is likely to study voting rules and other aspects of collective decision-making, while a psychologist is likely to study the behavior of individuals in making decisions, and a philosopher will consider the requirements for rationality in decisions. There is substantial overlap however, and the subject has benefitted from the variety of methods that researchers with different backgrounds have applied to the same or similar problems.

Decision theories here are discussed concerning a concept that I prefer to term "gray decision-making," which defines situations relating to the possibility of the existence of a degree of all decision-making approaches through the process. "Gray decision-making" can be also discussed as it relates to a philosophical controversy among three major schools of thought: Positivism, Interpretivism, and Critical Theory. Positivism says that reality is independent and objective, so it should be discovered. Interpretivism says that reality is not objective and is dependent on human interpretation and experience, and that reality is not independent of decision-makers and is socially constructed, thus can have many different meanings. Critical theory, meanwhile, says that reality is separate from the decision-maker and can be never found out. As a result, one can reach the conclusion that the differences in ways of knowing and deciding among Positivism, Interpretivism, and critical theory do not impede decision theory development. To some extent though, they provide a wider space for the future research of decision science. Decision theory has to confront the dilemma caused by this divergence and the corresponding conflict of basic methodology, since its research areas and contents include both natural science properties and humanities characteristics. Consequently, the study of decision theory seems to be better discussed under these three philosophical theories.

Firstly, it accentuates the positive and empirical observations and analyses of social phenomena. Secondly, it requires decision-makers to forge an interpretive understanding of these social objects that pays more attention to the inter-subjectivity and fusion of horizons. At the same time, it realizes that all social phenomena are affected by value ideologies. Decision-makers need to consider such effects on social knowledge construction. Associated with these distinct ways of knowing, the main traditional methodologies of deciding are conceived as the empirical-analytic, the hermeneutic-phenomenological, and the critical-dialectical (Manen, 1977). Individuals in a society can make their decisions by engaging their own knowledge and by using their own methods of applying this knowledge toward judging the given condition. Either individual or society acts in a distinct way, since their respective ways of knowing and ways of deciding are on different tracks. In other words, the acting of individuals or societies reflects, to some extent, the social philosophy with which they are agreed.

Deciding is a cognitive process toward reaching a decision, while acting is a practical process that follows a decision. Under different philosophical systems, the ways of deciding are entirely different from one another. Most decision-makers who ascribe to Positivism choose to accept empirical-analytic methodology. The Positivism applies quantitative research methods mainly, and emphasizes their demonstration upon research hypotheses. Positivism assumes that the research object is an operational non-living thing, rather than a human being with its own subjective consciousness. All social actions of the research object and the causality among social phenomena can be observed, measured, explained, analyzed, and predicted. The corresponding decision-making is then based on this objective and scientific evidence, such as numbers, curves, etc., and without any prejudices from decision-makers and/or researchers. Decision-makers can reach their decision by the objective evidence they find or the prediction they make. The actors in social science under Positivism always follow such decisions, which are based on the knowing they obtained, and that this knowing is gained upon the rules from natural science. Thus, ways of knowing, deciding, and acting are all objective in the view of Positivism. The actors obey these objective rules and methods to operate the decisions with strong scientific evidence, but without any human feelings.

Interpretivism, conversely, criticizes such ways of deciding and acting. It points out that decision-makers and researchers impose their own ideas and wills on the objects being researched under Positivism, which ignores the different conditions and distance between decision-makers and the objects being researched; it puts the researchers' value-preference upon these objects. Although it claims that all the research pursues "objectivity," it actually conceals the real condition of the objects. And so, Interpretivism proposes another way of deciding and acting.

It follows the interpretive and dialectic rule; that is, in the decision-making process, Interpretivismit firstly admits that reality can be affected by location and circumstance conditions. Because of such properties, the deciding process should accentuate the understanding of society's current condition and interpret the social actions themselves. The research results are then created through these understanding and interpretations on social actions. This way of deciding avoids a shortcoming of Positivism which assumes that research objects observed in social science studies are without any emotions, or are "machines" with no freedom or creativity.

Interpretivism applied in decision-making assists people to understand and interpret social actions in a thorough and dialectic way, but it prevents generating a general rule for social behaviors. Researchers can only reach one conclusion per a single current social problem. They can say nothing about the future, or with regard to other similar social problems. Due to this manner of deciding, the way of acting for both individual and society under Interpretivism is also interpretive and condition-based. Both start from daily and common objects, then try to understand the meaning of human behaviors in social actions through interpretation of them and the interactions between them.

Both Positivism and Interpretivism provide some fundamental frameworks to tell people how to know the given reality, how to make decisions based upon it, and how to act with respect to it. Neither make people completely rethink this reality, nor what their own situation ought to be in society.

Critical Theory, however, makes people rethink. It encourages researchers to put the social event in context of the history of human beings, and lets them know that the results of the research will not be the same each time, when engaging different time periods, under various social structures, or with different value concepts imposed by culture, economics, race, etc. In this way, Critical Theory steers researchers toward creating an attitude of critique on social reality, rethinking social reality or social irrationality through critique, as well as trying to build a new social structure. There are two obvious differences between the basis for Critical Theory and that of both Positivism and Interpretivism. First, Critical Theory protests to justify social events from a historical point of view or a vertical perspective, whereas the other two choose a horizontal viewpoint. The other difference, perhaps the more important of the two, is that Critical Theory stimulates people to rethink and to criticize the social reality on their own initiative. This way of deciding and acting fully represents these two differences.

People who accept Critical Theory apply a critical viewpoint onto social events in order to make decisions. They observe events, criticize their irrationality, and rethink why such irrationality (or unfairness) exists, and they will, in turn, act in a socially reconstructive manner when they reach their decisions. The deciding process of Critical Theory comprises absorbing knowledge and rethinking social reality, while the acting process is one of changing either the individual's own status or that of society. All deciding and acting behaviors therein are spontaneous. Critical Theory offers people a way to critically observe and justify things and lets them know, for themselves, what to do next – as opposed to just instructing their behavior in deciding and acting in their social lives.

In summary, "gray decision-making" can be defined as a synthesis of all three philosophical schools and their associated decision-making approaches. That is to say, in decision-making, there may be moments and situations in which a decision-maker is completely informed and has vast amounts of information, as well as the ability to predict the future consequences of specific decisions made. And yet, in other moments and situations, s/he may not be completely informed and may need to procedurally modify and evaluate what is not necessarily the best but, rather, a good enough option in the direction of maximization, without ever having it as a deliberate goal. Sometimes s/he needs to follow a step-by-step evolutionary process in which s/he compares among the current state of affairs and develop small adjustments that are completely manageable.

A public or governmental organization's values, authority, and cultures influence almost all decision-making situations in public affairs. Therefore, decision-makers in this context need to scan the environment on multiple levels (broad and detail,) and then choose relevant strategies and tactics to address what they found there. There are also some situations in which solutions may be proposed even when problems do not exist, and choices are made without solving actual problems. In these situations, a decision process cannot be a sequence of steps that begins with a problem and ends with a solution. Problems may persist without being solved, and just a few out of the total number present may find solutions.

Decision-makers for public affairs need to access a blend of intuition and analysis in many decision-requiring situations. They must generate a single option or course of action, then modify it to meet the demands of the situation. This requires extensive, relevant experience among decision-makers. Decision-making basically demands human judgment, which can be affected by personal preferences and, sometimes, by institutional values. Different decision-making styles used by different people, as influenced by their individual backgrounds and personalities, might be comprised of different methods and come to different conclusions because of differing personalities among them.

Finally, yet significantly, it is important to point out that in all decision situations, decision-makers are influenced by some sort of power relations and structures which inevitably blur the dividing line between rationality and rationalization. So, it is important to define the rationality that is used by decision-makers for public affairs, in terms of the context within which they act. That is to say, public decision-makers should be well aware that rationality yields to power, and those interactions between rationality and power tend to stabilize power relations.

2.2 Policymaking Frameworks and Theories

With the specific goal to see how received wisdoms discover and form expression, as a strategy, it is important to have some theoretical concept of how policy is made and, more comprehensively, what policy really is. The conventional beginning stage for defining policy is that it constitutes the choices or decisions made by policymakers with responsibility for a specific policy area, and that these choices or decisions usually take the form of formal positions or statements on a problem, which, in turn, are then implemented by the bureaucracy.

But, in reality, policy is hard to define from a practical standpoint. As Cunningham indicated: "Policy is rather like the elephant – you know it when you see it but you cannot easily define it" (Cunningham, 1963, cited in Hill, 1997, p.6). As opposed to considering it as just a solitary choice, actualized in a linear way, many policy scholars have indicated that, in reality, policies comprise of a web of interrelated decisions that evolve over time, during the process of their implementation (Hill, 1997) or broad course of in/action (Smith, 1976). Moreover, policy should be viewed as an intrinsically political process, instead of just as the instrumental execution of rational decisions.

Both the approach and the underlying process are instrumental for the success of any efficient policymaking. Its components are governed by different public sector areas, calling for negotiation and concentration whenever hierarchies are absent or unclear. Political science has always been challenged by the relationships among power, policymaking, and knowledge. Many political scientists have conducted their research projects based upon this triad and, to reach a more profound comprehension of policy development. We will undertake a review of literature that leads us to better understand the relationship between institutions, policies, and instruments.

Despite the amount of knowledge produced in policy research, there is a solid proof that policymaking has, in many respects, been more about "muddling through" instead of defining a procedure in which policy science can have an influential role. The goal of developing more efficient policy packages has the implicit consequence of trying to improve the methods and techniques for managing, developing, and controlling the policymaking process (Parsons, 2002).

This part reviewed twenty-three major theories, frameworks, and models of policymaking processes from different scientific disciplines, so as to delineate the public policymaking topic in its entirety:

1. Elite Theory explains public policy in terms of the preferences of the elite class in society. Elites are the people that have power and the ability to allocate value accordingly. Public officials merely carry out policies decided on by these elites. The non-elite public is apathetic, while elites agree upon the norms. Political action is merely symbolic and protects the status quo (Henry, 1992; Bottomore, 1993; Domhoff, 1998; Mills, 1999; Dye, 2001).

2. The Institutional approach focuses on institutional structures, organization, duties, and function, without investigating their impact on public policy, which is considered as an institutional output. The policy is authoritatively determined, enforced, and implemented by these institutions (legitimacy, universality, and coercion). Individuals have little impact upon this, whereas structure/design affects the outcomes. Institutional rules change the conduct of strategic and rational actors seeking self-interested goals (Anderson, 1979; Dye, 1978; Hanekom, 1987; North, 1990).
3. The Policy Stages model divides policy process into stages (agenda setting, policy formation, legitimation, implementation, evaluation, etc.). It was popular in the 1970s and 80s, but is now considered to lack a causal theoretical basis and to be overly simplistic, yet it still has value in policy research (Simon, 1947; Lasswell, 1956; Boyer, 1964; Mack, 1971; Rose, 1973, Jenkins, 1978; Hogwood & Gunn, 1984; Bridgman & Davis, 1998, Bardach, 2005).
4. In Group Theory, public policy is seen as defining group equilibrium. Interest groups and their allies in governments struggle among many others, with legislature/executive oversight to manage group conflict and establish rules of the game. Groups will always form coalitions to press for specific problems. All interests will have a representation opportunity (Bentley, 1908; Latham, 1952; Truman,1971; Dahl, 2005).
5. Rationalism sees public policy in terms of maximum social gain. Policymakers act (with regard to all social, political, economic values

sacrificed or achieved by a policy choice) irrespective of dollar amount to select policy alternative(s) that allow(s) gains to society to exceed benefits by the greatest amount. It assumes that the values preferences of the society as a whole can be known and weighted (Dror, 1968; Anderson, 1979; Simon, 1997; Dye, 2004).

6. Public policy is considered per variations on the past in Incrementalism. Policymakers, legislators, as well as others with a stake in ongoing programs or problems are in charge of policymaking. It offers a continuation of past government activities with only incremental modifications. It accepts the legitimacy of established programs, fears unintended consequences, and may minimize opportunities for radical change due to sunk costs in other existing programs (Lindblom, 1959; Etzioni, 2001; Dror, 1997; Kingdon, 2010).
7. In the Punctuated Equilibrium Model, policy process tends to include long periods of incremental change, punctuated by brief times of significant policy change. The latter happen when opponents manage to fashion a “new policy image or images” and exploit the multiple policy venues of the government (legislatures, courts, executives at the local, state, and federal level) (Baumgartner & Jones, 1993; Baumgartner, Green-Pedersen, & Jones, 2006; Robinson S. E., 2007; True, Jones, & Baumgartner, 2014).
8. In Systems Theory, public policy is understood as a system output. Participants may be individuals, groups, or nations depending upon the scope of the problem. The environment may stimulate inputs into a

political system, producing outputs and feedback. Systems imply an identifiable set of institutions and activities in society that function to transform calls into authoritative decisions requiring the support of the entire society. If the system works as described, then we have a stable political system. If it fails, then we have a dysfunctional one (Dawson & Robinson,1963; Easton, 1965; Dye, 1965; Warne, 2008).

9. The Public Choice Theory describes public policy as collective decision-making by self-interested individuals. Rational self-interested individuals will, in both economics and politics, cooperate to achieve their objectives. People come together in politics for their common benefit; interest groups, like other political actors, pursue their self-interest in the political marketplace. Individuals have sufficient information to understand what is in their best interest (Buchanan, 1984; Shughart II, 2008; Kumar De, 2012).
10. Institutional Rational Choice shows how institutional rules change the behavior of strategic and rational actors pursuing self-interested goals. Arguably the most developed and most widely used in the U.S., this framework understands public policy as sets of institutional arrangements comprised of rules and norms that pattern the interactions and strategies of actors. It starts with individual actors – their preferences, interests, and resources – as the core unit of analysis, and then examines how institutional rules can affect behavior (Kiser & Ostrom, 1982; March & Olsen, 1984; Moe, 1984; Sabatier, 2014; Ostrom, 2014).

11. Critical Theory directs our attention to both the content and practice of discourse within a policy arena. It bridges the divide between macro and micro levels of analysis to explore the impact of macro-level discourses on micro-level behavior. Critical Theory examines the ways in which material and discourse shape power relations among actors in a policy context (Dallmayr, 1976; De Haven-Smith, 1988; Dryzek, 1992; Forester, 1993;Warne, 2008).
12. In Game Theory, public policy denotes a rational choice in competitive situation. Participants are decision-makers who have the decision to make, and the result relies upon the choice made by each (rational choice assumption). Each player has objectives and resources; a strategy forms that can respond to possible actions of the opponent and the payoff values that shape the results of the game; repeated plays should lead to better policy outcomes. Notwithstanding, in most such cases, it is extremely difficult for both policymakers and policy analysts to know the real values of their payoffs, or of their opponents themselves, due to the uncertainty and complexity of actor strategies therein (Morrow, 1994; Kelly, 2003; Fischer & Miller, 2006).
13. The Policy Network Framework focuses on the interdependence of and connections among public and governments sections and other societal actors, aiming to understand their respective policymaking processes and public policy outcomes. This framework tries to explain policy development by analyzing networks of actors concerned with a specific policy issue, across private and public sectors and various levels of

governance. The policy network concept is strongly influenced by inter-organizational theory (Thompson, 1967; Benson, 1978; Stone, 1996; Adam & Kriesi, 2007).

14. The Advocacy Coalition Framework (ACF) explains the interaction of advocacy coalitions (each comprised of actors from various institutions who share a set of policy beliefs). Herein, policy change is understood to be a function of both events outside the subsystem and competitions within them. This framework spends much time mapping the belief systems of policy elites and analyzing the conditions under which policy-oriented learning across coalitions can happen (Sabatier & Jenkins-Smith, 1988, 1993; Sabatier, 2014).
15. The Policy Diffusion Framework was developed to explain variation in the adoption of specific policy innovations across regions of the world or within a country. Factors that likely play roles in policy diffusion include political, cultural, and economic similarities among regions, competition with other areas, as well as geographic and temporary proximity (Berry & Berry, 1990, 1992, 1999; Jensen, 2004; Volden, 2006; Weyland, 2009).
16. Policy Transfer refers to the process of using knowledge regarding policy development, along with all of the administrative arrangements and institutions necessary for their development, and transferring them to another time and/or place. This framework differs from policy diffusion frameworks since it is concerned with process, not substance (Dolowitz & Marsh, 1996; Stone, 2000; Evans, 2013).

17. The Policy Narratives Framework emphasizes how language or discourse shapes policy agendas, and how problems and solutions are understood. It is not external factors that cause policy change but, rather, how these factors are perceived. Policy narratives are constructed "stories" that contain predictable element, as well as strategies whose aim is to influence public opinion toward support for a particular policy preference (Row, 1991; Sutton, 1999; Stone, 2002; Layzer, 2006; Jones & McBeth, 2010).
18. The Multiple Streams Framework explains policy process as composed of three streams of processes and actors: a problem stream (comprising issues and their proponents); a policy stream (consisting of various policy solutions and their proponents); and a politics stream (comprising public officials and elections). These streams often function independently, except during "windows of opportunities" when some, or all, of the streams may cross and cause significant policy change (Cohen, March & Olsen, 1972; Kingdon, 1984, 2010; Zachariadis, 2014).
19. The Arenas of Power Framework introduces public policy as an independent variable that can influence the practice of politics. In this approach, public policies fall into one of four categories: constituent policy, distributive policy, regulatory policy, and redistributive policy. It tries to specify who motivates action or change (Lowi's, 1964, 1972; Lowi, 2009; Purdy, 2012).

20. Constructivist Frameworks focus on the “social construction” of policy problems, policy belief systems, and/or frames of reference, and find greater acceptance in Europe than they do in the U.S. The concept of social construction emerged from the observation that policymakers typically project a certain social aura – either positive or negative – onto the particular segment of the population that will be its target for a policy. When this social construction is positive, it helps to justify the distribution of benefits to this target population. At the same time, penalties are understood to be clearly warranted for segments of the population for whom the social construction is negative (Ingram, Schneider, & Deleon, 2007; Haas, 2011; Sabatier, 2014).
21. Cultural Theory views policy as essentially dominated by four different general ideologies: individualism, hierarchicalism, egalitarianism, and fatalism. As a theory of cultural change, it can be used to anticipate and explain political and policy change (Douglas & Wildavsky, 1982; Swedlow, 2014).
22. Interactive Policymaking is a process whereby government bodies collaborate with other authorities, citizens, and private organizations to develop a policy. It is a complex procedure through which a majority of political and social actors, with diverging interests, interact to formulate, promote, and achieve common goals by means of deploying, exchanging, and mobilizing a range of resources, ideas, and rules (Friedmann, 1973; Grindle & Thomas, 1990, 1991; Healey, 1993,

1997; Innes, 1995; Forester, 1999; Driessen, Glasbergen, & Verdaas, 2001; Fung & Wright, 2003).

23. Chaos and Complexity theory argues that socioeconomic systems sometimes experience highly chaotic and erratic behaviors. In these periods, it becomes almost impossible to predict the future behavior of a system, even when considering its entire past history. That said, such systems may also exhibit "intermittency," that is, periods of simple order which emerge, again and again, out of chaos. This theory also indicates that changes in socioeconomic systems are not necessarily the outcome of external shocks or perturbations but rather, from the natural unfolding of the internal dynamics of the system (Lorenz, 1963; Peat, 1990; Kramser, 1990; Kellert, 1993; Overman, 1996; Medd, 2004; Kayuni, 2010).

As reviewed above, the study of public policy is widely concerned with procedures and processes for identifying and analyzing public problems, as well as the means by which a collective course of in/action is taken by an authoritative decision-making body in response to perceived public issues. Understanding policy processes requires knowledge of the goals and perceptions of hundreds of actors, possibly involving legal, technical, scientific problems over a decade or more, while most of the actors are also actively seeking to propagate their specific spin(s) on events.

Over the past decades, some new theoretical frameworks of policy process have either been developed or extensively modified. This section has tried to, briefly, present most of the more promising ones. All discussed frameworks have been the subject of a fair amount of recent conceptual developments and empirical studies.

Those presented in this section are characterized by their relative richness of approaches and assumptions, sometimes exhibiting similarities in basic theoretical concepts, and sometimes differences therein, since they refer to different parts or stages of the policymaking process, whether in formulation or implementation.

The task of comparing these frameworks is confronted with the following issues. Which part of the public policymaking and implementation process do these frameworks refer to, and what are they trying to explain? What are the key assumptions of each model and how do they function in comparison to one another? Are they alternatives for the study of the same issue, adopting different approaches and perspectives, or are they better understood as complementary ones, in the sense that, when combined, they provide a powerful tool for achieving a more holistic approach towards public policy analysis?

In general, the Stages or Policy Cycles framework has been the popular model for public policymaking research in the past years, although it has been severely criticized for its linearity and ideal representation of process sequencing that, in some cases, is far away from the real system. Most frameworks assume the pure rationality of the individuals involved in the process, which, in light of information asymmetries, is bounded, as are the choices that the individual makes in this context. The stages model is more process-oriented than behavior-oriented, however. Thus, in general terms, the Policy Cycle model constitutes the starting point and then, depending on the unit and level of analysis, as well as how policy change is initiated, the appropriate framework is chosen.

Also interesting is that sometimes different frameworks provide different analysis outputs for the very same case study; one benefit of the multi-lenses approach. Indeed, since policy issues are not clear-cut and the influencing factors are many, this practice is encouraged, at least in the cases that it makes sense.

Another point worth noting is that the lack of empirical evidence with regard to the implementation of various frameworks in real case studies does not allow for the identification of the full spectrum of weaknesses and strengths. This is of particular importance when we consider that some public policymaking frameworks have been revised and improved in light of such studies. For instance, the Advocacy Coalition Framework (AFC) was revised so as to incorporate fruitful criticism of it by the scholarly community, as well as to enhance its applicability and to encompass the particularities of non-US policymaking processes.

Similarly, as far as policy implementation is concerned, theoretical implementation models are either strategic or completely operational, with the tactical or planning level, or else are overlooked or under-treated. Thus, the role of the planning processes and outputs such as official planning documents are "fed" from the strategic or higher level processes, then go on to "feed" the operationalization of the planned policy objectives needs to be taken into account. Furthermore, the different particularities of implementing policies in various administrative and spatial scales comprise another issue that needs to be taken into consideration.

Research in public policy will continue with the quest of identifying the causal mechanisms driving policy change, in a dynamic and evolutionary path, while taking into account actors, actions, structures, networks, behaviors, preferences, and relationships, to ensure efficient and effective policymaking and implementation. Furthermore, the plurality of interests – which, most of the time, conflict with one another – increases the complexity of the process and requires careful and subtle choices to be made in policy measures that will be adopted, whether considered from an acceptability or an implementation effectiveness perspective.

Since policy issues represent different socioeconomic and political contexts and, recognizing that the implementation of the policy is itself an act of policy change, the frameworks that are herein presented provide useful guidelines for policy analysis. In the case of coalitions with great lobbying influence and political entrepreneurs among their membership, the ACF should be preferred over the Punctuated Equilibrium model (where policy monopoly is what characterizes the political monopoly). It also should be noted that the tools with which public policy literature provides us should be used in an optimal and complementary way, so as to minimize individual limitations and weaknesses of these analytical frameworks, while highlighting the particularities and synergies of areas that need to be addressed.

Some policy theories demonstrate that, while a rational framework supports methods by which policy analysts handle their craft, the post-Positivist view (e.g. Cultural Theory and Constructive Theory) still lives on the belief systems of those professionals, as reflected in the experience and education of each individual policy analyst. Determining how one should operate starts with asking what their role has to be.

If the analyst functions as just a human interface to a set of technical algorithms and computational routines, the post-Positivist view would require an acknowledgment that the correct answers derived in the analysis will have an insignificant effect on the final decision. The sense of intellectual prevalence that may correspond to that experience may sustain the analyst for some time. Ultimately, however, a sense of futility may set in. Meanwhile, the image of the policy analysts as technocratic problem-solvers is further undermined in its failure to recognize that to say anything of importance in public policy requires making value judgments, which must then be explained and justified (Majone, 1989).

Some scholars argue that the failure of policy analysis to have an effect on policymaking originates from an individual professional's powerlessness or unwillingness to grasp the political nature of his or her work. If policy analysis is to matter, they argue, it should become an enthusiastic participant of the political process (Heineman et al., 2002). To do as such in a way that does not abandon the rules that gave rise to the policy sciences – i.e., to provide a framework for precisely evaluating public problems and developing effective solutions – is a concern, however, when trying to operationalize the post-Positivist approach. Preceding the boundless rise of the post-Positivist perspective in policy analysis, the name 'policy advocate' crawled from the pages of policy analysis literature. For example, Dye (1992) defined a policy advocate as one who couples policy analysis with the skills of rhetoric, persuasion, organization, and activism to urge a government to seek a specific policy, while only hinting at his despise for these political agents.

The complexity of policymaking process can be partly attributed to the numerous actors and their attributes (objectives, interests, and influence power) and partly to the environment that they act and interact within, approximated by the institutional, organizational, cultural, and socioeconomic parameters that define this environment. Public policy addresses a considerable variety of areas and so accordingly, what is next to be explored in light of the theoretical endowment of the different disciplines illustrated here, is the way in which these problems play out in the context of economic development policy. That is to say, how policy is defined, its evolution throughout the decision-making process, and its final outcomes and impacts when compared to a certain performance concept that will indicate the success of the policy per se, and the process to which it subscribes. The various types of barriers and constraints (with emphasis on the decentralization of policymaking), and the role of policy networks (with a focus on participatory, collaborative, and evidence-based policymaking) are considered quintessential for analyzing the complexity of policymaking and its successes.

As Jones (2009) indicates, it is important to recognize the role of power in forming the knowledge-policy interface. Policy is developed in the interaction between actors, institutions, and discourse at various stages of the process and in various spaces; this determines not only what knowledge is 'utilized' in policy, but how it is utilized. It is critical to reach an understanding of these dynamics so as to inform action that can help the powerless.

Many types of knowledge need to be incorporated in order to make effective policy. Reflexive and critical work needs to be promoted in order to guarantee that it is based on the right values. Moreover, systems should be set up to take advantage of data and information generated in the procedure of implementing development policies and programs, wherein the voices of the poor have to be recognized and respected as not only valid but also instrumentally useful inputs to the policy process. A number of activities can facilitate the incorporation of knowledge into policy: communication, translation, interaction, and exchange, through social influence and intermediaries. The message that is stressed, again and again, is that these are more art than science, requiring not just extensive amounts of judgment but also luck.

Policy approaches that offer longer-term solutions to these need careful and cautious planning, and it is critical to ensure that within this, uptake is not promoted ahead of getting the right influence. It is also crucial to investigate links between knowledge and policy in development from an open-ended stance, that will draw out what the key issues are and when different models of the link are most appropriate. The best way to do this is to structure work around common, straightforward, and clear analytical categories, such as: different national contexts; different levels of policymaking; different sectors; different stages of the policy process; and so on. Through empirical investigation into the links between knowledge and policy in these areas, further light can be shed on the relevance of the different paradigms, the role of the various types and sources of knowledge in development policymaking, and the role of different actors.

The question of how to redress power imbalances in policymaking remains untackled. A common criticism of the political approaches (e.g. policy network, agenda setting, policy narratives, and policy transfer and diffussion) to the policy process is that they do not translate into policy. This remains to be seen, however. Asking a question 'What makes a policy process pro-poor?' for example, and knowing how to promote this, is crucial. In particular, 'discourse' approaches toward understanding knowledge and power in development have yet to be adequately applied, and it is important to how it is that certain ideas have come to be adopted as the dominant thinking in international development policymaking bodies.

The challenge of complexity represents a strong but implicit theme running through the literature. Recognizing that problems faced in development are multidimensional, context-specific, dynamic and uncertain, places certain demands on the policy process theories. In response to them, it is argued that policymakers and practitioners should draw on particular sources of knowledge: knowledge generated in the process of implementation and about these processes; voice and participatory knowledge of those affected by problems; and integration of multiple disciplines and multiple sources of knowledge. They should also use knowledge in a different way; rather than seeing it as providing answers to best practices, it should focus on providing good principles for navigating uncertainty.

Decision-makers need to be given practical tools and capacities to help them make interventions adapted to local contexts and to ongoing signals about their effects, rather than applying narratives and blueprints from the top-down. Enabling this is likely to require institutional change and new organizational forms, to facilitate innovation and to put in place feedback mechanisms to make interventions sensitive to ongoing changes. In turn, this presents a challenge to power structures: the status quo serves certain interests in policymaking, and institutional incentives may make it difficult to either voice concerns about prevailing paradigms or trial new approaches. Despite the fact that complexity has been moving up economic development agendas and some theoretical headway has been made, there is scope for bringing it more solidly into the policy debate.

It is the conclusion of this paper that, among all these policy theories and frameworks, Chaos and Complexity theory best explain uncertainties and complexities in the policymaking process. Chaos theory is a field of study in mathematics, with applications in several disciplines including meteorology, sociology, physics, engineering, economics, biology, and philosophy. Above all, chaos theory seems to provide a way for both comprehension and analysis of many of the non-linearities, uncertainties, and unpredictable parts of social systems behavior (Kramser, 1990).

Chaos theory studies the behavior of dynamic systems that are highly sensitive to initial conditions – a response popularly referred to as the “butterfly effect.” [The name of the butterfly effect, coined by Edward Lorenz (1963) is derived from the metaphorical example of the details of a hurricane being influenced by minor perturbations such as the flapping of the wings of a distant butterfly several weeks earlier.]

Considering the variety of actors, it becomes obvious to most analysts that the policy environment is unpredictable, complex, and confusing, much the same as chaos. But, chaos and complexity theory provides an appreciation for, as opposed to a doubt of, chaos and uncertainty. It further emphasizes that real change and new structures are found in the very chaos managers and policymakers try to prevent (Overman, 1996). This theory is not entirely new to policy analysis. Policy systems theory forms the basis of chaos theory which, as Overman (1996) observes, has its roots in simple systems theory and owes much to this approach. It has been developed further, however, by generating its own perspectives on the comprehension of policy procedures.

A system is a set of parts which interact with each other and operate as a unified whole. As discussed before, the policy systems approach argues that government or decision-makers receive inputs in the form of demands or support from the social, economic, and political environment that they process and then make choices or take actions, which are referred to as outputs. An output may also be viewed as input through the feedback process. The Policy Systems Framework asserts that it is the goal of the system to achieve and sustain a state of equilibrium, and therefore to guarantee policy stability and progress. Chaos theory argues that policy stability is hardly achieved through this and, furthermore, has not necessarily even been the objective of said policy system. As a rule, they are in a state of disequilibrium, which seemingly leads to a chaotic situation. Along these lines, Chaos theory can be understood as an evolutionary systems theory (Kayuni, 2010).

David Peat (1990) indicates that a non-linear system can, over its lifespan, enter into a series of unique economic behaviors and regimes. Moreover, it must be emphasized that these changes need not always be the outcome of external shocks or perturbations, but may also derive from the natural unfolding of internal dynamics within the system itself. Policymakers should therefore consider that a system may at some point be insensitive to control, while at another point be infinitely sensitive. And, that major changes in a system may not always be the result of an external event. A seemingly-negligible effect may, given time, swamp the behavior of the entire system. When a system, controlled by a particular policy, undergoes a sudden radical change, one natually looks for some external cause or factor. But, what if this radical fluctuation or qualitative change has nothing to do with external events or circumstances, but is instead endogenous – the result of purely internal dynamics? A small regular, periodic internal fluctuation can suddenly swamp a system, and therefore the iteration of an output into the next cycle will result in qualitatively new behavior. It is critical to be able to distinguish endogenous from exogenous events and factors. Systems sometimes enter into very chaotic and erratic regions. In such cases, it becomes impossible to predict the future circumstance and behavior of the system, even when considering its whole history.

A chaotic system may seem wholly random and unpredictable in its behavior, impervious to corrective measures, but researchers are now finding that what is called deterministic chaos represents certain regularities. For instance, erratic swings, while totally unpredictable and random, may nevertheless be confined to a particular, limited region called a chaotic, or strange, attractor. So, while the moment-to-moment behavior of the system is unpredictable and random, uncovering the geometry of strange attractors provides information about their whole range of behavior. It is also a matter of debate as to whether a chaotic system should be viewed as totally devoid of any order or, instead, as exhibiting a very complex order (Peat, 1990).

The link between chaos and complexity is complicated by the fact that current literature on complexity science provides little detail to assist in the understanding complexity itself (Medd, 2004). This is considerably clear regarding the difficulty in providing definitions and measurements of complexity (Medd, 2004). Thus, the connection between complexity and chaos has always been problematic.

Luhmann (in Medd, 2004) asserts that we live in a world in which it is not quite possible to connect the totality of anything. Chaos' link with complexity comes about because it views a system as constantly transforming to a higher level of complexity, and making changes therewith that are irreversible. A dynamic system may therefore appear to be chaotic; its identity, history, and sense of purpose define its boundaries and guide its evolution and growth (Bechtold, 1997). As Cohen & Stewart (1994) suggest, one of the great surprises of chaos theory is the discovery of totally new simplicities; that is, deep universal patterns which are concealed within the erratic behavior of chaotic dynamical systems. Specifically, this complexity is ultimately achieved when a dynamic system that is self-organizing (in how it orders and structures itself) grows and changes.

Bechtold (1997) points out that the perceived progression in complexity-chaos theory is that a policy system begins at an optimistic level of high predictability and stability and, as the predictability horizon is achieved, small uncertainties will start to crawl into the system, which will tend to twist or distort the rules on which the initial predictions were founded on. Ultimately, these uncertainties will be self-accelerating and lead, inevitably, to the point of rapid move into chaos. The edge of chaos is somewhere between disorder and order, or, between a complex and chaotic situation (Cloete, 2004). According to complexity-chaos theory, this offers the best scenario for an organization or policy system, since there is a greater degree of "innovativeness and creativity," (Praught, 2004) hence, the term "thriving on the edges of chaos." Bechtold (1997) indicates that a system creates its own future, betters itself, and constantly adapts to its environment, based on its information and intelligence. For this purpose, it needs to tap not only its more stable and predictable parts, but also the ones at the edge of chaos that are random, chaotic, or even dissipative. Through the freedom it has in operating with an open flow of information from its edge, the system stays connected to its simultaneously-evolving environment, and enhances its ability to handle environmental changes. Table 2-1 summarizes the key components of conventional, chaotic, and complex policy situations.

Table 2-1- Differences amongst Conventional, Chaotic, and Complex Policy (Kayuni, 2010)

Conventional (Traditional) policy system	**Chaotic policy situation**	**Complex policy situation**
Control	Chaos	Complex
Order	Disorder	Order within chaos
Objective	Subjective	Interconnected
Safe	Unsafe	Dynamic
Certain	Uncertain	Adaptive
Predictable	Unpredictable	Pattern
One best way	Any way	Multiple approach
Structured	Unstructured	Codetermined
Equilibrium or homeostasis	Disequilibrium	Dissipative Structures
Holism: the whole is equal to the sum of the parts	Irreducibility	Inexplicable by the parts
Feedback	Irreversibility	Self-regulating

Roe (1991) argues that when policymakers think about alternative policy approaches, they are observed to simplify issues in order to understand a situation better. This is often an attempt to develop some order out of chaos, that is, to weed out some threads of causation from very complex situations. While often necessary, the main drawback of this strategy is that it can go too far, misrepresenting a situation and producing false information, upon which decisions are then based. Leach and Mearns (1996) state that traditional rationality and wisdom obscure a plurality of other possible views and lead, ultimately, to misguided or even flawed development policy.

About policy changes, Parsons (1995) argues that public policy scholars face a contradictory and complex body of analyses. All policy choices involve both risk and uncertainty, which are heightened by the fact that public policy analysis is shrouded in three methodological problems (Grindle & Thomas,1991; Nagel & Treaser, 2004):

1. Complexity that leads to problems associated with multiple conflicting criteria and conditions of multidimensional measurement;
2. Uncertainty of the consequences of current decisions;
3. Effectuality, or, how to ably communicate in a convincing way and, hence, convince public policymakers.

Based on the three observations, uncertainty is probably the most common problem that policymakers and analysts are confronted with. Taking into consideration the assertion by the complexity-chaos theory that even a minor change in a policy can have huge effects that will lead to unexpected outcomes. As complex systems change over time, the potential manifestation of a crisis cannot be underestimated (Kayuni, 2010).

Referring to change in American policymaking, stasis, rather than crisis, characterizes most policy areas. However, crises do still often occur (True et al., 2014). Embedded in them is chaos. Crisis forms a critical element in the policy procedure and, according to chaos theory, it ushers in an institution or the policy problem to be correctly placed on the edges of chaos. Grindle & Thomas (1991) argue that if elites perceive a crisis, the issue will command the attention of senior policymakers and, in this case, their decisions are likely to be more radical or innovative than when a crisis does not exist. Thus, action will often come quite quickly. Conversely, if there is no perception of crisis, the stakes for government are lower (Kayuni, 2010).

2.3 Regional Economic Development

Regional economic development, as a policy field, offers a window into the evolving interaction between the spatial distribution of economic activities and the multiple levels of government. Planning and developing relevant policies for regions, localities, and places have been fundamental issues for politicians, policymakers, academics, researchers, and practitioners. This task is getting increasingly problematic in the face of rapid global economic change that has now become even more complicated, and it indicates a need to understand the regional dimension of growth more than ever. This section offers a review of the main concepts explored in regional economic development literature. This includes explaining the rationale for a regional approach to development, in the context of growing globalization of the world economy. It also tries to explain the challenges that analysts and researchers experience when they want to translate the processes that shape regional economies into policies and programs to serve at both the national and regional levels.

2.3.1 Regional Economic Development in a Global Context

Over the past decades, the process of globalization resulted in major changes in the economic landscape. Beginning in the 1980s, unprecedented growth in the volumes of global trade and capital mobility across countries has drastically changed pre-existing equilibria, based on the strong role of nation-states in regulating, orienting, and restricting such flows. Globalization gradually frayed nation-state level economic institutions, as they were known in the post World War II era. At the same time, it lead to the progressive evolution of the industrial organization paradigm of mass production, to more efficient and flexible production systems, as a way to respond to the increasingly competitive pressure from global markets. As a result, standardized production has become progressively obsolete within what has become a specialized system that is more flexible and more likely to demand changes which allow firms and corporations to survive the uncertainty of international challenges.

Along with these changes, the importance of Multinational Enterprises (MNEs) has risen. This has contributed further to the weakening of national economic institutions and borders, in both managing and controlling international flows of capital and goods. The increased importance of MNEs seems to be a reaction to the changes determined by the process of globalization, as a bypass for firms and corporations in order for them to be able to adapt their industrial governance and competitiveness to the new economic order. The magnitude of this process has encouraged some researchers to conceive of the globalized world as a flat world (Friedman T., 2005) and to evoke notions such as the end of geography (O'Brien, 1992) and the death of distance (Cairncross, 1997). According to this view, globalization has basically eroded the differences between places through the worldwide reach of its socioeconomic and technological forces. In that capacity, locations appear to be emptied of their specific characteristics, while local actors lose the capacity to form regional destinies.

Enhancements in communication technologies, as well as the fall in transportation costs, decrease the significance of physical distance with regard to the location of productive activities. Consequently, economic development may occur virtually anywhere, without any role being played by spatial/local factors. A convergence in incomes across regions and countries would thus represent the ultimate result of globalization. This conceptualization, of both the nature and trajectory of the process of globalization, is in clear contrast with the empirical evidence and theoretical insights developed by a large body of literature in evolutionary and institutional economics, economic geography, and internal business studies (Ascani, Crescenzi, & Iammarino, 2012). In all these disciplines, there is increasing awareness that the process of globalization is progressively increasing the role of local actors and the importance of regional processes in forming development trajectories. It is apparent that some regions have followed successful post-Fordist development paths.

Some scholars stress the experience of flexible specialization, trust, and face-to-face social relationships in the industry of 'Third Italy' as a case study of regional economic success, in an era of worldwide economic expansion (Bagnasco, 1977; Piore & Sabel, 1984). Ultimately, the importance of local specificities and their relative advantages has increased, rather than been marginalized, in the context of increasing globalization and functional economic integration (Storper, 1995). The emergence of a regional world is, essentially, underpinned by the spatially-bounded localized forces that stimulate economic development and drive welfare to accumulate in particular areas within countries. Thus, economic development that stems from industrial renovation after mass production also appears to match with regional development (Amin & Thrift, 1992). In that capacity, regardless of some evidence for convergence among nations and countries, in the most recent decades (Sala-i-Martin, 2006), disparities within countries have expanded in various cases (Brakman &van Marrevijk, 2008), proposing that solid spatial agglomeration portrays economic development patterns at the regional level, and that geography and distance significantly matter in a global world.

Such insights and propositions also propose that national economic growth is driven by the performance of a small number of local economies within nation-states. Urban areas and metropolitan regions seem to be the physical loci where economic growth are most likely to concentrate. In reality, most skilled labor, industrial production, and higher wages tend to concentrate in cities and urban areas where geographical proximity among economic agents facilitates communication and interaction, and also creates an environment that provides frequent flows and interaction of ideas. This is basically comprised of the Marshallian view of agglomeration economies, identified by their knowledge diffusion and transfer. These important interactions, which give rise to positive externalities in the form of knowledge and technology spillovers, are critical for economic development (Grossman & Helpman, 1991; Coe & Helpman, 1995). Moreover, empirical evidence proposes that knowledge externalities provide a better explanation for spatially-uneven economic and innovative performance (Jaffe et al., 1993; Audretsch & Feldman, 1996).

Following this line of reasoning, knowledge-intensive activities become fundamental to economic performance, following distinctive patterns of geographical distribution and contributing to the generation of localized sources of competitive advantage (Rodríguez-Pose & Crescenzi, 2008). Essentially, path-dependent and cumulative processes of agglomeration of knowledge form the dissemination of welfare across space, proposing the presence of a more complex economic geography than that of a so-called flat world. Such development is thus prodded at the local level, where knowledge externalities are produced.

As codified knowledge becomes more broadly accessible, due to enhancements in communication technologies, tacit and implicit knowledge becomes spatially bounded. Its economic value has even increased, as a consequence of its relative scarcity in regard to codified knowledge (Sonn & Storper, 2008). Similarly, while globalization has determined a net fall of the transmission costs of codified knowledge, the economically valuable knowledge that is tacit and complex by nature increasingly requires spatial proximity to be transferred, absorbed, and successfully reused (McCann, 2008). Fast-growing locations are not closed, independent economies, but rather, are most likely to be areas hosting MNEs and their international investment, which critically links the region with foreign resources and markets (McCann & Acs, 2009). The mobility of global capital has increased to an outstanding degree in the past decades.

While the dispersion of global investments across different countries and nations has increased and expanded, it still tends to concentrate in particular regions within these countries. Each area where MNEs invest, along these lines, becomes part of a global production network (GPN) at various phases of the production process (Ernst & Kim, 2002) or, as it has been recommended, neo-Marshallian hubs within global networks (Amin & Thrift, 1992). Furthermore, those regions and areas which are involved in such GPNs may, likewise, benefit from channels for both global knowledge diffusion and local capacity building. The creation and sustaining of external linkages, such as hosting global investment, to access external innovation and knowledge, is recognized to be a key method for local economies to supplement and enrich locally-generated knowledge therein (Bathelt, Malmberg, & Maskell, 2004).

The boom of the host regions and areas, in securing the advantages of knowledge diffusion and transfer through international networks, critically depends on structural and fundamental characteristics arising from the local knowledge-base and absorptive capability to institutional and social infrastructure. In this regard, the system of innovation, at the local level, provides a critical element of the attraction and exploitation of external knowledge at the local level. The system of innovation approach, when applied to developed countries, implies that the linkages between organizations and actors within a framework of favorable institutional and social contexts elevates the creation of new knowledge, the positive dynamics of learning, and their exploitation (Ascani, Crescenzi, & Iammarino, 2012). These dynamics are systemic in nature, as the innovation process is a far-from linear phenomenon. On the contrary, it is the result of complex patterns of interactions among various elements acting together, based on common norms and historical inheritance.

As mentioned, in combination with highly localized drivers of economic performance, the process of globalization has stressed the developmental effect of firms' and corporations' international reach, to determine the degree of worldwide connectivity and global competitiveness of their host regions and areas (McCann & Acs, 2009). What emerges from this picture is, fundamentally, that increasing global trade and capital mobility critically sharpen the regional character of development processes, stressing the role of geographical proximity in forming successful economic performance. Obviously, it is not those factors alone that generate growth. Rather, they are vital factors in forming the location behavior of economic agents, as well as the intensity of connections between them. That is to say, geographical proximity can provide the necessary environment for other positive forces to happen (Rodríguez-Pose & Crescenzi, 2008) or, comparatively, it provides a setting favorable to development, through the occurrence of complex and intangible untraded interdependencies among economic actors (Storper, 1995).

2.3.2 Regional Economic Development and Sustainability

Today, a core aim of many public policies around the world is to support and promote sustainable development. As an important global agenda, the need for this in all countries was widely discussed for the first time in 1987 (WCED, 1987). It has arisen because of the increase in environmental problems, which have resulted from rapid development since Industrial Revolution. Many of the planet's ecosystems have been degraded, species have been threatened, and global warming has become increasingly apparent. To slow and mitigate the harm caused by rapid human development, it is crucial that our actions become more sustainable.

As Wheeler (2004) indicates, the concept of "sustainable development" has been employed to denote alternatives to traditional patterns of economic, social, and physical development in both developed and developing countries. These alternatives can mitigate problems such as pollution, exhaustion of natural resources, overpopulation, loss of species, destruction of ecosystems, and the degradation of human living conditions. Growth management and sustainable development are widely considered essential to maintaining the quality of life. However, determining what and how policies, decisions, and actions would guarantee this sustainability is complicated, and needs to deal with the fuzzy world of uncertainties.

Sustainability can be studied and managed over many levels or frames of space and time, in many contexts of economic, social, and environmental organization. The scope encompasses from the total carrying capacity (sustainability) of planet Earth to the sustainability of economic sectors, ecosystems, countries, states, metropolitan areas, municipalities, neighborhoods, home gardens, individual lives, personal lifestyles, behavior patterns, goods and services, occupations, and so on. In short, it can entail the full compass of human and biological activity, or any part of it (Conceptual Framework Working Group of The Millennium Ecosystem Assessment, 2003). As Daniel Botkin has stated: "We see a landscape that is always in flux, changing over many scales of time and space" (Botkin, 1990, p. 84). However, Wheeler (2009) believes that the regional scale is vitally important to sustainability planning. He reiterates that while regions can be a source of great dynamism and initiative, their growth is problematic for sustainable development in a number of ways which differ from the similar growth patterns contained within more localized communities.

As discussed above, sustainability plays a key role in discussions, research, and planning, and this discourse “is being more widely deployed as an urban and regional development strategy than ever before” (Krueger & Gibbs, 2007, p. 1). These concepts, however, are not free from criticism. After the introduction of the term “sustainable development” in 1980, much has been written on sustainability in the literature. In 1981 for example, Brown (1981) took up the threat in his book “Building A Sustainable Society,” wherein he explains several environmental issues and how we can develop solutions in order to create a more sustainable society and environment. The term sustainable development would become more commonplace, as a “bandwagon” for many politicians and scientists to jump on, with the report, “Our common future,” written by the World Commission (also known as Brundtland Commission) on Environment and Development, published in 1987. It states, “Sustainable development is [a] development that meets the needs of the present [,] without compromising the ability of future generations to meet their own needs” (World Commission On Environment & Development, 1987, p. 43). Zuindeau (2006) writes, “Current development should not harm the interests of future generations” (Zuindeau, 2006, p. 461), which comes very close to the Brundtland Commission’s definition.

Today, the terms sustainable development and sustainability imply three dimension as core components thereof: economic, social, and environmental (or ecological) (Munier, 2005; Basiago, 1999). It is also crucial to note that sustainability can be viewed, also, as sustaining the present. But, that is neither what it is or has to be about. Sustaining the current situation or status quo would actually mean that the destruction of the environment and related inequalities would just go on like they are (Buckingham, 2007).

The three aforementioned dimensions of sustainability are applied in various ways. Critical scholars carry on the most crucial arguments around the terms of sustainable development and sustainability, and the theoretical use thereof, analyzing the links between social and ecological issues and economic solutions. Much of the research body in the economic and ecological field of sustainability is "hands on," concentrating on environmental and ecological issues to seek solutions to them. Ecological/environmental sustainability, in an urban setting, often means in-field measurements for factors such as instances of air pollution, as in the article "Life satisfaction and air quality in London" (MacKerron & Mourato, 2008). On a more regional scale, studies about the industrial metabolism indicate material transformations and flows caused by various industries. The fact that there are many different perspectives of what ecological/environmental sustainability is contributes to the different interpretations thereof.

The body of research on economic sustainable development is, in the theoretical dimension, similar to the literature about the ecological/environmental side. It comprises more "hands on" concepts and theories built on development theory with frameworks from economics but also to explain how cities, regions, or states can achieve economic progress and sustainable economic development. The key difference between economic and ecological/environmental sustainability is that the theoretical frameworks of the former are grounded on more broad theoretical and conceptual models and perspectives than the latter.

The term “economic sustainability” can be defined as economic progress and economic growth, although “Economic growth does not necessarily mean a better living...” (Munier, 2005, p. 17). Munier further explains that economic sustainable development is a growth that puts profit into action to create a more sustainable society, ecological modernization, higher wages, more effective technologies, and so on. However, the economic progress or growth has to be sustainable for future generations as well, so that they can have work and economic progress for themselves, too. This means that natural capital, which cannot be replaced by human-made capital, should be preserved for future generations. It is also crucial to point out that economic progress is critical for questions of overall welfare, and therefore for social sustainability.

Social sustainability is less represented in the hands-on literature about sustainable development, but it is more frequent within important discussions about social problems in general, in urban and regional contexts, and among theoretical/ideological perspectives. The literature about the other two perspectives/dimensions of sustainability, which are more policy-oriented, is more practical and less critical about the development of societies. Social sustainability is often related to problems such as poverty, social exclusion, unemployment (although this has also to do with economic sustainability), inequalities, and the like, for not only the present but also for future generations (Ekins, 2008; Partridge, 2005). At a general or basic level, social sustainability can be seen as “a system of social organization that alleviates poverty.” However, at a more fundamental level, it “establishes the nexus between social conditions (such as poverty) and environmental decay” (Basiago, 1999, p. 152).

In sum, there are many different interpretations of what sustainable development and sustainability mean and how these concepts should be applied in a practical context in policymaking and planning. Due to their broad definition however, their interpretations are often in conflict with each other and mean many different things, which lead to problems when trying to engage sustainable development and sustainability in policymaking.

One of the main goals in planning for sustainable development is to identify and choose the most sustainable scenario and policy from among different alternatives. Facilitating and resolving such difficult decision situations can be complex. Large-scale policy and planning interventions, population, and environments share several general features: uncertainty, complexity, and dynamics. Standard analytical methods and models go far toward adequately modeling dynamics and complexity, but incorporating uncertainty presents additional difficulties. Missing or inaccurate information, errors in forecasting future data, and external uncontrollable occurrences all introduce uncertainty. Ignoring uncertainty and complexity, and their potential costs, can prove perilous and result in irreversible harm to the environment and society. To make decision models effective and responsive to uncertainty, policymakers must actively take these into consideration. Thus, additional research needs to be conducted in order to acquire further knowledge and understanding of different types and sources of uncertainty (e.g., knowledge, variability, decision, and linguistic) inherent in planning for sustainable development, and how these sources of uncertainty impact the quality of policies rendered.

2.3.3 Regional Economic Development in Federal Policies

Economic development is a top priority of the federal government. Over the past decades, the United States Congress has made an array of policies and programs for economic development in various regions and communities. These have sprung up at various times, with different goals, objectives, and action plans. Taken together, they add up to a high priority and represent much investment. In the course of recent decades, the process of globalization has resulted in significant changes in the economic landscape.

Globalization of markets for capital, currencies, goods, and services has dramatically changed the rules of the game in economic development. The issue is very straightforward: most federal policies and programs for economic development were developed for the economy of the past century, not the 21st century. The primary goal of the federal government is to spur the macro economy, and many specialists conclude that vibrant regional economies beef up macroeconomic growth. Others assume, however, that the ability of the U.S. economy to compete on the international stage is determined by how well individual regions of the nation compete; in other words, that the drivers of national economic competitiveness are now regional in nature. Focusing federal policy on regional development, therefore, ensures profits for everyone (Drabenstott, 2006).

Even economists who write the textbooks on economic development lack consensus on a singular definition, although there is general acceptance among them that economic development does include both the growth and restructuring of an economy to improve the economic well-being of people who live in a specific place (IEDC, 2005). While employment and jobs are the means to this goal, economists believe that its main outcomes are increasing income and wealth. The process of economic development includes combining the capital, labor, and technology found in that place in innovative ways that prompt to rising economic welfare (Blair, 1995; Blakely & Bradshaw, 2002; Cheshire & Malecki, 2004).

Among the primary actors in the economic development process are the government and the public sector. Government's role is that of referee, setting up the "rules of the game" through business, legal, and regulatory systems. It also makes essential investments that the private sector would not make (i.e. public goods). These investments take many forms but, overall, serve to improve a region's infrastructure, workforce, and technology (IEDC, 2005). In the United States, all levels of government – local, state, and federal – are involved in shaping economic development. The United States Government Accountability Office (GAO) (2000) describes an economic development program that does one or more of the following things:

- Plan and develop economic development strategies;
- Construct or renovate nonresidential buildings;
- Establish business incubators;
- Construct industrial parks;
- Construct and repair roads and streets; and
- Construct water and sewer systems.

However, these development initiatives target infrastructure as the core driver for economic development. Today, most economists have a much broader perspective on how government forms and drives development. Along these lines, the GAO list can be extended to encompass the following items as well: technical assistance and technology transfer, business development, workforce training, and other forms of infrastructure not included above. Lastly, it should be accepted that defining federal policies and programs which have impacts on economic development is more of an art than a science.

As confirmed by a research project conducted by The Center for the Study of Rural America that examined 180 federal government programs on the current federal economic development policy, the federal government's bulk of development policies and programs represent a highly dispersed economic development policy. The programs rely on nearly every corner of the government, including the Department of Defense. No single agency and department coordinates or oversees the overall effort. Indeed, many agencies are engaged in the same activities, in parallel. For instance, there are three extension services in the federal government: one in the Department of Commerce, one in the Department of Agriculture, and one in the Department of Defense. Those 180 programs have increased around very broadly scattered pieces of legislation. Development efforts focused on housing, for example, occur in four distinct departments (Drabenstott, 2006).

Today, most federal programs are founded based on the notion that all regions grow in the same way. But, it is important to note that the U.S. regional development outlook is no longer homogeneous. It is increasingly diverse. Economic development policies and strategies are now steered by a region's unique market opportunities and its distinct economic assets. That will drive demand for industrial development in some regions, to be sure, but in far fewer than in the past. Tourism, high technology, and services have now bloomed as economic drivers alongside industry.

In brief, federal policy for economic development is a comprehensive and widespread activity in D.C., spreading across most of the federal government entities – that is not by coincidence. Several hundred laws and regulations have posited the vast variety of programs and policies where they are today. Their scope is impressive, as is their underlying assumption that the U.S. economic development outlook is largely homogeneous. Significantly more flexibility and adaptability will be required for a 21st century development landscape that represents a much richer range of development outcomes.

Another approach to portray the federal government's economic development policy is to trace the money flow. The Office of Management and Budget can help us with that. One of its 20 general classifications of federal spending is "community and regional development." This includes economic development programs focused on specific places (i.e. regional development programs). It does not, however, include the full sweep of economic development programs that invest in infrastructure, but without a specific place in mind (called broad-based development programs) (Drabenstott, 2006). With an overwhelming emphasis on industrial development, funding for physical infrastructure is a top priority.

For instance, from 2000 to 2004, almost $190 billion was spent in each of those years on development. This was more than one out of every four federal dollars spent. A significant portion of this spending went into critical efforts, such as highways and education; programs that aimed at developing the economy broadly, not in any given place. The federal government role in programs aimed at economic development in specific locations, or regional development, was much smaller. In those five years, such spending increased to up to $9 billion a year. Much of that was spent through the Department of Housing & Urban Development's Community Development Block Grant program (Drabenstott, 2006).

Experts have been struggling with economic development for a long time. It remains a continuously evolving field of study and discovery, constantly reformed by innovations in markets, human behavior, and technology. While many challenging questions are still being examined, a consensus has nearly been achieved that regional economic development is driven today by principles very different from the ones that guided economists in the 20th century. These new principles have significant value for public policy, as benchmarks to evaluate where it is today and as a guide to where it may go in the future.

Over the past half century, economic development thinking has passed through three eras (Table 2-2); that is, three periods of thinking and practice with major overlap among them, which can inform the future. Industrial recruiting (known as smokestack chasing), was dominant from the 1950s through the 1980s, with its objective to bring factories to towns. Then, the onset of deregulation in the early 1980s ushered in an era of cost competition. It was a driving force as policy officials developed ways to drive down the costs and expenses of doing business. Since the early 1990s, experts have recognized that regional economies should constantly create new value in international markets by exploiting their indigenous strengths and relative advantages. This is a complex process, but one that many economists now refer to as regional competitiveness.

Table 2-2- Three Eras in Regional Economic Development Theory & Practice (Drabenstott, 2006, p:124)

	Industrial recruiting 1950s to early 1980s	**Cost competition Early 1980s to early 1990s**	**Regional competitiveness Early 1990s to present**
Driver	Export base	Scale economies	Innovation & entrepreneurship
Strategies	Financial incentives to firms Industrial parks	Industry consolidation & cost-cutting deregulation	Entrepreneurship Clusters Commercializing research
Keys to Success	Government funds for subsidies and tax breaks for Industrial infrastructure	Health of existing industries	Distinct regional assets, such as Human capital and Higher Education Amenities

In sum, local, state, and federal economic development policies are not currently designed to help regions build and sustain a competitive edge. Changing that will require policy shifts in Washington, as well as within state and local governments. Federal policy is a good place to start, since it creates the broadest framing for public policy on economic development. Putting regional competitiveness at the heart of federal policy will align it with what drives regional growth in the 21st century. It will also be the first time that federal policy has really had a unifying goal. In that respect, it should make federal programs both more effective and more efficient, a salutary outcome in a period of large budget deficits.

The current economic development policy reflects a conventional goal of recruiting and building infrastructure – primarily for an industrial economy. Fresh thought needs to be given to finding the right goal to guide policy in the future. Based on what is known about what makes regions grow in the 21st century, the best candidate for this goal is the following: to help regions find and sustain a competitive edge in rapidly changing markets. This goal would align economic development policy with state-of-the-art economic theory. It would also be consistent with a commitment often reflected in past development efforts – equal access to economic opportunity for all. And, it would elevate the need for the nation as a whole to engage what may be its biggest economic challenge – staying competitive on a global stage. Making regional competitiveness a goal for federal development policy will require constructing a coherent policy framework, rethinking the federal (and state and local) role in regional development, and "proofing" other federal policies for their impact on regions.

2.3.4 Discussion and Conclusion

As discussed in this section, the increasing interest in regional development interventions has indicated the importance and urgency of the need to revisit development policies in accordance with global socioeconomic trends. This drive has provided compelling insights into policy but has neglected to address a dominant paradigm for development interventions. While some place-neutral or spatially-blind policies may represent the best way to spur economic growth and facilitate the catch-up of lagging regions, for others, even the best spatially-blind development policy may be undermined by poor institutional environments and, along these lines, place-based options are needed (Barca, McCann, & Rodríguez-Pose, 2012).

This discussion has revolved around the essential question of whether efficiency has to be concentrated in the core or there is potential for development and growth in every territory and locality. Place-based discussions infer that taking advantage of unused potential in intermediate and lagging regions is not only a deterrent for aggregate growth, but can really improve development and growth at both the national and local levels (Farole, Rodrıguez-Pose, & Storper, 2011). Increasing the capability of noncore peripheral areas in an integrated way may upgrade national growth by a significant amount. In the meantime, major urban centers will continue to grow without the need of major policy intervention, although some significant long-term challenges related to the difficulties associated with the social inclusion issues, as well as management of the environment, will require considerable attention (Garcilazo, Martins, & Tompson, 2010).

The place-based argument suggests that development policies have to concentrate on mechanisms that develop local potential and spur innovative ideas by the interaction of both local and general knowledge, and endogenous and exogenous players in the design and delivery of public policies (Rodrik, 2005; OECD, 2009). This will build multi-sectoral policy framework which involves the provision of various bundles of public goods to various localities. As a result, evaluating development policy solely by convergence criteria alone makes little or no sense (Rodrıguez-Pose & Fratesi, 2004) because convergence does not capture the socioeconomic objectives of the policy: to stress institutional and learning behavior. What subsequently arises from this discussion is the need to make development policies more capable of being responsive to contemporary challenges, and more efficient and effective than past interventions. The place-based discussion infers that this can only be accomplished by attempting to make development and growth policies more "place-aware" by considering the vast variety of factors and elements in diverse geographical locations that may impact the potential returns of policies. Only by making policies that are both people- and place-based will a solid case for regional development intervention be made.

On the other hand, the regional economic development literature focuses on the processes that favor learning and new knowledge creation at the local level. One particularly relevant role is played by the socio-institutional and cultural characteristics of regions, which drive the economic behavior and attitudes of local actors by providing the appropriate structural and relational assets to the regional economy (Storper, 1997; Scott & Storper, 2003). This makes innovation and development no longer a linear but a multidimensional process, by influencing local rules, relations, and the capability to re-use knowledge. Globalization sharpens the localized nature of innovation and development, rather diminishing it, since prosperous regions become capable of exploiting external knowledge toward serving global markets. Recognizing that development is a localized procedure relying on spatially-bounded components as well as past trajectories (i.e. path dependency) provides an explanation for inequalities between regions and areas within countries. Localized bottom-up policies and initiatives are delicately developed to consider forces that influence development and innovation in particular locations. Such policies and strategies are in contrast with conventional and centralized top-down interventions that suggest the same general measures of economic policy regardless of local characteristics and conditions.

Crescenzi and Rodríguez-Pose (2011) argue for a reconciliation of top-down and bottom-up policies to approach regional development problems from a meso-level perspective. This ‘integrated framework’ makes it possible to analyze with the same theoritical tool various regions, and to recognize both specificities in the functioning of the economic system related to particular places, and regularities across space and time, in the development trajectories of various locations. The increasing awareness about the relevance of local forces in forming regional economic development paths is augmented by the growing demand for power decentralization from national to regional governments in the past decades. Decision-making at the local level could be significantly positive for regional development by empowering collective action and tailoring strategies to local needs and capabilities, although a few disadvantages also exist regarding efficiency and equity.

In general, regional economic development theories stress that competitive advantage and development potential are unequivocally localized components. Therefore, what development policies have to target is to adopt balanced policies that build upon local advantages and strengths, while attempting to alleviate local weaknesses, as the only strategy to root economic activity in the areas in a sustainable way (Pike, Rodríguez-Pose, & Tomaney, 2010).

The theories and frameworks, through which experts and researchers involved in the processes and procedures that form regional economies, are difficult to translate into regional economic policies and programs. This is especially true at the federal level, not only because the theories are partial but because they are all-too constantly promulgated by 'gurus' concerned for the primacy of their own thinking (Taylor & Ersoy, 2012). The translation is made harder by politicians and policymakers who must cope with the realities of economies that are in a constant state of 'becoming,' and the vagueness of theories that allows them to be shaped to meet any political goal, or distorted at the local level to accommodate local bureaucratic objectives. At the same time, local communities are often, from the evidence available, only partially aware of the weaknesses and potentials of their own local economies and communities, as well as the problems facing them. It can be argued that what is needed at the local and regional levels to promote and encourage appropriate economic growth that contributes positively to the national economic effort is facilitation, rather than centralized direction.

On federal policies, creating a strong delivery system for federal programs will be critical to ensuring that regional development policy is effective. As mentioned earlier, the federal development effort currently flows through 180 programs. In most cases, they flow through a different network of regional offices throughout the nation, and often have different standards for evaluating performance among them. This adds to the cost of these programs. Regardless of the direction that federal economic development policy may take in the future, programs should be delivered to the regions themselves. In the past, the federal presence throughout the nation developed strictly along departmental lines. From the standpoint of helping regions compete, however, geography matters more than the department.

A region needs a variety of funds and supporting services from Washington, but it is less interested in from which department's regional office they flow. Thus, a comprehensive review of the "geography" of existing federal offices throughout the nation would likely yield valuable opportunities to make the overall network more efficient. More fundamentally, clear standards for evaluating the performance of federal programs will be essential to making the federal policy effective. Several federal agencies involved in economic development have made significant strides in setting clear standards for monitoring and evaluating results from federal programs aimed at regional development. For example, EDA has developed new evaluation metrics to gauge the impact of its grants (EDA, 2004). Economists have been working on other metrics that may gain acceptance in Washington (Robinson & Johnson, 2005). Such standards are critical for ensuring equity of administration across regions and for ensuring that federal funding is put to good use. With so many federal economic development programs in Washington today, however, it is not surprising that there are scores of metrics for measuring performance. A major feature of moving to a more coherent federal policy will be establishing common metrics for measuring performance.

2.4 Uncertainty

Uncertainty is a construct that policymakers, planners, managers, and all other decision-makers struggle to define. The various definitions of the term reflect its utilization significantly meaningless (Shimizu, McIver, & Kim, 2009). Nonetheless, it appears that regardless of how uncertainty is characterized, it remains a vital concept that impacts decision-making.

It has been a focal concept for strategic management researchers, as well as organizational theorists, for a long time. The number of empirical research projects and studies utilizing the uncertainty concept continues to grow. Confusion around the measurement and conceptualization of the uncertainty, however, remains a subject for academic and professional debate. The following pages deal with existing literature about uncertainty conception, the difference between uncertainty and risk, uncertainty typology, and methods of uncertainty analysis.

2.4.1 Uncertainty Conception

Uncertainty is a term used to encompass many concepts (Morgan & Henrion, 1990). Among various fields that are concerned with it, there is no common agreement on its proper terminology, definition, or classification (Schultz, Mitchell, Harper, & Bridges, 2010). Although uncertainty is extensively deployed in academic discourse, it is rarely elucidated. As Ascough et al., (2008) indicated, it is a non-intuitive term that can be interpreted differently, depending on the discipline and context where it is applied. Scholars from various academic disciplines, such as public policy, management, economics, planning, finance, engineering, and ecology, among others, extensively utilize uncertainty to address unforeseeable circumstances they may confront in the future. It has been defined as a degree of ignorance (Beven, 2009), a state of incomplete knowledge (Cullen & Frey, 1999), of insufficient information (Murray, 2002), or as a departure from the unattainable state of complete determinism (Walker et al., 2003). In truth, the scientific literature contains many definitions, descriptions, and typologies of uncertainty. This picture is further complicated by different lexicons that use different names for the same thing and, occasionally, the same name for different things. In between, as Lefebvre (1991) observed, academic disciplines rely mainly on scientific techniques to provide certainty in the future.

Scientific understandings suggest various meanings for uncertainty; nevertheless, these understandings mostly concentrate on the lack of scientific knowledge as the primary challenge. “We [as scientists] believe we can calculate and control, whereas the disaster arises from what we do not know and cannot calculate” based on scientific knowledge, particularly from post-Positivist's perspective (Beck, 2006, p. 330). Moreover, “uncertainty is a perceived lack of knowledge, by an individual or group, that is relevant to the purpose or action being undertaken” (Abbott, 2005, p. 238). Thus, it seems critical to consider knowledge and then its limitations as the primary cause of lack of control on uncertainty’s agents.

Christensen (1985) argued that imperfect knowledge and pressure to act often result in a premature choice of policies or programs, which policymakers later regret. Her matrix conveys two synoptic categories of unknown and known, but this simplistic categorization is insufficient to address knowledge. Notably, this synoptic classification seems more problematic when scientific knowledge inherently fails to provide certainty or, more radically, creates uncertainty through its implementation (Beck, 2006).

Thus, the critical definitions of knowledge may assist in addressing the ontological challenge that exists in the process of decision-making. Slovenian Marxist and Lacanian thinker, Slavoj Žižek, critically conceptualized the relationship between known and unknown in four combinations: known-knowns, known-unknowns, unknown-unknowns, and most crucially, unknown-knowns (2006). He claimed that these combinations significantly shape our decisions, theorizing their relationships as a way to grasp the kernel of political decisions and actions.

Known-knowns mean “things we know that we know” (Žižek, 2006). Known-knowns, or at least what we perceive them with regard to our own knowledge, essentially shape our decisions and actions in general. Flyvbjerg (2001) observed that the science is largely based on the dominant knowledge that embeds in the natural science, which reinforces human control over the natural environment. “Episteme concerns universals and the production of knowledge that is invariable in time and space and achieved with the aid of analytical rationality” (Flyvbjerg, 2001, p. 55). It corresponds to the modern scientific ideal as expressed in natural science. After industrialization, knowledge based on scientific empirical observation has been progressively accepted, and legitimized as a consistent, universal reality. Despite the global endorsement of scientific rationality however, its inherent ontological and epistemological limitations influence our perceptions about the world and, more importantly, ourselves.

Foucault, in *Discipline and Punish* (1991), comprehensively elucidated how power institutions have dramatically adjusted scientific knowledge by asserting control over educational systems. Lefebvre addressed those same inadequacies of scientific methods in analyzing everyday life (1991). Furthermore, Beck was one of the first social scientists to identify the "strange paradox in modern society; that risk might in fact be increasing due to technology, science, and industrialism rather than being abated by scientific and technological progress" (Jarvis, 2007, p. 23). These views profoundly challenge the reliability of scientific understandings.

Known-unknowns, meanwhile are "things that we know we don't know" (Žižek, 2006). Researchers are aware that these gaps in knowledge exist. These voids are recognized among the sources of uncertainty. "Something is uncertain if it is unknown or cannot be known" (Abbott, 2005, p. 237). After the failures of science and technology to control both environmental and social phenomena, many thinkers over the past decades have argued that the world is too complex and always-changing to be entirely known through the scientific methods. In fact, the world becomes even more complex as a result of new knowledge, technologies, and increasing global linkages. The future, therefore, looks more unpredictable and uncertain as a consequence of the existing trends of constantly changing and increasing complexity (Beck, 2006).

Uncertainty has always been part of the ongoing processes of nature, however, and so the future has always been complex and indeterminate. "[It] is the great unknown" (Abbott, 2005, p.237). Known-unknowns also reveal the limitations that researchers confront in their scientific investigations, particularly in addressing the agents of stability in the future. Christensen (1985) argued that technologies are rarely either entirely known or wholly unknown; over time, they present themselves to be more or less effective. The recognition of these knowledge limitations impacts the process of decision-making mostly by including unpredictability and unknowability in consideration. Thus, the utopic-Positivistic or techno-utopian perspectives which were the dominant way of thinking in the early 20th century transformed into others ways, such post-Positivist and post-Structuralist. In the policy and planning domain, the recognition of known-unknowns assists decision-makers to deploy dynamic plans and policies, such as strategic plans, instead of solid plans, which are mostly embedded in natural science (Khakee, 1991).

Then, unknown-unknowns are “things we don't know we don't know” (Žižek, 2006). These phenomena and their consequences exist mostly outside of current human knowledge. Kartez and Lindell (1987) revealed that a lack of experience with specific incidents, particularly disasters, generates (besides the lack of organizational preparation for these events) chaotic situations. For example, recent epidemic diseases such as SARS (Severe Acute Respiratory Syndrome), HIV, and Swine flu can be categorized as unknown-unknowns.

Unknown-unknowns are mostly assumed to be the fundamental obstacles confronting the process of decision-making, as well as implementation, of policies, plans, and projects. Decision-makers must pragmatically consider the existing condition to avoid such unknowns. But, as Beck (2006) added, “[t]he non-compensatibility irony comes to a head in tragic fashion: if risks are held to be non-compensatible, the problem of not-knowing is radicalized. If catastrophes are anticipated whose potential for destruction ultimately threatens everyone, then a risk calculation based on experience and rationality breaks down. Now all possible, more or less improbable scenarios have to be taken into consideration; to knowledge, therefore, drawn from experience and science there now also has to be added imagination, suspicion, fiction, [and] fear." (p. 340). Unknown-unknowns can be at the root of decisions resulting in traumatic consequences, when the accepted rationality is incapable to engineer unforeseeable phenomena. "The Freudian name for the 'unknown-unknowns' is trauma, the violent intrusion of something radically unexpected, something the subject was absolutely not ready for, and which it cannot integrate in any way" (Žižek, 2011, p. 292).

And finally, unknown-knowns mean "things we don't know that we know" (Žižek, 2006). This concept precisely embeds in the Freudian unconscious; the 'knowledge which doesn't know itself.' "From a psycho-analytical point of view, the unconscious is exactly about a knowledge which doesn't know itself; it is not some deep buried unknown secret, it is the self-evident lying at the very surface" (Vos, 2009, p. 225). From a Žižekian perspective, unknown-knowns drive most decisions. Or, at least, their impact on the process of decision-taking are significant. He added that "'unknown-knowns' are the disavowed beliefs, suppositions, and obscene practices we pretend not to know about, although they form the background of our public values" (Žižek, 2011, p. 293). Despite common perceptions to the contrary, Žižek (2008) states that 'unknown-knowns' comprise the most problematic issue in the process of decision-making in general; for planning in particular.

The ignorance inherent in them, of appeared weaknesses, failures, and side effects of the dominant scientific knowledge seems more challenging than that presented by the unknown-unknown, which is otherwise perceived as the primary challenge. "These disavowed beliefs and suppositions [unknown-knowns] are the ones which prevent us from really believing in the possibility of the catastrophe, and they combine with the 'unknown-unknowns.' The situation is like that of the blind spot in our visual field: we do not see the gap, the picture appears continuous" (Žižek, 2008, p. 457). In other words, despite the scientific base of these decisions, including any policies and plans they may generate, catastrophes can be addressed as failures of policies and programs. The dominant rationalistic knowledge yet impedes decision-makers, including policymakers, from believing in its weaknesses. Thus, "contrary to what the promoters of the principle of precaution think, the cause of our non-action is not the scientific uncertainty. We know it, but we cannot make ourselves believe in what we know" (Žižek, 2009, p. 454). The latest economic recession in 2008, for example, makes clear the failures of scientifically-based policies and plans. Yet, decision-makers largely fail to utilize that knowledge to address the problem.

The present research is mostly concerned with 'unknown-knowns' as a paradox that inherently exists in contemporary policymaking. Žižekian critical definitions challenge the conventional boundaries between known and unknown, in the process of decision-making for the future. They do not merely distinguish the unknown as primary uncertainty creator, but also critically dispute the hegemony of scientifically-based knowledge. To reveal the 'unknown-knowns' as agents of existing uncertainty, it seems necessary to consider the global mechanism by which the scientific knowledge, in spite of all its failures, is extensively promoted and, more importantly, legitimized to generate the illusion of certainty.

2.4.2 Uncertainty and Risk

Knight (2012) stated, the concept of risk should be considered as drastically distinct from that of uncertainty, from which it has never otherwise been appropriately separated. In some cases, risk implies a quantity that is susceptible to measurement, while in others, it is distinctly not of this character. In Knight's (2012) view, uncertainty arises out of our partial knowledge. His use of partial knowledge reveals that his distinction between risk and uncertainty is more related to the initial classification of random and unpredictable outcomes than with the calculation of probabilities to those outcomes. Knight's major concern has to do with the possibility of classification regarding the states of nature. His concern was not so much that we are unable to estimate probabilities, as that we cannot classify their outcomes. In his view, uncertainty arises from the impossibility of any thorough classification of states. Knight noted that, due to the non-mechanical nature of the world, novel outcomes and possibilities are continually developing, and these cannot be simply classified in an inter-subjective way as repeatable examples. To manage this uncertainty, one should rely on judgment. Such judgment will be one of the skills in which experts specialize, yielding the usual Smithian economies (Langlois & Cosgel, 1993).

Tversky & Fox (1995) recognized distinctions between risky prospects, where the probabilities associated with the possible outcomes are thought to be known, and uncertain prospects, where these probabilities are not supposed to be known. In other words, the risk is tangible; uncertainty is not. One can define risk, but one can barely delineate the outer layers of uncertainty. Risk can be rendered concrete; uncertainty cannot.

Tenembaum (2012) suggests that we can identify risk like we would a distant train coming towards us. The train might change its course before reaching us; it may slow down or, ultimately, stop. Risk, after all, is not the train that has hit us. That does not constitute the risk. Instead, the danger still-looming – whether far away or close by

– represents the risk. Danger and threat, once realized, no longer constitute a risk. Uncertainty, on the other hand, has too many unknown variables, much the same as how we may not not aware of whether the train has left the station or not; and if it has, whether or not it would be taking tracks that lead to us; and if we are aware that it has, in fact, used the tracks leading to us and has in fact left the station, whether we are sure that it finally will hit us; or, maybe someone who we are not previously aware of just pushes us away from the track, before the train hits us. Uncertainty would be much like knowing there is a dog somewhere in the neighborhood, without us knowing as to whether it would be heading towards us or not. It may not bark at us at all.

In a similar vein, the French Revolution in 1789 was, to the other European countries, an uncertain event; its outward expansion constituted a risk for them. The world powers of 1939, meanwhile, viewed the popularity of the Nazi Party in Germany as more of an uncertain event than a risky threat. The German triumph over Czechoslovakia in March 1939, in any case, persuaded the leaders of democratic nations that Germany constituted a risk to the international community.

Thus, the difference between risk and uncertainty may be, more than anything, a matter of perception. All of this is a matter of perspective. The distinction between uncertainty and risk can be expressed objectively, but when it comes to developing public policy, whether an event or phenomenon is considered as uncertain or risky is a matter of perception. Risk and uncertainty provide different thresholds.

2.4.3 Uncertainty Typology

Although many types of uncertainty are recognized, there is still a lack of information and agreement as to their characteristics, relative magnitudes, and available means for dealing with them. In addition, typologies have been developed to serve different purposes, as pointed out by Walker et al. (2003): "within the different fields of decision support (policy analysis, integrated assessment, environmental and human risk assessment, environmental impact assessment, engineering risk analysis, cost–benefit analysis, etc.), there is neither a commonly shared terminology nor agreement on a generic typology of uncertainties"(p. 5). This point is illustrated in Table 2-3, which shows both divergence and overlap in classifying uncertainties according to various literature sources over the past decades.

Table 2-3- Uncertainty Typologies from the Literature (Ascough et al, 2008)

Reference from literature	**Types of uncertainty considered**
US-EPA (1997)	Scenario uncertainty, parameter uncertainty, model uncertainty
Morgan & Henrion (1990)	Statistical variation, subjective
Hofstetter (1998)	Judgment, linguistic imprecision, inherent randomness disagreement, approximation
Funtowicz & Ravetz (1990)	Data uncertainty, model uncertainty, completeness uncertainty
Bedford & Cooke (2001)	Aleatory uncertainty, epistemic uncertainty, parameter uncertainty, data uncertainty, model uncertainty, ambiguity, volitional uncertainty
Huijbregts et al. (2001)	Parameter uncertainty, model uncertainty, uncertainty due to choices, spatial variability, temporal variability, variability between sources and objects
Bevington & Robinson (2002)	Systematic errors, random errors
Regan et al. (2002)	Epistemic uncertainty, linguistic uncertainty
Walker et al. (2003)	*Location*: context uncertainty, model uncertainty (input, structure, technical, parameter, outcome); *level*: statistical uncertainty, scenario uncertainty, recognized ignorance, total ignorance; *nature*: epistemic uncertainty, variability uncertainty
Maier et al. (2008)	Data uncertainty, model uncertainty, human uncertainty

This dissertation offers a simple generic typology that encompasses all those kinds of uncertainties introduced by the literature as follows:

- State Uncertainty (variability & randomness)
- Epistemic Uncertainty (linguistic, values, & understanding)

These types of uncertainty are inherently intertwined and may exist concurrently in all phases of decision/policymaking process. I prefer not to expand this classification with more types and sub-types here, which would still result in, as Knight noted, a non-exhaustive classification. With this proposed typology, analysts and researchers can be more flexible in distinguishing between different types of uncertainties, whether synthetic or emerging. State uncertainty encompasses the variability and randomness of states. Epistemic uncertainty refers to the limitations of our knowledge and understanding, which may be reduced by additional research and empirical efforts. It encompasses linguistic uncertainty as well, in that it is about the vagueness, ambiguity, context dependency, and underspecificity of our natural language. It also may arise where there is ambiguity or controversy about how to interpret or compare a phenomenon, which is also referred to as value uncertainty. In the following pages, these two categories of uncertainties will be discussed in detail.

2.4.3.1 State Uncertainty

This is a general term to describe those types of uncertainty inherent in 'states of nature', on which an analysis is based. It is also referred to as aleatory uncertainty, variability uncertainty, and the impossibility of exhaustive classification of states. In Knight's view, it regards the possibility of classifying the "states of nature." "When our ignorance of the future is only partial ignorance, incomplete knowledge, and imperfect inference," Knight says, "it becomes impossible to classify instances objectively" (Langlois & Cosgel, 1993, p. 259). The point is not so much that we do not know the probabilities, as that we do not know the classification of outcomes. Knight indicates that there is no valid basis of any kind for classifying instances that require judgment and intuition, rather than calculation.

When it comes to the process of knowing, we have things that we know and are confident that we know them. For instance, there might be some parameter of a process that we are eager to learn. We collect the evidence (data) and, based on this evidence (data), are confident that we know everything about it. But our process might not be deterministic; we may be looking instead at one that is random or stochastic, where there is some baffling indeterminacy about how the process will evolve over time. Again, we can collect some data and information about this aleatory or randomness uncertainty, and express it as a probability distribution and its moments.

In another example, having thrown a coin a thousand times, we would be able to show with a high confidence via a probability distribution the probability of a head or tail occurring. Paradoxically, that is all we can say about the next coin toss. While we can characterize aleatory uncertainty very well, it also represents an irreducible boundary to our knowledge. Thus, state uncertainty arises from a randomness or stochasticity of phenomena occurring. It concerns the occurrence of the events that express the various possible accident scenarios, the time for a component to reach failure, or the random variation of the actual physical dimensions, and material properties of a component or system (USNRC, 1990; Helton, 1998; USNRC, 2002).

On the other hand, state uncertainty is referred to as external and objective. It is related to the inherent variability manifested in natural and human (i.e., economic, social, and technological) systems. This type of variability is critical in management decisions, yet is usually poorly understood and confused with epistemic uncertainty as a result of "ignorance" by managers, lawyers, and stakeholders (Rose & Cowan, 2003). Components of variability uncertainty include natural, human, institutional, and technological factors (Ascough et al, 2008).

As Ascough et al., (2008) addressed, natural variability is related to the inherent randomness of nature, i.e., the chaotic and unpredictable quality of natural processes. The uncertainty associated with human input has received limited attention in the literature; however, this type of uncertainty can have a significant impact at all stages of the decision-making process. For example, the values and attitudes of the manager/decision-maker, as well as the current political climate, can influence whether or not a problem is addressed, which alternative solutions will be considered, which assessment criteria will be used, and which alternative is ultimately selected. The knowledge base, education, attitudes, and political "clout" of stakeholder and lobby groups can also have a major influence on the final outcome.

For example, whether a particular problem is drawn to the attention of the manager/decision-maker, and how seriously it will be treated, can be a function of the above factors. Similarly, stakeholder groups can have an input into the choice and screening of potential solutions, as well as the assessment process via the development of appropriate assessment criteria and the provision of weightings (if multi-criteria decision approaches are utilized). Even the more "technical" aspects of the decision-making process are not immune from uncertainty due to human input. Refsgaard, van der Sluijs, Højberg, & Vanrolleghem (2005) found that the results of a modeling exercise varied significantly when different modelers were presented with the same problem and data. In other words, the knowledge, experience, and preferences of the modelers significantly impacted the modeling outcomes. Institutional uncertainty is represented by social, economic, and cultural dynamics (societal variability). The need to consider societal and institutional processes as a major contributor to uncertainty due to variability can be inferred from Funtowicz and Ravetz (1990) and De Marchi et al. (1993). New developments or breakthroughs in technology, or unexpected consequences ('side-effects') of technologies, contribute to technological uncertainty. All of the above types can contribute to state uncertainty, but it may be difficult to identify precisely what is reducible through investigations and research and what is irreducible (i.e., an inherent property of the phenomena of concern). Either way, it is important to make an assessment, because the information may be essential to the evaluation process.

In sum, state uncertainty (also referred to as aleatory, variability, stochastic uncertainty, or irreducible uncertainty) is the variability present in the system being analyzed, or in its environment. It is not strictly due to a lack of knowledge and cannot be reduced. The determination of conditions of a system typically leads to state uncertainties; additional experimental characterization may provide a more conclusive explanation of the variability but cannot eliminate it entirely. State uncertainty is typically characterized using probabilistic approaches.

2.4.3.2 Epistemic Uncertainty

Heazle (2012) defined epistemic uncertainty as gaps in our knowledge of the system, which are reducible through experimentation and research to at least the boundaries of the system. Epistemic uncertainty expresses a general lack of resolvable knowledge, and so the opportunity presents itself for us to reduce this uncertainty. In the coin toss example, we don't know if the coin is true in the first toss or not, but once we begin to toss it multiple times, we quickly get a feel for its trueness. The longer we toss the coin, the greater the reduction in the epistemic uncertainty. Benda et al. (2002) asserted that epistemic uncertainty is fundamentally related to the limits of scientific understanding; for example, what knowledge is lacking or what spatial or temporal mismatches exist among disciplines. This type of uncertainty is related to the "structure of knowledge," and includes four categories that limit our understanding of phenomena across various disciplines: (1) disciplinary history; (2) spatial and temporal scales of knowledge; (3) precision; and (4) availability of data to validate predictive models. It is important to note that new knowledge of complex processes might indicate the presence of uncertainties that had been previously understated or completely unknown (Walker et al., 2003). Taking this into consideration, additional knowledge shows that our understanding is more bounded or that the processes are more complex than we thought (Ascough et al., 2008).

Epistemic uncertainty can also arise from policy/decision model structures. Models are necessarily simplified representations of the events and phenomena being examined, and a major aspect of the modeling process is the judicious choice of model assumptions. An optimal model will provide significant simplifications, while providing an adequately precise representation of the processes impacting the phenomena of interest. Thus, the structure of models utilized to represent real-world systems is often a major source of uncertainty. In addition to the significant approximations inherent in modeling, often-competing models may be available as well. Consequently, uncertainty about the structure of the system that we are attempting to model implies that multiple model formulations might be a plausible representation of the system, or, that none of the proposed system models are adequate representations of the real system (Walker et al., 2003). Model structure uncertainty arises from the use of surrogate variables, the exclusion of variables, the relationship between variables and input/output, from approximations and functional forms, equations, and from mathematical expressions used to represent the physical and biological world. To select the best policies or strategies, models of the underlying processes that take into account the best scientific knowledge (and the uncertainties associated with this knowledge) need to be available to test the robustness of different policies or strategies (Harwood & Stokes, 2003). It is important to note that the best model may not be the most complex or complete, in the sense that quantitatively incorporating every aspect of the system under study may result in more uncertainty than if only the salient processes (if known) are considered. A reductionist approach, where every minute detail is represented in a model's structure, may be capable of reproducing the real system, while an understanding of dynamic mechanisms essential to decision-making may still be lacking. This leads us to understanding uncertainty about modeling philosophy as a major component to epistemic uncertainty.

This may also arise from decision uncertainty, which is related to what Morgan and Henrion (1990) refer to as "value" uncertainty. Most descriptions of incorporating uncertainty into analysis consider the modeling aspect of physical systems, and therefore exclude discussions pertaining to decisions about valuing social objectives. In studies that estimate the economic costs and benefits of policy changes, however, decision uncertainties are vital because they go to the heart of how these social objectives are determined. Decision uncertainty may also be strongly related to the way model predictions are interpreted and communicated, especially with regard to future courses of action. When high uncertainty is not properly explained or understood, it can delay action or cause the selection of values at the extreme of the ranges, thus resulting in very risky management decisions (Cowan, 2003).

Linguistic uncertainty, one of the primary sources of epistemic uncertainty as defined by Regan, Colyvan, & Burgman (2002), arises because our natural language is vague, ambiguous, and context dependent, and because the accurate meaning of words can change over time. Elith, Burgman, & Regan (2002) emphasize that linguistic as well as epistemic uncertainty can be presented in model predictions and provide further elucidation of the linguistic uncertainty typology. Ambiguity arises because some words have more than one meaning and it is not always clear which meaning is intended in a given scenario. For instance, terms applied to the general notion of a weed include exotic, noxious, invasive, naturalized, volunteer, and non-indigenous. Indiscriminate application of these terms would render often unclear exactly what is meant in a given context. Ambiguity can be a problem in modeling when records from some sources are being used, but the original researcher is not accessible for, or cannot help with, clarification of the record. Vagueness is a type of linguistic uncertainty that arises because natural and scientific language allows cases where a precise description of a quantity or entity is not available, i.e., a "borderline" case that does not exactly fit into a category. The words "remote," "low," and "endangered," for instance, are vague in the expressions "the risk of gene transfer is remote," "the chance of a ship collision is low," and "the species is endangered." Vagueness can be found in concepts with a natural numerical ordering (i.e., growth stages for a soybean plant) but also in concepts without a numerical order, such as vegetation classes (Elith, Burgman, & Regan, 2002). Underspecificity is present where there is unwanted generality in data; i.e., the original data on which a data record is based were more exact than a newer and less accurate version. It can also arise as a result of epistemic uncertainty, i.e., if data are measured using GPS in a precise location in an agricultural field but are otherwise generally recorded (e.g., the location is in the southeast corner of the field).

In sum, epistemic uncertainty (also called reducible uncertainty or incertitude) is a potential deficiency that is solely due to a lack of knowledge. It may arise from assumptions in the derivation of the model used or simplifications related to the correlation or dependency between processes. It can be reduced by a combination of calibration and improvement of models, as well as the inference from experimental observations. Epistemic uncertainty cannot be explained by probabilistic approaches because it is too difficult to infer any statistical information, due to the nominal lack of knowledge.

2.4.4 Uncertainty Analysis

Cox and Baybutt (1981) define uncertainty analysis as a process that quantifies the uncertainty in a risk estimate and partitions this uncertainty among the variables or risk factors that contribute to it. Helton and Davis (2002) define it similarly as the answer to the question: what is the uncertainty in f (X) given the uncertainty in X? Hayes (2011) defines uncertainty analysis as a three-step process that: 1) recognizes, identifies, and minimizes linguistic uncertainty; 2) recognizes, identifies and, whereever possible, characterizes variability and epistemic uncertainty in the risk factor X and the risk function f (X); and, 3) estimates the effect of epistemic uncertainty and variability on the outcomes of a risk assessment and reports this effect in an open and clear fashion. This definition emphasizes different types and sources of uncertainty in risk assessment, and the importance of propagating epistemic uncertainty and variability through the assessment in an honest fashion. Methods for uncertainty analysis have been broadly discussed in various academic disciplines. In the following pages, a brief summary of them will be discussed.

2.4.4.1 Expert Assessment

Expert assessment is an established methodology for obtaining estimates of relationships that cannot be, or are too expensive or impractical to be, observed directly, such as hypothetical scenarios (Krueger, Page, Hubacek, Smith, & Hiscock, 2012). It can also be used to obtain estimates of the variance around model parameters (O'Hagan, 2012) and model-predicted values, although estimating variance or variability is a challenging task, especially if several conditioning factors need to be taken into account simultaneously (O'Hagan et al., 2006). Expert assessment is used, for example, in the general framework for uncertainty and global sensitivity analysis proposed by Baroni and Tarantola (2014) in an informal manner, in conjunction with data; they state that the uncertainty of each source has to be characterized by all available data and information: measurements, estimations, physical bounds considerations, and expert opinion. They also define the uncertainties of the model components by evaluating field-collected data. If such data is available, it may be used to help the experts also evaluate the uncertainties associated with the model outputs; however, if the modelling results are based on scenarios that have not yet taken place, the experts need to be careful in how much they rely on current data in evaluating these yet-unseen conditions.

When using expert knowledge to estimate the uncertainty around model-predicted values, the following aspects need to be considered: Which experts should be chosen: the modelers who have made the original deterministic model, or, other scientists who are familiar with the domain, but not necessarily with the model? Knowledge of the workings of the deterministic source model is not necessary for the estimation task; the relevant thing is to understand the dynamics of the system and factors that may affect it. It is important that the expert understands the definitions of the variables and the general description of the system as represented in the models; otherwise, they may evaluate a different quantity from that intended to be represented in the decision support model. To guarantee this, the decision modeler and the domain expert need to take enough time for the task, and to then discuss the assumptions and restrictions of the decision support model. Several experts can be used, and each of them can evaluate the uncertainties related to their respective area of expertise. Should several experts separately estimate the uncertainty of the same variable, a technique for combining these estimates need to be decided upon. Several techniques for interviewing such experts and combining expert estimates have been proposed: Morgan and Henrion (1990), O'Hagan et al. (2006), and O'Hagan (2012). It is also possible to include the different views of the experts as a set of distributions (Rinderknecht, Borsuk, & Reichert, 2012) or as an auxiliary variable (Uusitalo et al., 2005; Lehikoinen et al., 2012), which enables analysis of the relevance of the difference in expert opinions, from the decision analytic point of view. As Uusitalo et al. (2015) describes, expert judgment as the source of uncertainty estimates can easily be criticized as subjective. However, lacking data to estimate the variances by the experts who have devoted their careers to studying these questions might be better sources of information than any hasty quantitative models made for this purpose.

Various methods exist to help and support the experts in the evaluation task. However, the facilitator has to be careful to also make sure that the experts in fact evaluate the desired quantity, not something that is related but distinct. The experts' task may be eased by investigating areas, or cases, that are deemed sufficiently similar, and upon which data exists. The range of values that have been observed in distinct but relevant cases informs the plausible range of values that this variable can get and, therefore, may also indicate how large is the uncertainty associated with the prediction of the deterministic model.

2.4.4.2 Probabilistic Approach

Zio & Pedroni (2013) describe probabilistic analysis as the traditional tool used to express the uncertainties in risk assessment. It tries to estimate chances that represent fractions in a large (in theory, infinite) population of similar items. The assessment is consistent with the probability of frequency approach. This method utilizes the subjective probabilities to explain epistemic uncertainties of unknown frequencies, called chances. The probability of frequency approach forms the highest level of uncertainty analysis according to a commonly used uncertainty treatment classification system. Probabilistic analysis is the most broadly used method for characterizing uncertainty in many models. In this approach, uncertainties are characterized by the probabilities associated with events that correspond to any of the possible states a system can assume, or, to any of the possible predictions of a model describing the system.

One typical approach in probabilistic analysis is the use of a Monte Carlo Simulation (MCS), as described by Ang, Tang (2007) and others. In this, a model is repeatedly run, using different values for each of the uncertain input parameters each time. The values of these are generated based on the probability distribution for the parameter. If there are two or more uncertain input parameters, one value from each is sampled simultaneously, in each repetition in the simulation. Over the course of a simulation, perhaps 20, 50, 100, or even more repetitions may be made. The result, then, is a set of sample values for each of the model output variables, which can be treated statistically as if they were an experimentally or empirically observed set of data. Although the generation of sample values for model input parameters is probabilistic, the execution of the model for a given set of samples within a repetition is deterministic. The advantage of the Monte Carlo method is that these deterministic simulations are repeated in a manner that yields valuable insights into the sensitivity of the model or variations in the input parameters, as well as into the likelihood of obtaining a particular outcome. They also allow the modeler to use any probability distribution for which values can be generated on a computer, rather than be restricted to forms that are analytically tractable.

MCS belongs to a class of computational algorithms generally known as Monte Carlo methods. The class of Monte Carlo methods is large and varied, but all of its algorithms rely on randomly generating samples from a defined input domain, such as a set of probability density functions, to solve problems that do not have analytical solutions. Monte Carlo methods have a long and successful history that dates back to at least the turn of the 20th century, although the term "Monte Carlo" was coined only in the 1940's, by John von Neumann, as a code word for secret work on the diffusion of neutrons (Burgman, 2005). In risk assessment circles, MCSs are used to propagate the effects of variable risk factors through n-dimensional risk functions, in cases where the complexity of the risk function and/or the distribution of the individual risk factors preclude an analytical solution. In this context, MCS can be considered the mainstay of probabilistic quantitative risk assessment (Vose, 2000). Monte Carlo methods also have a much broader application than quantitative risk assessment however, and are also used widely in a range of statistical problems to solve analytically intractable optimization and integration problems, such as finding the maximum of a multi-modal likelihood function or estimating the normalizing constant (an integral) in a Bayesian Hierarchical Model (Robert & Casella, 1999).

However, the probability-based approaches to risk and uncertainty analysis can be challenged under the common conditions of limited or inadequate knowledge about a given high-consequence risk problem, for which the information available does not provide a solid foundation for a particular probability assignment. In such a decision-making context, certain stakeholders may not be satisfied with a probability assessment made solely on the basis of subjective judgments by a group of analysts. In this perspective, a broader risk description is demanded where all the uncertainties are laid out plain and flat, with no additional information or data inserted in the analytic evaluation in the form of assumptions and/or hypotheses that cannot be proven wrong or right. This concern has sparked some investigations in the field of uncertainty analysis, which has resulted in the rise of alternative frameworks only classified in four main categories (Aven, 2010, 2011; Aven & Steen, 2010; Aven & Zio, 2011; Ferson & Ginzburg, 1996; Flage et al., 2009):

- Imprecise probability and the robust statistics area (Walley, 1991; Berger, 1994).
- Probability bound analysis, combining probability analysis and interval analysis (Moore, 1979; Ferson & Ginzburg, 1996; Ferson & Hajagos, 2004; Ferson et al., 2010).
- Evidence theory, in the two forms proposed by Dempster (1967) and Shafer (1967).
- Possibility theory (Baudrit & Dubois, 2006; Baudrit et al., 2006, 2008; Dubois, 2006).

2.4.4.3 Bayesian Approach

A central assumption underlying the probabilistic approach is that a true, fixed value for each parameter of interest exists, the expected value of this parameter is obtained by random sampling as repeated and infinitum, and the underlying parameter distribution is known. True randomization is difficult though, and replication is often small or nonexistent. Random samples within a population are not alike nor will they be alike in the future (Ellison, 1996; Reckhow, 1990). However, as an alternative to this paradigm, Bayesian inference provides a mechanism to quantify uncertainty in parameter estimates, and to determine the probability that an explicit scientific hypothesis is true conditioned upon a set of data (Ascough et al., 2008).

The Bayesian approach crosses the divide between qualitative models, mechanistic models, and statistical models. It is one of the few methods with which one can perform uncertainty analysis with little or no data. This approach provides a transparent, mathematically coherent method to express one's belief in a theoretical model, and the conditional probability of events, in a way that can be updated as data are collected during the monitoring and validation phases of the analysis. It has much to offer as a risk assessment tool, and has been recognized as a scientific and pragmatic approach to modeling complex systems in the presence of high uncertainty (Hart & Pollino, 2008).

The Bayesian method is a relatively new tool, which emerged during the late 1980s and early 1990s as a synthesis of developments in statistical graph theory (Shipley, 2000) and Artificial Intelligence; specifically, as solutions for conditional probability distributions within complex causal networks (Lauritzen & Spiegelhalter, 1988). The initial development and uptake of the Bayesian method, focused largely on medical applications and examples relevant to the diagnosis of medical conditions, dominates the early statistical literature. The advantages of a probabilistic description of the relationships in a complex system were quickly recognized by ecologists, meanwhile, and by the late 1990's the Bayesian method was being applied to prediction and diagnosis in ecological systems (McCann, Marcot, & Ellis, 2006). Today it is a relatively popular method of uncertainty propagation (and inference) with some examples in the literature (McMahon, 2005; Peterson et al., 2008; Hood et al., 2009).

The term Bayesian Network (BN) was coined by Pearl (1986) to describe the "dependency-graph" representation of any joint distribution $P(x_1; \ldots; x_n)$. The graphical representation of this function is achieved via a Directed Acyclic Graph (DAG), which consists of a set of nodes linked by directed (one-way) arrows that indicate the conditional relationship between nodes. Nodes are comprised of states that are independent, mutually exclusive, and exhaustive propositions about the values that the variable represented by the node can take. The arrows between nodes describe the particular product-rule decomposition of the joint distribution that, in turn, reflects the presumed or inferred cause and effect relationship in the system being studied.

For example, this factorization of a three-variable joint distribution:

$$p(x_1, x_2, x_3) = p(x_3|x_1, x_2)p(x_2|x_1)p(x_1) \qquad (2.1)$$

represents a unique DAG with two arrows linking the node x_3 to its "parents" (x_1, x_2) to represent the factor $p(x_3 \mid x_1, x_2)$, and one arrow linking the node x_2 to its parent x_1 to represent the factor $p(x_2 \mid x_1)$ (Bishop, 2006).

More generally, the unique decomposition of any joint distribution of a set of risk factors (nodes) represented by a BN can be written:

$$p(X) \quad = \prod_{k=1}^{k} p(x_k|pa_k) \qquad (2.2)$$

where K represents the number of nodes in the DAG, pa_k denotes the set of parents of each node, and x_k equals the values of the variable at the node conditional on the values of its parents.

The structure of a BN represents an assumption about the joint distribution of the risk factors (represented by the nodes of the directed acyclic graph) that are deemed relevant to the problem in hand. In other words, the DAG represents a qualitative conceptual model of cause and effect. The conditional probability models associated with each node are a quantitative, statistical, or mechanistic model of these causal relations.

BNs offer an uncertainty analysis tool that is attractive for many reasons. They are well-suited to problems with small or incomplete data sets, and when parameterized manually they are not restricted by a minimum sample size (Uusitalo, 2007). BNs are very flexible – they can be constructed using empirical data, expert opinion, or a mixture of both (Wooldridge & Done, 2004). BNs can also incorporate prior information from a diverse range of disciplines in participatory settings; this facet, together with their graphical representation of cause and effect, make them well suited to cross-disciplinary collaboration (Pollino, Woodberry, & Nicholson, 2007).

Perhaps the biggest advantage of BNs, however, is that the process of building the DAG and then quantifying the conditional relationships between the nodes of the network force the analysts to think very carefully about the mechanisms, processes, and contexts of their problem. The BN allows the analyst to express their beliefs about things that are and are not casually connected. Then, the graphical presentation of this information facilitates the participation of, and communication to, stakeholders and other interested parties. Furthermore, the BN approach acknowledges that dependencies between nodes may be uncertain and/or variable, and the explicit use of the conditional decomposition of the joint probability distribution forces experts to express probabilistic dependency in a mathematically coherent manner. The use of conditional probability tables, for example, quickly exposes any inconsistency between an expert's belief in an event A and his/her conditional belief in event A given B (Moskowitz & Sarin, 1983).

Overall, Bayesian decision analysis has provided a systematic and intuitive approach to guiding the decision-making process, by allowing the use of the best available information in a rigorous statistical framework. This involves stakeholders at several stages of the evaluation, taking into account the key uncertainties affecting management decisions, and explicitly conveying the uncertainties in potential decision outcomes with the use of Bayesian probability statements.

Bayesian inference has been criticized howver, for its subjectivity and apparent lack of explanatory power (Dennis, 1996). Thus, in some cases, it may indeed be difficult to use true Bayesian methodologies. For example, we may not be sufficiently skilled at translating our subjective prior beliefs into a mathematically formulated model and prior probabilities. Further research is needed to address this difficulty, particularly when dealing with models that have an extremely large number of parameters. Modern methods of Bayesian statistics can employ the highly computationally-intensive Markov Chain Monte Carlo techniques to draw inferences and identify sources of uncertainty (Lee & Kim, 2008). Increased computational efficiency is crucial to the further application of these techniques and the emerging success of the Bayesian approach in decision analysis.

2.4.4.4 Sensitivity Analysis

Methods of sensitivity analysis can be used to identify parts of integrated policy/decision models, to which model outputs are relatively insensitive. This enables insensitive model components to be treated as deterministic or, alternatively, to be removed from the model altogether. The goal of sensitivity analysis is to characterize how model outputs respond to changes in inputs, with an emphasis on finding the input parameters to which outputs are the most sensitive (Saltelli et al., 2000; Kennedy & O'Hagan, 2001). This can be achieved by using various approaches, ranging from simple one-factor-at-a-time methods to more comprehensive approaches, usually based on Monte Carlo methods (e.g. Saltelli et al., 2005; Cariboni et al., 2007; Yang, 2011).

The basic idea of sensitivity analysis is to alter model input values (Chu-Agor, Muñoz-Carpena, Kiker, Emanuelsson, & Linkov, 2011) and/or parameters (Tomassini, Reichert, Knutti, Stocker, & Borsuk, 2007) of the model, and study the subsequent changes in model output. If the output value changes only a little, then the model is robust to changes in the input parameter values within the model. In that case, it seems probable that uncertainty about that particular parameter value is relatively small. If, on the other hand, the value of the variable under interest changes markedly when we change parameter(s) in the model within their reasonable range, this indicates that there is great uncertainty about the variable(s) value. It is unrealistic to assume that the values used in the model would be exactly those that take place in reality. Given this, small differences in these values will cause large differences in the outcome, which is bound to be rather uncertain. However, as with uncertainty analysis, making a reasonably thorough sensitivity analysis, through the process of altering the parameter(s) and initial values, may require a large number of model runs (Saltelli et al., 2010; Baroni & Tarantola, 2014).

The number of the combinations increases exponentially, however, as the number of these parameters and their possible values increase. Also, if the model takes a long time to run, this may render the process infeasible. Some techniques can be used to minimize the number of model runs. The number otherwise required can, to some extent, be reduced by making a preliminary sensitivity analysis. This is based on its result, which is focused on the variables with stronger effects on the response variable and a sparser grid of values for the less influential variables (Uusitalo, Lehikoinen, Helle, & Myrberg, 2015). Morris (1991) presented a well-known screening method that ranks the input factors in order of importance. It was later revised and its sampling strategy improved (Campolongo, Cariboni, & Saltelli, 2007). These approaches, however, account only for the uncertainty in the model's input values and parameters (such as the slope and intercept of a linear function), not in the model structure (i.e., the existence and functional form of dependencies between variables, etc.) (O'Hagan, 2012). At the same time, one problem with this approach is that traditional sensitivity analysis types, such as the Morris method (Morris, 1991), are ill-equipped to deal with the high degree of non-linearity and interaction that characterize integrated models. Monte Carlo methods overcome these problems, but are generally too computationally expensive. More computationally efficient alternatives include the Extended Fourier Amplitude Sensitivity Testing (FAST) method (Saltelli, Tarantola, & Chan, 1999) and the sensitivity analysis approach proposed by Norton et al. (2005).

Structural uncertainty can be evaluated by comparing model results with real observations. However, there may not be enough data for the results of this approach to be conclusive, and therefore expert assessment is seen as key to evaluating structural uncertainty (O'Hagan, 2012). Model sensitivity analysis can be combined with expert assessment; the final variance estimates would be crafted by experts, aided by the results of the sensitivity analysis. This approach combines the advantages of both expert and model sensitivity assessments; namely, the quantitative rigor of the model itself, as well as insights about the potentially relevant factors outside of it (Uusitalo, Lehikoinen, Helle, & Myrberg, 2015).

2.4.4.5 Markov Decision Processes

A notable resurgence in both applied and theoretical research on Markov decision processes has emerged during the past decades. These models have gained recognition in such diverse fields as ecology, economics, and communications engineering. Markov Decision Processes (MDPs) are strong analytical methods used for sequential decision-making under uncertainty, that have been broadly used in many industrial and manufacturing applications but are as yet underutilized in public policy. They generalize standard Markov models in that their process is embedded within the model, and multiple decisions and choices are made over time. Furthermore, they have significant advantages over standard decision analysis (Puterman, 2014).

Formal decision analysis has been broadly used to deal with complex problems in public policy, which demands the use of more advanced modeling methods. The common methodology utilized to assess decision analysis issues had long been the standard decision tree, which has critical limitations in its ability to model complex situations, especially when events or outcomes occur over time. Now, it is generally replaced by Markov process-based methods so as to better model recurrent states and future events (Alagoz, Hsu, Schaefer, & Roberts, 2010).

MDPs, also known as stochastic control problems or stochastic dynamic programs, are analytical models for sequential decision-making under uncertainty. This type of model includes decision epochs, states, actions, rewards, and transition probabilities. Selecting an action within a state produces a reward and determines the state at the next decision epoch by a transition probability function. Strategies or policies are prescriptions of which action to select under any eventuality, at every future decision epoch. Decision-makers pursue policies that are optimal in some sense. Any analysis of this model includes (Puterman, 2014):

1. Providing conditions under which there exist easily implementable optimal policies;
2. Determining how to recognize these policies;
3. Developing and enhancing algorithms for computing them; and
4. Establishing convergence of these algorithms.

Surprisingly, these analyses depend on the criterion used to compare policies. Puterman (2014) presents a model for sequential decision-making under uncertainty, which takes into account both the outcomes of current decisions and future decision-making opportunities. While this model (see Figure 2-1) may appear quite simple, it encompasses a broad range of applications, and has generated a rich mathematical theory. At a specified point in time, a decision-maker observes the state of a system. Based on this state, the decision-maker chooses an action, which then produces two results: the decision-maker receives an immediate reward (or incurs an immediate penalty cost), and, the system evolves into a new state at a subsequent point in time, according to a probability distribution determined by the action choice. At this subsequent point in time, the decision-maker faces a similar problem, but now the system may be in a different state and there may be a different set of actions to choose from. The key ingredients of this sequential decision model are the following:

1. A set of decision epochs.
2. A set of system states.
3. A set of available actions.
4. A set of state and action-dependent immediate rewards or costs.
5. A set of state and action-dependent transition probabilities.

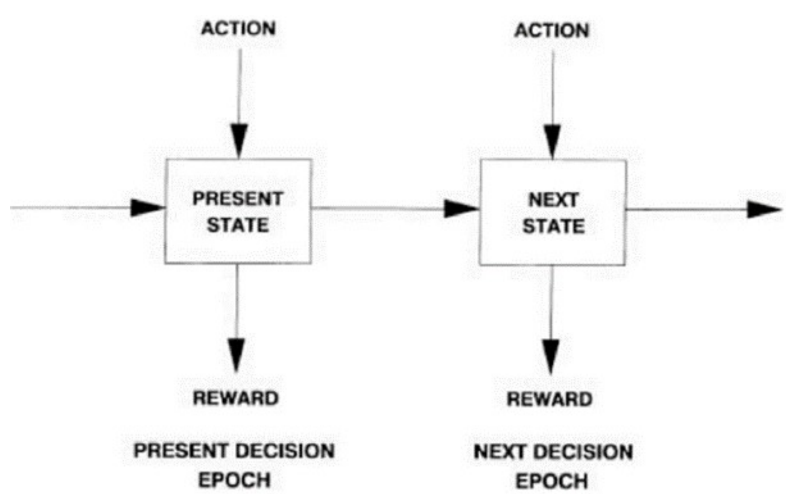

Figure 2-1- Symbolic Representation of Sequential Decision Problem (Puterman, 2014, p. 23)

As Puterman (2014) indicates, this model assumes that all of the above elements are known to the decision-makers at the time of each decision. At each decision epoch (or time), the system state provides the decision-maker with all essential information for selecting an action from the set of available actions in that state. As a result of choosing an action in a state, two things happen: the decision-maker receives a reward, and the system evolves to a possibly different state at the next decision epoch. Both the rewards and transition probabilities depend on the state and the choice of action. As this process evolves through time, the decision-maker receives a sequence of rewards.

At each decision epoch, the decision-maker chooses an action in the state occupied by the system at that time. A policy provides the decision-maker with a prescription for choosing this action in any possible future state. A decision rule specifies the action to be selected at a particular time. It may depend on the present state alone or together with all previous states and actions.

A policy is a sequence of decision rules. Implementing a policy generates a sequence of rewards. The sequential decision problem, meanwhile, is to choose, prior to the first decision epoch, a policy to maximize a function of this reward sequence. Puterman chooses this function to reflect the decision-maker’s inter-temporal tradeoffs. A possible choice for three functions includes the expected total discounted reward for the long-run average reward. In this model, the set of available actions, rewards, and transition probabilities depends only on the current state and action, and not on states occupied and actions chosen in the past. This model is sufficiently broad to allow for modeling the most realistic sequential decision-making problems.

As Nadar (2012) notes, MDPs offer an elegant mathematical framework for addressing arbitrarily challenging, sequential decision problems that arise in the fields of operations research, management science, finance, and computer science, among others. Fundamentally, MDPs enable researchers to analyze the dynamics of a stochastic process whose transition mechanism is controlled over time: The state of the process provides the decision-maker with all the information necessary to choose a feasible action in that state. The process responds to the selected action by randomly evolving into a new state, and yields either costs to or rewards for the decision-maker. While MDPs capture complex systems, they still enable clean analytical formulations with the help of abstractions and assumptions. Most importantly, it is assumed that the probability that the controlled process transitions into its new state depends only on the current state and the chosen action. In other words, the state transitions of a MDP possess a memoryless property, which greatly simplifies the analysis of stochastic processes.

Due to this memoryless assumption in a MDP, one needs to make decisions only at certain time epochs. Therefore, one strength of MDPs lies in their ability to be used to formulate a discrete recursive value function to capture the expected cost or reward; the optimal action as a function of the current state can be derived by calculating this value function. Many researchers have studied various techniques in this context, including dynamic and linear programming, to compute value functions. However, most computational methods suffer from multiple dimensionality; their practical applications are limited to cases where the state space is manageably small and/or the value function has a simple analytical form. To solve computationally nontrivial problems, many other researchers have focused on characterizing the structural properties of value functions. Establishing basic properties of value functions in MDPs, and showing that they survive under iteration, forms the basis of the inductive proof technique, which allows the structure of the optimal policy to be deduced. Structural properties provide a powerful methodology for either partial or complete characterization of optimal policies, which might present important managerial implications and/or offer smarter computational methods (Nadar, 2012).

MDPs also have some limitations and drawbacks. First, they have huge data requirements, which are necessary to estimate both transition probability and reward functions for each possible action. Unlike Markov-based simulation methods, infinite-horizon MDPs assume that both the rewards and the transition probabilities are stationary. Furthermore, because there is no available easy-to-use software for solving MDPs, some extra programming effort is demanded (Alagoz, Hsu, Schaefer, & Roberts, 2010). As the problem size grows, it becomes computationally difficult to solve MDPs in an optimal way, which is referred to as the curse of dimensionality. Corresponding to this, there is an increasing area of research in approximate dynamic programming, to develop algorithms that can solve MDPs faster and, to some extent, overcome these limitations (WB., 2007).

2.4.4.6 Loop Analysis

All risk assessments and uncertainty analyses, whether qualitative or quantitative, are constructed around a conceptual model of the system in question. Loop analysis (also known as qualitative modeling) provides a quick, rigorous, and transparent method that enables certain predictions to be made about the behavior of this model and to explore the effects of model uncertainty on these predictions. Qualitative modeling is best suited to the early “problem formulation” stage of a risk assessment (USEPA, 1992), before the identification of hazards and estimation of risk (Hayes, Regan, & Burgman, 2007).

Qualitative modeling proceeds by determining the system's structure, which is defined by the variables of the system and the relationships by which they are linked. The dynamics of human social and economic systems can be described by the interactions of different sectors and entities of society (such as governing bodies, social customs, and markets) that control flows of resources, goods, and services that are either measurable, such as money, or immeasurable, such as status and worldview (Hayes, 2011).

Variables and relationships in loop analysis are portrayed by Sign-Directed Graphs (SDGs) (or signed digraphs), where a link from one variable to another ending in an arrow (→) represents a positive direct effect, such as births produced by consumption of prey, and a link ending in a filled circle (─●) represents a negative direct effect, such as death from predation. All possible relationships can be described in this manner. Importantly, loop analysis ignores the strength of the pairwise relationships in the SDG by assigning one of two unit signs -1; or + 1 to each interaction. Furthermore, interactions in the SDG are typically considered to be fixed and independent of the population size. However, There can be interactions, however, that are modified by the abundance of a third variable, which creates additional direct effects in the system (Dambacher & Ramos-Jiliberto, 2007).

Once the structure of a system is defined, then it is possible to: (1) analyze the system's feedback, which determines the qualitative conditions for system stability; and (2) examine its response to sustained (press) perturbations. System feedback is governed by the products of the interactions in the SDG. Negative feedback returns the opposite effect to an initial change in a variable, and acts to maintain a system's equilibrium. The overall stability of a system can be judged and understood according to two criteria that depend on the relative sign and balance of the system's feedback cycles (Dambacher, Luh, Li, & Rossignol, 2003). In general, stability requires that the net feedback in a system is negative, and that feedback at lower levels of the system is stronger than that at higher levels. Negative feedback ensures that a system's dynamics are self-damped, and stronger feedback at lower levels ensures that a system will not overcorrect and exhibit unrestrained oscillations. Meanwhile, as system size and complexity increase, symbolic contingencies underlying the conditions for stability in any model become too complex to interpret through the Signed Digraph. To address this problem Dambacher et al. (2003) developed a set of stability metrics that can be used to judge the potential for stability in such large complex models.

The utility of loop analysis in a risk assessment context is as a method of forward uncertainty propagation for model structure uncertainty and scenario uncertainty. SDGs can be quickly constructed with a range of different stakeholders to capture different conceptual models, and thereby investigate the potential effects of model structure uncertainty, and/or different perturbation scenarios. Hayes et al. (2008) coined the term "pressure scenarios" to describe the combination of uncertain model structure and uncertain future stresses on systems and used loop analysis to identify system responses that were either consistent across, or idiosyncratic of, these scenarios.

The advantages of qualitative analysis of conceptual models early in the risk assessment process are numerous: loop analysis can represent conceptual models in a transparent fashion and help minimize the effects of linguistic uncertainty. Like

Bayesian Networks, the graphical structure of the SDG is attractive to stakeholders without mathematical training, and can be used to elicit conceptual models from a diverse range of different disciplines. Loop analysis also has a rigorous mathematical foundation that can identify unstable (and therefore potentially implausible) conceptual models, the direction of the response of variables subject to multiple, simultaneous, pressures, and the probability of sign determinacy - i.e. the probability that the direction of response will be correct, irrespective of the magnitude of the interaction strengths (parametric uncertainty) that it otherwise ignores. By ignoring the magnitude of the interaction coefficients in the community matrix, qualitative modeling achieves generality and realism, but at the expense of precision. The lack of precision and the other equilibrium assumptions associated with loop analysis present a number of important drawbacks (Hayes, 2011):

- The technique assumes that all interactions within the SDG are equally "strong." The implications of this assumption can only be examined in a limited sense, by considering models with and without interactions that are deemed "weak" or otherwise unimportant to the overall dynamics of the system;
- The technique cannot address questions such as "how much should we spend on x to get more of y?" The predictions of loop analysis are restricted to the direction (increase, decrease, or ambiguous) of change of each variable in the SDG; they say nothing about the magnitude of change;
- Qualitative modeling describes system dynamics through a set of linear differential equations. It therefore assumes that the system's equilibrium, whether it is described by fixed points or sustained bounded fluctuations,

will exhibit familiar levels or trajectories of abundance. Furthermore, qualitative predictions of a variable's response to press perturbations describe a linear shift from one equilibrium to another, and do not address transient behavior between equilibria, nor can they make predictions for systems that are always held away from an equilibrium by constant external forcing.

In practice, the assumptions associated with qualitative modeling require that: (1) there is some level of resolution (in space and time) as well as some level of aggregation of the system's variables, at which the system displays familiar dynamics that can be adequately described by linear differential equations; (2) that these dynamics are relevant to the problem at hand; and, (3) that the model is built at this level of resolution. Hence, when building qualitative models, the modeler must choose from among a hierarchy (systems-based, ideally) of possible structures at, for example, increasing spatial resolution, such that the variables within the model are relevant to the question being answered, whilst the constant, non-linear, or random variations that are omitted from it are not (Levins, 2006).

2.4.4.7 Fuzzy Approaches

The fuzzy system approach's potential for modeling uncertainty in policy/decision-making lies in several critical features, including: (1) fuzzy logic as a method to capture the imprecision associated with everyday reasoning; and (2) the representation of human judgment models as fuzzy rules (Dorsey & Coovert, 2003). Furthermore, fuzzy systems offer opportunities to model economic processes for which only a linguistic description is available; non-fuzzy techniques (e.g., probabilistic tools and Monte Carlo simulations) cannot handle the imprecision and vagueness of semantic aspects that are inherent in linguistic uncertainty.

There are two major fuzzy approaches in uncertainty analysis and risk assessment: Fuzzy Set Theory and Fuzzy Cognitive Maps. In the following pages, I will try to briefly describe these two approaches. As a non-probabilistic method, fuzzy set theory generalizes several classic notions of concise sets that underlie, for example, the axioms of probability theory. Two important concepts generalized by the fuzzy set theory are the notions of membership and the relation that describe the presence or absence of association. Membership degree in a fuzzy set is specified as a real number on the interval [0, 1] where 0 indicates that the element does not belong to the set and 1 indicates that the element completely belongs to the set (Ascough et al, 2008). The ability to integrate expert knowledge (structured mainly by means of linguistic expressions) concerning regional economic relationships, as well as the availability of qualitative data, are frequently cited as important reasons to use fuzzy system tools (e.g., fuzzy-rule-based models for decision support and predictive modeling) to deal with uncertainty inherent in public policy. Fuzzy sets and rules have been constructed for implementation in integrated regional economic development and sustainable development (Cornelissen, van den Berg, Koops, Grossman, & Udo, 2001).

By addressing areas of uncertainty, ambiguity, and dissent in the decision process, fuzzy set techniques provide the opportunity to improve both immediate short-term decisions and long-term strategic aspects of management. However, a number of problems remain to be solved (Ascough et al, 2008):

- Exploring the meaning of linguistic terms and assigning fuzzy values to linguistic terms are essential in resolving vagueness, fuzziness, uncertainty, and imprecision in decision-making problems. There are, however, few practical systems to capture linguistic terms from decision-makers and systematically convert them into fuzzy sets.

- New methods for generating reasonable membership functions are needed, especially those that are intuitive, simple to use, and based on input from decision-makers or historical resources.
- A significant amount of fuzzy set application to policy/decision-making in the literature is based on hypothetical information or test cases. Applications of fuzzy systems to real policy/decision-making problems with real decision-makers are urgently needed to demonstrate the efficacy of the fuzzy systems approach for solving real-world problems.
- Validation and optimization problems have resulted in numerous non-reliable models. This problem can be overcome through the development of hybrid approaches combining fuzzy-rule-based models with probabilistic data-driven techniques. Hopefully, more reliable modeling results will convince managers and policymakers to apply fuzzy models in practice.

Kosko (1986), meanwhile, coined the term Fuzzy Cognitive Map (FCM) to describe a cognitive map in which “causal weights” – numbers on the interval [-1, 1] – are added to the direct links of the Signed Directed Graph. The term cognitive map is used to describe a variety of conceptual constructs but it is most commonly associated with an influence diagram (or causal map) that shows variables (variously termed states, nodes, concepts, etc.) deemed to be important to a problem, and the direct effects (variously termed as arcs, edges, links, interactions, etc.) between these variables (Siau & Tan, 2005). It was first used in the 1970s by the political scientist Robert Axelrod to represent graphical portrayals of social scientific knowledge (Kosko, 1986). These maps are precisely the Sign Directed Graphs that support loop analysis – i.e. qualitative, graphical models that allow two-way, positive and negative causal effects between variables of a system.

It is instructive to note that Kosko (1988) refers to Signed Digraphs as "simple FCMs" with causal edge weights in the set f {-1; 0; 1}, hence causality occurs to a "maximal degree;" whereas FCMs allow "degrees of causality" to be represented. This helps illustrate the similarities and differences between loop analysis and FCM. The use of the term "fuzzy" in FCM, however, seems to be open to interpretation. In some applications of it, the causal weights placed upon the cognitive map are precise numbers (Ozesmi & Ozesmi, 2004) whereas, in other applications, they are fuzzy sets describing, for example, linguistic measures of relative abundance (Ramsey & Norbury, 2009).

Hayes (2011) indicates that graph theory enables a number of similarity statistics to be derived from FCMs, describing (for example) the connectivity of a map. The utility of FCMs in risk assessment, however, again lies in exploring the implications of model structure and scenario uncertainty. The perturbation analysis is achieved by solving different maps (with and without the press perturbation) via an iterated matrix operation that finds the roots of the linear differential equations represented by the "adjacency matrix": the FCM equivalent of the community matrix in loop analysis.

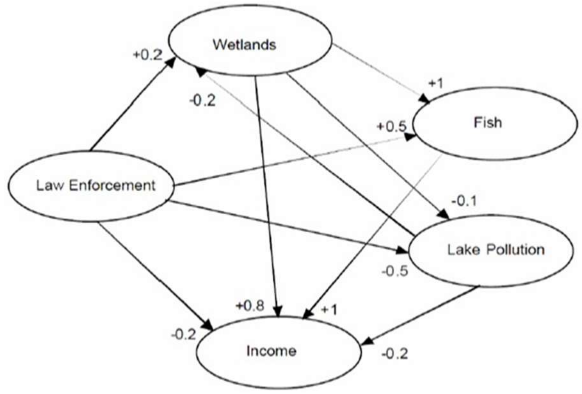

Figure 2-2- Fuzzy Cognitive Map (top) for Uluabat Lake, Turkey (Ozesmi & Ozesmi, 2004).

FCMs have many advantages: they are relatively quick, transparent, graphically based, and therefore good ways to elicit conceptual models from a diverse range of stakeholders. They can examine the implications of diverse opinions about plausible model structures, and can be used to examine the implications of scenario uncertainty through, for example, different management regimes associated with different pressure scenarios. The sign and magnitude of the steady-state values also provide additional information on the direction and relative magnitude of change in each of the map's nodes. The steady-state solution can also incorporate the effects of linguistic uncertainty via the use of fuzzy sets for the causal weights, and it seems possible to generalize this to parametric uncertainty via the use of an interval. There are, however, some drawbacks with FCMs (Hayes, 2011):

- Simple signed FCMs (Signed Directed Graphs) are easier to construct with experts and are more reliable than real-valued FCMs because experts are more likely to agree on the causal sign of a direct effect than on its magnitude (Kosko, 1988);

- The units of causality in an FCM can be vague however, this can create problems when interpreting the results;
- There does not appear to be any explicit stability analysis applied to FCMs, therefore in many applications, there are no self-effects applied to the variables in the maps – the diagonal elements of the adjacency matrix are zero.

2.4.4.8 Adaptive Management

In general, adaptive management incorporates initial uncertainty, treats decisions as hypotheses to be tested, and demands that managers not only learn from the consequences of their decisions but also alter their decisions (or implement new ones) accordingly (Ascough et al., 2008). A major hurdle in reducing uncertainty in model predictions used for policymaking and management activities is having to convince both scientists and policymakers to follow through with research, by performing adaptive management and consistent monitoring and comparison between model outcomes and the trajectory of target systems. For example, periodic data collection, following management activities fed back into a reconfigured or re-parameterized model, can facilitate "running predictions" that can reduce uncertainty (Haff, 1996) and achieve realization of the management objectives. These techniques can be used to control divergence between model predictions and target systems over time. In addition, if adaptive management activities can be accomplished within a divergence time scale (Haff, 1996), defined as the time scale over which uncertainty in model predictions results in irreconcilable divergence between predictive capability and system trajectory, uncertainty may be mitigated by corrective action.

Interestingly, adaptive management is precisely analogous to the iterative Bayesian learning and decision process. Prior information is specified, decisions are made, and consequences are observed. The consequences are not treated as final events, but rather as new sources of information (new prior probability functions) that can lead to modifications in management practices (e.g., new decisions) (Ascough et al, 2008). The main core of adaptive management is its ambition to collect and integrate the necessary knowledge about how systems are likely to respond to alternative management schemes and changing conditions, into policymaking and management, within a continuous decision process (Yousefpour et al., 2012). There are two existing adaptive planning approaches, 'Adaptive Policymaking' and 'Adaptation Pathways.' The first is a theoretical approach explaining a planning process with various types of actions (e.g. 'hedging actions'and 'mitigating actions') and signposts to monitor to see if adaptation is required. In contrast, the second provides an analytical approach for exploring and sequencing a set of possible actions based on alternative external developments over time. In the following pages, I will describe these two approaches.

The Adaptation Pathways approach is summarized in Figures 2-3 and 2-4 (Haasnoot, Middelkoop, Offermans, Van Beek, & van Deursen, 2012). Central to the Adaptation Pathways approach are adaption tipping points (Kwadijk et al., 2010), which are the conditions under which an action no longer meets clearly specified objectives. The timing of an adaptation point for a given action, i.e., its sell-by date, is scenario-dependent. After the adaptation point is reached, additional actions are needed and, as a result, a pathway emerges. This approach presents a sequence of possible actions after a tipping point in the form of adaptation trees (e.g. like a decision tree or a roadmap), and any given route through a tree is an adaptation pathway. Typically, this uses computational scenario approaches to assess the distribution of the sell-by date of several actions, across a large ensemble of transient scenarios. This distribution can be summarized in a box-and-whisker plot and the median, or quartile, values used to generate an adaptation map. The exact date of a tipping point is not important, though it should be at least roughly right – for example, on average, the tipping point will be reached within 50 years; at earliest within 40 years, and at latest within 60 years. The effects of action sequences can be assessed in the same way as individual actions. To overcome the presence of different stakeholders with different values and worldviews, cultural perspectives can be engaged to map these out (Haasnoot, Kwakkel, Walker, & ter Maat, 2013).

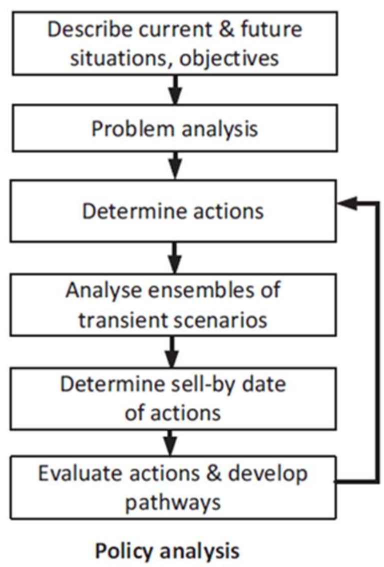

Figure 2-3- Stepwise Policy Analysis to Construct Adaptation Pathways. (Haasnoot, Middelkoop, Offermans, Van Beek, & van Deursen, 2012)

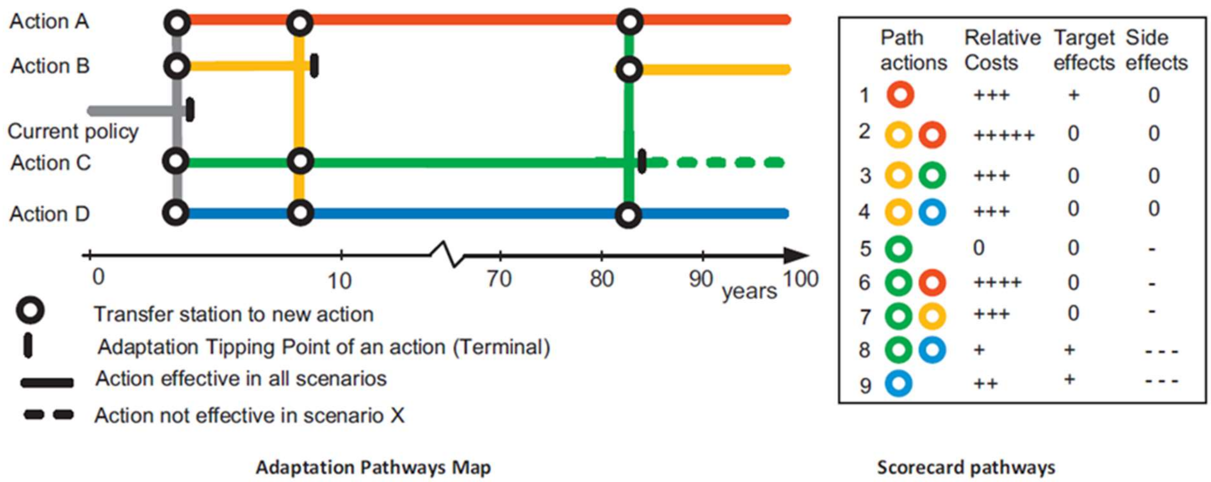

Figure 2-4- An example of an Adaptation Pathways (adaptive management) map (left) and a scorecard presenting the costs and benefits of the nine possible pathways presented in it. In the map, starting from the current situation, targets begin to be missed after four years. Following the gray lines of the current policy, one can see that there are four options. Actions A and D, as noted, should be able to achieve the targets for the next 100 years, in all climate scenarios. If Action B is chosen after the first four years, a tipping point is reached within about five years; a shift to one of the other three actions will then be needed to achieve the targets (follow the orange lines). If Action C is chosen after the first four years, a shift to Action A, B, or D will be needed in the case of Scenario X (follow the solid green lines). In all other scenarios, the targets will be achieved for the next 100 years (the dashed green line). The colors in the scorecard refer the actions A (red), B (orange), C (green), and D (blue) (Haasnoot, Kwakkel, Walker, & ter Maat, 2013).

The Adaptation Pathways map, manually drawn based on model results or expert judgment, presents an overview of relevant pathways (see Figure 2- 4 for an example). Similar to a Metro map (e.g. Washington, D.C. subway), it presents alternative routes to get to the same desired point in the future. All satisfy a pre-specified minimum performance level, such as a safety norm (a threshold that determines whether results are acceptable or not). They can, thus, be considered as ‘different ways leading to Rome’ (as is true of various routes to a specified destination on the Metro). The moment of an adaptation tipping point (terminal station), and the available actions after this point, are shown (via transfer stations). Due to the unacceptable performance of some actions in a selection of scenarios, some routes are not always available (dashed lines). Decision-makers or stakeholders may have a preference for certain pathways, since their relative costs and benefits may differ. An overview of such costs and benefits for each pathway can be presented in a scorecard (Haasnoot, Kwakkel, Walker, & ter Maat, 2013).

With an adaptation map, decision-makers can distinguish opportunities, no-regret actions, lock-ins, and the timing of an action, to help decision-making in an evolving domain. This map can be utilized to provide a plan for actions to be taken promptly, as well as for preparations that should be made in order to be able to implement an action in the future, in case the situation changes. The example of Figure 2-4 shows that actions are needed in the short term. Selecting action B may be ineffective as, soon, additional actions are needed. Selecting option C, meanwhile, involves taking a risk, as additional actions may be needed should scenario X become a reality. In combination with a scorecard of the relative costs and benefits for these pathways, a decision-maker could make an informed decision (Haasnoot, Kwakkel, Walker, & ter Maat, 2013).

Adaptive Policymaking is a generic, structured approach for designing dynamic robust plans (Ranger et al., 2010). Conceptually, Adaptive Policymaking is rooted in Assumption-Based Planning (Dewar, Builder, Hix, & Levin, 1993). Figure 2-5 shows the steps of this approach for designing a dynamic adaptive plan (Kwakkel, Walker, & Marchau, 2010). In Step I, the conditions of a system are analyzed and the goals for future development are determined. In Step II, the way in which these goals are to be achieved is determined by assembling a basic plan, which is made more robust by four types of actions (Step III): mitigating actions (to reduce the likely adverse impacts of a plan); hedging actions (to spread or reduce the uncertain adverse impacts of a plan); seizing actions (to seize likely available opportunities); and shaping actions (to reduce failure or improve success).

Even with these, there is still the need to monitor and control plan performance and to take action if necessary. This is called contingency planning (Step IV). Signposts specify information and data that need to be tracked to specify whether or not the plan meets the conditions required for it to succeed. Also, critical values of signpost variables (triggers), beyond which additional actions should be implemented, are determined. There are four different types of actions that can be triggered by a signpost, as specified in Step V: defensive actions (to clarify the basic plan, preserve its benefits, or meet outside challenges in response to specific triggers that leave the basic plan unchanged); corrective actions (adjustments to the basic plan); capitalizing actions (to take advantage of opportunities that can improve the performance of the basic plan); and a reassessment of the plan (initiated when the analysis and assumptions critical to the plan's success have clearly lost validity). Once the complete plan has been designed, the actions to be taken are immediately (from Step II and Step III) implemented, and a monitoring system (from Step IV) is established. Then, time starts running, signpost information related to the triggers is collected, and actions are started, altered, stopped, or expanded in response to this information. After implementing these initial actions, the implementation of other actions (from Step V) is suspended until a trigger event occurs (Haasnoot, Kwakkel, Walker, & ter Maat, 2013).

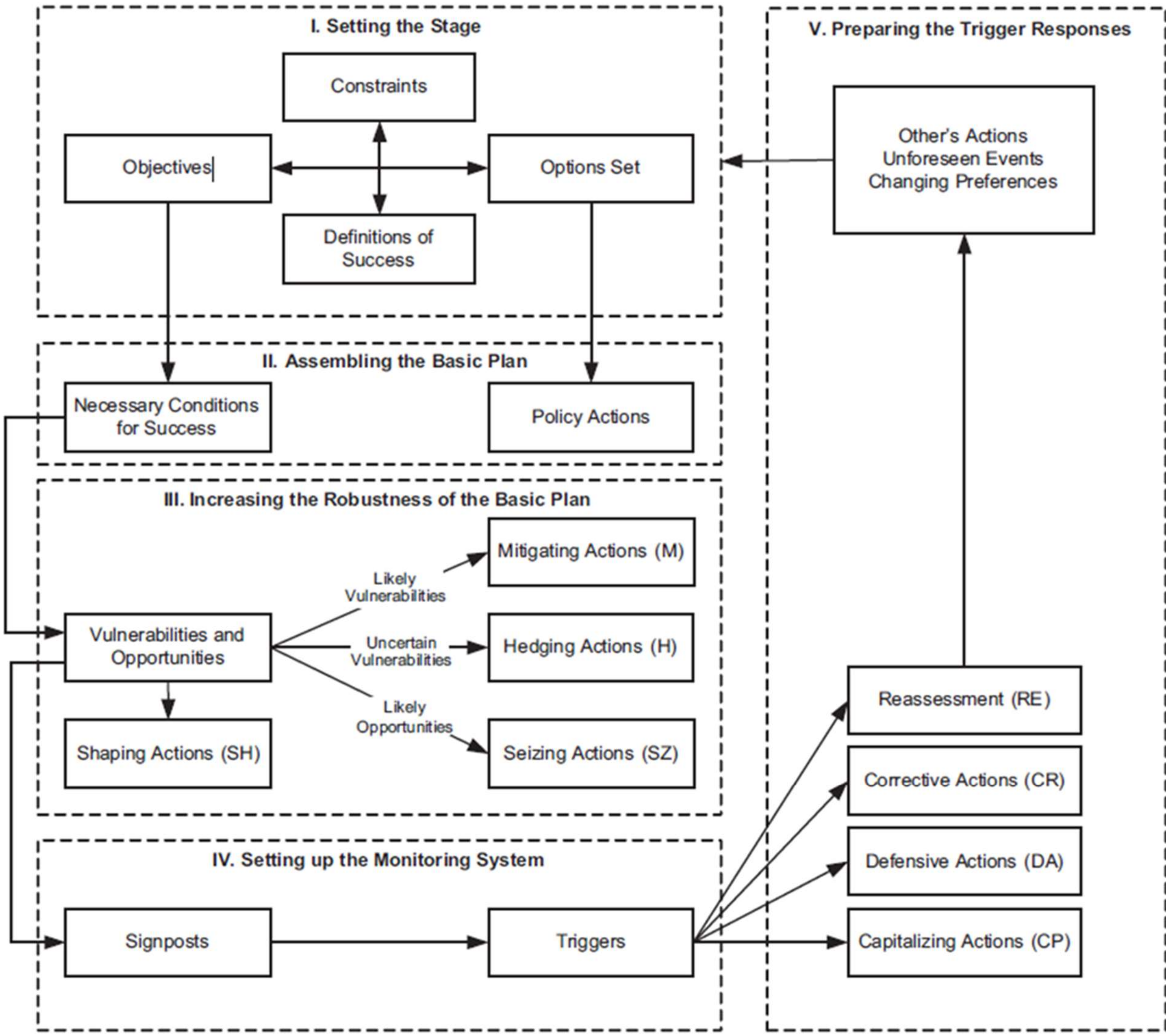

Figure 2-5- The Adaptive Policymaking approach to designing a dynamic adaptive plan (Kwakkel, Walker, & Marchau, 2010)

2.4.5 Discussion and Conclusion

As discussed in this section, the key to eliminating uncertainty and analyzing risks is information. It is important to eliminate as much uncertainty as possible about the nature of the problems and opportunities presented. This can be done by first understanding how information will be used in planning and risk and uncertainty analysis, and then systematically setting out to collect as much information as is needed. There is a temptation, if not a tendency, to define problem statements with regard to their solutions, and to accept the available information that is consistent with the "solution-defined" problem, while often overlooking other relevant information and views. One can easily point to studies in which the concerns of a group had, often, been overlooked early on in the development of a study, in deference to the views of the power structure, only to have that decision cause substantial problems later on in the study. It is far preferable, then, to make the effort to identify the concerns of all groups that may be relevant to the planning process.

On the other hand, general perceptions about the uncertainty that mostly address a lack of knowledge as the primary agent of the existing instabilities should be revisited. The insufficiency of synoptic scientific-based understanding between knowns and unknowns to address the agents of ambivalences in the process of decision-making is also highlighted. I have mentioned four combinations of knowns and unknowns that convey all possible combinations in the process of decision-making. This definition assists decision-makers in addressing various sources that may generate uncertainty.

As discussed, academia considers 'known-unknowns' and 'unknown-unknowns' as the primary sources of instabilities. Despite the importance of both mentioned combinations of lack of knowledge in the generation of uncertain conditions, another category of lacked knowledge, 'unknown-knowns,' which is also problematic within the process of decision-making, particularly in analyzing uncertainty. Yet, academia disavows the failures of dominant scientific knowledge as 'knowledge that does not know itself'. The Foucauldian works, particularly his notion of 'Power/Knowledge,' precisely elucidate how common knowledge, in general, is largely channeled and adjusted by the dominant power mechanism. While Foucault's investigations focused mostly on the industrial society, his notion of 'power/knowledge' is also valid in the post-industrial society in which schools and universities are, for the most part, privatized and commercialized in order to merely respond to market demands as the dominant power constitution. The side effects and failures of science, particularly social science, are largely disavowed, or at least neglected, under the hegemony of market-driven values. As Beck (2006) observed, market operations largely rely on certainty, or at least the illusion thereof, whereupon, they then support only the scientific knowledge that generates the illusion of stability. In this context, the weaknesses of these understandings are extensively disavowed, but 'unknown-unknowns' and 'known-unknowns' are still considered in the creation of instabilities.

This chapter presents an overview of uncertainty and also different types and approaches to uncertainty analysis. Due to the various assumptions and implications inherent in each approach, there are limitations on which types of uncertainty analyses can be performed. The biggest obstacle to performing one fully, that includes all variables, is the lack of sufficient information resources. Given current limitations, a tradeoff needs to be made of model detail and uncertainty analysis. If a problem is characterized by significant uncertainty or potentially important feedback, research resources might be better spent on the exploration of a large number of alternative problem formulations, rather than to increase resolution in the best-estimate model. One goal of performing uncertainty analyses is to increase the usefulness of integrated assessment models to policymakers. This goal should be kept in mind when communicating the results of an uncertainty analysis. Quantifying the many types of uncertainty about a given model, as well as the underlying processes and values thereof, can be a daunting task, and communicating all the results can leave the end-user confused. While modelers should perform as many types of uncertainty analyses as their resources will sustain, only a subset of their results should be considered for publication to policymakers, while others should be performed mainly as good modeling practice, and to increase confidence in model structure and choice of parameters (Kann & Weyant, 2000).

As reviewed, in practical risk assessments, uncertainty is commonly treated by probabilistic methods; in their Bayesian, subjective formulation for the treatment of rare events and poorly known processes, typical of high-consequence technologies. Some theoretical and practical challenges seem to be still somewhat open, however. This has sparked the emergence of a number of alternative approaches, which have been here considered in relation to their support for the decision-making that they can provide. Many researchers and analysts are skeptical of the use of "non-probabilistic" approaches for the representation and treatment of uncertainty within risk assessment for decision-making. An imprecise probability result is considered to provide a more complicated representation of uncertainty. By arguing that the simple should be favored over the complicated, it takes the position that the complication of imprecise probabilities seems unnecessary. However, the decision basis cannot be restricted to subjective probabilities: there is, therefore, a need to go beyond the Bayesian approach (Zio & Pedroni, 2013).

In the end, any method of uncertainty analysis in risk assessment must address some very practical questions before being applicable in support of decision-making: how completely and faithfully does it represent the knowledge and information available? how costly is the analysis? how much confidence does the decision-maker gain from the analysis and the presentation of the results? and, what value does it bring to the dynamics of the deliberation process?

Any method that intends to complement, or in some justified cases supplement, the commonly-adopted probabilistic approach to risk assessment, should demonstrate that the efforts needed for its implementation and familiarization by analysts and decision-makers are both feasible and acceptable, in view of benefits gained in terms of the stated questions and, eventually, of the confidence in the decision to be made.

This research aligns with Hayes's (2011) strategy for uncertainty analysis in data-poor situations:

1. Use formal elicitation techniques to canvass the opinions, construct conceptual models, and parameterize the beliefs of stakeholders and experts. Use either predictive or structural elicitation methods to convert conceptual models into statistical, qualitative and/or mechanistic models, and convert beliefs about stochastic variables into numerical intervals with assigned levels of confidence;
2. Ensure feedback is embedded within the elicitation procedure (to minimize the potential for misunderstanding) and apply an advocacy-like

procedure to ensure that all aspects of the risk assessment are rigorously reviewed;

3. State risk-decision criteria (risk acceptability levels) in a numeric, measurable fashion for as many of the steps in the risk-generating process as is possible, including steps leading up to the overall assessment endpoint;

4. Maintain plausible diverse opinions and, in the first instance, envelope this diversity using techniques such as loop analysis, comparisons of alternative risk functions, interval analysis, probability boxes and probability bounds analysis. If the upper bound on the subsequent risk estimate is lower than the decision criteria associated with the assessment endpoint, report this result and consider the need for monitoring strategies that enable (in)validation of as many of the steps in the risk-generating process as possible, within the resources available to the assessment. If possible, collect data and use statistical inference methods to check that the risk-generating process is operating within the bounds predicted for each step of the process by the risk assessment;

5. If the lower bound on the enveloped risk estimate is higher than the decision criteria associated with the assessment endpoint, consider prohibiting, stopping or otherwise mitigating the risk-generating process and, if necessary, repeat the risk assessment with risk management steps in place and include, within the assessment, the impact of management and the effects of decision uncertainty upon this; and,

6. If the upper and lower bounds of the enveloped risk estimate straddle the decision criteria associated with the assessment endpoint, consider first the effects of dependence and the mitigating effects of positive or negative dependence. For example, a potential application of positive quadrant dependence arises in import risk assessment because the probability of detecting organisms at the border should be positively dependent on the number of organisms that arrive there - i.e. as the number of infected units rises, so should the probability of their detection. Treating these events as independent denies the reality of inspection regimes, inflates uncertainty bounds, and can lead to paradoxical simulations wherein large numbers of infected units are multiplied by a small probability of detection (and vice-versa) in naive simulations.

Last but not least, uncertainty analysis and risk assessment entail judgments and arithmetic operations with stochastic variables. Uncertainty enters the process via the language used to describe and contextualize the assessment, via our limited knowledge about the most appropriate structure of a risk function and the inherent variability of the variables in these functions. There are important theoretical and practical reasons to keep these different sources of uncertainty separated throughout the risk assessment process. They are motivated primarily by the need to separate uncertainties that, in theory, can be reduced by allocating additional resources (epistemic uncertainty) from that which cannot (variability). Moreover, experience shows that risk assessments that do not explicitly attempt to separate epistemic uncertainty from state uncertainty can provide ambiguous and/or overconfident predictions.

Chapter 3

CONCEPTUAL FRAMEWORK

Policymakers need to be given practical tools and capacities to help them make interventions that are adapted to local contexts and any ongoing signals with regard to their effects, rather than just applying ‘narratives’ and blueprints from the top-down. This is likely to require institutional change and new organizational forms, not only to facilitate innovation, but also to put in place feedback mechanisms that can make such interventions sensitive to ongoing changes. This presents a challenge to the existing power structures, as the status quo serves certain interests in policymaking. As such, institutional incentives may make it difficult to voice concerns about prevailing paradigms and also to trying new approaches. Some conceptual headway has been made with regard to uncertainty. It has been moving up development agendas, and there is space for beginning to bring it more concretely into the policy debate.

The study of public policy is broadly concerned with the processes of identifying and analyzing public issues, the means by which a collective course of action (or inaction) is taken by an authoritative decision-making body in response to perceived public problems. This includes how an effect is given to that course of action as well as what impact the entire process will have on the issue or problem being addressed. Information is key to eliminating uncertainty and analyzing risks. It is important to eliminate as much uncertainty as possible as to the nature of any problems and opportunities presented. This can be done by first understanding how information will be used in the risk and uncertainty analysis, then systematically collecting the required information. There is the tendency to define problem statements in terms of solutions, and to accept readily available information that is consistent with the ‘‘solution-defined’’ problem, while overlooking other relevant information and views. For example, the concerns of a group may be overlooked early on in the development of a study and in deference to the views of the power structure, causing substantial problems later on in the course of things. In light of this, it is far preferable to make an effort to identify the concerns of all groups that may be relevant to the planning process before the study itself is underway.

This study addresses that issue in the form of applied research, aiming to develop a new solution to the specific problem of uncertainties embedded in policymaking at the regional level. Building upon the foundation of complexity and chaos theory, this research considers small regular, periodic internal fluctuations (variability) as "unknown-knowns," which can suddenly swamp the whole socioeconomic system. Therefore, it develops a new policy framework called “Vectorial Policy Process” to understand and then incorporate uncertainties (unknown-knowns) into the policymaking process. There is no precedent in public policy literature for this kind of framework that provides a concrete context for the conceptualization of uncertainties embedded in policymaking process. By conducting a case study of the Delaware Brownfield Development Program, this study builds a spatial policy support process that reduces uncertainty through collecting more information and converting more “unknown-knowns” to “known-knowns” in the policymaking process. The outcome is an effective policy support solution for aiding policymaking under uncertainty, which can be employed by decision-makers on a regional scale.

3.1 Vectorial Policy Process (VPP)

Vectorial Policy Process can help us to understand various components and factors that play crucial roles in policymaking and implementation under uncertainty. Inspired by Euclidean vector theory, each factor that has an impact on policymaking and implementation process is considered as an "impact vector" that has a magnitude (represented as length & thickness) and direction, and can be added to other impact vectors. An impact vector is represented by a line segment with a definite direction or, graphically, as an arrow connecting an initial point A with a terminal point B, denoted by $\overrightarrow{AB}$. "Resultant impact vector" (the sum of impact vectors) represents the final policy outcome. Impact vectors represent the impact of various components and factors that have an impact on policy outcomes, including but not limited to: knowledge, innovation, local government, NGOs, the private sector, political parties, specific events (natural disasters or anthropogenic events), market conditions, legal frameworks, resources, stakeholders, problems, solutions, timing, social, political and economic contexts, budgeting, public support, state uncertainty (data uncertainty), epistemic uncertainty, etc. Figure 3-1 illustrates Vectorial Policy Process (VPP) conceptual framework.

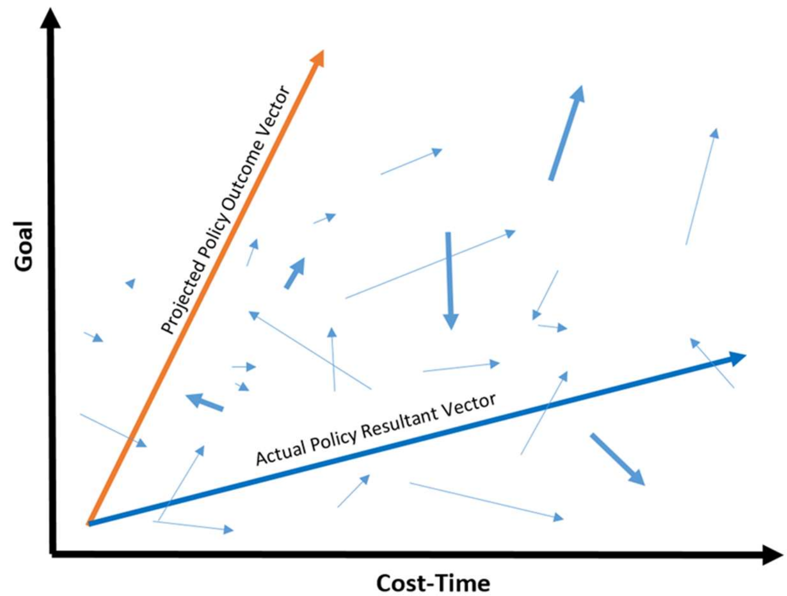

Figure 3-1- Vectorial Policy Process (VPP)

Using VPP, policymakers can conceptualize uncertainties and their impact on policymaking and implementation. In Figure 3-1, the big orange arrow shows the desired or projected policy outcome within a specific time frame, and the big dark blue arrow shows the actual policy outcome, with respect to the projected goal and cost-time period.

For example, let's assume the Delaware Brownfields Program had projected 200 Brownfield sites could be redeveloped over 20 years and, as a result, Brownfield employment would thereby increase by 2000 jobs statewide. But what actually happened was that only 100 Brownfield sites were actually remediated and redeveloped, creating only 700 jobs statewide. This kind of scenario can happen when policymakers fail to effectively predict and incorporate all factors and uncertainties into policymaking, and thus may have a fast or slow, strong or weak impact on the outcome vector.

In Figure 3-1, a quick and strong impact is represented by a short, thick arrow, a slow and weak impact by a long thin one, a quick and weak impact by a short thin one and, finally, a slow and strong impact by a long thick arrow. Some of these factors and uncertainties, such as financial crises or natural disasters, are classified as "unknown-unknowns," i.e., that which policymakers can neither foresee nor do anything about. There are some uncertainties however, that can be incorporated into policymaking to make the angle between projected and actual policy outcome vectors more acute.

As discussed in the literature review chapter, the relevant scientific literature contains many definitions, descriptions, and typologies of uncertainty. The picture is further complicated by different lexicons using different names for the same thing and, occasionally, the same name for different things. This research shares the same conception of uncertainty with critical definitions of knowledge that assist in addressing the ontological challenge that exists in the process of decision-making. Žižek (2006) critically conceptualized the relationship between known and unknown in four combinations: known-knowns, known-unknowns, unknown-unknowns and, most crucially, unknown-knowns. He claimed that these combinations significantly shape our decisions. In the same vein as his statement, this research is most concerned with unknown-knowns, as a paradox that inherently exists in contemporary policymaking.

The term unknown-knowns means the things we don't know that we know (Žižek, 2006). This concept precisely embeds in the Freudian unconscious, as the ‘knowledge which doesn’t know itself.’ “From a psycho-analytical point of view, the unconscious is exactly about a knowledge which doesn’t know itself; it is not some deep buried unknown secret, it is the self-evident lying at the very surface” (Vos, 2009, p. 225). From Žižekian perspective, unknown-knowns constitute most decision-making – or at least, their impact on the process of decision-taking is significant. He adds that “‘unknown-knowns’ are the disavowed beliefs, suppositions, and obscene practices we pretend not to know about, although they form the background of our public values” (Žižek, 2011, p. 293). Despite the common perceptions, Žižek (2008) states that ‘unknown-knowns’ comprise the most problematic issue in the process of decision-making in general, and planning in particular. The ignorance inherent in appeared weaknesses, failures, and side effects related to dominant scientific knowledge seems more challenging than is the unknown-unknown, despite the latter most commonly perceived as the primary challenge. “These disavowed beliefs and suppositions [unknown-knowns] are the ones which prevent us from really believing in the possibility of the catastrophe, and they combine with the ‘unknown-unknowns.’ The situation is like that of the blind spot in our visual field: we do not see the gap, the picture appears continuous” (Žižek, 2008, p. 457). In other words, despite all that scientifically-based decisions, policies, and plans may generate, catastrophes can be addressed as failures of policymaking and programming. The dominant rationalistic knowledge yet impedes decisionmakers, including policymakers, from believing in its weaknesses. Thus, “[c]ontrary to what promoters of the principle of precaution think, the cause of our non-action is not the scientific uncertainty. We know it, but we cannot make ourselves believe in what we know.” (Žižek, 2009, p. 454).

With respect to risk and uncertainty differentiation, this research is founded on the notion that the difference between risk and uncertainty is a matter of perception; a perspective. The distinction between uncertainty and risk can be defined objectively but, when it comes to shaping public policies, it is often more a matter of perception about whether an event or a process is seen as either risky or uncertain. That is to say, uncertainty and risk provide different thresholds.

Regarding uncertainty typology, this study is concerned with both state uncertainty and epistemic uncertainty, which are inherently intertwined, and may exist concurrently in all phases of decision/policymaking process. However, this research keeps these different sources of uncertainty separated throughout the risk assessment process because, otherwise, it provides ambiguous and/or overconfident predictions. State uncertainty is a general term used to describe those types which are inherent in the 'states of nature' on which an analysis is based. It also refers to aleatory uncertainty, variability uncertainty, and the impossibility of any exhaustive classification of states. Epistemic uncertainty, meanwhile, relates to the limitation of our knowledge and understanding, which may be reduced by additional research and empirical efforts. It encompasses linguistic uncertainty, which refers to the vagueness, ambiguity, context dependency, and underspecificity of our natural language. It also may arise where there is ambiguity or controversy about how to interpret or compare a phenomenon – this is also referred to as value uncertainty.

This research aims to incorporate the uncertainty factor into policymaking, by viewing public issues from different angles. It entails collecting as much information as possible while examining problems and solutions through the perspectives of the financial & insurance industry, investors and the private sector, rather than public entities, in order to transfer more ‘unknown-knowns’ to ‘known-knowns’ in shaping public policies, especially with regard to the Brownfield Development Program.

If the goal of state and federal policies is to achieve ‘balanced’ regional economic development, especially through Brownfields, those policies should therefore be developed in a ‘balanced’ way. Providing incentives such as grants and loans, evenly throughout the region, does not achieve this. There are many Brownfield sites which will be redeveloped by the private sector anyway, with or without federal or state incentives. Conversely, there are many others, mostly located in distressed areas, which need stronger and more tempting federal/state incentives to attract investors for redevelopment.

From another perspective, an important consideration with regard to public funds utilized to promote brownfield revitalization is whether or not the targeting of the most marketable sites causes geographic and social inequities as outcomes of the policy implementation (Meyer, 2010). In many states, the dependence on private capital allows a prospective developer to select and target the areas for the use of available public funds for brownfield revitalization. As a result, developers are most likely to choose sites offering the best economic potential, such as waterfront properties or those along major roadways, potentially neglecting contaminated sites in low-income and minority neighborhoods. For example, a detailed study of brownfield efforts in Milwaukee demonstrated that while low-income and minority neighborhoods had a higher density of brownfields than other areas, they had below-average brownfield program assisted redevelopment projects (McCarthy, 2009). Others have also found that by focusing primarily on the most marketable brownfield properties, many contaminated sites in distressed neighborhoods are neglected and not being remediated (Leigh & Coffin, 2005; Hula, 2012). Through their work in Atlanta and Cleveland, Leigh and Coffin have concluded that U.S. cities "can expect widening urban inequality if the predominantly market-based approach to public brownfield redevelopment continues unabated" (Leigh & Coffin, 2005, p. 15).

On the other hand, many studies on the economic impact of brownfield programs have failed to address reverse causality, while exaggerating the local and regional economic impact of brownfield redevelopments. As Joshua Linn (2013) indicates, two likely sources of bias correlated with brownfields are unobserved variables and reverse causality. Specifically, the presence of a brownfield is likely to be associated with local dis-amenities; failing to control for local amenities would bias the estimated impacts of cleanup or certification. Moreover, the value of remediating or certifying a brownfield increases with regard to nearby property values, such that increasing nearby property values typically corresponds to an increase in remediation or certification. The direction of causality can be from nearby property values to certification, thereby raising the possibility of a spurious outcome.

To tackle this issue, this study employs the exclusive analysis and in-depth market-driven data in real time, as used by the banking, financial services and insurance industries, in order to conduct an investment-based risk assessment of brownfield sites. This is intended to help public funds target those sites in manner that is discriminatory in a positive way, to achieve more balanced regional economic development. Thus, as applied research, this study will accomplish two major goals, as follows:

1. Developing a general conceptual framework for understanding the impact of uncertainty in the process of policymaking and implementation: Vectorial Policy Process (VPP)
2. Introducing a new 'Fuzzy Approach' to deal with uncertainty through conducting an investment-based risk assessment of brownfield sites, aiming for a balanced regional economic development:
    i. Applying Analytical Hierarchy Process (AHP) method along with Fuzzy Set Theory for the overall risk assessment of brownfield sites. AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It was developed by Thomas L. Saaty in the 1970s and has been extensively studied and refined since then.
    ii. Applying Empirical Bayesian Kriging (EBK) for a geostatistical analysis of spatial financial and economic data. EBK Regression Prediction is a geostatistical interpolation method that uses EBK with explanatory variable rasters that are known to affect the value of the data being interpolated. This approach combines Kriging with regression analysis, to make predictions that are more accurate than either can achieve on their own.
    iii. Using financial industry and investment bank sources to conduct a fuzzy risk assessment, this study employs two major databases: S&P Global Market Intelligence (S&P Capital IQ and SNL Financial) and the Federal Deposit Insurance Corporation (FDIC) Database.

Chapter 4

INTRODUCTION TO THE CASE STUDY

4.1 U.S. Brownfield Policy

The (public) U.S. Brownfield Policy provides great hope for community revitalization efforts. It is unique in its potential to address multiple public concerns simultaneously, such as those about ground and water pollution, human health, economic development, urban revitalization, and even the protection of undeveloped land. Brownfield revitalization also brings together social policy concerns including housing provisions, economic opportunity, sustainability, community social capital and the empowerment of communities. This policy enjoys broad public support, however, some concerns have arisen, related to contaminated land revitalization. In particular, concerns persist about whether or not the U.S. Brownfield Policy's potential for community development is effectively realized in many decaying urban neighborhoods, where contaminated land is often concentrated.

A series of environmental health crises in the 1970s, epitomized by the Love Canal disaster, led to federal legislation designed to identify and clean up hazardous waste sites. The Comprehensive Environmental Response Compensation and Liability Act (1980), more commonly known as CERCLA, i.e., the Superfund law, requires the EPA to identify and gauge potential risks of contaminated properties. Sites posing the greatest threat to the environment and public health are placed on a National Priorities List (NPL). The law originally followed a "polluter pays" principle, authorizing the EPA to collect monetary damages from potentially responsible parties (PRPs). It also established the Superfund, financed with revenues generated from a tax on petroleum and chemical products, to cover the cost of cleaning up "orphaned sites" for which no PRP could be identified (Kramer, Dsouza, Schramm, Griffin, & Teron, 2014).

CERCLA (1980) initially enjoyed broad public support, however its "strict" and "joint and several" liability provisions raised equity concerns. Under these provisions, any party involved with a given property (including those bearing no responsibility for its contamination) could be held accountable for the entire cost of cleanup. This led to costly litigation and alienated prospective purchasers who, because of this, elected to develop elsewhere. As a result, many abandoned and contaminated sites languished, pushing development further into the suburbs, and thus exacerbating urban sprawl (Greenberg, 2007).

In response to such problems with the implementation of the Superfund law, the EPA launched the brownfields pilot program in 1993, providing seed money to local governments in order to incentivize urban redevelopment (EPA, 2016a). The program quickly gained broad public and political support, and the EPA further expanded the program in 1995 (Greenberg and Hollander, 2006). Congress later passed the Brownfields Tax Incentive Act (1997) and the Small Business Liability Relief and Brownfields Revitalization Act (2002). These provided tax subsidies, liability protection, and financial support to prospective purchasers who agreed to clean up and redevelop brownfield properties (EPA, 2016a).

The brownfields laws were the culmination of a gradual shift from a regulatory to an incentive based national redevelopment policy. Funding from the federal government to lower levels of government currently comes, principally, from two primary sources: non-competitive grants (CERCLA Section 128a) and competitive grants (CERCLA section 104k). Noncompetitive ones are distributed to state and tribal (Native American governed) brownfields programs, on the basis of past performance. They can be used for assessment, cleanup, and redevelopment, as well as for administrative, legal, and insurance purposes. Competitive grants are divided into four categories: assessment, cleanup, revolving loan fund, and job training. Parties eligible for competitive grants include governmental entities and non-profit organizations. Applications are ranked according to project feasibility, community need, expected benefit, and public involvement. The 2002 brownfields law authorizes up to $50 million in annual funding for noncompetitive, and up to $200 million for competitive grants. As of 2012, the EPA has awarded $968.7 million in competitive grants, and close to $500 million in noncompetitive grants overall (Kramer et al., 2014).

As of March 1st, 2016, the EPA's Brownfields Program has funded 23,932 property assessments and cleanups, resulting in an estimated gain of 108,924 jobs, and $20.96 BN leveraged due to cumulative program accomplishments (59,149 acres made ready for anticipated reuse). It also estimates that through fiscal year 2013, $17.79, on average, was generated for each of its brownfields dollars, with 7.3 jobs created per $100,000 of funds expended on assessment, cleanup, and revolving loan fund cooperative agreements. Despite this investment and the program's accomplishments, only a fraction of the total number of brownfields have been assessed and remediated. The EPA estimates there are more than 450,000 brownfield sites remaining in the country, while other estimates place the number closer to one million (EPA, 2016b).

The investigation and cleanup of brownfields in the United States is regulated primarily by state environmental agencies, as part of cooperative agreements with the U.S. Environmental Protection Agency. The authorities are typically based on state code, with guidance, funding and technical assistance provided by the EPA. State eligibility for federal funding requires its programs to survey and inventory brownfield sites, develop its own authorities to ensure the protection of human and environmental health, provide for public participation in brownfield processes, and ensure that they have a mechanism through which to review, approve, and certify the completion of clean-up projects (Small Business Liability Relief and Brownfields Revitalization Act, 2002). State programs are typically modeled on federal law, and encourage the remediation and private development of brownfield sites through both financial assistance and liability protection. Nearly all states and many U.S. territories have developed some form of state-run brownfield and voluntary clean-up program that reduces liability to prospective purchasers interested in the revitalization of land. These programs also provide tax incentives for cleanup (Taxpayer Relief Act, 1997). Other incentives, financial and tax-related, are included under state programs and authorities. Many of the provisions on liability relief and local funding included in state authorities differ significantly from state to state, however (EPA, 2014).

The Federal Brownfield Act includes several distinct statutory parts. Under it, Subtitle A authorizes $200 million annually to incentivize brownfield assessment and clean-up efforts. These grant funds are made available to a range of "eligible entities for brownfields funding include states, tribes, local governments, land clearance authorities, regional councils, redevelopment agencies, and other quasigovernmental entities created by States or local governments" (Small Business Liability Relief and

Brownfields Revitalization Act, 2003). Nonprofit organizations that own contaminated land, but did not cause or contribute to the site's contamination, are also eligible for remediation grants up to $200,000. The policy provides the opportunity for a broad range of organizations to participate, including those communities or organizations working in distressed neighborhoods. Subtitle B clarifies liability issues, essentially releasing an owner or prospective buyer who did not contribute to the contamination from any legal liability for damages cause by past contamination, provided they meet specified due-diligence steps. Finally, Section C authorizes $50 million per year in grant funding for state-operated contaminant response programs. This is provided to states that conduct Voluntary Response Programs in accordance with an approved memorandum of agreement between the federal and state governments.

In all cases where federal funding is provided, the EPA grant criteria require consideration of the "extent to which the grant would facilitate the identification and reduction of threats to the health and welfare of children, pregnant women, minority or low income communities, or other populations." And, the "extent to which the community has the ability to draw on other sources of funding for environmental remediation and subsequent redevelopment of areas in which a brownfield is located because of the small population or low income community" (Small Business Liability Relief and Brownfields Revitalization Act, 1980). Table 4-1, presents the summary of federal brownfields policy and legislation:

Table 4-1- Summary of Federal Brownfields Policy and Legislation, (EPA, 2015b)

Resource Conservation and Recovery Act (1976)–Authorized the EPA to monitor hazardous wastes from “cradle to grave,” including their generation, transportation, treatment, storage, and disposal.
Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) (1980)–Authorized the EPA to identify and clean up hazardous waste sites that posed a threat to human health and the environment. Gave EPA the power to hold potentially responsible parties accountable for the cost of their investigation and cleanup, through “strict” and “joint and several” liability provisions. Created a "Superfund" to clean up orphaned sites, when potentially responsible parties could not be identified or located.
EPA Brownfields Pilot Program (1993)–Established an experimental grant program to incentivize urban redevelopment. Thirty-one grants for pilot projects were awarded to local governments during its 2-year trial period.
EPA National Brownfields Program (1995)–Expanded the brownfields pilot project program, which was initially financed through the Superfund.
Taxpayer Relief Act (Brownfields Tax Incentive) (1997-2011)–Allowed developers to fully deduct costs associated with brownfields assessment and cleanup, including those incurred prior to passage of the law. It expired in 2011 and has not been renewed by Congress.
Small Business Liability Relief and Brownfields Revitalization Act (2002)–Granted liability waivers to non-responsible parties that agreed to remediate brownfield properties. Authorized up to $250 million in funding for competitive and non-competitive brownfield grants to incentivize urban redevelopment.
American Recovery and Reinvestment Act (2009)–Allocated a one-time stimulus of $100 million to the EPA Brownfields Program for the assessment and cleanup of brownfield properties.

From the outset of its efforts, the EPA has viewed the Brownfields Program as more than just another tool for economic redevelopment. It has sought to address the inequities common to brownfield-containing communities and has declared its intent to promote sustainable development therein. Applicants for grant funding are required to demonstrate how project proposals will both involve and benefit local residents, to ensure equitable development outcomes. Moreover, community participation, in the EPA’s view, should be proactive, not reactive. That is, it should not be limited to just soliciting feedback on predetermined projects. Both competitive and noncompetitive grants can be used to fund community participation efforts, and the EPA encourages grant recipients to create programs through which residents are empowered to steer redevelopment to promote general welfare through the improvement of public health and safety, the economy, and the environment of targeted communities (EPA, 2015a). The EPA defines the goals of brownfield programs as follows (EPA, 2016c):

- Protecting the Environment: Addressing brownfields to promote the health and wellbeing of America's people and environment.
- Promoting Partnerships: Enhancing collaboration and communication essential to facilitate brownfield cleanup and reuse.
- Strengthening the Marketplace: Providing financial and technical assistance to bolster the private market.
- Sustaining Reuse: Redeveloping brownfields to enhance a community's long-term quality of life.

4.2 The Delaware Brownfield Development Program

Brownfield efforts in Delaware have been ongoing for more than 20 years. As with the federal government, the state initially adopted a command-and-control framework to manage contaminated sites, with the reduction of environmental risk as the paramount good. The Hazardous Substance Cleanup Act (HSCA), enacted in 1990, empowers Delaware Department of Natural Resources & Environmental Control (DNREC) to identify and remediate sites that threaten human health or the environment; in particular, those sites not covered by the Superfund program (O'Mara, 2011; DNREC, n.d.). Like the federal CERCLA (1980), Delaware's HSCA contains "strict" and "joint and several" liability provisions, giving the state broad power to collect compensation from responsible parties. This law also follows in the footsteps of CERCLA (1980) by creating a fund (the HSCA fund) to help the state pay for the cleanup of orphaned sites (HSCA-7 Del. Chapter 91).

To address liability concerns and avoid costly litigation, Delaware amended the HSCA in 1995 to create a state-run Voluntary Cleanup Program (VCP), which can grant conditional liability protection to current site owners when they make a good-faith effort to clean up the property (HSCA-7 Del. Chapter 91). Although it proved to be an effective negotiating tool when responsible parties could be found, abandoned properties continued to pose a dilemma. Contamination was suspected at many of these sites but, without expensive testing, those suspicions could not be confirmed. Prospective purchasers, faced with the prospect of being held liable for the actions of previous owners, were hesitant to invest in these properties.

To address these concerns and stimulate redevelopment, Delaware defined "brownfields" in 2001 (see Table 4-2) and authorized funding through its Delaware Economic Development Office (DEDO) for their assessment and remediation. In 2005, the Brownfields Development Program (BDP) was created, extending liability protection to prospective purchasers. Developers who entered into a Brownfield Development Agreement (BDA) under the BDP could then qualify for monetary assistance, tax incentives, and conditional liability protection, once remediation was completed (HSCA-7 Del. Chapter 91).

Table 4-2- Summary of Delaware Brownfields Policy and Legislation, (DNREC, n.d.)

Hazardous Waste Management Act (1980)–Authorizes the state to regulate hazardous waste from "cradle to grave," including its generation, transport, treatment, storage, and disposal.
Hazardous Substance Cleanup Act (1990)–Authorizes DNREC to identify and clean up hazardous waste sites that pose a threat to human health or the environment; in particular, those sites not remediated under the Superfund program. The state may hold potentially responsible parties liable for the cost of investigation and cleanup through "strict" and "joint and several liability" provisions. Created a fund (HSCA fund) to clean up orphaned sites when potentially responsible parties cannot be identified.
Voluntary Cleanup Program (1995)–Amends the HSCA to include the Voluntary Cleanup Plan. Responsible parties that agree to complete an approved plan of remediation become eligible to receive a certificate of completion of remedy (COCR), providing conditional liability protection which may be passed on to subsequent purchasers.
Funding and Defining of "Brownfields" (2001)–Authorizes DNREC, per HSCA amendment, to certify brownfields, officially defined as "any vacant, abandoned or underutilized real property, the development or redevelopment of which may be hindered by the reasonably held belief that the real property may be environmentally contaminated." Authorizes the Delaware Economic Development Office (DEDO) to disburse up to $1 million in grants for brownfield assessment and remediation.
Expanded Liability Protection (2003)–Extended, per HSCA amendment, conditional liability protection to non-responsible prospective purchasers willing to conduct assessments and cleanups.
Brownfields Development Program (2004)–Created, per HSCA amendment, the Brownfields Development Program, codifying an agreement for prospective purchasers (referred to as a Brownfield Development Agreement [BDA]), in which they enter into a BDA, receive state certification (certified brownfields) and qualify for state funding. Conditional liability waivers are also granted, once remediation plans are implemented, after which the owner may apply for a certificate of completion of remedy (COCR) that can be passed on to subsequent purchasers.
Brownfields Advisory Committee (BAC) (2005)– Created to provide advice to DNREC on brownfield rules, policies and procedures and to represent the public interest and community perspectives for Delaware's Brownfields Program.
Hazardous Substance Cleanup Act Policy on Brownfield Grants (2006)–Appropriated $5 million from the HSCA Fund to reimburse the costs of site investigation and remediation to parties that have entered into a Brownfield Development Agreement (BDA).
Hazardous Substance Cleanup Act Advisory Committee (2013) –The former BAC changed its name to HSCA Advisory Committee (or HAC Committee) to better reflect the scope of the committee's activities.

Overall, Delaware's brownfields focus and its strategic efforts have mirrored the federal shift from a command-and-control to an incentive-based model. While the state retains the authority to pro-actively clean sites that pose immediate environmental or health risks, brownfield redevelopment has been its focus since 2005, with the state aiming to harness the power of the market using an array of grants, loans, and tax breaks to entice investors to redevelop contaminated properties. Initially reliant on enforcement, Delaware now attempts to negotiate settlements with potentially responsible parties (PRPs) prior to exercising any coercive action, and has largely abandoned the polluter-pays principle. Although DNREC-SIRS investigates each brownfield applicant to assess whether they are responsible for existing contamination or not, efforts to seek damages from prior owners, even when they can be found, have been abandoned.

While the market-driven approach has resulted in the assessment, remediation and redevelopment of several brownfield properties, many have criticized the policy as being overly-friendly to developers and over-reliant on economic factors (Greenberg, 2007). Since this funding only covers a portion of redevelopment costs, only those with substantial resources can afford to participate. This, critics contend, gives absentee-owners a distinct advantage and influence in guiding brownfield decision-making (for example, which sites are given priority, which are redeveloped, and for what purpose), diminishing the ability of brownfield communities to self-determine the development pathway of their neighborhood. Moreover, since the force behind the program is primarily economic, investigation and remediation are more likely to prioritize and occur at sites with economic potential, rather than at sites that pose environmental, health or social risks to the community (Kramer et al., 2014).

4.2.1 Program Overview

The state defines an individual brownfield as "any vacant, abandoned or underutilized real property, the development or redevelopment of which may be hindered by the reasonably-held belief that the real property may be environmentally contaminated" (HSCA-7 Del. Chapter 91). To obtain state certification, developers must demonstrate that a prospective property meets the state's definition of a brownfield (DNREC, 2006). Once approved, the developer may negotiate a Brownfields Development Agreement (BDA) with the state. To enter into a BDA, the applicant cannot: (a) be responsible for any contamination present on the property; (b) be affiliated with any potentially responsible parties; or (c) currently own the property. Current site owners must instead negotiate an agreement through the Voluntary Cleanup Program.

Upon entering into a BDA, the developer agrees "to assess and respond to the actual, threatened, or perceived release of hazardous substances at the site" (DNREC-SIRS, 2008). An initial (Phase I) assessment, which includes a review of past land use/site history, is used to determine the potential for contamination. If concerns are found, a more comprehensive (Phase II) assessment is conducted, which includes soil and water sampling, as well as assessing the risks posed by contamination. If it is discovered, a proposed plan of remediation is then developed. Once approved, the proposal is implemented as a final plan. Remediation requirements for sites vary, contingent upon the toxicity and mobility of the pollutants present, as well as the future planned use of the property. For example, a redevelopment project with a future use as a commercial property for stores will require a lower level of cleanup than one which is to be used as a park or open space (Kramer et al., 2014).

Sites that are fully remediated require no further action, however those that require continued monitoring or maintenance must enter into Long-term Stewardship (LTS) agreements with the state (DNREC, 2010). Developers that fulfill the requirements of the BDA are granted liability protection against harm caused by existing contamination, provided they adhere to the requirements of the BDA and LTS agreements, and take no action that may exacerbate or release existing contamination into the environment (DNREC-SIRS, 2008). Those that meet these conditions may apply for a Certificate of Completion of Remedy (COCR). The COCR, and the liability protection it represents may, in turn, be passed on to subsequent purchasers. It does not provide liability protection for any future releases unrelated to the original contamination, however (HSCA-7 Del. Chapter 91).

4.2.2 Program Funding

Between 1994 and 2011, the state of Delaware spent more than $63 million on all HSCA activities, including brownfield redevelopment, voluntary cleanup, hazardous substance cleanup, storage tank monitoring, and emergency response actions (O'Mara, 2011). Together, DNREC-SIRS and DEDO have spent more than $33 million on brownfield assessment, remediation and redevelopment activities (Kramer et al., 2014). Delaware’s brownfields program, administered by DNREC-SIRS, receives funding from multiple sources, the bulk of which comes from its HSCA fund and federal non-competitive brownfields grants (Kramer et al., 2014):

- DNREC-SIRS receives $5 million annually from the HSCA fund to finance brownfield efforts. The HSCA law levies a 0.9% tax on the sale of all petroleum products, (except for crude oil), with revenues accruing in the HSCA fund. Fines collected via enforcement actions are also added to the fund. As of 2013, it had a balance of more than $10 million. The money may be used for assessment, cleanup, and administrative purposes, including employee salaries. DNREC also plans to request another $1 million annually for groundwater remediation.

- The EPA's State and Tribal Response Program (CERCLA Section 128a) allocates non-competitive grant money to state programs. Funds may be used for a variety of purposes, including public and community outreach activities. DNREC-SIRS has received consistent non-competitive grant funding since 2003, an average of $600,000 per year.
- The EPA awards competitive grants for brownfields. Combined, DNREC-SIRS and the City of Wilmington have received more than $2 million in competitive grants for brownfields assessment, job training and to recapitalize a revolving loan fund between 1997 and 2013. A summary of Delaware's competitive awards is listed in Table 4-3.

Table 4-3- EPA Grant Funding For Delaware, (Kramer et al., 2014)

EPA Competitive Grant Funding (1997-2014)		
Year	**Grant Type**	**Award**
1997	Pilot Grant (Wilmington)	$200,000
1998	Pilot Grant extension (Wilmington)	$200,000
2002	Job Training (DNREC-SIRS)	$200,000
2006	Job Training Extension (DNREC-SIRS)	$141,764
2006	Assessment (Wilmington)	$200,000
2006	Revolving Loan Fund (DNREC-SIRS)	$1,000,000
2009	Assessment (DNREC-Coastal Programs)	$200,000
2012	Remediation (Wilmington UDAG)	Application pending
EPA Competitive Grant Funding (2003-2014)		
2003-2012	CERCLA Section 128a-Subtitle C (DNREC-SIRS)	$6.12 million

Participation in the state BDP is voluntary and applicant-driven, and public and non-profit entities may apply for funding up to $1 million per brownfield redevelopment project and/or applicant in any fiscal year. Private applicants may be reimbursed up to $225,000 for any individual project (the first $125,000 on a dollar-for-dollar reimbursement, and the next $100,000 on a fifty-cents-on-the-dollar reimbursement) and up to $1 million per applicant in any fiscal year. If it is depleted, additional applicants are rolled over into the next fiscal funding cycle, however in most years, the amount of funding available has exceeded applicant demand. As a consequence, no formal ranking system has been adopted by DNREC-SIRS when it comes to brownfields properties (Kramer et al., 2014).

DEDO's brownfields assistance program is funded through the Delaware Strategic Fund. The state capitalized the fund with $2.25 million in 2001 and is authorized to appropriate additional funding of up to $1 million per year (HSCA-7 Del. Chapter 91). Applicants may use DEDO grants to help cover the cost of phase II assessments and cleanup activities. Between 1994 and 2013, they have supported 27 brownfield redevelopment projects, spending $2,084,526. The City of Wilmington does not receive consistent local funding for brownfields, however it was awarded $600,000 in federal funding through the EPA's competitive brownfields grant program from 1997-2013, beginning with a Brownfields Pilot Project grant in 1997. In 2012, it applied (through the Wilmington Urban Development Action Grant Corporation) for a grant to help cover the cleanup costs of a former electroplating facility in Northeast Wilmington; the application has been pending. The city considers several factors when selecting projects, including their potential risk to public health and the environment. Priority is given to projects that are most likely to result in redevelopment (Flynn, 2013: Deputy Director of the Mayor's Office of Economic Development, City of Wilmington, cited in Kramer et al., 2014).

4.2.3 Program Challenges

The redevelopment of contaminated lands has been shown to result in a broad range of positive impacts, and to be essential to urban revitalization in many cities (De Sousa, 2006; Brown, Laznik, & Ratledge, 2010; Sun & Jones, 2013). While the contaminated land policy was initially concerned with human health and environmental protection, it has been reframed in recent decades to emphasize economic priorities (Hula, Reese, & Jackson-Elmore, 2012). This has contributed to concerns about unintended consequences and equity (NEJAC, 2006; EPA, 2011; Hula et al, 2012). The program has demonstrated a high level of success in the revitalization of land, however significant challenges for the future include building upon this success so that it can fully realize the policy potential in poor and minority communities, as well as addressing unintended consequences of revitalization and other emerging issues.

Economic, social, and environmental benefits of brownfield revitalization may not be given the same emphasis during the implementation of this public policy, leading to the inequitable geographic targeting and socio-economic distribution of program funds which are used to encourage private investment. This has generated concerns about environmental justice or, at least, who benefits most from the policy (McCarthy, 2009; Sousa, Wu, & Westphal, 2009; Meyer, 2010; Lee & Mohai, 2012). The problems appear to arise from the policy's dependence upon the flow of private-sector capital to the projects. Brownfield revitalization is a big business, where profits are given far more importance than are community concerns. The EPA's Brownfields

Program is designed to empower states, communities, and other stakeholders in economic redevelopment to work together promptly to prevent, assess, safely clean up, and sustainably reuse brownfields (EPA, 2015a). While this focus on economic development helps with the promotion of site re-use, its heavy reliance on private investment has led to other problems, such as a process known as "creaming" or inequitable selection of the most economically profitable sites, adverse consequences of realizing economic benefits such as gentrification and displacement, and the lowering of clean-up standards due to economic considerations (McCarthy, 2009; Hula, 2012; Lowham, 2012;). These concerns are often highlighted as part of the discourse on the impacts of the Brownfield policy, and were clearly articulated by the National Environmental Justice Advisory Council in their report on the unintended impacts of revitalization efforts (NEJAC, 2006).

As brownfields are revitalized, their value increases, which (it has also been proven) increases the value of surrounding properties, too (Brown, Laznik, & Ratledge, 2010; De Sousa, 2012; Meyer 2012). This increased property value has the potential to result in a process known as gentrification.

Gentrification has generally, and often over simplistically, been defined as a process in which higher-income households move into low-income neighborhoods, in a way that causes property values to increase to a level which creates displacement of existing residents, thereby changing the character of the area (Smith & Williams, 2013). A strong racial component has, historically, often been associated with this process, as low-income minorities, especially African Americans, are often replaced with higher income white residents (Levy, Comey, & Padilla, 2006). While it can be a productive byproduct of neighborhood revitalization, gentrification also has the potential to profoundly impact some residents who are least able to afford the consequences of it, due to its potential for population displacement (Fraser, 2004). In the case of brownfields, public investment to promote their revitalization may cause gentrification to occur. The extent to which it can be problematic, meanwhile, has not been clearly determined, mainly due to a lack of data and demographic information at the community scale needed for this type of evaluation (NEJAC, 2006).

Regarding the allocation of brownfield funds, an important consideration for public resources utilized to promote their revitalization is whether prioritizing the most marketable sites for receiving this directly causes geographic and social inequities, as outcomes of the policy implementation (McCarthy, 2009; DeSousa, 2009; Meyer 2010). The dependence on private capital allows a prospective developer to select and target its preferred areas for the use of available public funds for brownfield revitalization. As a result, they are likely to choose the sites with the best economic potential, such as waterfront properties or those along major roadways, potentially neglecting contaminated sites in less desirable low-income and minority neighborhoods.

Past studies have shown that decisions relating to brownfield redevelopment often overlook key stakeholders – the people who actually live in these communities (NEJAC, 2006; Lee & Mohai, 2012). This observation may explain the trend observed in Wilmington and other cities where the bulk of cleanup and redevelopment activities take place in high-income, low-minority areas that least resemble brownfield communities (McCarthy, 2009).

To counter this trend, the EPA instituted requirements to bolster community participation in its brownfields application process (EPA, 2015). The City of

Wilmington, in its 1997 pilot grant application to the EPA, recognized the need to improve this. “There is a need to involve the community-at-large in the planning and project development process. Current participation is selective and sporadic. The goal of ensuring environmental justice by empowering, educating, and protecting the community is best achieved through shared knowledge… Our intention is to intimately involve the communities in the development projects at an early stage.” (City of Wilmington, 1996).

In keeping with this commitment to community participation, one-fifth of Wilmington’s original Pilot Project grant award was allocated to the Urban Environmental Center (UEC), an organization dedicated to improving citizen awareness on issues related to land use, water quality, soil contamination, and brownfield redevelopment. The UEC received additional grants in subsequent years, from both the EPA and the state, to continue its efforts. It never received consistent funding and its staff was comprised entirely of volunteers however, and finally the UEC was forced to close its doors (in 2012) after long time administrator Dolores Washam retired (Kramer et al., 2014).

4.2.4 Policy Solutions

While there is clear evidence of the benefits of the Delaware Brownfields Program, it remains unclear if they will be effectively realized among the many poor and minority communities that are most in need of land revitalization. Despite purposeful intent and deliberate actions to implement the policy in an environmentally just manner, it does not appear that these efforts to-date have overcome the constraints placed on the policy from its dependence on private investment. Market forces may therefore still be leading to unintended consequences. The EPA acknowledged this problem by stating that while communities continue to impress it with their dedication, innovative ideas, and most importantly their ability to bring real change to their communities, it has realized that far too many still lack the capacity to affect environmental conditions on their own (EPA, 2011).

Changing this situation will likely require increased intervention and specific policy prioritization of the social and environmental benefits of brownfield redevelopment. The full extent and context of the equity problems are not well understood. It remains unclear if the brownfield policy is a major barrier to revitalization in low-income and minority communities or if those issues are more due to other factors. It may be severely limited by other urban problems that deter private investment in low-income communities. Additional research is needed to improve our understanding of the complex issues related to brownfield revitalization in decaying neighborhoods, within local contexts. Such studies provide promise for developing critical insights needed to create new or modified policy approaches that will lead to realization of the full potential of Delaware's brownfield policy.

The base for any understanding of the actual impact of this program starts with a better assessment of the communities affected by the presence of brownfields. There is a need for a much more rigorous assessment of policy, in particular through private sector perspective, for investment in brownfield sites, as well as to better understand the full range of factors influencing their redevelopment in decaying neighborhoods. What are the obstacles to utilization of the brownfield policy by low-income communities, and, will changes in the policy help to overcome these barriers? It is clear that brownfields are just one consideration among many, and may or may not comprise a primary factor in redevelopment decisions. Others such as neighborhood market conditions, crime, and location, may be more important in explaining redevelopment investment choices. As such, simply focusing on brownfield policy and blindly increasing incentives for redevelopment in these communities may have minimal impact on their revitalization.

In short, there is a need to more directly address the question of whether the presence of contaminated sites is a significant deterrent to new investment in decaying communities, or, if other localized social problems, locational disadvantage, and other factors better explain the current situation. Although a better understanding is needed, there are, in the meantime, promising policy interventions and approaches that could encourage more utilization of the policy in blighted communities. These include more deliberate integration of brownfields into broader urban planning efforts, more specific requirements for public participation by affected communities, and the innovative use of urban land banking that can provide a quasi-public intermediate organization to incentivize the revitalization of land in low-income and minority communities.

The EPA appears to recognize this community planning need, as indicated by its funding of area-wide planning grants, but securing and administering these funds may be beyond the capacity of many communities that would otherwise benefit from these efforts. It may be that, without a formal requirement for this as part of this policy, mobilizing the community involvement potential toward improving the benefits of the program in low-income and minority areas will be much harder to achieve. Additional tools however, such as the development of land banks as part of the policy, may provide critical mechanisms for community input on the final disposition of banked land, prior to its being returned to the private market (Carter, 2014). A more direct consideration of policy options that utilize public acquisition and clean-up of brownfields, for the specific purpose of resale at market rate for redevelopment in stressed community areas, would be a promising intervention in this context (Mallack, 2006).

Increased community involvement in brownfield revitalization is critical to their ability to provide benefits to the impacted neighborhoods. However, achieving a meaningful level of this involvement requires that brownfields be considered within the broader community or neighborhood context, rather than the more common, isolated site-by-site approach to clean-up and redevelopment. This is particularly challenging in low-income and minority communities, where social capital is often limited and participation is low (Hula, 2012; Lee & Mohai, 2012).

The final consideration that has otherwise received little attention in the literature is whether the market will eventually begin to address some of the inequity in brownfield program efforts, or not. Since the passing of the first Superfund and Brownfield Acts, the number of new contaminated sites rising up remains small, while legacy sites with contamination are being cleaned up (Carter, 2014). It is likely to continue like this as the supply of the most economically-promising sites is further reduced by revitalization. This may enable funds to be directed to the more economically marginal sites in poor communities at a greater level than before. Studies are needed in representative cities to evaluate if this market phenomenon is a likely model for future brownfield expenditures. If so, then interventions such as land banking would be even more effective as a mechanism to help catalyze a policy shift toward the more equitable distribution of benefits associated with brownfield revitalizations, due to their complementary design and neighborhood-level focus on land redevelopment.

Chapter 5

METHOD, DATA, AND ANALYSIS

5.1 Data Analysis Process

As mentioned earlier, this study employs the exclusive analysis and in-depth market-driven data, which predominate in use by the banking, financial services and insurance industries, in order to conduct an investment-based risk assessment of the brownfield sites. The goal is to help public funds target those sites in a positively discriminatory way in order to achieve more balanced regional economic development. This, in turn, will enable funds to increasingly be directed to more economically marginal sites in poor communities.

By employing Fuzzy Set Theory, this study develops a composite fuzzy membership function, which defines the transition from investment risk to investment safety. Then, each brownfield site is assessed based on its degree of membership to each of these fuzzy sets (Investment Risk and Investment Safety). By employing this solution, policymakers can see how safe or risky each site is from the investors' perspective. This incorporates the principle of uncertainty into policymaking process by viewing the brownfield development inequality problem through the looking-glass of investors and the private sector, rather than via public entities, in order to transfer more 'unknown-knowns' to 'known-knowns' in shaping brownfield policies.

In the mathematical sciences, fuzzy sets are those whose elements have degrees of membership. In classical set theory, the membership of elements in a given set is assessed in binary terms, according to a bivalent condition – an element either belongs to or does not belong to the set. By contrast, the Fuzzy Set Theory allows the gradual and continuous assessment of the membership of elements within a set. This is described with the aid of a membership function valued in the real unit interval [0, 1]. Fuzzy sets generalize classical sets, since the indicator functions of classical sets are special cases of fuzzy set membership functions, if the latter only take values 0 or 1 (Dubois & Prade, 1980). In Fuzzy Set Theory, classical bivalent sets are usually called crisp sets (see Figure 5-1).

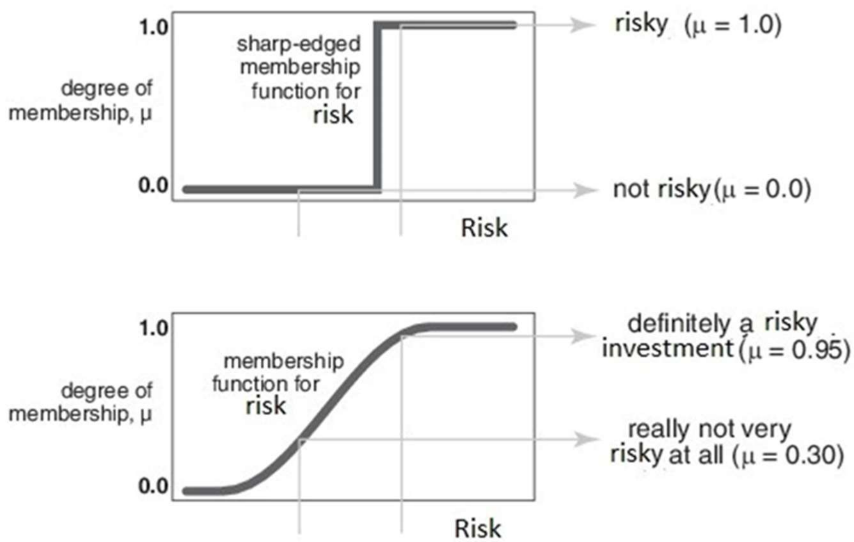

Figure 5-1- Classic & Fuzzy Membership Graphs (MathWorks, 2016)

In other words, in classical mathematics one deals with collections of objects called (crisp) sets. Sometimes, it is convenient to fix some universe U in which every set is assumed to be included. It is also useful to think of a set A as a function from U which takes a value of 1 on objects which belong to A and 0 on all the rest. Such functions are called the characteristic function of A, X_A:

$$X_A(x) = def \begin{cases} 1 & if\ \ x \in A \\ 0 & if\ \ x \notin A \end{cases} \qquad (5.1)$$

There exists a bijective correspondence between characteristic functions and set, but fuzzy sets generalize this definition, allowing elements to belong to a given set with a certain degree. Instead of just considering characteristic functions with value in {0, 1} we can also consider now functions valued in [0, 1]. A fuzzy subset F of a set X is a function μ_F (x) assigning to every element x of X the degree of membership of x to F:

$$x \in X \rightarrow \mu_F(x) \in [0, 1] \qquad (5.2)$$

In classical set theory, there are some basic operations defined over sets. Let X be a set and P(X) be the set of all subsets of X or, equivalently, the set of all functions between X and {0, 1}. The operation of union, intersection, and complement are defined in the following ways:

$$A \cup B = \{x \mid x \in A\ or\ x \in B\}\ i.e.\ \ X_{A \cup B}(x) = \max\{X_A(x), X_B(x)\} \qquad (5.3)$$

$$A \cap B = \{x \mid x \in A\ and\ x \in B\}\ i.e.\ \ X_{A \cap B}(x) = \min\{X_A(x), X_B(x)\} \qquad (5.4)$$

$$A' = \{x \mid x \notin A\}\ i.e.\ \ X_{A'}(x) = 1 - X_A\ (x) \qquad (5.5)$$

Zadeh (1965) defined the following operations for fuzzy sets as generalization of crisp sets and of crisp statements (Zimmermann, 2011):

Let F and S be fuzzy subsets of X given by membership functions μ_F, and μ_S:

- Union (exclusive or): the membership function of the union is defined as:

$$\mu_{F \cup S}(x) = \max\{\mu_F(x), \mu_S(x)\} \; \forall x \in X \qquad (5.6)$$

- Intersection (logical and): the membership function of the intersection of two fuzzy sets F and S is defined as:

$$\mu_{F \cap S}(x) = \min\{\mu_F(x), \mu_S(x)\} \; \forall x \in X \qquad (5.7)$$

- Complement (negation): the membership function of the complement is defined as:

$$\mu_{F'}(x) = 1 - \mu_F(x) \; \forall x \in X \qquad (5.8)$$

Figure 5-2 uses a graph to show the same information. In this figure, a plot of two fuzzy sets is applied together to create one single set. The upper part of the figure displays plots corresponding to two-valued variables (crispy sets), while the lower part of the figure displays how the operations work over a continuously varying range (fuzzy sets) of values A and B, according to the fuzzy operations.

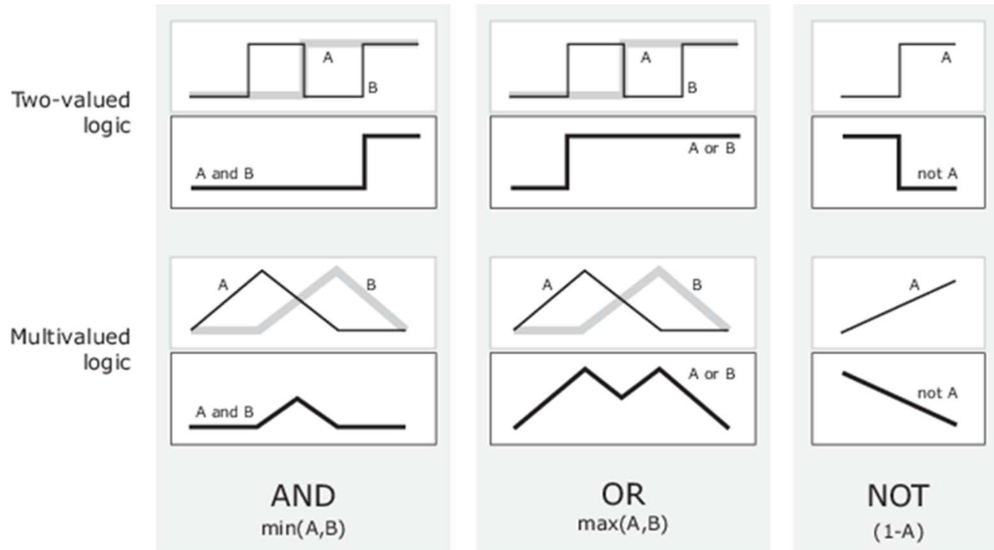

Figure 5-2- Fuzzy Set Operations Graphs (MathWorks, 2016)

To sum up, fuzzy sets describe vague concepts (hot weather, fast runner, weekend days), which also include the possibility of partial membership within same (the weather is rather hot; Friday is sort of a weekend day). The degree to which an object belongs to a fuzzy set is denoted by a membership value between 0 and 1. (Friday is a weekend day to the degree 0.7). A membership function associated with a given fuzzy set maps an input value to its appropriate membership value. Mathematically speaking, a membership function is a sort of curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. It is sometimes referred to as the universe of discourse.

The aim of the membership function here is to capture differences in the investment risk of brownfield sites. Thus, it has spatial aspects and can be understood in terms of probability or likelihood of the occurrence of losses, relative to the expected return linked to a location. Stated simply, it measures the level of uncertainty to achieving returns as per the expectations of the investor with regard to a brownfield site. Risk is a critical component to assessing the prospects of an investment. Most investors consider less risk to be more favorable while making an investment. The lesser it is, the more lucrative the investment typically is. However, conversely, the generally accepted thumb rule states that the higher the risk, the better the return. One investor can, for example, acquire a cheap brownfield site in a very distressed area, then redevelop the site, and then gain a considerable amount of return, should the investment be successful.

Areas that produce an optimum combination of location factors offer a lesser investment risk to investors, hence attracting greater investment. The membership function here is characterized by the basis of real estate investment factors, as well as data availability. Real estate investment risk is a multidimensional matter and is perhaps the broadest and most challenging area to assess. It can include rental rate decline, fluctuations in local, state, or national real estate markets, tenant rolls and vacancy, and so on. The membership function analyzes several dozen variables which form the basis for assessing geographical diversification of specific brownfield location benefits (risk factors). These risk factors include, but are not limited to: accessibility to transport; quantity and quality of labor resources; absorption capacity of the real estate market; declines in the value of real estate; declines in rental or occupancy rates; risks related to general and local economic and social conditions; possible lack of available funds to refinance mortgage loans at maturity; extended vacancies in properties; expenses incurred in the cleanup of environmental problems. (These can be reduced extensively by securing liability insurance provided by the Delaware Brownfields Program.)

On the other hand, by employing the Analytic Hierarchy Process (AHP), it becomes possible to develop a complex membership function to include all the above-mentioned factors in assessing the real estate investment risk for brownfield sites. The Analytic Hierarchy Process (AHP) is a structured method for organizing and analyzing complex decisions, based on mathematics and psychology. It was developed by Thomas L. Saaty in the 1970s and has been extensively studied and refined since then. The primary advantage of AHP is its capability to check and reduce the inconsistency of otherwise expert judgments. While reducing bias in the decision-making process, this method also provides group decision-making through consensus using the geometric mean of the individual judgments. AHP derives scales of values from pairwise comparisons in conjunction with ratings, and is suitable for multi-objective, multi-criterion, and multi-actor decisions with any number of alternatives. AHP involves assessing scales rather than measures; hence, it is capable of modeling situations that lack measures (e.g., modeling uncertainty and risk). AHP comprises three major principles: decomposition of the given structure, comparison of judgments, and hierarchical composition (or synthesis) of priorities. Decomposing a decision problem into its constituent parts facilitates creating hierarchies of criteria in order to determine the relative importance of each criterion (Saaty, 2008).

Padma and Balasubramanie (2009) used AHP to develop a decision aid system to rank risk factors associated with the occurrence of musculoskeletal problems in the shoulder and neck. Zhang, Zhan, and Tan (2009) also employed AHP to compare risk factors related to human error and causes of accidents in the maritime transport sector. Kim, Lee, Park, and Lee (2010) proposed a safety risk assessment methodology that considers the risk influence factors of construction sites using expert surveys and the

AHP. Badri, Nadeau, and Gbodossou (2012) proposed a procedure for evaluation of Occupational Health and Safety risks based upon multi-criteria analysis techniques (e.g., AHP) and expert judgment.

In AHP, the decision problem is divided into a hierarchy of sub-problems, each of which can be analyzed independently. The components can relate to any aspect of the decision problem. Once the hierarchy is created, a numerical scale is assigned to each pair of n alternatives (Ai, Aj) by the experts (see Table 5-1).

Table 5-1- The Fundamental Scale of Absolute Numbers (Saaty, 2008, p. 86)

Intensity of Importance	**Definition**	**Explanation**
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
1.1-1.9	When activities are very close, a decimal is added to 1 to show their difference as appropriate	A better alternative to assigning small decimals is to compare two close activities with other, widely contrasting, ones favoring the larger one a little over the smaller one when using the 1–9 values.
Reciprocals of above	If activity i has one of	A logical assumption

	the above nonzero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	
Measurements from ratio scales		When it is desired to use such numbers in physical applications. Alternatively, often one estimates the ratios of such magnitudes by using judgment

Numerical scales are attributed by making pairwise comparisons among the alternatives (brownfield sites) with respect to their impact on an element placed at a superior level in the hierarchy. The term a_{ijk} expresses the individual preference of expert k, regarding alternative $A_{i,}$ and compared to alternative A_j. Once the overall expert judgments are created and computed using their geometrical mean (5.9), they are inserted into the comparison matrix D (Saaty, 1990):

$$Geometrical\ Mean: \quad a_{ij=}\sqrt[n]{a_{ij1}Xa_{ij}\ \ X\ldots Xa_{ijn}} \quad (5.9)$$

$$D = \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ a_{n1} & a_{n2} & \ldots & a_{nn} \end{bmatrix} \text{(5.10)}$$

Matrix D is a comparison matrix and has the following properties:

$$a_{ij} > 0;\ a_{ij} = \frac{1}{a_{ji}}\ ;\ \forall\ \ i\ where\ j = 1,2,\dots,n. \quad (5.11)$$

Matrix D is considered as consistent when its elements meet the following condition (5.12) while also satisfying this condition (5.11):

$$a_{ij}.a_{jk} = \ a_{ik}\ \ ;\ \forall\ \ k\ \ where\ i,j = 1,2,\dots,n. \quad (5.12)$$

The ordering of alternatives is taken as a result of the approximation of comparison matrix D using matrix P:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \quad (5.13)$$

The elements of matrix P are consistent judgments presented in the form of weight ratios among alternatives:

$$p_{ij} = \frac{p_i}{p_j} \quad where\ i,j = 1,2,\dots,n. \quad (5.14)$$

p_i signifies the weights of the alternatives of the order vector p:

$$p \quad = (p_1, p_2, \dots, p_n)^T \quad (5.15)$$

The standardized order vector after the arithmetic normalization is obtained as follows:

$$p^* = (p_1^*, p_2^*, \dots, p_n^*)^T \quad (5.16)$$

where:

$$p_i^* = \frac{p_i}{\sum_{i=0}^{n} p_i} \quad (5.17)$$

Saaty (1990) proposed using the maximum eigenvalue method to determine the judgment matrices as:

$$D.p = \lambda_{max} p \quad (5.18)$$

Where λ_{max} is the maximum eigenvalue of matrix D.

For a reliable comparison, it is important to note that the inconsistency of comparison matrix D must be less than 10%; that is, the number of times condition (5-12) is not met must be below 10%. According to Saaty (1990), the consistency of judgments can also be evaluated using the Eq. (5.19):

$$\text{Consistency ratio} = \text{CR} = \frac{\text{CI}}{\text{RC}} \quad (5.19)$$

And,

$$\text{Consistency index} = \text{CI} = \frac{\lambda_{max} - n}{\text{n} - 1} \quad (5.20)$$

RC (random consistency index) can be acquired from Table 5-2. Since the column(s) of any 1 × 1 or 2 × 2 comparison matrices are dependent, RC is assumed to be 0. This means that division by zero in Eq. (5.19) and causes CR to tend toward infinity; that is, matrices of sizes 1 and 2 are always consistent.

Table 5-2- Random Consistency (RC) Index [n = size of the reciprocal matrix] (Saaty, 1990)

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RC	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

5.2 AHP as Fuzzy Membership Function in Investment Risk Assessment of Brownfield Sites

As mentioned above, the AHP and the Fuzzy Set Theory are combined in this research by an alternative means. Moreover, the Fuzzy AHP is applied in the investment assessment of brownfield sites, which has not previously been seen in the literature, to date. The method includes four major procedures as follows:

1. Establish the risk factor hierarchy model;
2. Define the weights of risk factors;
3. Define the quantitative basis for risk factors;
4. Establish the comprehensive risk assessment model.

5.2.1 Setting up The Risk Factors Hierarchy

When solving any complex problem or situation, the most logical way to begin to analyze it is by breaking it up into smaller, more manageable parts; in such a way that as a general order is established and maintained, the “big picture” can still be seen. By breaking up large complex elements, structuring their elements hierarchically and analyzing their components, judgments can be made that will conform to the general answer or proper solution to the proposed problem. As Saaty (1990) stated, these hierarchies must interconnect one to another, clustering those elements which have similar magnitudes and effects upon our whole case. The approaches taken on how to constitute the hierarchies will depend on the type of decision to be made. For the case of investment risk assessment, the analysis begins by listing the alternatives (brownfield sites); for each site, a comparative evaluation is performed. The next step takes us to a general comparison among the criteria (risk factors) used for judging the alternatives (brownfield sites) listed. Each of these criteria may have sub-criteria, and so on, and each of these sub-levels is further broken down into its respective sub-criteria. The top level of this structure represents the objective of the analysis, which in this case is to assess the level of investment risk for each brownfield site, as well as the degree of membership of the given brownfield sites to investment risk set. The approach uses a hierarchy structure as a base framework, which can be seen in Figure 5-3. This hierarchy divides the risk assessment of brownfield sites into five main areas of concerns for the investor:

1. Socioeconomic Risk
2. Demographic Risk
3. Infrastructure Risk
4. Spatial (Proximity) Risk
5. Financial Demand Risk

The structure presented is completely flexible and may be modified and adapted to fit policymaker's needs. It is possible to add or remove some risk factors, depending on what types of risk characterize the policies or what drives the DNREC and EPA risk attitude, as well as the knowledge that the policy analysts may have about them, without necessarily complicating the analysis.

Policy analysts may sometimes want to discard, unconsciously, some of the risks herein proposed at the beginning of their assessments, either to ease or reduce the extent of the evaluation process, or just because they lack sufficient knowledge of the related areas or believing many of these factors as incapable of impacting the development of a policy. This is exactly what should be avoided. Policymakers should instead be encouraged to take into consideration all possible risks, from the start. Later, during the calibration and run of the model, a more accurate view on the general risk aversion of the policy process can be obtained. Afterward, some of the original risk factors can be effectively discarded, once their individual weights or effects on the overall goal have been determined to be negligible.

It is important to identify and briefly define common risk factors that are being considered, the basis for their consideration, and why they ought to be taken into account for every assessment. Some are explicit by themselves (Table 5-3):

- Brownfield Investment Risk Assessment
    - Socioeconomic Risk
        - Wealth
            - Median HH Income
            - Per Capita Income
            - Families, At-Above Poverty/Total Families
        - Housing

    - Owner Occupied Housing Units
    - CAGR: Owner Occupied Housing Units
    - Homeownership Rate
    - Average Value of Owner Occupied Housing
    - Owner Occupied Housing Units (100K-200K)
    - Owner Occupied Housing Units (200K-300K)
  - Employment
    - Unemployment Rate
    - Civilian Labor Force, Employed
    - White Collar Workers
    - Blue Collar Workers
- Demographic Risk
  - Population Density
  - CAGR: Population Density
  - Millennial Population Percent
  - Population 25+ with Bachelor's Degree/ Edu Base
  - Group Quarter Population
- Infrastructure Risk
  - Average Year Housing Units Structure Built
  - Average Number of Vehicles Available
  - Access to Major Roads

        - Access to 1-95
        - Cleanup expenses per sq. ft.
        - Access to shopping centers
        - Traffic Count 2014
    - Proximity Risk (Empirical Bayesian Kriging Modeling)
        - Proximity Financial Institutions' Performance Trend
        - Proximity Financial Institutions' Deposit
        - Proximity Businesses' Annual Sale
    - Financial Demand Risk
        - Depository Product Balance
            - Deposit Balance
                - CD Products (excluding CD IRAs)
                - Interest DDA Products
                - Regular/Non-Interest DDA Products
                - Transaction/DDA Products
            - Saving Balance
                - Fixed Interest Savings Products (excluding IRAs)
                - Money Market Savings Products
                - Regular/Liquid Savings Products (excluding CD IRAs)

        - Variable-Interest Saving Products (excluding IRAs)
    - Asset/Cash Management Product Balance
- Credit Product Balance
    - Credit Cards Balance
        - Discover Card
        - Master Card
        - Visa Card
    - Line of Credit Balance
        - HELOC
        - PLC Other Types
        - PLC Overdraft Protection
    - Mortgage Balance
        - First Mortgage
        - Fixed Rate Mortgage
        - Adjustable Rate Mortgage (ARM)
        - Other Type of Rate Mortgage
    - Loan Balance
        - Personal Loans
        - Personal Loans, Other Type
        - Personal Loan, Second Mortgage

            - Auto Loans
- Investment Product Balance
    - Stock Market Balance
        - Commodities/Warrants/Options
        - Money Market Mutual Funds (excluding retirement)
        - Government Securities
        - Mutual Funds (excluding 401k)
        - Stock
    - Bond Market Balance
        - Corporate/Municipal Bonds
        - US Saving Bond/T-Bills/T-Bonds
    - Real Estate Investment
    - Other Investment
        - Collectible/Precious Metals/Other
        - Tax-Advantaged College Savings Products
        - RE Secured Credit Product (ex 1st mortgage)

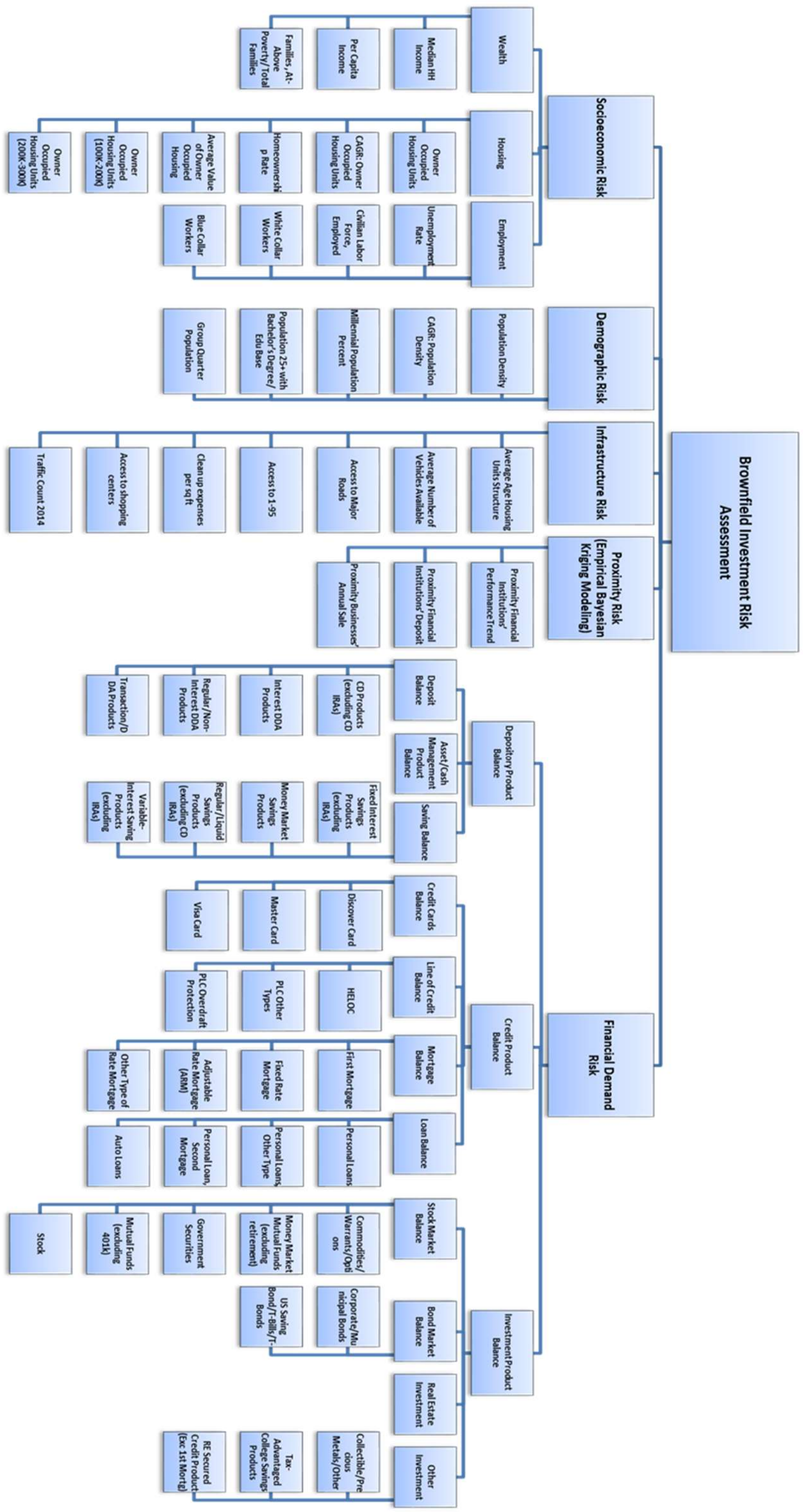

Figure 5-3- Proposed Risk Factors Hierarchy

Table 5-3- Risk Factors Descriptions

Level 1 Risk Factors	Level 2 Risk Factors	Level 3 Risk Factors	Level 4 Risk Factors	Risk Factors Descriptions	Reverse
Socioeconomic Risk*	Wealth	Median HH Income		Median household income	
		Per Capita Income		Total personal income, divided by the total population	
		Families , At-Above Poverty/ Total Family HH		Number of families that are at or above the poverty level, divided by total number of households	
	Housing	Owner-Occupied Housing Units		Number of owner-occupied housing units	
		CAGR: Owner-Occupied Housing Units		Compound annual growth rate of owner-occupied housing units	
		Homeownership Rate		Percent of housing units that are owner-occupied	
		Average Value of Owner-Occupied Housing		Average value of owner-occupied housing units	
		Owner-Occupied Housing Units (100K-200K)		Number of owner-occupied housing units valued between $100,000 and $199,999	
		Owner-Occupied Housing Units (200K-300K)		Number of owner-occupied housing units valued between $200,000 and $299,999	
	Employment	Unemployment Rate		Population of civilian labor force age 16 and older who are unemployed, divided by the total age 16 and older	●
		Population 16+, Civilian Labor Force, Employed		Population of civilian labor force age 16 and older who are employed	
		Emp Civ Pop 16+, Occ: White Collar		Population of employed civilians age 16 and older with an occupation classified as white collar	
		Emp Civ Pop 16+, Occ: Blue Collar		Population of employed civilians age 16 and older with an occupation classified as blue collar	●
Demographics Risk*	Population Density			Population Density	
	CAGR: Population Density			Compound annual growth rate in population density	
	Millennial Population Percent			Percent of population age 15 through 34	
	Population 25+, Bachelor's Degree /Educ Base			Percent of the population age 25 and older with a bachelor's degree	
	Group Quarter Population			Anyone who lives in institutions such as jails, college dormitories, hospitals, military bases and nursing homes	●
Infrastructure Risk	Average Age Housing Units Structure*			Average age the housing unit structure	●
	Average Number of Vehicles Available*			Average number of vehicles that are kept at home for use by members of the household	
	Access to Major Roads			Direct distance to the nearest major roads	●
	Access to 1-95			Direct distance to I-95 interstate highway	●
	Cleanup Expenses Per Acre			Total dollars spent on the property for cleanup purposes, divided by acreage	●

	Access to shopping centers			Direct distance to the nearest major shopping centers	●
	Traffic Count 2014			Annual average of daily traffic volume of the nearest major road	
Spatial (Proximity) Risk	Proximity Financial Institutions' Performance Trend Risk			Empirical Bayesian Kriging Estimation of 5YR growth of Capped Deposit of vicinity financial institutions	
	Proximity Financial Institutions' Deposit Risk			Empirical Bayesian Kriging Estimation of 2015 Deposit of the vicinity financial institutions	
	Proximity Businesses' Annual Sale Risk			Empirical Bayesian Kriging Estimation of Annual Sale 2015 of vicinity businesses	
Financial Demand Risk*	Depository Product Balance	Deposit Balance	CD Products (excluding CD IRAs)	Average balance per Households with certificates of deposits (CDs), not including CDs held in individual retirement accounts (IRAs)	
			Interest DDA Products	Average balance per Households with interest-bearing demand-deposit accounts (DDA)	
			Regular/Non-Interest DDA Products	Average balance per Households with non-interest/regular demand-deposit accounts (DDA)	
			Transaction/DDA Products	Average balance per Households with transaction/demand-deposit (DDA) accounts, including non-interest/regular and interest-bearing accounts	
		Saving Balance	Fixed Interest Savings Products (excluding IRAs)	Average balance per Households with a regular savings account in which deposits and withdrawals of any amount can be made at any time and interest is paid at a low fixed rate, not including those within an IRA account	
			Money Market Savings Products	Average balance per Households with variable-interest money market savings accounts or IRAs invested in savings accounts	
			Regular/Liquid Savings Products (excluding CD IRAs)	Average balance per Households with any liquid savings, including regular savings accounts and variable-interest/money market deposit accounts (not including funds invested as IRAs)	
			Variable-Interest Saving Products (excluding IRAs)	Average balance per Households with money market savings accounts that pay a variable-interest rate (not including funds invested as IRAs)	
		Asset/Cash Management Product Balance		Average balance per Households with asset/cash management accounts that typically combine an array of investment services, accessible by check writing, credit or debit card, and a combined statement covering all assets in the account	
	Credit Product Balance	Credit Cards	Discover Card	Average balance per Households with a Discover credit card on which an outstanding balance can be carried from month-to-month	
			Master Card	Average balance per Households with a MasterCard credit card on which an outstanding balance can be carried from month-to-month	
			Visa Card	Average balance per Households with a Visa credit card on which an outstanding balance can be carried from month-to-month	
		Line of Credit Balance	HELOC	Average balance per Households with a Home Equity Line of Credit (HELOC) that is collateralized by the equity consumer has in their home	

			PLC Other Types	Average balance per Households with other credit lines, other than HELOCs or overdraft lines, against which the household can borrow, usually by writing a check (not including credit cards)	
			PLC Overdraft Protection	Average balance per Households with overdraft lines of credit which protect against overspending from a checking account	
		Mortgage Balance	First Mortgage	Average balance per Households with a first mortgage made for the purpose of buying a home or real estate, not including mortgages on land-only	
			Fixed Rate Mortgage	Average balance per Households with a first mortgage offering a fixed interest rate for the life of the loan	
			Adjustable Rate Mortgage (ARM)	Average balance per Households with an adjustable rate mortgage, or ARM, with an interest rate that varies over the life of the loan, typically with a low initial fixed rate for the first few years	
			Other Type of Rate Mortgage	Average balance per Households with a first mortgage offering rate types other than fixed or adjustable	
		Loan Balance	Personal Loans	Average balance per Households that have personal loans, including home equity loans, second mortgages and student loans	
			Personal Loans, Other Type	Average balance per Households that have personal loans other than home equity loans, second mortgages and student loans	
			Personal Loan, Second Mortgage	Average balance per Households that have home equity loans or second mortgages	
			Auto Loans	Average balance per Households with an auto loan	
	Investment Product Balance	Stock Market Balance	Commodities/Warrants/Options	Average balance per Households owning commodities, warrants or options	
			Money Market Mutual Funds (excluding retirement)	Average balance per Households with money market mutual fund shares, not including shares owned as a part of any retirement accounts (such as an IRA or 401k plan)	
			Government Securities	Average balance per Households owning government securities, such as investments offered by Fannie Mae, Ginnie Mae and Sallie Mae	
			Mutual Funds (excluding 401k)	Average balance per Households with mutual fund shares, not including shares owned as a part of any retirement accounts (such as an IRA or 401k plan)	
			Stock	Average balance per Households owning stock	
		Bond Market Balance	Corporate/Municipal Bonds	Average balance per Households owning corporate or municipal bonds	
			US Saving Bond/T-Bills/T-Bonds	Average balance per Households owning U.S. savings bonds, treasury bills or treasury bonds	
		Other Investment	Collectible/Precious Metals/Other	Average balance per Households owning collectibles or precious metals which increase in value over time because of scarcity or rarity, including (but not limited to) gold, silver and platinum, jewelry, stamps, baseball cards, dolls, and/or antique toys	
			Tax-Advantaged College Savings	Average balance per Households with tax-	

			Products	advantaged college savings accounts, including 529 educational savings plan, educational IRA, prepaid tuition	
			RE Secured Credit Product (ex 1st mortgage)	Average balance per Households with real estate-secured credit products, including home equity lines of credit, home equity loans, and second mortgages, but not including first mortgages	
		Real Estate Investment		Average balance per Households with real estate investments other than their primary residence	

Notes:
**All values measured within 3-mile radius of each brownfield site at census tract level. Demographic, Socioeconomic, and Consumer Financial Demand data pulled from S&P Global Market Intelligence (www.SNL.com). SNL platform is now sourced from The Nielsen Company©. Nielsen bases its data on the Census and the annual American Community Survey (ACS) along with many other current sources such as the Bureau of Labor Statistics, USPS, new construction data, Bureau of Economic Analysis (BEA), Internal Revenue Service (IRS), and may other data providers that provide real-time insight on the national population. All calculations and spatial interpolation and overlaying have been done within Advanced ArcGIS Desktop 10.4 under the University of Delaware license.*

As mentioned before, this proposed hierarchy is entirely flexible, and in cases where other relevant information can be found readily, they should be included or even replace any of the criteria in the proposed hierarchy. With the notion of "the more flexibility, the less uncertainty" in mind, the intention here is not to provide a rigid structure to follow but rather, to present the reader with ideas as to how this method can be focused on the specific requirements of investment risk assessment. By considering such a broad range of possible risk factors, the AHP becomes a very powerful tool for investment risk assessment of brownfield sites.

5.2.2 Spatial Risk Assessment: Empirical Bayesian Kriging

This research introduces a method for spatial (proximity) risk assessment which has been incorporated into the proposed risk factor hierarchy within the fuzzy AHP risk assessment model. This method empirically estimates three risk factors (1- Proximity Financial Institutions' Performance Trend Risk; 2- Proximity Financial Institutions' Wealth Risk; 3- Proximity Businesses' Annual Sale Risk) using geostatistics that automate the most difficult aspects of building a valid Kriging model. Geostatistics is the common name for a family of techniques and methods which are utilized for the mapping of surfaces from limited sample data and the estimation of values at unsampled places. First developed by Georges Matheron and named in honor of Danie Krige, these techniques are now broadly used in the minerals industry and have disseminated out into many other fields where spatial data is studied.

Geostatistical estimation is a two stage process:

1. Examining the collected data to build the predictability of values from location to location in the study region; this study results in a graph called a semi-variogram which models the difference between a value at one location and the value at another location, based on the direction and distance between them;
2. Estimating values at unsampled locations. This process is known as Kriging. The basic method, ordinary Kriging, employs a weighted average of nearby samples to estimate the unknown value at a specific location. The semi-variogram model helps optimize the weights among the sampled locations, and for the relevant inter-relationships between unknown and known values. It also provides a standard of error which may be used to quantify confidence levels.

Kriging, as a complex geostatistical process, generates an estimated surface from a scattered set of points. Unlike other interpolation methods, it efficiently involves an interactive examination of the spatial behavior of a phenomenon, selecting the best estimation method for generating the output surface. Other methods, like the IDW (Inverse distance weighted) and Spline interpolation, are known as deterministic interpolation techniques, since they are based on the surrounding measured values or on specific mathematical formulas that delineate the smoothness of the output surface.

Interpolation techniques that include geostatistical methods, such as Kriging, are based on statistical models. They utilize autocorrelation, which measures the statistical relationships among both sampled and measured points. For this, geostatistical techniques not only have the capability of generating a prediction surface, but can also provide some measure of the accuracy or certainty among the predictions (ESRI, 2016).

As Krivoruchko (2012) indicates, obtaining reliable spatial measurements can be laborious and costly. In many cases, samples may not have been collected where the information is most needed. Accordingly, the ability to predict values where observations are otherwise not available is paramount. Interpolation is the procedure through which to obtain a value of a variable of interest, at a location where data has not been measured or observed, by using data from adjacent locations where it has been collected and measured.

There are many methods and techniques useful to interpolate spatial data, classified into two broad categories: deterministic and probabilistic. Deterministic methods utilize predefined functions of the distance between observation locations and those for which interpolation is required (for instance, inverse distance interpolation). Probabilistic methods have a basis in statistical theory. These predictors quantify the uncertainty of the interpolated values. The requirement of providing data and information on prediction uncertainty limits the choice of interpolators to statistical ones.

The development of reliable automatic statistical interpolation models has been a focus of the GIS community for a long time; a very challenging task, since each statistical model is based on the individual users' data – data that is, generally, so complex that it can be very difficult to describe mathematically without interaction. Extensive testing, using a large variety of data, showed that EBK is a reliable automatic interpolator (Krivoruchko, 2012).

Kriging, as a statistical methodology, offers optimal spatial prediction. It was developed by Lev Gandin in 1959 for meteorological applications initially, but since then has been employed in many other disciplines, including mining, agriculture, and the environmental sciences. It is a probabilistic predictor, which assumes a statistical model for the data. Kriging predictors include standard errors that quantify the uncertainty associated with the predicted values, and are known as optimal predictors. The prediction error is minimized and, on average, the predicted value and the true value coincide.

Kriging predictors(Krivoruchko, 2012):

- Have smaller prediction uncertainty than other prediction models;
- Have the ability to filter out measurement errors; and,
- Use data on the correlation between the variable of interest and covariates.

When Kriging predictors are applied to brownfield investment risk assessment, they can be used to determine the probability of investment failure with respect to the performance of neighboring (proximity) businesses or financial institutions (samples).

Kriging is similar to IDW in that it weights the neighboring measured values to conduct a prediction for unmeasured places. The general formula for both interpolators is formed as a weighted sum of the data:

$$\hat{Z}(S_0) = \sum_{i=1}^{N} \lambda_i Z(S_i) \qquad (5.21)$$

where:

$Z(s_i)$ = the measured value at the ith location

λ_i = an unknown weight for the measured value at the ith location

s_0 = the prediction location

N = the number of measured values

In IDW, the weight, λ_i, depends only on the distance to the prediction location. However, with the Kriging method, the weights are estimated based not only on the distance between the measured points and the prediction location but also on the entire spatial arrangement and order of the measured points. To utilize the spatial arrangement in the weights, their spatial autocorrelations have to be quantified. In this way, in ordinary Kriging, the weight, λi, depends on a fitted model to the measured points, the distance to the prediction location, and the spatial relationships among the measured points around the prediction place.

Kriging utilizes a semivariogram to quantify the spatial dependence in the data. Semivariogram is a function of the direction and distance separating two locations. A semivariogram is created by calculating half the mean-squared difference of the values of all the pairs of measurements, at locations separated by a given distance h. The semivariogram is plotted on the y axis against the separation distance h. Figure 5-4 shows the semivariogram values for the pairs of points (shown in red) and their averages for a set of the distance intervals between the points (shown as blue crosses). The blue line in Figure 5-4 shows the estimated semivariogram model. This semivariogram model is then used to define the weights that determine the contribution of each observed data point to the prediction of new values at unsampled locations.

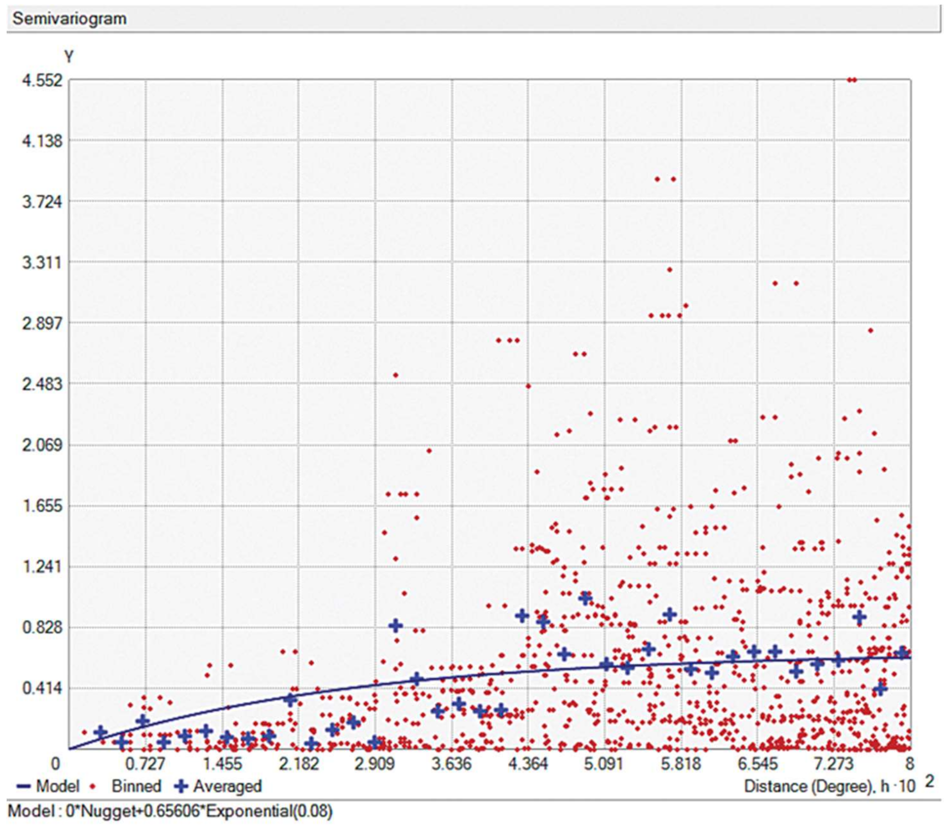

Figure 5-4- The semivariogram values for the pairs of points (red), their averages (blue crosses), and the estimated semivariogram model (blue line.) (Krivoruchko, 2012)

If the data distribution is Gaussian, the most optimal predictor is one that uses a linear combination of the neighboring data values. For other distributions, the optimal predictor is nonlinear and, therefore, more complex. Data can be transformed to follow a Gaussian distribution, making it possible to precisely back transform Kriging predictions to the original data scale (using ArcGIS Geostatistical Analyst). Classical Kriging also assumes that the estimated semivariogram is, ultimately, the true semivariogram of the observed data. This would indicate that the data was produced through Gaussian distribution, with the correlation structure defined by the estimated semivariogram. It is really a strong assumption, and hardly holds true in reality. Hence, action has to be taken in order to make statistical model more realistic (Krivoruchko, 2012).

To make a prediction with Kriging techniques, two tasks are essential:

- Uncovering the dependency rules.
- Making the predictions.

To realize these two tasks, Kriging goes through a two-step procedure:

1. It builds the variograms and covariance functions to estimate statistical dependence (spatial autocorrelation) values that depend on the model of autocorrelation (fitting a model).
2. It predicts the unknown values (making a prediction).

For these two distinct tasks, Kriging utilizes the data two times: first, to estimate spatial autocorrelation of the data, and second, to make predictions.

Spatial modeling, also known as structural analysis or variography, begins with constructing a graph of the empirical semivariogram, computed with the following equation for all pairs of locations and separated by distance h:

$$\textit{Semivariogram (distance h)} = 0.5 * \textit{average} \{\textit{valuei} - \textit{valuej}\}^2 \quad (5.22)$$

This formula calculates the difference squared between the values of paired locations, a procedure that continues for each measured location. Generally, each pair of locations has a unique distance, and includes many pairs of points. Plotting them all quickly becomes difficult, however, therefore such pairs are grouped into lag bins. For instance, to compute the mean semivariance for all pairs of points that are greater than 40 meters apart but less than 50 meters. The empirical semivariogram is a graph of the distance (or lag) on the x-axis, while the averaged semivariogram values are on the y-axis (see blue crosses in Figure 5-4).

Spatial autocorrelation quantifies a basic principle of geography: things that are closer are more alike than things farther apart. Thus, pairs of locations that are closer to one another (far left on the x-axis of the semivariogram cloud) should have values more similar to each other (low on the y-axis of the semivariogram cloud). As location pairs become farther apart (moving to the right on the x-axis of the semivariogram cloud), they should become more dissimilar and thus increase in the squared difference between them (moving up on the y-axis of the semivariogram cloud).

The next step is to fit a model to the points in building the empirical semivariogram. Semivariogram modeling is a major step between spatial description and spatial prediction. The primary application of Kriging is for the prediction of attribute values at locations which are not measured. The empirical semivariogram produces information on the spatial autocorrelation of datasets. It does not, however, gengenerate information for all possible distances and direction. Because of that, and to guarantee that Kriging predictions will have positive Kriging variances, it is essential to fit a model (a continuous function or curve) to the empirical semivariogram. Hypothetically, this should be very similar to regression analysis, in which a continuous curve or line is fitted to the data points.

To fit a model to the empirical semivariogram, one has to choose a function that serves as a model – for instance, a spherical type that rises and levels off for larger distances beyond a certain range. There are deviations of the points on the empirical semivariogram from the model; some points are below the model curve, and some points are above. However, if one adds up the distance of each point below the line and each point above it, the two values should be similar.

There are many semivariogram models from which to choose:

- Circular
- Spherical
- Exponential
- Gaussian
- Linear

The selected model impacts the prediction of the unknown values, specifically when the shape of the curve near the origin differs significantly. The steeper the curve near the origin, the more influence the closest neighbors will have on the prediction. Therefore, the output surface will be less smooth. Each model is designed to fit specific types of phenomena. The Spherical model, one of the most commonly used, illustrates a progressive decrease of spatial autocorrelation (equivalently, an increase of semivariance) until some distance, beyond which the autocorrelation is zero. It is applied when spatial autocorrelation decreases exponentially with an increase in distance. Here, the autocorrelation disappears completely only at an infinite distance. The exponential model is also commonly used.

The choice of which model to use is based on the spatial autocorrelation of the data, as well as on prior knowledge of the phenomenon. Below are the general shapes and equations of the mathematical models used to describe the semivariance (ESRI, 2011).

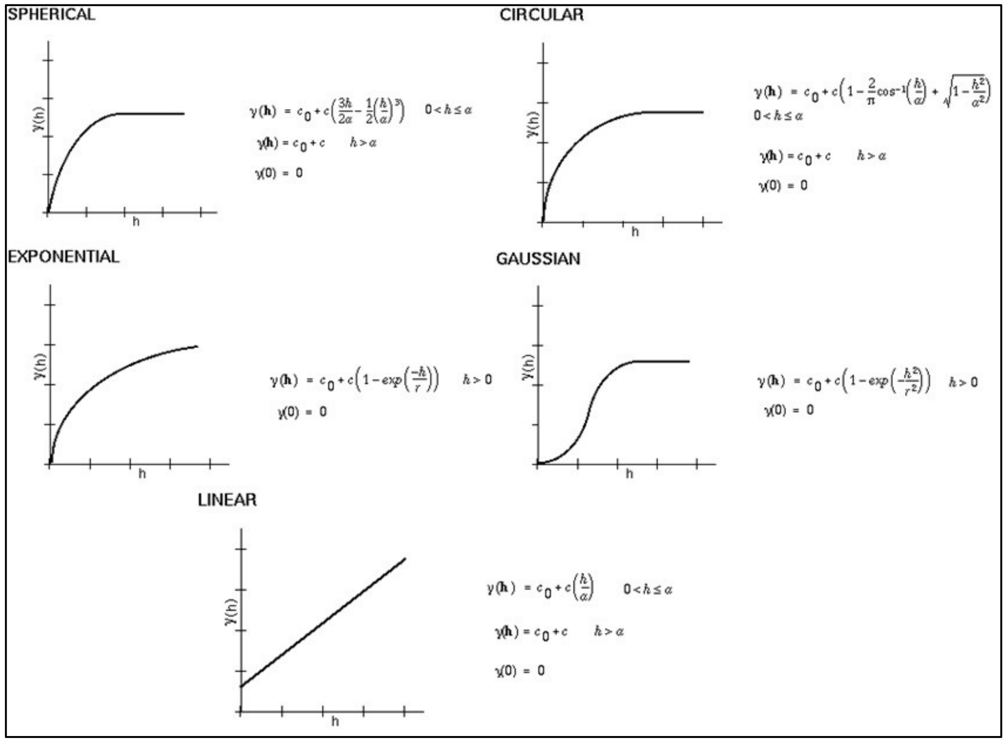

Figure 5-5- Different Semivariogram Models Illustration (ESRI, 2011)

After uncovering the autocorrelation or dependence in the data, computing distances, and modeling the spatial autocorrelation, one can make a prediction using the fitted model. Hereafter, the empirical semivariogram is set aside. Now the data can be used to make predictions.

There are two Kriging techniques: ordinary and universal. Ordinary Kriging is the most general and broadly used method. It assumes that the constant average is unknown; a reasonable assumption, unless there is a scientific or logical reason to reject it. Universal Kriging, meanwhile, is based on the assumption that there is an overriding pattern or trend in the data that can be modeled by a deterministic function:

a polynomial. This polynomial is subtracted from the original measured values, and the autocorrelation is modeled and calculated from the random errors. Once the model is made to fit the random errors, and prior to making a prediction, the polynomial is added back to the predictions to provide meaningful outputs. Universal Kriging must only be used when the analyst knows there is a trend or pattern in the data and can provide a scientific and rational justification to explain it.

Kriging is based on the regionalized variable theory, which assumes that the spatial variation in the phenomenon represented by the z-values is statistically homogeneous throughout the surface. For instance, the same pattern of variation can be observed at all locations on the surface. This hypothesis of spatial homogeneity is fundamental to the regionalized variable theory (ESRI, 2011).

On the other hand, Empirical Bayesian Kriging (EBK) automates the most difficult aspects of creating a valid model. While other Kriging techniques need a manual adjustment of parameters to receive precise results, EBK automatically estimates them by a process of subsetting and simulations. It differs from the classical techniques by taking into account the error introduced by estimating via the semivariogram model. This is done by estimating, then applying multiple semivariogram models, instead of just one.

The process includes the following steps (Krivoruchko, 2012):

1. A semivariogram model is estimated from the data;
2. Using this, a new value is simulated at each of the input data locations;
3. A new semivariogram model is then estimated from the simulated data. A weight for this model is then calculated using Bayes' rule, which shows

how likely the observed data can be generated from the semivariogram; and,

4. Steps two and three are then repeated.

With each iteration, the semivariogram estimated in step one is utilized to simulate a new set of values at the input locations. This data is then used to estimate a new semivariogram model and its weight. Predictions and prediction standard errors are then generated at the unmeasured locations using these weights; a process that produces a spectrum of semivariograms. Each semivariogram simulation is an estimate of the true semivariogram from which the observed process could be produced.

Figure 5-6 illustrates the spectrum of semivariogram models plotted together. The median of the distribution is represented by a solid red line. The 25th and 75th percentiles are colored with red-dashed lines. The width of the blue lines is proportional to the semivariogram weights, so that models with smaller weights are represented by thinner, less-saturated lines.

The default Kriging model in EBK represents the intrinsic random function of order 0, while the spatial correlation model is a power model where b, c, and α (the allowed value of power value α is between 0 and 2) represents the model parameters. They correspond to fractional Brownian motion, also known as the random walk process. It is comprised of steps in a random direction, and filters out a moderate trend in the data (Krivoruchko, 2012).

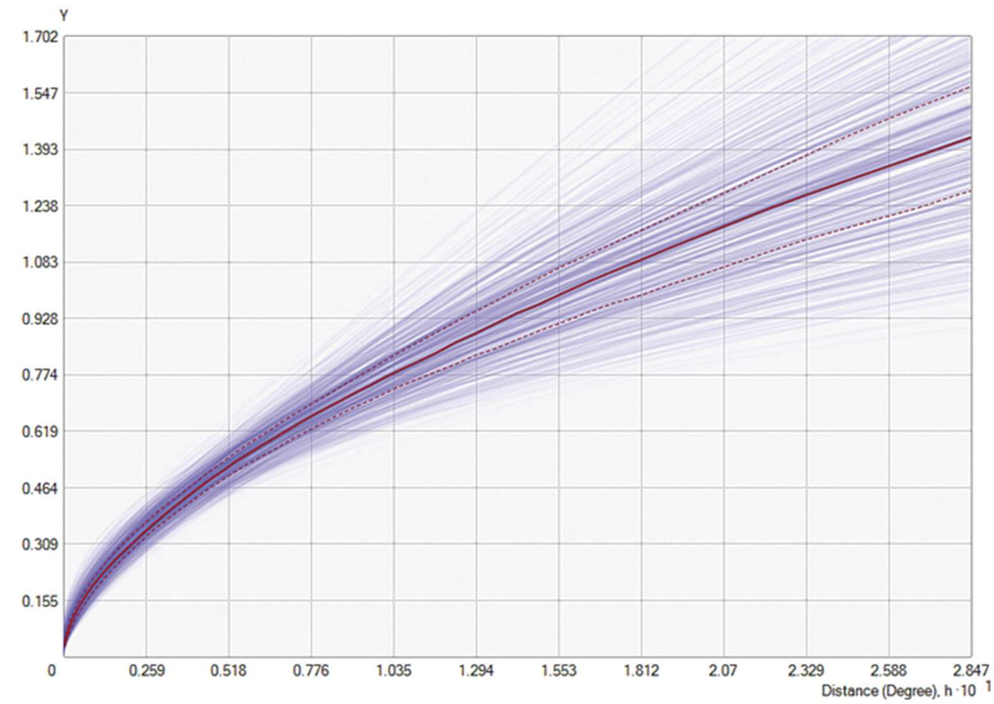

Figure 5-6- The spectrum of the Semivariogram Models Produced by EBK (Krivoruchko, 2012)

This research estimates spatial real estate investment risk for each brownfield site in Delaware, using the performance of vicinity businesses and financial institutions. That is to say, the better vicinity businesses perform, the less risky the real estate investment in the given brownfield. For that purpose, this study uses three primary datasets which are treated as measured points in EBK model:

1- Deposit balance of all vicinity financial institutions around each brownfield site (FDIC, 2015).
2- 5-year deposit growth rate (2010-2015) of all vicinity financial institutions around each brownfield site (FDIC, 2010 and 2015).

3- Estimated Annual Sale of all vicinity businesses around each brownfield site (DatabaseUSA, 2015).

Deposit balances of all financial institution branches in the US are collected and published annually by the Federal Deposit Insurance Corporation (FDIC), the United States government corporation providing deposit insurance to depositors in the United States banks. The FDIC was created by the 1933 Banking Act after the Great Depression, to restore trust in the American banking system. Prior to its creation, more than one-third of US banks failed, and bank runs were common. The insurance limit was initially US$2,500 per ownership category. Since the passage of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2011 however, the FDIC has insured deposits in member banks for up to US$250,000 per ownership category (FDIC, 2016).

The Summary of Deposits (SOD) is the annual survey of branch office deposits for all FDIC-insured institutions, including insured U.S. branches of foreign banks, including data as of June 30. The public can access these data by (1) single institution, (2) institutions within a geographic area, or (3) aggregated within a geographic area. SOD features include custom market share reports and downloads. To provide a tool for measuring deposits in local banking markets, the surveys obtain deposit figures for each banking office of branch banking systems, as well as for each insured U.S. branch of a foreign bank. Deposit figures for unit banks (which do not have branch offices) were obtained from the June Reports of Condition. Deposit-reporting institutions must report their deposits in a manner consistent with their existing internal record-keeping practices, but other methods that logically reflect the deposit-gathering activity of their branches may be used. It is recognized that certain classes of deposits, and the deposits of certain types of customers, may be assigned to a single office. Because these publications are used as a source of market share information for individual banking markets, the figures for each geographical area only include deposits of offices located within that area. Several institutions have designated home offices that do not accept deposits; these have been included in the survey to provide a more complete listing of all offices.

With the exception noted above, 'banking office' is defined to include all offices and facilities that actually hold deposits, and does not include loan production offices, computer centers, and other nondeposit installations such as automated teller machines (ATMs). Institutions are allowed to combine deposit data from two or more offices within the same county for the following office types drive-in offices, seasonal branches, and military facilities. Where centralized bookkeeping or other conditions make it impossible to report exact figures, estimates are required. International Banking Facility (IBF) deposits are considered deposits in foreign offices and are not included in the Summary of Deposits Survey. Offices and deposits are reported by the institution that owned the office as of the close of business on June 30. The term 'offices' includes both main offices and branches. An institution with four branches operates a total of five offices.

All reports submitted to the FDIC have been validated and corrected to the extent possible. There may be rounding differences or minor reporting errors reflected in the tables. Savings institutions include all FDIC-insured financial institutions that operate under federal or state thrift banking charters. Before August 9, 1989, all institutions insured by the Federal Savings and Loan Insurance Corporation (FSLIC) and all savings banks insured by the FDIC are included in any applicable chart (FDIC, 2016). This research employs the 2010 and 2015 FDIC data which has been retrieved through S&P Global Market Intelligence (www.SNL.com).

Estimated annual sale of all businesses in Delaware is retrieved through the SNL Financials website, which collects this data from a third party data provider (DatabaseUSA). DatabaseUSA has developed a proprietary model that estimates the sales volume for each business. For estimating annual sales volume for each business location, DatabaseUSA uses data from the Department of Commerce, especially the economic wealth factor based on the geographic location, and that pertaining to employment. Where companies publish actual revenue figures, DatabaseUSA uses the published values to note this revenue. Sales volume is not estimated for some lines of business, such as educational institutions, government offices, associations, and organizations, because such industries do not typically generate sales. Generally, the data are compiled and updated monthly, from hundreds of public and proprietary sources including the U.S. Government, market data, utility data, phone validation, directories, and other proprietary sources.

Table 5-4 shows EBK model parameters for each of the spatial risk factors. Figures 5-7 to 5-12 show detailed information about EBK models for these spatial risk factors. All calculations and modeling have been done within Advanced ArcGIS Desktop 10.4, Geostatistical Analyst, under the University of Delaware license.

An important point worth noting here is that the regression function in EBK does not need to be statistically significant in order to forecast or estimate a real value, since EBK is primarily used here as an intelligent weighting method for measuring the vicinity activities.

Table 5-4- EBK Model Parameters for Spatial Risk Factors

EBK Model Parameters	FDIC Deposit Balance of Vicinity Financial Institutions	FDIC 5-year Deposit Growth Rate of Vicinity Financial Institutions	Estimated Annual Sale of Vicinity Businesses
Output type	Prediction	Prediction	Prediction
Transformation Type	None	Empirical	None
Semivariogram Model Type	Thin Plate Spline	Exponential	Power
Subset Size	100	100	100
Overlap Factor	1	5	1
Number of Simulations	100	100	100
Searching neighborhood	Standard Circular	Standard Circular	Standard Circular
Neighbors to include	15	10	30
Include at least	10	5	15
Sector Type	Full	Full	Full
Radius	2000 Meters	3000 Meters	500 Meters
Angle	160	340	150

EBK Model Parameters Description:

***Output Surface Type**: Empirical Bayesian Kriging can produce a prediction surface, a surface of prediction standard errors, a surface of probability indicating whether or not a critical value is exceeded, and a surface of quantiles for a predetermined probability level.*

***Transformation**: Empirical Bayesian Kriging offers the Multiplicative Skewing transformation with two base functions: Empirical and Log Empirical.*

***Semivariogram Type**: The type of semivariogram that will be used in the interpolation.*

***Subset Size**: Specifies the number of points in each subset.*

***Overlap Factor**: Specifies the degree of overlap between subsets. Each input point can fall into several subsets, and the overlap factor specifies the average number of subsets that each point will fall into. A high value of the overlap factor makes the output surface smoother, but it also increases processing time.*

***Number of Simulations**: Specifies the number of semivariograms that will be simulated for each subset.*

***Searching Neighborhood type**: The Standard option will assign weights based on distance from the target location. The Smooth option adjusts the weights using a sigmoidal function defined by the smoothing factor.*

***Neighbors to Include**: The maximum number of features to be included in each sector.*

***Include at Least**: The minimum number of features to be included in each sector.*

***Notes**: 1) The sectors will be projected outwards if the minimum number of features is not found inside the sector. 2) If there are no features within the searching neighborhood, then for most of the interpolation methods, it will mean that a prediction cannot be made at that location. 3) Although some interpolators, such as simple and disjunctive Kriging, predict values in the areas without features using the mean value, a common practice is to change the searching neighborhood so that some features are located in the searching neighborhood.*

***Sector type**: Allows a choice of 1, 4, 4 with an offset of 45º, or 8 sectors.*

***Radius**: The length of the radius of the search circle.*

***Angle**: This is the orientation of the major semiaxis (in degrees from North). This will also rotate the sectors.*

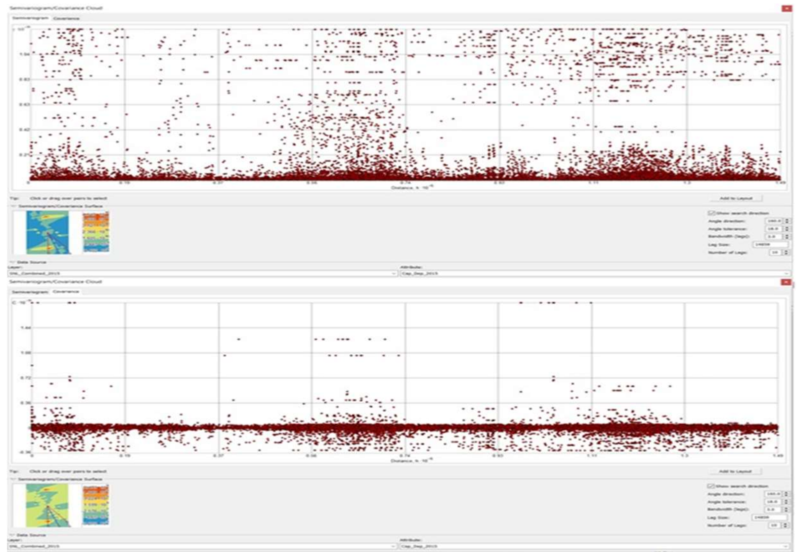

Figure 5-7- Semivariogram & Covariance of FDIC Deposit Balance of Vicinity Financial Institutions

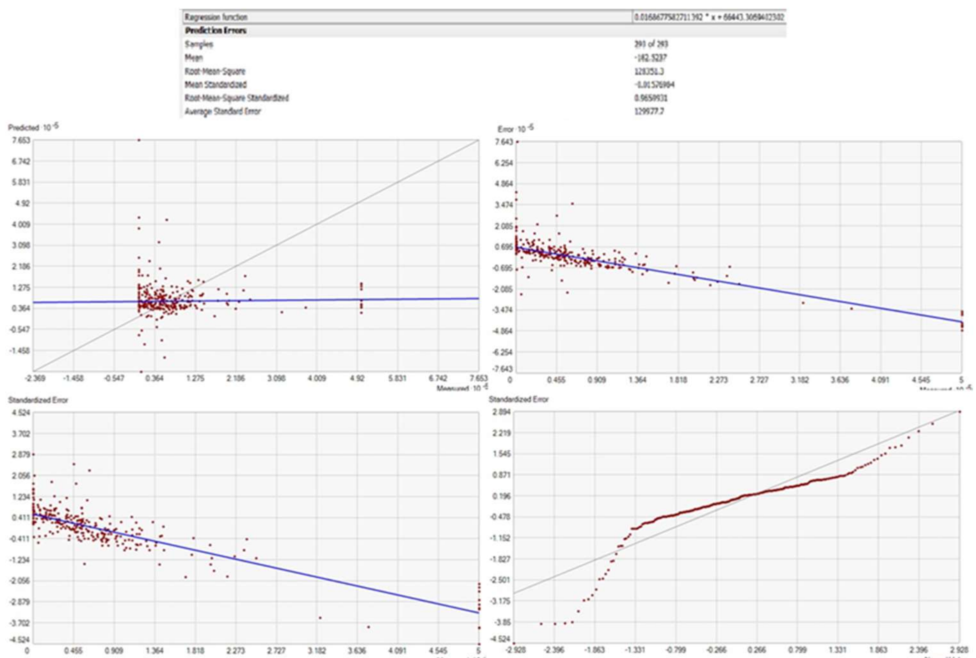

Figure 5-8- Regression Function and Curves of FDIC Deposit Balance of Vicinity Financial Institutions

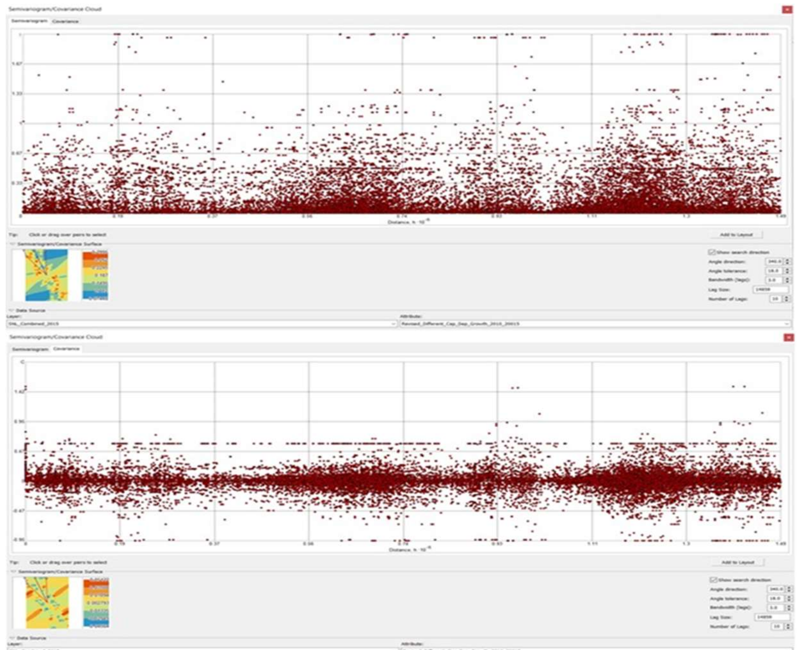

Figure 5-9- Semivariogram & Covariance of FDIC 5-year Deposit Growth Rate of Vicinity Financial Institutions

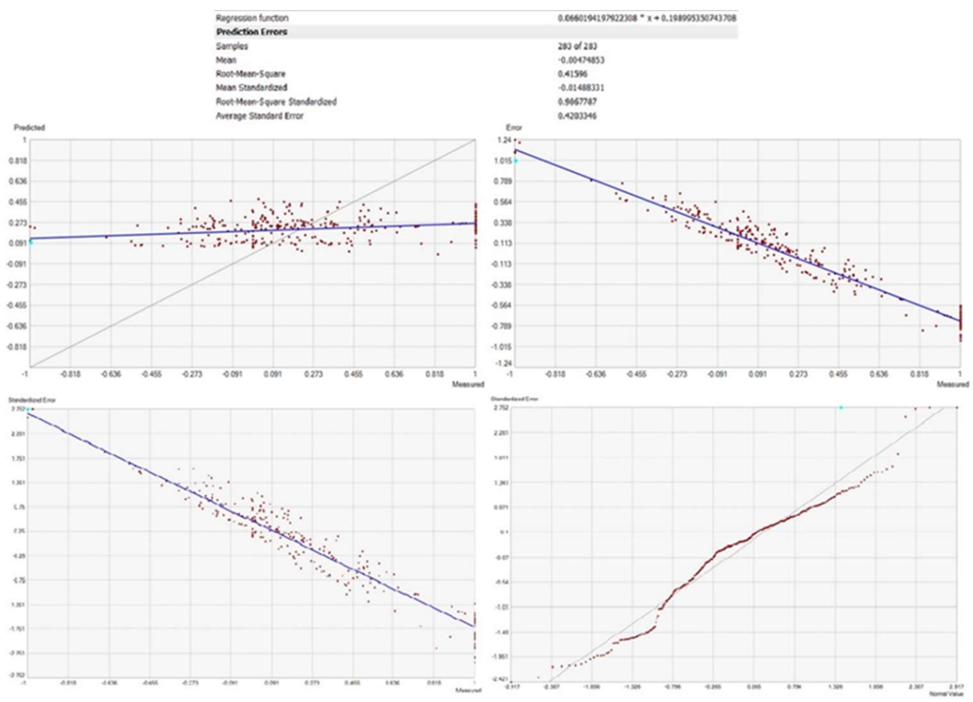

Figure 5-10- Regression Function and Curves of FDIC 5-year Deposit Growth Rate of Vicinity Financial Institutions

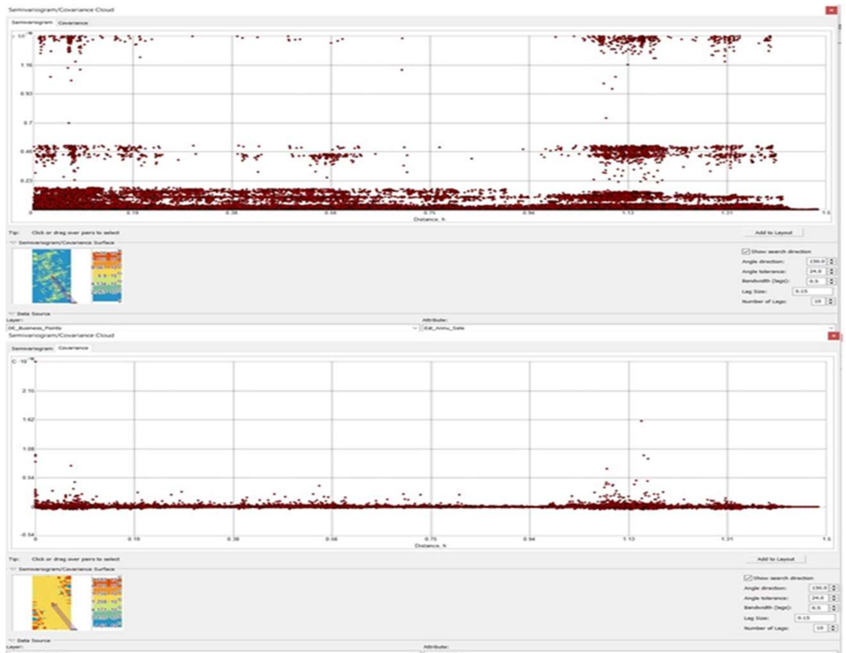

Figure 5-11- Semivariogram & Covariance of Estimated Annual Sale of Vicinity Businesses

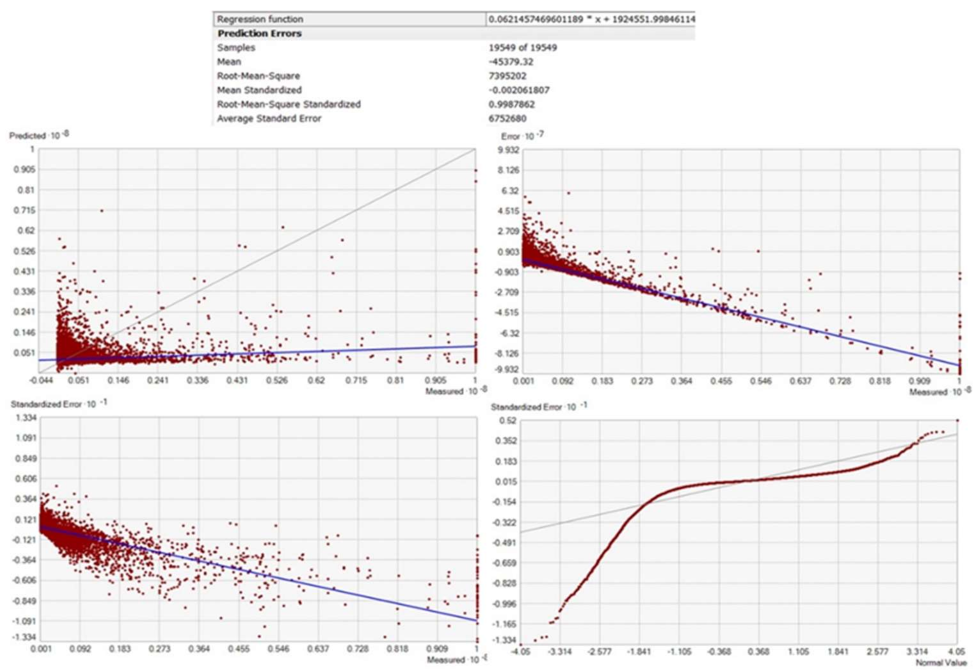

Figure 5-12- Regression Function of Curves of Estimated Annual Sale of Vicinity Businesses

5.2.3 Prioritizing The Risk Factors: A Pairwise Comparison

After arranging the risk factors in a hierarchy, the next step is to build priorities. Two types of pairwise comparisons are made in the AHP. The first is between pairs of risk factors and is used to show the priorities. The second type of pairwise comparison is between pairs of alternatives (brownfield sites) and is used to determine their relative merits. Since we use the absolute measurement of alternatives (brownfield sites) with respect to each risk factor, the study only conducts the pairwise comparison between pairs of risk factors.

Pairwise comparisons of the factors are made in terms of importance. When comparing a pair of risk factors, a ratio of relative importance of the factors can be established. This ratio does not need to be based on some standard scale, such as meters or feet, but merely represents the relationship between the two factors being compared. In AHP, the verbal scale is used to enter judgments. This is, essentially, an ordinal scale. When a decision-maker judges A to be strongly more important than B, we know that A is more important than B, but we do not know the interval between A and B or the ratio of A to B. Saaty (1994) proposed a 1 to 9 scale, which is the basis of what is known as a pairwise comparison (Table 5-1). The 1 to 9 scale is used to quantify how much more important one factor is than another. According to the reciprocal axiom, if factor A is absolutely more important than factor B, and is rated at 9, then B must be absolutely less important than A is, and be valued at 1/9. According to Saaty (1982), studies have confirmed that the human brain is well adapted to discriminate intensities, initially into three basic levels: low, medium, and high; and that subsequent discrimination within each of these ranks can also be well sorted into low, medium, and high values. Thus, we have an appreciation scale of 3 times 3, which yields the 9-value basis used for the AHP process. This scale is used to compare each risk factor at the same level and its contribution to the parent level (Mota-Sanchez, 2007).

What is the relative importance, to the investors, of the financial demand risk as compared to infrastructure risk when it comes to real estate investment in brownfield sites? This type of question should be asked by analysts to choose whether financial demand risk is very much more important, rather more important, as important, and so on, down to very much less important, than the infrastructure risk. These pairwise comparisons are carried out for all factors to be considered, and the matrix of judgments is completed.

Tables 5-5 to 5-25 show pairwise comparison matrices for all the risk factors. In these tables, the criteria (risk factors) listed on the left are, one by one, compared with each criterion listed on top as to which is more important, with respect to the goal of selecting the safest, least risky brownfield site for investment. Two criteria are evaluated at a time, regarding their relative importance. Index values from 1 to 9 are used. If criterion A is exactly as important as criterion B, this pair receives an index of 1. If A is much more important than B, the index is 9. All gradations are possible in between. For a "less important" relationship, the fractions 1/1 to 1/9 are available: if A is much less important than B, the rating is 1/9. The values are entered row by row into a cross-matrix. The diagonal of the matrix contains only values of 1. First, the right upper half of the matrix is filled until each criterion has been compared to every other one. If A to B was rated with the relative importance of n, B to A has to be rated with 1/n. For reasons of consistency, the lower left half of the matrix can thus be filled with the corresponding fractions. The core of the AHP resides in the prioritization, and in order to obtain useful results, these must be checked for consistency. Consistency ratio values are shown in the last column on the right of each matrix. As previously stated, this value must lie close to 0.1 or 10% of inconsistency, in order to have trustworthy results.

Table 5-5- Main Risk Factors Pairwise Comparison Matrix

Level 1	1	2	3	4	5	Risk Weight	Consistency Ratio
1- Socioeconomic Risk	1	0.5	0.333	0.25	0.2	0.063716184	0.016405906
2- Demographics Risk	2	1	0.5	0.333	0.333	0.106963967	
3- Infrastructure Risk	3	2	1	0.5	0.5	0.18001316	
4- Spatial (Proximity) Risk	4	3	2	1	0.5	0.272848929	
5- Financial Demand Risk	5	3	2	2	1	0.37645776	

Table 5-6- Socioeconomic Risk Factors Pairwise Comparison Matrix

Level 2	1	2	3	Risk Weight	Consistency Ratio
1- Wealth	1	3	2	0.549945607	0.015771299
2- Housing	0.333	1	1	0.209843523	
3 - Employment	0.5	1	1	0.24021087	

Table 5-7- Demographic Risk Factors Pairwise Comparison Matrix

Level 2	1	2	3	4	5	Risk Weight	Consistency Ratio
1- Population Density	1	2	4	3	4	0.41077	0.035963586
2- CAGR: Population Density	0.5	1	3	2	3	0.255854715	

3- Millennial Population Percent	0.25	0.333	1	0.333	2	0.09249	
4- Population 25+, Bachelor's Degree /Educ Base	0.333	0.5	3	1	2	0.16487	
5- Group Quarter Population	0.25	0.333	0.5	0	1	0.07601	

Table 5-8- Infrastructure Risk Factors Pairwise Comparison Matrix

Level 2	1	2	3	4	5	6	7	Risk Weight	Consistency Ratio
1- Average Age of Housing Units Structure	1	0.333	0.25	0.2	0.11111	0.16666	0.14285	0.022475846	0.071319217
2- Average Number of Vehicles Available	3	1	0.333	0.25	0.14285	0.2	0.16666	0.035991222	
3- Access to Major Roads	4	3	1	0.333	0.16667	0.25	0.2	0.057933991	
4- Access to 1-95	5	4	3	1	0.2	0.3333	0.25	0.094178284	
5- Clean UP Expenses per Square Foot	9	7	6	5	1	4	3	0.394625818	
6- Access to shopping centers	6	5	4	3	0.25	1	0.5	0.162227318	
7- Traffic Count 2014	7	6	5	4	0.333	2	1	0.232567521	

Table 5-9- Spatial (Proximity) Risk Factors Pairwise Comparison Matrix

Level 2	1	2	3	Risk Weight	Consistency Ratio
1- FDIC Deposit Balance of Vicinity Financial Institutions	1	2	4	0.558424543	0.015771299
2- FDIC 5-year Deposit Growth Rate of Vicinity Financial Institutions	0.5	1	3	0.319618264	
3- Estimated Annual Sale of Vicinity Businesses	0.25	0.333	1	0.121957193	

Table 5-10- Financial Demand Risk Factors Pairwise Comparison Matrix

Level 2	1	2	3	Risk Weight	Consistency Ratio
1- Depository Product Balance	1	3	2	0.549945607	0.015771299
2- Investment Product Balance	0.333	1	1	0.209843523	
3- Credit Product Balance	0.5	1	1	0.24021087	

Table 5-11- Wealth Risk Factors Pairwise Comparison Matrix

Level 3	1	2	3	Risk Weight	Consistency Ratio
1- Average HH Income	1	2	4	0.558424543	0.015771299
2- Per Capita Income	0.5	1	3	0.319618264	
3- Families , At-Above Poverty/ Total HH	0.25	0.333	1	0.121957193	

Table 5-12– Housing Risk Factors Pairwise Comparison Matrix

Level 3	1	2	3	4	5	6	Risk Weight	Consistency Ratio
1- Owner Occupied Housing Units	1	2	0.5	3	4	4	0.249072622	0.013012689
2- CAGR: Owner Occupied Housing Units	0.5	1	0.333	2	3	3	0.15690592	
3- Homeownership Rate	2	3	1	4	5	5	0.379441062	
4- Average Value of Owner Occupied Housing	0.333	0.5	0.25	1	2	2	0.096923088	
5- Owner Occupied Housing Units (100K-200K)	0.25	0.333	0.2	0.5	1	1	0.058828654	
6- Owner Occupied Housing Units (200K-300K)	0.25	0.33	0.2	0.5	1	1	0.058828654	

Table 5-13- Employment Risk Factors Pairwise Comparison Matrix

Level 3	1	2	3	4	Risk Weight	Consistency Ratio
1- Unemployment Rate	1	2	3	4	0.466848564	0.011473026
2- Population 16+, Civilian Labor Force, Employed	0.5	1	2	3	0.277589817	
3- Emp Civ Pop 16+, Occ: White Collar	0.3333	0.5	1	2	0.160266555	
4- Emp Civ Pop 16+, Occ: Blue Collar	0.25	0.33333	0.5	1	0.095295064	

Table 5-14- Depository Product Balance Risk Factors Pairwise Comparison Matrix

Level 3	1	2	3	Risk Weight	Consistency Ratio
1- Deposit Products Balance	1	0.25	3	0.225535	0.073936803
2- Saving Products Balance	4	1	5	0.673811	
3- Asset/Cash Management Product Balance	0.333	0.2	1	0.100654	

Table 5-15- Credit Product Balance Risk Factors Pairwise Comparison Matrix

Level 3	1	2	3	4	Risk Weight	Consistency Ratio
1- Credit Cards	1	0.333	0.143	0.2	0.05439874	0.063259723
2- Line of Credit Balance	3	1	0.2	0.25	0.108369976	
3- Mortgage Balance	7	5	1	3	0.557421208	
4- Loan Balance	5	4	0.333	1	0.279810076	

Table 5-16- Investment Product Balance Risk Factors Pairwise Comparison Matrix

Level 3	1	2	3	4	Risk Weight	Consistency Ratio
1- Stock Market Balance	1	1	0.333	0.2	0.09632537	0.016067186
2- Bond Market Balance	1	1	0.333	0.2	0.09632537	
3- Other Investment	3	3	1	0.333	0.249484642	
4- Real Estate Investment	5	5	3	1	0.557864618	

Table 5-17 Deposit Balance Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	4	Risk Weight	Consistency Ratio
1- CD Products (excluding CD IRAs)	1	0.333	6	8	0.309424807	0.051904539
2- Interest DDA Products	3	1	7	9	0.573641529	
3- Regular/Non-Interest DDA Products	0.1667	0.1428	1	2	0.072272039	
4- Transaction/DDA Products	0.125	0.1111	0.5	1	0.044661624	

Table 5-18- Saving Balance Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	4	Risk Weight	Consistency Ratio
1- Fixed Interest Savings Products (excluding IRAs)	1	2	2	3	0.42334216	0.016922922
2- Money Market Savings Products	0.5	1	2	2	0.270491554	
3- Regular/Liquid Savings Products (excluding CD IRAs)	0.5	0.5	1	1	0.16083524	
4- Variable-Interest Saving Products (excluding IRAs)	0.3333	0.5	1	1	0.145331045	

Table 5-19- Credit Cards Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	Risk Weight	Consistency Ratio
1- Discover Card	1	0.25	0.2	0.097390069	0.021202645
2- Master Card	4	1	0.5	0.333069351	
3- Visa Card	5	2	1	0.569540579	

Table 5-20- Line of Credit Balance Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	Risk Weight	Consistency Ratio
1- HELOC	1	3	6	0.666667	0.00000000
2- PLC Other Types	0.333333	1	2	0.222222	
3- PLC Overdraft Protection	0.166667	0.5	1	0.111111	

Table 5-21- Mortgage Balances Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	4	Risk Weight	Consistency Ratio
1- First Mortgage	1	2	5	7	0.507438	0.060499751
2- Fixed Rate Mortgage	0.5	1	4	6	0.326515	
3- Adjustable Rate Mortgage (ARM)	0.2	0.25	1	4	0.117318	
4- Other Type of Rate Mortgage	0.1428	0.16667	0.25	1	0.048728	

Table 5-22- Personal Loan Balance Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	4	Risk Weight	Consistency Ratio
1- Personal Loans	1	4	2	6	0.492082566	0.050473784
2- Personal Loans, Other Type	0.25	1	0.3333	4	0.142052001	
3- Personal Loan, Second Mortgage	0.5	3	1	5	0.309380534	
4- Auto Loans	0.1667	0.25	0.2	1	0.056484899	

Table 5-23- Stock Market Balance Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	4	5	Risk Weight	Consistency Ratio
1- Commodities/Warrants/Options	1	1	2	2	0.5	0.217718698	0.017252699
2- Money Market Mutual Funds (excl. retirement)	1	1	1	1	0.5	0.164999919	
3- Government Securities	0.5	1	1	1	0.5	0.143640772	
4- Mutual Funds (excluding 401k)	0.5	1	1	1	0.5	0.143640772	
5- Stock	2	2	2	2	1	0.329999838	

Table 5-24- Bond Market Balance Risk Factors Pairwise Comparison Matrix

Level 4	1	2	Risk Weight	Consistency Ratio
1- Corporate/Municipal Bonds	1	1	0.5	0.00000000
2- US Saving Bond/T-Bills/T-Bonds	1	1	0.5	

Table 5-25- Other Investment Balance Risk Factors Pairwise Comparison Matrix

Level 4	1	2	3	Risk Weight	Consistency Ratio
1- Collectible/Precious Metals/Other	1	2	0.14285714	0.144075	0.069224003
2- Tax-Advantaged College Savings Products	0.5	1	0.16666666	0.095547	
3- RE Secured Credit Product (excluding 1st mortgage)	7	6	1	0.760377	

Next, we calculate the final (overall) weight of each sub-criterion by multiplying the parent weight by the weight of each of their subfactors. For example: First Mortgage Balance (individually weighted as 0.507438) is a subfactor of Mortgage Balances (individually weighted as 0.557421208), a subfactor of Credit Product Balances (individually weighted as 0.24021087), which is itself a subfactor of Financial Demand Risk (individually weighted as 0.37645776). So, the actual weight of First Mortgage Balance, within the complete hierarchy, will be the product of all weights (parents and sons), or $0.507438 \times 0.557421208 \times 0.24021087 \times 0.37645776 = 0.02557851$. In another example, Population Density (individually weighted as 0.41077) is a subfactor of Demographics Risk (individually weighted as 0.106963967), so the actual weight of Population Density within the complete hierarchy will be the product of all weights (parent and son), or $0.41077 \times 0.106963967 = 0.043937634$. The same calculations for the other subfactors are shown in Table 5-26.

As we can see in the ranking section, Proximity Financial Institutions' Deposit Risk, Proximity Financial Institutions' Performance Trend Risk, and Clean UP Expenses per Acre are the most important risk factors among all 62 risk factors.

Table 5-26- Overall Weight of All Risk Factors and Importance Ranking

Risk Factor	**Weight**	**Rank (Out of 62 Risk Factors)**
Median HH Income	0.019567439	17
Per Capita Income	0.011199563	24
Families , At-Above Poverty/ Total Family HH	0.004273433	34
Owner-Occupied Housing Units	0.003330208	41
CAGR: Owner-Occupied Housing Units	0.002097899	48

Risk Factor	Weight	Rank (Out of 62 Risk Factors)
Homeownership Rate	0.00507329	33
Average Value of Owner-Occupied Housing	0.001295903	55
Owner-Occupied Housing Units (100K-200K)	0.000786564	60
Owner-Occupied Housing Units (200K-300K)	0.000786564	61
Unemployment Rate	0.007145267	29
Population 16+, Civilian Labor Force, Employed	0.004248601	35
Emp Civ Pop 16+, Occ: White Collar	0.002452931	46
Emp Civ Pop 16+, Occ: Blue Collar	0.001458521	53
Population Density	0.043937634	6
CAGR: Population Density	0.027367235	11
Millennial Population Percent	0.009892998	26
Population 25+, Bachelor's Degree /Educ Base	0.017635283	18
Group Quarter Population	0.008130817	27
Average Age Housing Units Structure*	0.004045948	36
Average Number of Vehicles Available*	0.006478894	31
Access to Major Roads	0.010428881	25
Access to 1-95	0.016953331	19
Clean UP Expenses per Acre	0.07103784	3
Access to shopping centers	0.029203052	10
Traffic Count 2014	0.041865214	7
Proximity Financial Institutions' Performance Trend Risk	0.087207501	2
Proximity Financial Institutions' Deposit Risk	0.152365538	1
Proximity Businesses' Annual Sale Risk	0.033275889	9
CD Products (excluding CD IRAs)	0.014447943	22
Interest DDA Products	0.02678499	12
Regular/Non-Interest DDA Products	0.003374592	40
Transaction/DDA Products	0.002085381	49
Fixed Interest Savings Products (excluding IRAs)	0.059056178	4
Money Market Savings Products	0.037733537	8
Regular/Liquid Savings Products (excluding CD IRAs)	0.022436496	14
Variable-Interest Saving Products (excluding IRAs)	0.020273662	16
Asset/Cash Management Product Balance	0.020838513	15
Discover Card	0.000479085	62

Risk Factor	**Weight**	**Rank** **(Out of 62 Risk Factors)**
Master Card	0.001638447	52
Visa Card	0.002801705	43
HELOC	0.00653321	30
PLC Other Types	0.002177737	47
PLC Overdraft Protection	0.001088868	59
First Mortgage	0.025578515	13
Fixed Rate Mortgage	0.016458723	20
Adjustable Rate Mortgage (ARM)	0.005913687	32
Other Type of Rate Mortgage	0.002456255	45
Personal Loans	0.012451172	23
Personal Loans, Other Type	0.003594344	39
Personal Loan, Second Mortgage	0.00782826	28
Auto Loans	0.001429238	54
Commodities/Warrants/Options	0.001656717	51
Money Market Mutual Funds (excluding retirement)	0.001255556	56
Government Securities	0.001093025	57
Mutual Funds (excluding 401k)	0.001093025	58
Stock	0.002511113	44
Corporate/Municipal Bonds	0.003804718	37
US Saving Bond/T-Bills/T-Bonds	0.003804718	38
Collectible/Precious Metals/Other	0.002839524	42
Tax-Advantaged College Savings Products	0.001883105	50
RE Secured Credit Product (ex 1st mortgage)	0.014985965	21
Real Estate Investments	0.044069755	5
Sum	**1.00**	

5.2.4 Scaling The Risk Factors & Quantification of Risk

AHP works by developing priorities for alternatives (brownfields) and the criteria (risk factors) used to judge the alternatives (brownfields). Usually, the criteria whose choice is at the mercy of the understanding of the decision-maker (irrelevant criteria are those that are not included in the hierarchy), are measured on different scales, such as by length and weight, or are even intangible; i.e., for which no scales yet exist. Measurements calculated on different scales cannot be directly combined. First, priorities are derived from the criteria regarding their importance to achieving the goal; then, priorities are derived from the performance of the alternatives on each criterion. These priorities are derived based on pairwise assessments using judgment, or ratios of measurements from a scale if one exists. The process of prioritization solves the issue of having to deal with various types of scales, by interpreting their significance to the values of the user or users. Ultimately, a weighting and adding process is used to obtain overall priorities for the alternatives, as to how they contribute to the goal. This weighting and adding parallels what one would have done arithmetically prior to the AHP to combine alternatives measured under several criteria having the same scale (a scale that is often common to several criteria is money) to obtain an overall result. With the AHP, a multidimensional scaling problem is thus transformed to one that is unidimensional.

Ratio scales, proportionality, and normalized ratio scales are the core of generation and synthesis of priorities, whether in the AHP or any other multicriteria techniques that need to integrate existing ratio scale measurements with its own derived scales. Moreover, ratio scales are the only way to generalize a decision theory applicable to the case of dependence and feedback, because ratio scales can be both multiplied and added when they belong to the same scale, such as a priority scale.

When two judges arrive at two different ratio scales for the same problem, one needs to test the compatibility of their answers and accept or reject their closeness. The AHP has a non-statistical index for doing this.

Ratio scales can also be used to make decisions within an even more general framework, involving several hierarchies for benefits, opportunities, costs, and risks, and using a common criterion, such as an economic one, to ensure commensurability. Ratio scales are essential in proportionate resource allocation, in order to deal with relative measurement for both the objective function and the constraints obtaining a ratio scale solution vector. It is also possible to decide on the relative values of the allocated resources, and so one can associate a vector of benefits, costs, and, etc., with each alternative, to determine the best one, subject to all these general concerns.

Even the most experienced decision-maker can have trouble coping with potential issues which are not explained by linear cause and effect but, rather, are driven by complex, unmeasured interactions with other variables. Science usually deals with matters that can be observed through the use of our physical senses, and thus measured. However, if a situation calls for dealing with ideas, rather than direct sense perceptions, the quantification of variables can become subjective, as it is mostly only words – from which meanings are imprecise – that are used. This is the point where variables arising from complex interactions, such as among social, political, and economic systems, can be misjudged at the time of decision-making. Appropriately chosen numbers can represent perceptions and feelings from variables and events more objectively than words or rhetoric, leaving less chance of misunderstandings among the individuals involved (who may comprise a decision-making team), and thus less room for gray areas.

Numbers are used, to some extent, to reflect perceptions related to political, social, and economic matters. Typical scales of time, length, temperature, and money may represent many of the variables taken into consideration for a decision process. But what happens when we look at the same time, into all these variables, with different scales? The main challenge is to know how important, for example, the economic impact of a redeveloped brownfield site could be, in contrast with the likelihood of natural disasters in the area of the development, possibilities of war or terrorist attacks, as well as the abundance of (or lack thereof) prospects' resources. It can be seen that there is not one single scale that can cover as many variables as those which decision-makers confront (Mota-Sanchez, 2007).

As discussed in the literature review, a risk will be a risk only if the user perceives it as such and, in any case, the importance or quality that a person can assign to a given risk is not necessarily the same for another one. Through AHP, the user is capable of devising a scale that enables him/her to measure intangible qualities, applying dimensionless scales to uncertainties where measures do not necessarily exist. By use of relative scales, taken from experienced people, the decision-making framework can be shifted, from a situation of high uncertainty into one of measurable risk. Where a typical alternative can involve multiple input conditions, AHP can be used to combine such criteria into a single measure. It may be very difficult to estimate intensities, probabilities, or the chances of success for one event over another on an absolute basis, but it is certainly possible to compare the available alternatives (brownfield sites) and rank which is better than the other, and by how much.

Relative scales can be used to derive relative rankings. These values cannot be seen as indicators of high or low probabilities, but rather, mainly to indicate ranking among other choices. When we compare different brownfield sites, we can determine with high certainty, based on the relative comparison approach, which would represent the highest – and lowest – risk (Millet & Wedley, 2002). Relative scales can also use information from standard scales by transforming measurements into a relative ratio through a normalization process. Relative scales are the best way to represent subjective understanding, related to intangible properties or characteristics.

Saaty (1994) developed a 1 to 9 scale, which forms the basis of what is known as a pairwise comparison (Table 5-1); that is, a direct one-on-one comparison between two different elements. The 1 to 9 scale is used to quantify how much better (or worse) one element is than another. It is much easier for any decision-maker involved in an analysis to estimate a reasonable value to weigh each of the factors concerned, using a subjective comparison. Given this approach, for many factors of a single policy, a judgment matrix can be built according to the relative importance of the elements in the same hierarchy. In the case of brownfield investments, different factors should be clustered around different hierarchies. Socioeconomic characteristics, demographics, infrastructure, spatial, and financial factors would be the most important areas to analyze.

There is an important consideration related to the type of comparison that can be made among the available alternatives (brownfields). One could pairwise compare each of the alternatives to a “hypothetical” option, used as a fixed point (like measuring a length with a yardstick). This is called absolute measurement, and is done in reference to an ideal option. This kind of comparison is used when the alternatives are expected to be independent of one another. It is a useful variant of the scaling process, which can give the AHP the capability of assisting decisions related to planning, forecasting, and tracking of future policies.

However, although the type of alternatives (brownfields) specified by DNREC seem to be independent initially, there would be a change in preference if, while having a given set of alternatives, suddenly one is replaced with a much better or worse option. Then, the preferences for the remaining choices are expected to shift, making the previous ranking invalid. In other words, if an option that would not normally seem to be very a good alternative is compared with much worse options, it would be the best among that particular group. But, if any of those are replaced by a far better alternative, the preferences will once again be displaced.

When alternatives (brownfields) are compared in pairs, they become structurally dependent. In such cases, anything can happen to their initial priorities or ranks when new ones are added. Therefore, if there is any change in perception about the feeling of a given investment alternative (perhaps because of an improvement in certain conditions), the model should be rerun to focus on those judgments that concern the new or changed alternative. An iteration process can be also beneficial, acting as a sensitivity analysis, by allowing further refining of those judgments whose consistency may be low.

In order to avoid structural dependency of alternatives (brownfield sites), this study uses absolute measurement of all criteria (risk factors) instead of pairwise comparison. However, for a consistent and logical synthesis process it uses information from the standard scale by transforming measurements into a relative ratio through a normalization process. Although an absolute measurement is used here, employing a relative ratio normalization formula helps the alternatives' (brownfields) risk level, measured relatively. That said, measurements of all criteria (risk factors) for each alternative (brownfield site) should be scaled in the same direction. This means that the bigger the value, the less risky the alternative; the smaller the value, the riskier the alternative. For instance, brownfield site A, located in an area with an average household income of 80K, is less risky, with respect to real estate investment, than brownfield site B, located in an area with lower average household income of 40K. This also implies that site B is doubly riskier than site A. On the other hand, brownfield site C, located in an area with unemployment of 15%, is triply riskier than brownfield site D, located in an area with unemployment of 5%. For risk factors such as average household income, this study uses the following formula to normalize all values between 0 and 1 [0,1]:

$$\mathrm{Z}_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \qquad (5.23)$$

Where $X_i = (x_1, x_2, \ldots, x_n)$, $X_{min} = \mathrm{Min}\,(x_1, x_2, \ldots, x_n)$, $X_{max} = \mathrm{Max}\,(x_1, x_2, \ldots, x_n)$ and Z_i is ith normalized data.

For risk factors such as the unemployment rate (Y_i) for which the natural value is in the opposite direction of the perceived risk order (the bigger the value, the less risky the site), before normalization, it has to get scaled by the following formula:

$$\mathrm{X}_i = \frac{1}{Y_i} \qquad (5.24)$$

Where $Y_i = (Y_1, Y_2, \ldots, Y_n)$.

Column "Reverse" in Table 5-3 shows which risk factor should be reversed (aligned) before normalization. Next, we calculate the final (overall) risk score by summarizing all weighted, normalized, and measured risk factors for each brownfield site. For instance, overall risk score for brownfield DE-0066 is calculated as shown in Table 5-27. Risk Score column is the product of Normalized Data and Weight. The bigger the overall risk score, the safer the brownfield site for investment.

Table 5-27- Overall Risk Score Calculation for Brownfield Site DE-0066

Risk Factor	Raw Data	Aligned Data	Normalized Data	Risk Weight	Risk Score (Normalized Data × Weight)
Median HH Income	48924.07692	48924.07692	0.093201767	0.019567439	0.00182372
Per Capita Income	26127.69231	26127.69231	0.126753937	0.011199563	0.001419589
Families , At-Above Poverty/ Total Family HH	0.864683129	0.864683129	0.432971342	0.004273433	0.001850274
Owner-Occupied Housing Units	14638	14638	0.272070269	0.003330208	0.00090605
CAGR: Owner-Occupied Housing Units	0.74783349	0.74783349	0.292089582	0.002097899	0.000612775
Homeownership Rate	54.50593053	54.50593053	0.282583098	0.00507329	0.001433626
Average Value of Owner-Occupied Housing	212723.7692	212723.7692	0.092573582	0.001295903	0.000119966
Owner-Occupied Housing Units (100K-200K)	5594	5594	0.343265093	0.000786564	0.00027
Owner-Occupied Housing Units (200K-300K)	4237	4237	0.197590902	0.000786564	0.000155418
Unemployment Rate	11.98461538	0.083440308	0.073275371	0.007145267	0.000523572
Population 16+, Civilian Labor Force, Employed	25439	25439	0.251938583	0.004248601	0.001070387
Emp Civ Pop 16+, Occ: White Collar	14626	14626	0.227981692	0.002452931	0.000559223
Emp Civ Pop 16+, Occ: Blue Collar	5561	0.000179824	0.16819884	0.001458521	0.000245322
Population Density	1603.602454	1603.602454	0.155650906	0.043937634	0.006838933
CAGR: Population Density	0.665360835	0.665360835	0.283071019	0.027367235	0.007746871
Millennial Population Percent	30.78307946	30.78307946	0.650272615	0.009892998	0.006433146
Population 25+, Bachelor's Degree /Educ Base	15.24460354	15.24460354	0.305789429	0.017635283	0.005392683
Group Quarter Population	3804	0.000262881	0.006323503	0.008130817	5.14152E-05
Average Age Housing Units Structure*	35.46153846	0.028199566	0.240327388	0.004045948	0.000972352
Average Number of Vehicles Available*	1.669230769	1.669230769	0.414031475	0.006478894	0.002682466
Access to Major Roads	1153.889768	0.000866634	0.01454317	0.010428881	0.000151669

Risk Factor	Raw Data	Aligned Data	Normalized Data	Risk Weight	Risk Score (Normalized Data × Weight)
Access to 1-95	54028.62655	1.85087E-05	0.000596469	0.016953331	1.01121E-05
Clean UP Expenses per Acre	3485.842586	0.000286875	2.86472E-06	0.07103784	2.03503E-07
Access to shopping centers	1615.934225	0.000618837	0.030677456	0.029203052	0.000895875
Traffic Count 2014	10469	10469	0.085572	0.041865214	0.00358249
Proximity Financial Institutions' Performance Trend Risk	0.228694305	0.228694305	0.586103799	0.087207501	0.051112648
Proximity Financial Institutions' Deposit Risk	135480.7813	135480.7813	0.763344896	0.152365538	0.116307456
Proximity Businesses' Annual Sale Risk	1291223.875	1291223.875	0.025614898	0.033275889	0.000852359
CD Products (excluding CD IRAs)	86182.60923	86182.60923	0.640210599	0.014447943	0.009249726
Interest DDA Products	10999.79	10999.79	0.425192166	0.02678499	0.011388768
Regular/Non-Interest DDA Products	5786.800769	5786.800769	0.377382305	0.003374592	0.001273511
Transaction/DDA Products	8933.559231	8933.559231	0.291195413	0.002085381	0.000607253
Fixed-Interest Savings Products (excluding IRAs)	15127.72462	15127.72462	0.163916105	0.059056178	0.009680259
Money Market Savings Products	49682.89	49682.89	0.676626362	0.037733537	0.025531506
Regular/Liquid Savings Products (excluding CD IRAs)	24930.02538	24930.02538	0.213819801	0.022436496	0.004797367
Variable-Interest Saving Products (excluding IRAs)	42240.93769	42240.93769	0.651199463	0.020273662	0.013202198
Asset/Cash Management Product Balance	360078.2769	360078.2769	0.583919189	0.020838513	0.012168008
Discover Card	2104.025385	2104.025385	0.388618239	0.000479085	0.000186181
Master Card	2815.345385	2815.345385	0.230836309	0.001638447	0.000378213
Visa Card	3426.176923	3426.176923	0.412949074	0.002801705	0.001156962
HELOC	23912.42538	23912.42538	0.03190508	0.00653321	0.000208443
PLC Other Types	7468.040769	7468.040769	0.003373847	0.002177737	7.34735E-06
PLC Overdraft Protection	5960.658462	5960.658462	0.08327595	0.001088868	9.06765E-05
First Mortgage	122664.4815	122664.4815	0.095762844	0.025578515	0.002449471
Fixed Rate Mortgage	121432.4577	121432.4577	0.099865801	0.016458723	0.001643664
Adjustable Rate Mortgage (ARM)	128395.3608	128395.3608	0.103201251	0.005913687	0.0006103
Other Type of Rate Mortgage	97121.31923	97121.31923	0	0.002456255	0
Personal Loans	15309.43385	15309.43385	0.044178456	0.012451172	0.000550074
Personal Loans, Other Type	8055.924615	8055.924615	0.04744779	0.003594344	0.000170544
Personal Loan, Second Mortgage	24731.51308	24731.51308	0.04462203	0.00782826	0.000349313

Risk Factor	Raw Data	Aligned Data	Normalized Data	Risk Weight	Risk Score (Normalized Data × Weight)
Auto Loans	14047.26538	14047.26538	0.690168902	0.001429238	0.000986416
Commodities/Warrants/Options	41216.03	41216.03	0.623106277	0.001656717	0.001032311
Money Market Mutual Funds (excluding retirement)	94575.64769	94575.64769	0.456731084	0.001255556	0.000573452
Government Securities	9847.193077	9847.193077	0.006454817	0.001093025	7.05528E-06
Mutual Funds (excluding 401k)	124182.3723	124182.3723	0.161153274	0.001093025	0.000176145
Stock	138514.6808	138514.6808	0.209153413	0.002511113	0.000525208
Corporate/Municipal Bonds	67871.41231	67871.41231	0.446242678	0.003804718	0.001697828
US Saving Bond/T-Bills/T-Bonds	12054.12385	12054.12385	0.626194523	0.003804718	0.002382494
Collectible/Precious Metals/Other	20595.97154	20595.97154	0.333180985	0.002839524	0.000946076
Tax-Advantaged College Savings Products	32070.69846	32070.69846	0.312751023	0.001883105	0.000588943
RE Secured Credit Product (excl. 1st mortgage)	26597.31462	26597.31462	0.032703227	0.014985965	0.000490089
Real Estate Investments	257676.2208	257676.2208	0.030537716	0.044069755	0.00134579
ΣSum (Overall Risk Score)					**0.320472188**

The overall risk score for all 196 brownfield sites in Delaware is calculated in the same way. Since the measured risk for each criterion, normalized relatively using formula 5.23, the overall risk score also needs to be normalized relatively. So, we employ the same normalization formula (5.23) to relatively normalize the risk score. The new normalized risk score, between [0,1], is then subtracted from 1 in order to reach the final risk indicator.

Since AHP is employed here as a fuzzy membership function, which assesses the degree of membership of each brownfield site to each of the fuzzy sets (Investment Risk Set and Investment Safety Set), the final risk indicator here represents the degree of membership. For example, the final risk indicator of brownfield site DE-0066 is 0.610495084. This means that 61.05% of it belongs to Investment Risk Set and 38.95% belongs to Investment Safety Set. That is to say, this site is 61.05% as risky as the riskiest one, brownfield site DE-1431 (with full membership to Investment Risk Set), and 38.95% as safe as the safest one, brownfield site DE-0071 (with full membership to Investment Safety Set). For a more comprehensive understanding of risk composition, the final risk indicator (risk membership degree) also calculates for each main risk factor separately (Socioeconomic Risk, Demographic Risk, Infrastructure Risk, Spatial (Proximity) Risk, and Financial Demand Risk. Table 5-28 shows the final relative risk indicator for all 196 brownfield sites in Delaware. Figure 5-13 to 5-18 shows the geographic distribution of these, with respect to all risk indicators. In all maps, risk levels classified as follows:

- Low Risk (0% - 40%)
- Moderate Risk (40%-60%)
- Medium Risk (60%-80%)
- High Risk (80%-100%)

This analysis method here presents a new framework for uncertainty analysis and risk assessment in public policy. It employs AHP to quantify risk and EBK to incorporate spatial uncertainty into policymaking process. The proposed method empirically addresses the question of whether the presence of contaminated sites is a significant deterrent to new investment in decaying communities, or, if other localized social problems, locational disadvantage, among other factors, better explain the current situation. By knowing the relative level of investment risk embedded in each brownfield site, policymakers can intelligently incentivize their redevelopment in a more effective way, in order to balance the economic development throughout the state.

Table 5-28- Final Relative Risk Indicator

Brownfield Site	Socioeconomic Risk	Demographic Risk	Infrastructure Risk	Spatial Risk	Financial Demand Risk	Overal Invetsment Risk
DE-0066	87.34%	71.59%	95.69%	21.25%	74.95%	61.05%
DE-0071	0.00%	69.47%	96.17%	17.57%	0.00%	0.00%
DE-0084	75.89%	73.75%	38.97%	37.85%	71.34%	50.61%
DE-0105	65.72%	41.52%	92.62%	14.41%	66.46%	47.03%
DE-0107	62.14%	48.62%	30.78%	30.85%	47.83%	26.11%
DE-0131	73.54%	12.43%	94.00%	39.83%	81.85%	66.84%
DE-0149	62.46%	47.00%	95.28%	26.57%	47.70%	40.11%
DE-0151	61.65%	46.86%	93.78%	32.95%	47.11%	41.93%
DE-0163	59.29%	44.99%	88.17%	2.35%	64.43%	39.16%
DE-0167	80.56%	77.25%	97.59%	39.54%	75.62%	69.52%
DE-0197	63.75%	10.81%	91.80%	40.46%	72.21%	58.91%
DE-0199	57.27%	47.88%	38.45%	9.81%	62.28%	28.55%
DE-0270	79.07%	11.18%	96.43%	47.20%	85.85%	73.68%
DE-0280	75.44%	6.87%	40.58%	48.72%	82.07%	57.18%
DE-0281	72.31%	8.94%	99.15%	45.37%	79.88%	68.68%
DE-0324	72.31%	8.94%	97.03%	45.86%	79.88%	68.36%
DE-0325	74.55%	11.16%	90.36%	38.28%	82.54%	65.74%
DE-0326	77.65%	9.50%	95.42%	57.00%	85.39%	76.96%
DE-0327	68.83%	9.28%	94.85%	67.27%	76.75%	74.38%
DE-0328	75.44%	6.87%	40.48%	47.67%	82.07%	56.71%
DE-0339	73.73%	10.37%	97.42%	43.59%	81.63%	68.96%
DE-0355	72.31%	8.94%	95.62%	50.71%	79.88%	70.05%
DE-0359	83.07%	67.00%	90.17%	31.11%	73.24%	61.87%
DE-045	81.56%	78.66%	96.91%	40.13%	77.55%	71.13%
DE-1057	75.16%	12.06%	88.04%	35.39%	83.24%	64.56%
DE-1068	73.20%	15.37%	89.59%	31.74%	82.45%	62.98%
DE-1083	73.44%	11.07%	93.79%	28.52%	82.21%	62.15%
DE-1087	81.56%	78.66%	96.87%	40.65%	77.55%	71.34%
DE-1109	72.31%	8.94%	92.36%	34.70%	79.88%	62.51%
DE-1110	83.07%	67.00%	95.48%	26.15%	73.24%	61.10%
DE-1123	88.85%	5.03%	96.16%	83.86%	92.74%	94.12%
DE-1131	79.49%	6.68%	96.78%	44.91%	85.98%	72.55%
DE-1147	75.44%	6.87%	98.26%	49.31%	82.07%	71.74%
DE-1149	63.47%	26.77%	96.19%	47.55%	72.74%	64.68%
DE-1153	56.60%	47.66%	92.59%	12.14%	62.06%	42.73%
DE-1158	71.14%	18.51%	69.98%	33.09%	81.97%	58.42%
DE-1167	58.51%	43.21%	95.39%	33.10%	46.80%	41.58%
DE-1169	78.29%	10.11%	91.27%	30.27%	85.46%	64.86%
DE-1171	83.07%	67.00%	93.39%	29.66%	73.24%	62.06%
DE-1173	76.14%	14.55%	90.29%	28.91%	84.38%	63.48%
DE-1175	78.29%	10.11%	92.11%	31.37%	85.46%	65.53%
DE-1181	75.12%	16.51%	91.27%	33.28%	84.32%	65.60%
DE-1198	72.31%	8.94%	97.17%	46.73%	79.88%	68.76%
DE-1206	71.36%	10.33%	33.01%	37.00%	79.78%	48.72%
DE-1224	74.55%	11.16%	95.20%	37.64%	82.54%	66.67%
DE-1237	73.54%	12.43%	36.35%	36.75%	81.85%	51.25%
DE-1248	74.11%	9.02%	96.94%	28.33%	81.96%	62.57%
DE-1252	83.58%	75.09%	96.29%	33.99%	62.22%	57.78%
DE-1263	80.48%	0.00%	97.64%	47.12%	82.52%	70.85%
DE-1277	86.35%	22.74%	32.46%	42.81%	92.78%	62.38%
DE-1281	73.62%	68.68%	39.97%	28.86%	69.57%	45.22%
DE-1291	76.33%	10.32%	91.28%	35.29%	83.80%	65.67%
DE-1293	73.73%	10.37%	98.20%	48.86%	81.63%	71.36%
DE-1294	74.72%	9.02%	98.47%	43.58%	81.98%	69.43%
DE-1300	75.44%	6.87%	40.72%	47.12%	82.07%	56.54%
DE-1304	66.19%	9.55%	100.00%	41.25%	73.99%	62.61%
DE-1309	73.54%	12.43%	70.77%	38.93%	81.85%	60.70%
DE-1310	8.02%	59.40%	91.96%	9.10%	10.89%	2.74%
DE-1314	83.07%	67.00%	95.30%	28.87%	73.24%	62.20%
DE-1322	56.12%	51.03%	96.44%	17.83%	52.07%	39.48%
DE-1324	74.36%	73.24%	96.53%	27.16%	70.10%	59.36%
DE-1328	74.72%	9.02%	98.39%	49.01%	81.98%	71.69%
DE-1329	75.19%	15.57%	91.42%	34.31%	84.50%	66.11%
DE-1332	75.91%	7.79%	94.83%	40.81%	82.57%	67.77%
DE-1334	83.07%	67.00%	95.62%	29.83%	73.24%	62.68%
DE-1342	84.81%	90.42%	97.06%	39.40%	64.59%	63.29%
DE-1345	79.49%	6.68%	97.36%	46.59%	85.98%	73.40%
DE-1347	68.83%	9.28%	97.76%	35.33%	76.75%	61.68%
DE-1358	74.55%	11.16%	29.18%	37.45%	82.54%	50.22%
DE-1359	68.42%	8.45%	95.52%	47.78%	75.46%	65.36%
DE-1360	80.51%	71.67%	96.68%	34.06%	70.10%	62.73%
DE-1367	55.44%	47.98%	88.06%	0.00%	61.20%	35.83%
DE-1369	72.31%	8.94%	93.46%	47.96%	79.88%	68.36%
DE-1372	72.31%	8.94%	37.65%	47.89%	79.88%	54.49%
DE-1374	72.25%	17.06%	93.79%	43.30%	82.46%	68.93%
DE-1377	72.62%	14.52%	69.50%	38.77%	81.79%	60.37%
DE-1382	68.83%	9.28%	98.02%	70.32%	76.75%	76.45%
DE-1383	79.52%	8.28%	92.43%	37.60%	86.09%	68.61%
DE-1384	77.36%	8.28%	88.26%	50.90%	84.23%	71.70%
DE-1385	73.54%	12.43%	94.02%	39.62%	81.85%	66.76%
DE-1389	73.54%	12.43%	90.47%	37.07%	81.85%	64.81%
DE-1392	71.14%	18.51%	66.72%	41.48%	81.97%	61.14%
DE-1393	73.44%	75.19%	92.17%	24.07%	64.66%	53.33%
DE-1394	84.78%	7.60%	94.92%	46.61%	90.39%	76.40%
DE-1395	74.79%	9.39%	96.95%	42.80%	82.04%	68.80%
DE-1396	77.65%	9.50%	90.02%	47.06%	85.39%	71.45%
DE-1397	75.44%	6.87%	99.46%	42.14%	82.07%	69.01%
DE-1401	75.16%	12.06%	90.82%	34.99%	83.24%	65.08%
DE-1404	75.44%	6.87%	98.14%	46.66%	82.07%	70.59%
DE-1405	79.07%	11.18%	13.20%	41.30%	85.85%	50.56%
DE-1408	75.44%	6.87%	98.61%	46.59%	82.07%	70.68%
DE-1410	77.36%	8.28%	88.90%	61.49%	84.23%	76.31%
DE-1412	39.87%	20.13%	84.43%	28.49%	32.84%	23.66%
DE-1414	83.47%	90.44%	94.25%	35.55%	76.21%	68.81%
DE-1415	71.14%	18.51%	70.22%	39.12%	81.97%	61.02%
DE-1418	47.28%	66.19%	79.88%	7.82%	55.45%	33.95%
DE-1419	68.55%	12.29%	86.78%	45.49%	77.76%	64.15%
DE-1420	63.78%	67.92%	37.43%	46.79%	69.77%	51.28%

Brownfield Site	Socioeconomic Risk	Demographic Risk	Infrastructure Risk	Spatial Risk	Financial Demand Risk	Overal Invetsment Risk
DE-1421	74.72%	9.02%	99.39%	42.36%	81.98%	69.15%
DE-1423	29.10%	51.62%	75.12%	42.02%	24.21%	22.81%
DE-1424	64.02%	69.88%	94.22%	28.54%	62.34%	52.80%
DE-1425	73.54%	12.43%	94.62%	41.40%	81.85%	67.66%
DE-1426	74.55%	70.85%	97.70%	34.90%	71.27%	63.51%
DE-1427	73.44%	75.19%	84.69%	19.39%	64.66%	49.51%
DE-1428	56.59%	51.11%	81.88%	7.07%	66.60%	41.35%
DE-1429	68.83%	9.28%	98.22%	52.03%	76.75%	68.82%
DE-1430	75.14%	7.60%	94.83%	27.47%	82.68%	62.16%
DE-1431	94.14%	4.74%	98.21%	91.11%	95.44%	100.00%
DE-1433	70.97%	13.16%	94.38%	44.58%	80.01%	67.49%
DE-1434	73.20%	15.37%	70.62%	35.89%	82.45%	60.02%
DE-1438	88.64%	71.04%	81.39%	23.19%	75.53%	58.79%
DE-1442	76.44%	11.25%	96.39%	57.14%	84.79%	76.89%
DE-1444	70.73%	8.51%	98.04%	23.60%	78.18%	57.91%
DE-1445	59.78%	68.52%	40.51%	41.89%	64.09%	45.78%
DE-1446	72.31%	8.94%	91.97%	43.42%	79.88%	66.08%
DE-1448	75.89%	4.81%	98.44%	46.85%	82.12%	70.64%
DE-1449	40.94%	51.50%	85.51%	32.06%	39.84%	33.01%
DE-1450	77.65%	9.50%	97.08%	43.73%	85.39%	71.80%
DE-1451	83.07%	67.00%	95.45%	30.04%	73.24%	62.73%
DE-1452	72.31%	8.94%	91.21%	46.01%	79.88%	66.98%
DE-1453	73.31%	12.63%	83.84%	41.96%	81.87%	65.22%
DE-1455	88.01%	10.84%	97.81%	44.57%	92.63%	78.36%
DE-1458	71.14%	18.51%	95.62%	46.01%	81.97%	70.21%
DE-1460	83.58%	75.09%	95.78%	33.89%	62.22%	57.61%
DE-1462	78.29%	10.11%	96.73%	54.33%	85.46%	76.32%
DE-1464	61.98%	59.10%	87.28%	44.36%	68.93%	61.13%
DE-1465	72.31%	8.94%	91.73%	46.91%	79.88%	67.49%
DE-1466	74.11%	9.02%	98.31%	100.00%	81.96%	93.03%
DE-1472	88.63%	97.07%	37.08%	33.19%	75.17%	53.98%
DE-1474	78.73%	76.03%	95.81%	40.01%	74.45%	68.20%
DE-1481	74.72%	9.02%	98.31%	46.98%	81.98%	70.82%
DE-1482	35.02%	56.07%	92.27%	46.97%	33.81%	36.65%
DE-1483	38.64%	27.09%	85.36%	19.76%	33.21%	20.96%
DE-1484	71.20%	25.47%	99.06%	50.64%	82.79%	74.17%
DE-1486	55.11%	42.27%	0.00%	38.03%	63.96%	31.34%
DE-1487	80.66%	64.48%	93.18%	32.04%	72.78%	62.24%
DE-1490	81.37%	88.24%	90.29%	35.16%	72.68%	64.87%
DE-1491	83.95%	85.95%	90.34%	34.32%	72.66%	64.56%
DE-1493	72.40%	68.32%	7.79%	36.82%	70.59%	41.14%
DE-1494	76.02%	57.27%	94.25%	33.98%	56.06%	50.83%
DE-1495	40.83%	66.07%	77.69%	24.70%	51.61%	37.26%
DE-1496	75.16%	12.06%	89.83%	34.82%	83.24%	64.76%
DE-1497	69.52%	21.06%	97.33%	44.52%	79.93%	68.68%
DE-1498	73.84%	6.43%	92.62%	47.92%	80.34%	68.37%
DE-1500	78.29%	10.11%	90.83%	34.30%	85.46%	66.44%
DE-1502	75.12%	16.51%	89.97%	32.16%	84.32%	64.80%
DE-1503	71.14%	18.51%	68.38%	42.16%	81.97%	61.84%
DE-1504	72.63%	5.58%	95.74%	46.81%	78.59%	67.30%
DE-1505	72.69%	6.98%	94.60%	47.52%	79.87%	68.32%
DE-1507	77.13%	12.42%	96.44%	58.88%	84.50%	77.60%
DE-1510	70.84%	64.11%	73.93%	41.58%	70.33%	58.86%
DE-1512	59.05%	42.55%	57.94%	35.83%	62.85%	44.42%
DE-1513	74.79%	9.39%	91.54%	43.72%	82.04%	67.85%
DE-1514	71.62%	75.23%	84.16%	38.57%	76.45%	65.34%
DE-1517	72.82%	48.14%	95.55%	34.54%	54.10%	48.97%
DE-1518	56.03%	48.67%	94.30%	52.02%	47.99%	50.31%
DE-1520	60.56%	41.25%	82.33%	20.89%	64.27%	45.20%
DE-1523	80.66%	64.48%	93.14%	38.55%	72.78%	64.97%
DE-1524	59.51%	66.05%	98.35%	41.56%	64.83%	60.26%
DE-1526	82.57%	82.62%	95.59%	36.90%	73.08%	66.82%
DE-1527	62.36%	45.24%	93.24%	28.98%	47.05%	40.01%
DE-1528	75.89%	4.81%	92.74%	48.42%	82.12%	69.89%
DE-1530	79.52%	8.28%	96.52%	39.36%	86.09%	70.37%
DE-1533	92.45%	99.70%	94.81%	31.66%	75.62%	68.54%
DE-1534	72.31%	8.94%	88.02%	46.49%	79.88%	66.39%
DE-1535	70.37%	18.68%	98.33%	46.79%	79.72%	69.62%
DE-1536	69.23%	17.39%	93.29%	48.85%	68.92%	61.62%
DE-1537	55.24%	44.76%	80.79%	1.93%	62.15%	35.20%
DE-1538	68.83%	9.28%	96.49%	76.91%	76.75%	78.84%
DE-1539	77.65%	78.48%	76.76%	42.15%	77.82%	66.79%
DE-1540	72.31%	8.94%	93.85%	26.77%	79.88%	59.55%
DE-1542	72.31%	8.94%	95.36%	47.60%	79.88%	68.68%
DE-1543	56.60%	65.14%	88.65%	20.66%	62.15%	46.89%
DE-1544	68.83%	9.28%	98.60%	92.22%	76.75%	85.80%
DE-1547	100.00%	52.68%	74.96%	47.68%	100.00%	83.73%
DE-1550	81.01%	64.37%	81.39%	40.42%	72.15%	62.43%
DE-1552	84.51%	70.74%	84.99%	26.57%	75.20%	60.47%
DE-1553	73.31%	12.63%	27.65%	41.96%	81.87%	51.28%
DE-1555	83.80%	82.41%	94.66%	33.66%	76.52%	67.68%
DE-1557	70.15%	21.60%	94.97%	44.23%	80.82%	68.69%
DE-1558	92.84%	4.15%	95.33%	87.63%	94.79%	97.21%
DE-1562	41.53%	31.19%	78.38%	40.70%	39.55%	32.99%
DE-1563	73.73%	10.37%	97.35%	49.44%	81.63%	71.40%
DE-1565	64.02%	69.88%	95.68%	26.97%	62.34%	52.50%
DE-1568	67.78%	11.41%	35.97%	46.52%	74.79%	49.80%
DE-1569	60.73%	12.39%	31.57%	43.78%	70.30%	43.91%
DE-1570	59.76%	45.66%	96.93%	30.89%	56.88%	48.26%
DE-1572	51.05%	25.02%	37.76%	45.85%	54.35%	35.57%
DE-1574	80.56%	77.25%	39.72%	39.71%	75.62%	55.24%
DE-1575	75.91%	7.79%	36.74%	44.65%	82.57%	54.98%
DE-1576	68.99%	22.85%	37.14%	44.28%	80.62%	54.23%
DE-1577	95.75%	33.37%	38.80%	45.88%	98.21%	70.74%
DE-1578	75.89%	89.67%	37.47%	37.55%	61.62%	44.81%
DE-1579	71.14%	18.51%	11.12%	41.12%	81.97%	47.20%
DE-1582	65.06%	54.22%	23.57%	46.25%	71.67%	47.87%
DE-287	89.41%	100.00%	96.96%	33.64%	73.18%	67.97%

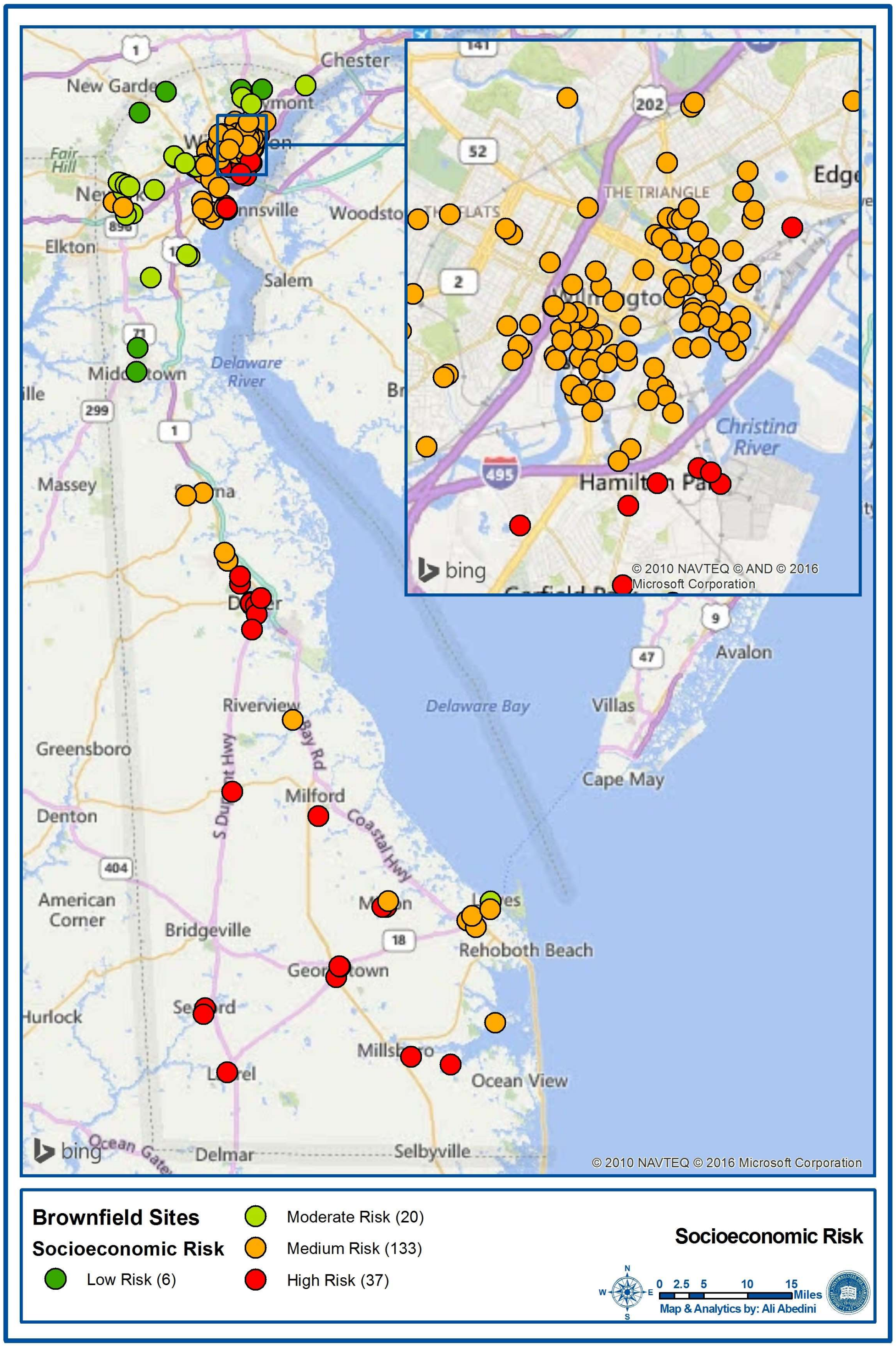

Figure 5-13-Socioeconomic Risk

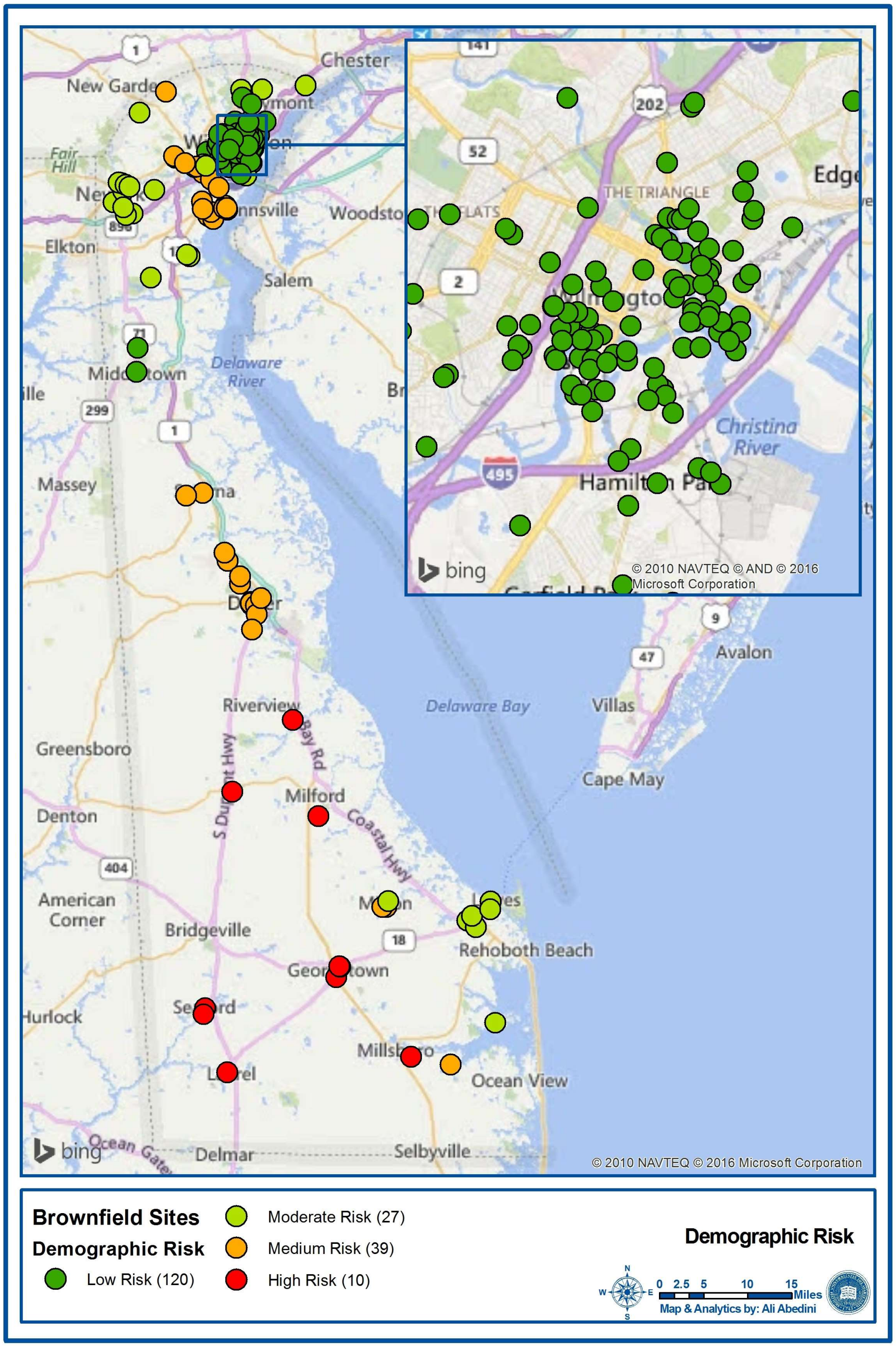

Figure 5-14- Demographic Risk

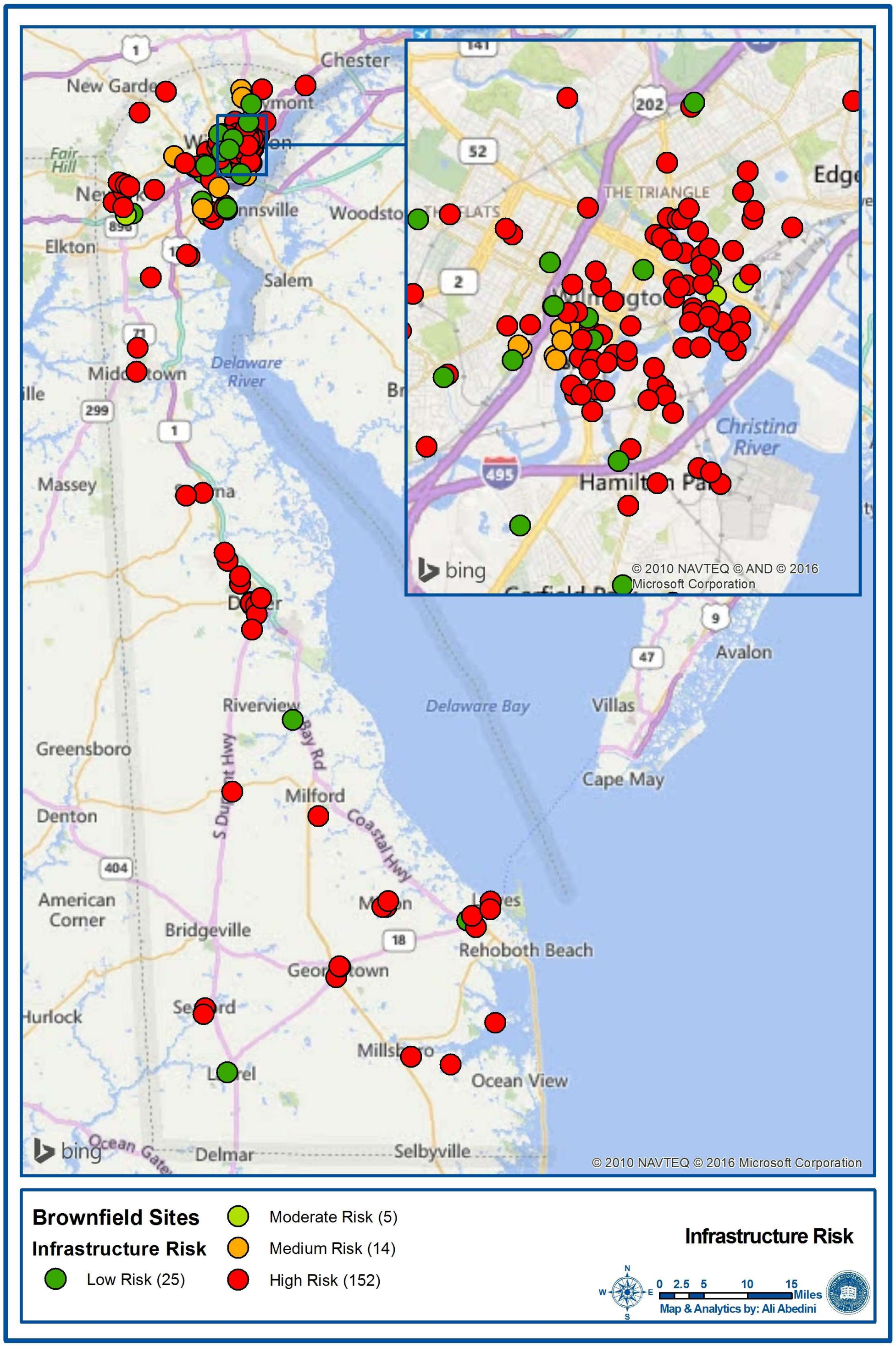

Figure 5-15-Infrastructure Risk

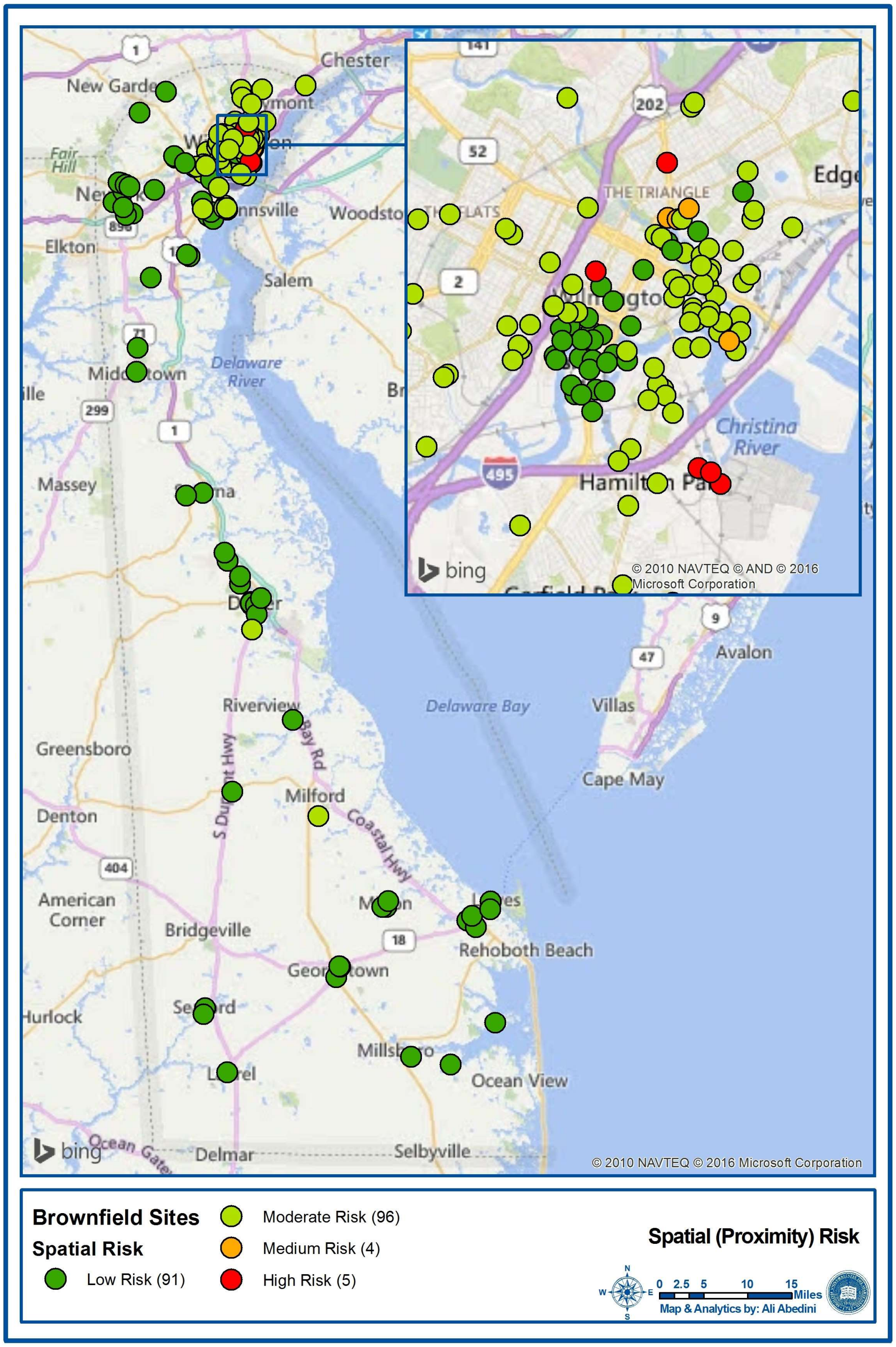

Figure 5-16- Spatial (Proximity) Risk

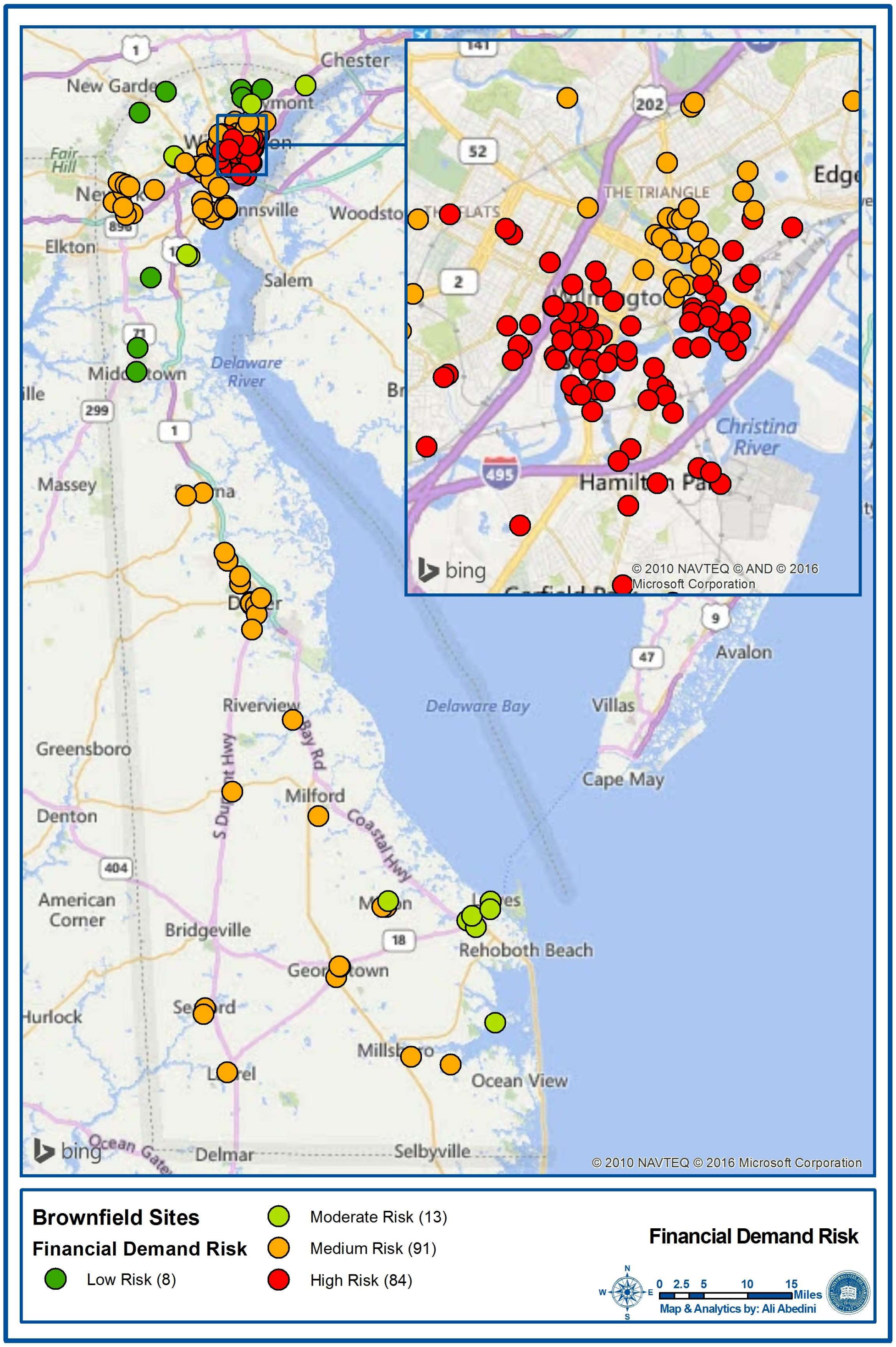

Figure 5-17- Financial Demand Risk

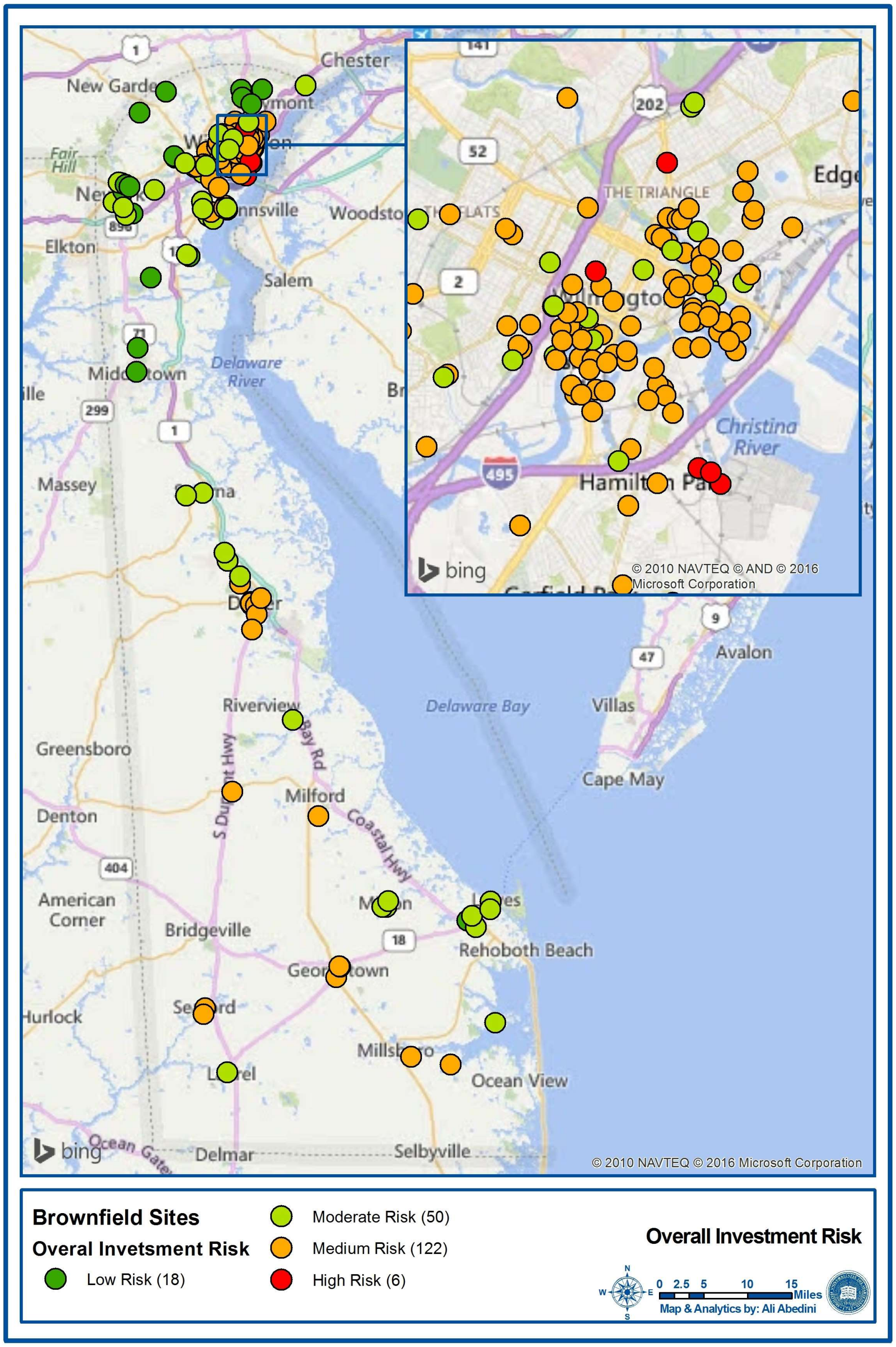

Figure 5-18- Overall Investment Risk

Chapter 6

CONCLUSION AND DISCUSSION FOR FUTURE RESEARCH

6.1 Research Contributions

As indicated in the introduction, this study is an applied research endeavor which started with a “how” kind of question, to address an ongoing problem in the public policy discipline. The research question is representative of the so-called dialectic of subjective-versus-objective methodologies:

“How can various kinds of spatial and non-spatial uncertainties in the policymaking process be recognized, classified, & structured,” and, “How can they be systematically incorporated into the process in a comprehensive way, so as to aid a balanced regional economic development?”

And, it concludes with the following answer:

“VPP (Vectorial Policy Process) provides a strong foundation for understanding and conceptualizing the notion of uncertainty and risk in the process of policymaking. Fuzzy Set Theory, AHP (Analytical Hierarchical Process), and EBK (Empirical Bayesian Kriging) help us to recognize, classify, and structure various kinds of spatial and non-spatial uncertainties embedded in the policymaking process and then incorporate them into the process in order to support balanced regional economic development.”

By applying the above answer into a real world example (the Delaware Brownfields Program), this research empirically proves the applicability of its framework foundations toward translating the research question into a real world example:

"Whether the presence of contaminated brownfield sites is the most significant deterrent to new investment in decaying communities, or, do other localized social problems, locational disadvantage, and other factors better explain the current situation."

To answer this question, the study employed the proposed framework to reduce uncertainty or, in other words, transfer "unknown-knowns" as much as possible to "known-knowns." The base for any understanding of the true impact of the Delaware Brownfields Program starts with a better assessment of the communities affected by the presence of brownfields. A rigorous assessment of policy has been conducted, especially through private sector perspectives on investment in brownfield sites, so as to understand the full range of factors influencing the redevelopment of these sites in all neighborhoods. Through this assessment, obstacles to the utilization of the brownfield policy by low-income communities can be understood. It is obvious that brownfields are just one consideration and, as such, may or may not be the primary factor in redevelopment decisions. Other factors such as neighborhood market conditions, socioeconomic conditions, infrastructure, and location also helped to explain redevelopment investment choices. Accordingly, simply focusing on the brownfield policy and blindly increasing incentives for redevelopment in these communities may have minimal impact on community revitalization.

By employing Fuzzy Set Theory, this study develops a composite fuzzy membership function which defines the transition from investment risk to investment safety. Then, each brownfield site has been assessed based on the degree of membership to each of these fuzzy sets (Investment Risk and Investment Safety). By employing this solution, policymakers are able to see how safe or risky each site is from the investors' perspective, with respect to their surrounding communities. This incorporates uncertainty into policymaking process, by viewing the brownfield development inequality problem through the lens of investors and the private sector, rather than public entities', in order to transfer more 'unknown-knowns' to 'known-knowns' in shaping brownfield policies. Through a data-driven approach, this study recognizes and classifies 62 different sources of uncertainty that may be considered as deterrents to new investments in communities affected by the presence of brownfields. By employing AHP method as a fuzzy membership function, all these uncertainty sources (risk factors) have been structured in a risk hierarchy and grouped into five main categories as follows:

1- Socioeconomic Risk
2- Demographic Risk
3- Infrastructure Risk
4- Spatial (Proximity) Risk
5- Financial Demand Risk

The proposed structure is entirely flexible and may be modified and adapted to fit the policymaker's needs in the future. It is also possible to add or remove some risk factors, depending on what types of risk characterize the policies or what drives the DNREC and EPA risk attitude, and the respective knowledge that policy analysts may have about them, without necessarily complicating the analysis.

Most importantly, this research introduces a method (EBK) for spatial (proximity) risk assessment, which has been incorporated into the proposed risk factors hierarchy in the fuzzy AHP risk assessment model. This method empirically estimates three risk factors, using geostatistics (the Kriging model):

1- Proximity Financial Institutions' Performance Trend Risk

2- Proximity Financial Institutions' Wealth Risk

3- Proximity Businesses' Annual Sale Risk

This is one of the first uses of Empirical Bayesian Kriging (EBK) in social sciences, especially public policy.

The overall approach to policymaking under uncertainty presented here is unique in public policy literature. It addresses this issue in the form of applied research, aiming to develop a new solution to the specific problem of uncertainties embedded in policymaking at the regional level. The combination of a robust framework (Vectorial Policy Process), an applied theory (Fuzzy Set Theory), a rigorous method (Analytical Hierarchical Process), and an advanced geostatistical tool (Empirical Bayesian Kriging) introduces a new approach to understanding and then incorporating uncertainties into the policymaking process. Figure 6-1 shows the components of this new approach.

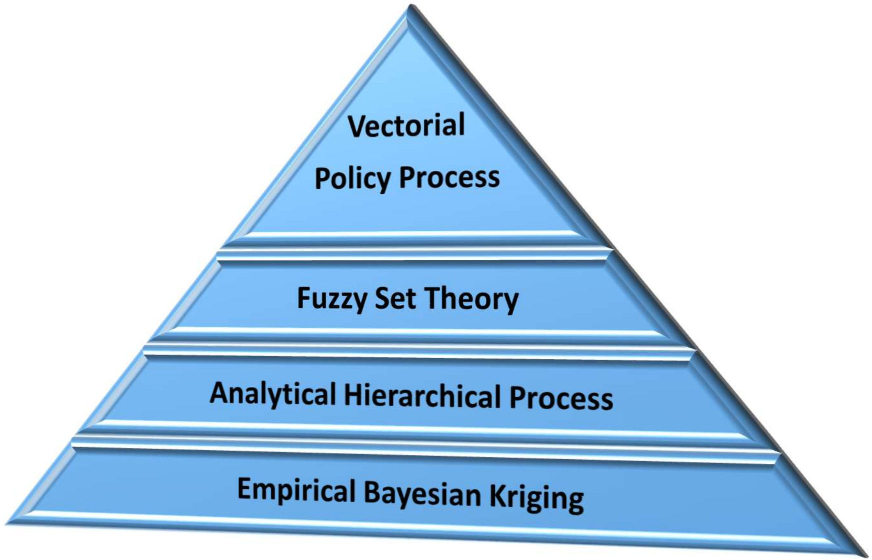

Figure 6-1- Conceptual Framework of Policymaking Under Uncertainty

There is no precedent for this kind of policy framework in public policy literature, through which to provide a concrete context for the conceptualization of uncertainties embedded in the policymaking process. Also, by conducting case study research on the Delaware Brownfields Development Program, this study builds a spatial policy support process to reduce uncertainty by collecting more information and transferring more "unknown-knowns" to "known-knowns" in the policymaking process. The research outcome is an effective policy support solution for aiding policymaking under uncertainty, which can be employed by policymakers on the regional (state) scale.

On the other hand, data-driven policies have a direct impact on people and the places they live. Across public or private sectors, policy analysts need to be able to understand places, people, and their inter-relationships. Analysts and policymakers also need to effectively communicate policy decisions and the information used to make policy. Public agencies and other organizations are now allocating resources and making long-term policies about the collection, management, and use of spatial data. Although these actions are influenced by current policies, priorities, and opportunities, their ultimate success depends on future developments and trends. For that purpose, this research employs Empirical Bayesian Kriging (EBK) to enrich the investment risk assessment by an in-depth spatial analysis of the proximity activities of each brownfield site and measure the level of investment risk by evaluating those nearby activities.

When it comes to the scientific contribution of this research to academic literature, this study offers a significant micro-contribution into the field of public policy in general, and decision science in particular. However, when it comes to micro-contribution in scientific research, there has always been a threat of neglecting the macro understanding of a phenomenon. For example, by over considering micro level risk factors and uncertainties, this study could put itself at a kind of risk to lose the macro vision of the problem. It avoids falling into that risk, however, by spotting the micro-contribution in the overall process of policymaking and connecting micro and macro level of the study of uncertainty, by specifically presenting Vectorial Policy Process. That is to say, VPP allows us to conceptualize or imagine all uncertainties (unknown-unknowns, known-unknowns, unknown-knowns) involved in the process, while the fuzzy AHP risk assessment model can only incorporate a subset of those uncertainties (unknown-knowns) in the process. The impact vectors represent the impact of various components and factors which have an impact on policy outcomes including, but not limited to, knowledge, innovation, local government, NGOs, private sectors, political parties, specific events (natural disasters or anthropogenic events), market conditions, legal framework, resources, stakeholders, problem, solution, timing, social, political and economic context, budgeting, public support, state uncertainty (data uncertainty), epistemic uncertainty, etc. The fuzzy AHP risk assessment model can only incorporate a subset of state uncertainty in the process.

Analytic Hierarchy Process (AHP) and Empirical Bayesian Kriging (EBK) introduced in this study can be used to break down complex problems into their parts, allowing systematic contemplation of the situation. This stage is the most critical part of setting up a good working model that will accomplish its purpose. By application of the proposed hierarchy (or any other proper modification of it), the AHP has proved to be a powerful tool for risk assessment. It can be seen as an iterative process. Model reruns, with adjusted perceptions in the judgment of alternatives, can become sensitivity analyses, while also reducing inconsistency. This becomes imperative if any of the conditions impacting an investment alternative are changed, or if a new alternative (brownfield) is considered. A reversal in the ranks of investment alternatives can be expected if new options (brownfields) are added to the decision set. However, this should be acceptable if done using the same decision process.

For new decision sets, independent assessment of the alternatives and their criteria should be performed in a new run of the model. The AHP has proved to be useful in many different types of industries and applications. The flexibility of the method allows it to be applied in the smaller and ordinary decision-making processes of economic development programs by properly building applicable hierarchies including decision criteria not necessarily related to risk. In cases where the consistency of the input data is good enough (i.e., having a consistency ratio close to zero), the results of an AHP analysis can be used to determine the split of available resources destined for non-mutually exclusive alternatives, providing not only the ranking of preferences, but also the percentage of resources to put into any given investment option.

To sum up briefly, the contribution of this applied study can be listed as follows:

1- Development of a new policy framework called "Vectorial Policy Process" to first understand and then incorporate uncertainties into the policymaking process.
2- Development of a method for quantifying the spatial and non-spatial uncertainty associated with brownfield development programs.
3- Improvement of fuzzy regional policymaking through the development of hybrid approaches: fuzzy-rule-based models (AHP) combined with Bayesian data-driven technique (EBK).
4- Explicit conveyance of the spatial and proximity uncertainties in regional policymaking, through the use of Geostatistical and Bayesian approaches.

6.2 Real World Application

The policy framework and model presented in this research can be employed by the Environmental Protection Agency (EPA) at national and regional levels for understanding and measuring risks in all brownfield sites across the country. The model can measure risk in five categories: (1) Demographic, (2) Socioeconomic, (3) Infrastructure, (4) Spatial (proximity), and (5) Financial demand. This can help policymakers and analysts to adjust their programs and revisit the incentives accordingly. In some cases, where there is a high level of risk investment for private sectors, this model can help policymakers to measure that risk and dedicate a public fund for redevelopment of those brownfield sites.

In the Delaware Brownfields Program, public and nonprofit entities may apply for funding of up to $1 million per redevelopment project and/or applicant in any fiscal year. Private applicants may be reimbursed up to $225,000 for any individual brownfield project, and up to $1 million per applicant in any fiscal year. In most years, the amount of funding available has exceeded applicant demand, but in the event that funds get depleted, additional applicants are rolled over into the next fiscal funding cycle. As a consequence, no formal ranking system has been adopted by the Delaware Department of Natural Resources & Environmental Control (DNREC) when it comes to brownfield properties. This model can help them to rank all those properties based on investment risk, then adjust and modify incentives and funds accordingly.

On the other hand, this risk assessment model can help DNREC to understand whether the presence of contaminated sites is a significant deterrent to new investment in decaying communities or if other localized social problems, locational disadvantage, and other factors better explain the current situation.

6.3 Research Critiques

Nevertheless, this research is not flawless. Like many other methods and techniques, AHP and EBK have their supporters and detractors. The idea of this study is to present AHP and EBK as tools, and to denote their advantages. In this study, AHP and EBK are presented as ways to address decision-making processes and, in the particular case of this work, to quantify risk.

A primary difficulty in applying AHP to multifactor risk analyses is the potentially large number of paired comparisons asked of decision-makers. However, paired comparisons have been demonstrated to be relatively easy to use in real applications. Further, focusing upon significant risk factors would reduce the number of paired comparisons needed, thereby enabling decision-maker attention to focus upon risk factors that are more important. Of probably more importance is the need to eliminate the impact of scale. It is hard to give a relative importance to risk measured in millions of dollars, with reduction of liability measured in cleanup expenses. This scalar complication can be reduced however, by focusing on the concept of profit-versus-(the idea of) risk, and eliminating differences in scale by other means, such as the use of the range in objective values obtained from spatial and non-spatial data available. AHP provides a valuable means of supporting multiple factor risk quantification, which has proven very powerful in comparing discrete alternatives and risk factors.

Care should be taken when building the hierarchical model though, since the formulation of hierarchies and selection of criteria (risk factors) involve some degree of subjectivity. It is possible for policymakers to derive different hierarchies for similar decision problems and, consequently, arrive at different solutions. Moreover, we should note that it would be a mistake to consider this hierarchy as the right model for all contexts and empirical situations. Decision-makers interested in using this tool must first determine the characteristics and dynamics of risk and uncertainty in a certain locale or region and, only after that, should they adapt or build an appropriate hierarchy. The AHP method can be the beginning point in the formulation of public policies, ensuring transparency and including all stakeholders' viewpoints and interests in the decision-making process, since they are the ones who will benefit from the implementation and consequences of the decisions made.

In this study, EBK is used to describe and predict the spatial variability of risk factors. A procedure is presented for quantification of proximity risk when data become available from the area of interest. The interpolation is carried out by Bayesian Kriging, where prior distributions of the variogram parameters are utilized. This process is different and unique from other, similar methods, since the commonly applied 'least squares estimation' for the variogram is avoided. The study is shown with data from banks and businesses in Delaware, where this type of extrapolation was compared to ordinary Kriging. When sufficient data and information are available, ordinary Kriging gave the most precise predictions. When the number of data were small however, predictions obtained with Bayesian Kriging were more accurate. This leads to a considerable reduction of costs, without loss of information. The main assumption of EBK here is that the performance of nearby businesses and banks is an indicator of the likelihood for success and profitability of the brownfield sites in the future. This assumption can be considered among the model's drawbacks though, since no study or research has been done in this regard yet, to show if there is any correlation between these two factors. Common sense and real estate market rationality however do support such an assumption.

6.4 Future Research Directions

Throughout the development of this study, AHP and EBK show themselves to be useful methods for quantifying the investment risk. Nevertheless, proper investment decisions cannot be based solely on the level of risk of the alternatives (brownfield). As discussed previously, depending on the risk attitude of brownfield investors, a high level of it could possibly be tolerated, depending on the relative benefits, costs, and opportunities that any given investment can present; especially those incentives that the Delaware Brownfields Program may offer.

Further steps to be taken in the development of this method would require this model to be transformed into an integral evaluation method, from which the assessment of risk is only one cornerstone of the larger, complete analysis of any brownfield programs. By incorporating, in a single analysis tool, the evaluation of benefits, costs, opportunities, and risk, the decision-maker can arrive at a much better-informed and integral alternative ranking of its brownfield policy directions.

The computational problem is: how can such a large amount of risk factors be integrated into one tool? Moreover, what happens if, by using AHP, the preferences or levels of one of the risk factors also impacts its costs criteria? In other words, it must be understood that dependencies do arise among the used risk factors, which further complicate the AHP process.

Suppose, as an example, we have a brownfield investment alternative that has a certain risk of high environmental pollution, and so cleanup expenses would be correspondingly high as well. We already know, from this study, that this issue would generate some risk, by representing additional costs for investors. The presence of environmental pollution also poses a financial issue for them, since future residential or commercial units in this brownfield site will typically have to sell at below-market value, due to the area's bad reputation. Thus, lower cash flows can be expected from the same issue.

Spatial policymaking, like that of the Delaware Brownfields Program, is extremely complex due to the intricacy of the systems and factors considered, and the competing interests of many stakeholders. More research is needed to acquire further understanding of knowledge, decision, variability, and linguistic uncertainty in spatial policymaking, and how these areas of uncertainty impact the quality of decisions rendered. Developing acceptable and efficacious policymaking approaches requires the enhancement of uncertainty analysis techniques, concepts, and assumptions in related research, with subsequent implementation, monitoring and auditing, and possible adjustment of selected management practices.

Many sophisticated approaches to decision-making contain a modeling, or some other type of formal decision-support, component. This study focused on the use of decision support tools, such as integrated models, geostatistical algorithms, and multi-criteria decision analyses, which are being used increasingly for comparative analysis and uncertainty assessment of policy alternatives. In this context, modeling for spatial decision support has to provide decision-makers and policy analysts with an understanding of the predictive uncertainty in the context of decisions being made. For a decision-maker, the possible outcomes resulting from a course of action are of major interest, where an outcome is defined with regard to the variables of interest to the decision-maker. Predicting outcomes demands the integration of all sources of uncertainty: in structure, model parameter, system variability, decision-making criteria, and linguistic interpretation. These sources can include economic and social endpoints and other variables outside the expertise of policymakers and decision scientists, which inevitably contribute to some of the challenges concerning the translation of scientific information into policy and action plans. These variables may be crucial for aiding decision-makers to select among various alternatives and options.

In conclusion, uncertainty has to be addressed in any efficient policymaking practice. Failure to do so invites potential unreliability within the results, which can result in a consequential loss of public trust and confidence. There also exists a need to consider financial, social, and economic systems in an integrated way, particularly for dealing with community or region-based problems or issues. There are important areas that need to be considered in relation to the incorporation of uncertainty in policymaking, including:

1- Incorporation of adaptive management practices, with correcting model divergence;
2- Development of approaches and strategies for increasing the computational efficiency of integrated models, optimization methods and methods for estimating risk-based performance measures; and
3- Advancement of integrated and comprehensive frameworks for addressing uncertainty as part of the public policymaking process.

It should be obvious that the above list is not inclusive, and leaves room for other methods or frameworks. The quality of the uncertainty assessment, the scientific methods, and tools used in that assessment should be decided pragmatically; part of the dynamics of the decision-making process. Moreover, the unfounded certainty about a perceived problem, developed by normative assumptions and societal beliefs, may far outweigh technical or scientific uncertainty in the decision-making process. The sharing of decision-making power, among representatives of technical, social, political, economic, and legal interests, creates tensions which help make regional development a very wicked problem (Rauscher, 1999).

It is essential, therefore, to stress the importance of developing innovative methods for uncertainty assessment by noting that human attitudes and beliefs provide a large area beyond scientific and technical uncertainty, in any solution to public and environmental problems. At the same time, the effects of the dominant market discourse on the conceptualization of uncertainty in public policies are mostly neglected. To address this issue, the more active, inclusive participation of all stakeholders (private and public) should be encouraged. Ultimately, this helps to address and then to incorporate more unknown-knowns into the policymaking process. Last but not least, the more flexible the policymaking process, the less uncertainty involved in the process.

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