Spatial-based assessment at continental to global scale

case studies in petroleum exploration and ecosystem services

Ruimtelijke analyse op continentaal en globaal niveau:
Case studies in petroleum exploratie en ecosysteem diensten

(met een samenvatting in het Nederlands)

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“We’re all fools,” said Clemens, “all the time. It’s just we’re a different kind each day. We think, I’m not a fool today. I’ve learned my lesson. I was a fool yesterday but not this morning. Then tomorrow we find out that, yes, we were a fool today too. I think the only way we can grow and get on in this world is to accept the fact we’re not perfect and live accordingly.”

The Illustrated Man by Ray Bradbury

“If you are not too long, I will wait here for you all my life.”

- Gwendolyn

The Importance of Being Earnest: A Trivial Comedy for Serious People by Oscar Wilde

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List of Acronyms

2D	two-dimensional
3D	three-dimensional
AON	AON Group, Inc.: UK-based professional services solutions firm (risk, health, retirement)
C	carbon
CBTH	Caribbean Basins, Tectonics, and Hydrocarbons consortium
DM2	Deep-Marine Depositional Margins consortium
ES	ecosystem service
EU	European Union
FAO	Food and Agricultural Organization of the United Nations
FLO	fuzzy logic operator
FMV	fuzzy membership value
GAEZ	Global Agro-Ecological Zones
GIS	geographic information system
GCM	general circulation model
InVEST	integrated valuation of ecosystem services and tradeoffs
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
KGCC	Köppen-Geiger climate class
LADA	Land Degradation Assessment
LUS	land use system
MEA	Millennium Ecosystem Assessment
MCE	multi criteria evaluation
ms	millisecond
NOAA	National Oceanic and Atmospheric Administration
NTFP	non-timber forest product
NUS	NUS Consulting Group: UK-based energy management firm
PM2.5	particulate matter with 2.5-micron-diameter
PM10	particulate matter with 10-micron-diameter
RCP	representative concentration pathway

SADC	SADC Trade Organization: South African Development Community Trade Organization, a partnership between the Australian Agency for International Development and Trade and Industrial Policy Strategies
SDSS	spatial decision support systems
TOC	total organic carbon
TWT	two-way-time
UK	United Kingdom
UN	United Nations
UNECE	United Nations Economic Commission for Europe
UNEP	United Nations Environment Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
USA	United States of America
UVB	ultraviolet B
VLIZ	Vlaams Instituut voor de Zee (Flanders Marine Institute)
WATCH	Integrated Project Water and Global Change project
WCMC	World Conservation Monitoring Centre
WGS	World Geodetic System
WHS	World Heritage Site

Thanks to my family and friends for their support throughout this adventure. You helped keep my focus and motivation when it waivered and reminded me what I was working towards.

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Chapter 1

Introduction

1.1. Challenge of continental scale spatial assessment

Current and future generations face problems related to access of natural resources, including food, water, and energy. Growing populations demand more attention to sustainable development for which the UN has created a task force in 2005 to develop indicators in order to compare statistics between countries and measure progress towards defined goals (UNECE, 2009). Goals included eradicating extreme poverty and hunger, ensuring environmental sustainability, and developing a global partnership to develop governments and economies, among others. In 2015, the task force shifted focus to sustainable development goals (UN, 2015). Because of growing populations and technological advancements, global economies have become more intermingled. This globalization has increased the importance of global assessments of available resources, change, and impacts, especially related to the environment. In order to assess changes and impacts, global, spatio-temporal data are required (Salafsky and Wollenberg, 2000). These data may originate from different sources, be from many different data types, must be combined in assessment models, have varying qualities of information that may or may not be quantified in terms of uncertainty, and have varying levels of accuracy.

Continental to global scale assessments require the combination of a large number of spatial data sets with wide spatial coverage, which can pose challenges to map results efficiently and accurately. Global scale spatial studies are found in many different disciplines from geology to socio-economics. Geological studies may focus on Earth processes or petroleum exploration, for example. Williams et al. (2012) used global data over geologic time for plate reconstructions of super continents. Plate reconstruction studies assist geologists in understanding the Earth and Earth processes. Palliggiano et al.

(2012) assessed the impacts of petroleum exploration on planned and ongoing activities onshore and offshore areas especially in sensitive ecological areas; the study was focused on a local area, but conceptually it can be applied to larger regions. On the other hand, socio-economic studies may focus on public health benefits and consequences of climate change. Viscarra Rossel et al. (2016) developed a world soil database (spectral library) to aid in the study of global health because health benefits from food, carbon storage, and greenhouse gas regulation and habitation depends on healthy soil. Grêt-Regamey et al. (2013) used a spatial-based ecosystem services assessment for forested areas of the Swiss Alps to show uncertainty in the way people will react to changes in the ecosystem due to climate and socio-economic changes, as well as other uncertainties related to general ecosystem modeling. Kelly and Adger (2000) assessed changes in vulnerable areas of Vietnam from climate change, particularly El Niño effects and tropical storms. Central to each of these studies is the need for spatial assessments to extract benefits from heterogeneous source data.

Geographic information science, which includes theory and concepts for geographic information, provides methods to combine data: from different sources, in different formats, and from local to global scale studies such as the aforementioned studies. Geographic information systems are the software and technology that supports application of geographic information theory. This thesis uses GIS to refer to both geographic information science and geographic information systems as in many cases it is interchangeable. GIS has the capability of achieving this because the methods are scalable, systematic, and repeatable; can provide source-ability; and can document uncertainty (Burrough and McDonnell, 1998). Furthermore, data can be organized from various sources, whether they are paper or digital, into different formats as either vector or raster (Bonham-Carter, 2000). A geographic information system, the software and hardware technology supporting geographic information science, provides a systematic methodology for rasterization of data, among other capabilities. GIS also facilitates decision support, which is a key aspect utilized by geoscientists in order to predict from spatial data (Chung and Fabbri, 1993).

Continental to global scale assessments provide model results that should include information to the decision-maker regarding reliability or uncertainty (McMaster, 1991; Brodaric, 1992). This communicated reliability of results is particularly important for Earth science cases (Chung and Fabbri, 1993). GIS can provide solutions for assessment techniques by implementing different methods tailored for specific case studies. For example, error propagation is an appropriate method to calculate defined uncertainty in data and models (Burrough and McDonnell, 1998; Heuvelink et al., 1989). Although it is established that uncertainty must be communicated in relation to the data, model, and results, there are still challenges in properly communicating uncertainty and ensuring the "naïve" user does not use the analysis results incorrectly (Goodchild, 2009).

The GIS challenges of combining continental to global scale data sets and incorporating uncertainty are addressed in this thesis in two case studies. The first case study looks at ecosystem service valuations and climate class transitions, and the second case study proposes a multi-criteria evaluation for petroleum exploration and assessing uncertainty using error propagation. Both case studies address uncertainty in various ways, and uncertainty is discussed as an overarching theme in Section 1.4 of this chapter and in Chapter 6.

1.2. Climate impacts on ecosystem service values

Understanding the impacts of climate change is of imminent importance because of documented global warming (e.g. IPCC, 2013). While it is intuitive that species and environments will be affected by changes in climate, those impacts need to be studied, documented, and quantified in order to start a public debate about declining resources and create reasonable mitigation and adaptation plans. Impacts of climate change have been studied from many different angles, whether looking at specific species (e.g. scleractinian corals by Okazaki et al., 2017) or specific geographic areas (e.g. Vietnam by Kelly and Adger, 2000). Other studies use ecosystem services (ESs), a construct to quantify the value of the environment from which humans derive benefits either directly or indirectly, in order to assess the impacts of climate change (Grimm et al., 2016).

A growing field of research is combining climate change models with ES assessments (e.g. Raymond and Brown, 2011; Landis et al., 2013). Hoegh-Guldberg and Bruno (2010) assessed climate change effects on oceanic ecosystems in a global study. The main effects such as loss of habitat are documented, and they suggested that policies need to be implemented to reduce risk of further damage. Lindner et al. (2010) studied climate change effects on forests in Europe and concluded that any benefits related to climate change in some areas are negated by consequences in others due to droughts. The ability of forests to adapt to climate change varies depending on the forest type and the economic impacts need to be further studied. Raymond and Brown (2011) showed spatial patterns and valuations when surveying people for their perceptions of the spatial valuation of land and climate change risks. They proposed that governments might use the approach to assist in creating "place-based adaptation strategies". Grêt-Regamey et al. (2013) used Bayesian Networks to model uncertainty in ES assessments, noting specifically that there is uncertainty in the way people will react to changes in ecosystems. Landis et al. (2013) proposed seven principles to improve ecological risk assessment frameworks to assist in improving decision-making related to global climate change. They used ES assessments as a metric in helping with trade-offs in decision-making by specifically investigating predicted responses of ESs to climate change. Nelson et al. (2013) assessed climate change effects on ESs that people rely on in the USA. Their findings predicted potential changes of specific services and suggested mitigation approaches. Grimm et al. (2016) summarized a report through USA national climate assessments and presented policy approaches for climate change and ESs. They documented changes in ESs and people's responses to those changes. The consensus of research, regardless of the approach and specific scope, is that a changing climate is most likely to decrease (and cause global shifts in) biodiversity, which in turn, decreases ES values in general. Previous work that combined climate change with ecosystem service assessments (i.e. ecosystem service valuations) is limited and except for one case reviewed (Hoegh-Guldberg and Bruno, 2010) are not global studies. By understanding the effects of climate change on ESs and by producing quantitative assessments, governments can discuss and formulate policies to reduce the impacts of climate change by either mitigation or adaptation (Grimm et al., 2016).

A spatially distributed global ESs assessment used in a climate change index transition map has not been studied before. Therefore, these two tasks are addressed in the following sections to assess the spatially distributed global ESs value (Section 1.2.1) and to evaluate the ES value changes in climate classes over time (Section 1.2.2).

1.2.1. Mapping global ecosystem services

Schägner et al. (2013) conducted a review of ES valuation assessments published through 2011. Only five publications covered the global scale. Fifty-seven studies assessed more than one ES; of those, 14 assessed 17 ESs, the maximum number of services mapped. The majority of the 69 studies (52%) used proxies to value services, which have low precision and unknown quality. Furthermore, global studies do not clearly define the methodology for calculating the global ESs values and the included services are not consistent (e.g. Costanza et al., 1997; Millennium Ecosystem Assessment, 2003; Naidoo et al., 2008; van der Ploeg et al., 2010; Li and Fang, 2014). Therefore, to create a more accurate ESs assessment, the following are necessary: clear definitions of the ESs required for a holistic assessment, a clear methodology for valuing the ESs, and the use of hard data and not proxies. Hence the central question is: *what is a suitable methodology for valuing and mapping global ESs so that the spatial pattern and values of the ES assessment are transparent and consistent?* Chapter 3 proposes such a methodology based on a comparison of existing ES assessments for consistency of included services that calculates ESs values in a spatially distributed manner for the globe.

1.2.2. Assessing climate change impacts on ecosystem services

Climate change and its effects on global ecosystems, both natural and anthropogenic, are of high interest to researchers and governments alike. Understanding how climate change influences ecosystems can be challenging because of the need to understand local, regional, and global changes. Previous studies that combine aspects from climate change and one or more ESs focused on mitigation and adaptation or localized areas (e.g. Kelly and Adger, 2000; Landis et al., 2013; Grimm et al., 2016). They did not provide a connection to Köppen-Geiger climate class (KGCC) transitions. KGCC has a clear connection between the climate change index, which integrates seasonal precipitation and temperature patterns (Baettig et al., 2007; Giorgi, 2006), and the ES by land use or ecosystem type (Köppen and Geiger, 1954). Therefore, quantifying the spatially explicit global values of ESs that experience a KGCC transition due to climate change has not been performed. Due to this lack of analysis, this thesis asks: *how much of ES values are impacted by a transition in KGCC and how can the effected value be mapped taking into account the uncertainty regarding climate change models?*

Chapter 2 provides an answer to this question by modeling the KGCC transitions and determining the value of ESs within those KGCC transitions. This analysis can be used in order to understand the potential impact of climate change.

1.3. Decision support in oil exploration

GIS is useful and important for performing spatial analysis and for elucidating the various relationships between geologic, geophysical, and topographic data, which can be applicable for petroleum industry needs in exploration. Thus, GIS would support geoscientists who typically use many different concepts, tools, and software packages by helping them to make decisions for exploration in an organized, repeatable, and data managed way, as geoscientists often work with heterogeneous (e.g. different coordinate systems, vector and raster systems, interpretation and hard data) geologic data (Aminzadeh, 1994; Coburn and Yarus, 2000).

Since the early 1980's, geographic information science and GIS software and technology have been increasingly incorporated into the petroleum industry (Coburn and Yarus, 2000). Based on the Web of Science, published papers since 1987 that include the words "GIS" or "geographic information" and "petroleum exploration" or "oil reserves" have increased over the last two decades; although, the total number of 239 publications is still low. The low numbers may indicate either limited publications, especially by industry related to the topic, or too restrictive search terms. However, the increasing number of publications is indicative of a growing field of interest in this industry and for publication.

Geologists use multi-criteria evaluation (MCE), also referred to as multi-criteria analysis or multi-criteria decision analysis, in their assessments for petroleum exploration (Aminzadeh, 1994). MCE is a subset of multidimensional decision and evaluation models. MCEs evaluate the trade-offs between alternatives (Carter, 1991; Heywood et al., 2006). There are different methods of carrying out an MCE, which use different criterion evaluation and score assignments, but all of them are subjective and yield different results (e.g., Heywood et al., 1995). MCE is not strictly a spatial analytical model (e.g., Saaty, 1987; Andriantiatsaholiniaina et al., 2004); however, this study is only interested in MCE for spatial analysis, particularly with application to economic geology settings, such as mineral or petroleum exploration. While spatial-based MCE has been applied in mineral exploration (e.g. Bonham-Carter et al., 1988; An et al., 1994; Tangestani and Moore, 2002), there is a lack of spatial-based MCE for petroleum exploration. Aminzadeh (1994) applied fuzzy logic and evidential reasoning in a 2D vertical spatial environment for seismic interpretation. Tounsi (2005) applied fuzzy logic for petroleum exploration, but it is unclear if it was in a spatial environment.

Data used in petroleum exploration is heterogeneous and from various sources with various levels of data quality (Aminzadeh, 1994). Therefore, the data used has a certain level of uncertainty. This uncertainty must be defined, quantified where possible, and evaluated when using mapping results for exploration decisions. By applying an MCE and an uncertainty analysis, a workflow for petroleum exploration can be proposed that creates consistency in decision-making when using heterogeneous geologic data with varying uncertainty.

Section 1.3.1 introduces the topic of MCEs and their applications in petroleum exploration, and Section 1.3.2 assesses approaches for evaluating uncertainty.

1.3.1. Multi-criteria evaluation for petroleum exploration

When MCEs are applied in economic geology settings (e.g. Bonham-Carter et al., 1988; Aminzadeh, 1994; An et al., 1994; Wright and Bonham-Carter, 1996; Carranza, 2002; Tangestani and Moore, 2002; Tounsi, 2005), two main types of methods are employed: Bayesian and fuzzy logic. These two methods are knowledge-driven models which means that they rely on input from an expert or hard data (Bonham-Carter, 1994), making them the most appropriate MCE for petroleum exploration.

The Bayesian method relies on a probability framework in which the modeler is required to calculate prior and posterior probabilities for each set of evidence used (Bonham-Carter, 1994), thus it can be applied to areas where sufficient amounts of well-distributed data are available. Therefore, this method is not appropriate for frontier areas (Bonham-Carter, 1994), where data is either not available or sparse.

Fuzzy logic as described by Bonham-Carter (1994) uses five operators, as will be discussed in Chapter 4, to combine a series of data sets for a final output map to indicate the favorability of the location for a specific purpose. Fuzzy logic does not require a probability framework and uses expert knowledge on the favorability of criteria combined in the evaluation. It, therefore, more readily mimics the thought processes of a geologist or other expert in a discipline (e.g. water well drilling, hazardous waste sites) allowing the expert to "fill in" unknown areas based on other indicators, knowledge, or previous experience.

There is a lack of established methodology that applies spatial-based MCE for petroleum exploration. Therefore, this thesis asks: *what is a methodology of spatial MCE that supports petroleum exploration and how can the resulting maps be used to support petroleum exploration?*

Chapter 4 proposes a methodology that assesses data used by geologists and integrates the data into an MCE methodology that mimics the workflow and thought process of a geologist. A case study at sub-continental scale of northern South America evaluated the methodology. Here, onshore areas are thoroughly explored and offshore areas are considered frontier because of a lack of proven reserves.

1.3.2. Error propagation of a multi-criteria evaluation

Spatial MCE is useful for modeling favorable locations on a set of criteria. However, it is extremely important that the modeler and the decision-maker understand the implications of subjectivity within the method (Heywood et al., 1995) and the uncertainty related to the MCE input, parameters, structure, and results (Thapa and Bossler, 1992; Heywood et al., 1995; Karssenberg and De Jong, 2005; Li et al., 2012). Because of the inherent subjectivity of MCE and the uncertainty both from the data and the parameters used in the MCE, the uncertainty requires quantification.

There are several methods for investigating uncertainty in models. Two main methods are testing the model against the real world and error propagation (Huisman and de By, 2009). Error propagation is an analysis used to investigate uncertainty and is a suitable method for calculating the uncertainty of the final output (Thapa and Bossler, 1992). The uncertainty from the beginning of the analysis (i.e. uncertainty from input, parameters, and structure), therefore, influences all subsequent calculations in the model.

There are a limited number of published examples of spatial MCE and error propagation combined. Moon (1998) combined spatial MCE, fuzzy logic, and error propagation in a theoretical presentation. Davis and Keller (1997) applied fuzzy logic with Monte Carlo simulation to investigate uncertainty related to slope stability. Carranza (2002) investigated several different MCE, including Dempster-Schafer belief function, for several case studies. Fernández and Lutz (2010) used a combination of defined and assumed uncertainties in error propagation. Feizizadeh and Blaschke (2014) compared different MCE methods. There is a lack of knowledge with regard to the specific application of error propagation to fuzzy logic MCE using Monte Carlo simulation.

Chapter 5 asks: *how can the proposed spatial MCE methodology for petroleum exploration be assessed for uncertainty and what is the uncertainty*? The uncertainty was assessed by evaluating different scenarios of data uncertainty (constant vs expert), weighting of evidence (fuzzy logic membership), observational data, and model uncertainty (fuzzy logic operators), and combinations thereof.

1.4. Uncertainty assessment

Maps help to frame and identify problems, assist in decision-making related to policy implementation and costs, and are used as a communication tool. They are indispensable for planning activities (Hauck et al., 2013). The user of a map or a spatial database should know and understand the uncertainty within the data and results (Fisher, 1999). At a minimum, uncertainty needs to be defined verbally to fully utilize model results (McMaster, 1991; Brodaric, 1992). According to Hauck et al. (2013), maps need to have uncertainty defined because of the issues related to mapping such as lack of data, resolution of data, scale of maps, mapping non-spatial data, mapped scale versus decision-making scale, and ensuring scientific credibility of data.

Fisher (1999) divided the concept of uncertainty into three main categories: probability, vagueness, and ambiguity. Defining uncertainty with probabilistic errors is well established via mathematics and statistics (Heuvelink et al., 1989; Fisher, 1999). Defining uncertainty related to vagueness can be achieved by using fuzzy set theory (Aminzadeh, 1965; Fisher, 1999). Ambiguity is further divided into discord and non-specificity, but is not thoroughly researched (Fisher, 1999). Fisher (1999) discussed several examples from research that define uncertainty in terms of probabilistic error or vagueness and concluded that uncertainty needs to be incorporated more fully in spatial results; however, popular GIS programs do not include uncertainty as part of metadata or attribute definitions (Burrough and McDonnell, 1998). It is up to the cartographer or other database curator to define and include this information (Hunter, 1999). After uncertainty is defined, the user of the data has two choices: to reduce uncertainty (uncertainty reduction) or to accept the uncertainty (uncertainty absorption) (Hunter, 1999).

When assessing uncertainty for continental to global scale studies, particular attention must be made to the data and the model due to the scale of the study and the number of data sets required for studies over large areas (Burrough and McDonnell, 1998). Common types of errors in databases are measurement, class assignment, class generalization, spatial generalization, data entry, object temporal consistency, and data processing (Heuvelink, 1998; Fisher, 1999). The resolution and scale of data is important for defining uncertainty (Heywood et al., 2006). Rasterization generalizes data sets, and within the grid cells, there may be more variation than what is shown (i.e. topological errors in Heywood et al., 2006). Additionally, there may be assumptions in data coverage that lead to additional generalizations over areas (i.e. class generalization in Fisher, 1999). Because of the lack of built-in uncertainty definitions or attributes in GIS programs, the quality of data may be erroneously assumed either more or less accurately than actually exists.

Because errors propagate through models, errors must be defined at every step of the analysis, beginning in the data collection, including the software or other technological uncertainties, and ending with decisions made in the model parameters (Heuvelink et al., 1989; Fisher, 1999). Each of these main uncertainty aspects may be defined and evaluated separately; however, they will each have some amount of influence on the results for decision-making (Heuvelink, 1998). Thus, the different aspects of the uncertainty may be modeled separately and then combined in order to elucidate which have the most influence on the uncertainty in the results.

Thus, it is imperative that the uncertainty in a modeling process are calculated and communicated. The overarching theme of this thesis is *how can uncertain information be defined and modelled for global scale studies?* Chapter 6 provides an answer and future pathways of research related to this theme.

The two case studies are related to each other and to the theory as illustrated in Table 1.1. A break-down of assessment, methodology, data, and uncertainty themes with technical information summarizes the thesis and shows knowledge overlaps between the chapters (Table 1.1).

Table 1.1 Properties specific to the thesis chapters.

Chapter	Methodology	Input of analysis				Handling uncertainty			Assessment	
		From heterogeneous sources	From spatial databases	From process-based modelling	From expert knowledge	Data uncertainty	Model uncertainty	Scenario uncertainty	Large Extent	Resources
2	Climate modeling and spatial statistics	20	N/A	Climate model	N/A	Quantitative	Qualitative	In climate model	Global	Value change
3	Spatial disaggregation and summation	91	Yes	N/A	N/A	Qualitative	Qualitative	N/A	Global	Value estimation
4	Fuzzy logic MCE	27	Yes	N/A	Yes	Qualitative	Qualitative	N/A	Regional-Continental	Estimation of availability
5	Error propagation	27	N/A	N/A	Yes	Quantitative	Quantitative	N/A	Regional-Continental	Estimation of availability

Chapter 2

Climate change impact on global ecosystem service values

This chapter is based on main paper submitted to Proceedings of the National Academy of Sciences: Watson, L., M. Straatsma, N. Wanders, J. Verstegen, S. M. de Jong, and D. Karssenberg, submitted, Climate change impact on global ecosystem service values.

2.1. Introduction

Ecosystem services (ES) were developed as a means to economically quantify the environment and ecosystem functions from which humans directly or indirectly derive benefits (Costanza et al., 1997; Grêt-Regamey et al., 2013). ES are valued following various methods (e.g. Costanza et al., 1997; Crossman et al., 2013), from the local to global scale (e.g. Kelly and Adger, 2000; Li and Fang, 2014), and spatially (e.g. Millennium Ecosystem Assessment) or nonspatially (e.g. de Groot et al., 2012). Chapter 3 discusses ES assessments in particular.

Climate change affects ecosystem functioning and their value to both humans and natural systems (Nelson et al., 2013). Schägner et al. (2013) conducted a review of ES valuation papers through 2011 and categorized the studies on topic, application, and geographic extent or scale. The main policy applications are related to green accounting, land use policy, resource allocation, and payments for ES. There were a small number of case studies that had no policy applications. None of the reviewed case studies by Schägner et al. (2013) had climate change policy applications. A growing field of research is combining General Circulation Models (GCMs), which simulate climate change impact, with ES assessments (Landis et al., 2013; Raymond and Brown, 2011). A combined ES-GCM framework helps governments during the decision-making process to quantify the economic impact of climate change on ecosystems (Grimm et al., 2016). While many studies have combined aspects of ES and climate change (Grêt-Regamey et al., 2013;

Grimm et al., 2016; Landis et al., 2013; Raymond and Brown, 2011), global studies are not available and existing studies focus on either specific geographic areas using Regional Circulation Models or specific services. Ecosystem services are connected to climate; however, ecosystem service values affected by climate change remained unclear.

This chapter shows the spatially distributed global ES values for 19 subservices affected by a transition in Köppen-Geiger climate class (Köppen and Geiger, 1954) (KGCC). KGCC changes were derived from an ensemble of five GCMs under the four IPCC representative concentration pathways (RCPs) (van Vuuren et al., 2011). The results show the projected impact of climate class change on current ES values.

2.2. Global ecosystem service assessment

Nineteen ES were mapped globally from the four ES categories (Provisioning, Regulating, Habitat, and Cultural; Table 3.2) and valued in monetary units (international dollar). The services were compiled from five studies (Böhnke-Henrichs et al., 2013; Costanza et al., 1997; Hattam et al., 2015; Kettunen et al., 2012; van der Ploeg et al., 2010) as no universally accepted list of ecosystem services and subservices existed. (Refer to Chapter 3 for a detailed explanation of the methodology.) Based on these publications (Böhnke-Henrichs et al., 2013; Costanza et al., 1997; Hattam et al., 2015; Kettunen et al., 2012; van der Ploeg et al., 2010), a comprehensive list of ecosystem subservices was created, and they were categorised based on inclusion in the ES assessment (used in the study or included in other services – Table 3.1; missing data, double-counting, or not used – Table 3.1) and if the subservice is calculable or not.

The ES assessment was calculated from maps at a 10-km spatial resolution for the year 2005 in international dollars per hectare (for the year 2005). The spatial extent was limited to terrestrial areas and their exclusive economic zones, excluding Antarctica. Using publicly available data (Costanza et al., 1997; FAO, 2013, 2014, 2015; FAO and International Institute for Applied

Systems Analysis, 2012; Freiwald et al., 2005; Geofabrik GmbH Karlsruhe, 2016; Hiederer and Köchy, 2012; IUCN and UNEP-WCMC, 2013; Nachtergaele and Petri, 2008; NUS Consulting Group, 2006; Ruesch and Gibbs, 2008; SADC Trade Organization, 2014; Spalding et al., 1997; Tol, 2009; UNEP-WCMC, 1999; UNEP-WCMC and Short, 2003; UNEP-WCMC et al., 2010; van der Ploeg and de Groot 2010; VLIZ, 2012; Wada et al., 2011; World Bank, 2014), a global ES map was created for each subservice using production values. These values were from official governmental statistics or estimates when official statistics were unavailable.

2.3. Climate change characterization

Climate change indices integrate seasonal precipitation and temperature patterns (Baettig et al., 2007; Giorgi, 2006) either globally or regionally. KGCC ordinal classification was selected because of the clear connection between the climate change index and the ecosystem service by land use or ecosystem type (Table 2.1).

The four RCP emission scenarios (2.6, 4.5, 6.0, 8.5) are those used by IPCC research (IPCC, 2013) and each scenario models an increase in temperature over the 21st century. All scenarios have a high confidence to increase in temperature 1-1.5°C (relative to 1850-1900 temperatures) by 2035; RCP 4.5, 6.0, and 8.5 have a high confidence to increase in temperature more than 1.5°C; and RCP 6.0 and 8.5 have a high confidence to increase in temperature more than 2.0°C (IPCC, 2013).

Climate change forecasts for the 21st century were based on the CMIP5 climate projections from the IPCC (Warszawski et al., 2014). The model used 20 projections based on five GCMs (HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M, and NorESM1-M) and four RCP emission scenarios (2.6, 4.5, 6.0, and 8.5). Daily temperature and precipitation fields from these five GCMs were bias corrected using the WATCH forcing dataset (Hempel et al., 2013) and converted to KGCC classes for each year based on a 30-year moving window. Due to the consistency in downscaling and bias correction, effectively removing the differences in the model's historic simulations, the uncertainty is reduced for the historic period (1970-2000) and all uncertainty is attributed for the future climate signal to the GCM's individual response to the RCP scenarios.

Table 2.1 Köppen-Geiger Climate Classification Definitions from Köppen and Geiger (1954).

Major class	**Minor class**		**Definition**
	Precipitation	Temperature	
A			Tropical
B			Arid
C			Temperate
D			Cold
E			Polar
	f		Without dry season
	m		Monsoon
	s		Dry summer
	w		Dry winter
	W		Desert
	S		Semi-arid
	F		Frost
	T		Tundra
		h	Hot
		k	Cold
		a	Hot summer
		b	Warm summer
		c	Cold summer
		d	Very cold winter

For each GCM, the KGCC map of 2005 is compared with those for the years between 2005 and 2099. The area of each ES that is affected by a change in KGCC and the ES value represented by that area were calculated. These two calculations are done for each KGCC separately which results in a transition matrix. The combination of the five models enabled the calculation of the ensemble mean and range of the ES value affected by climate change per year (the script is available upon request). A minor transition is a change in either the precipitation or temperature and is represented by the second letter in the KGCC type (e.g. f in Af). While a major transition is a change in the climate group and is represented by the first letter in the KGCC (e.g. A in Af). Table 2.1 provides the description of major and minor KGCC.

2.4. Results

The total global ES value (1.9×10^{13} international dollars; Figure 2.1) is the sum of four service categories: Provisioning (1.9×10^{13} international dollars; Figure 2.2.), Regulating (1.0×10^{10} international dollars; Figure 2.3), Habitat (7.5×10^{6} international dollars; Figure 2.4), and Cultural (1×10^{8} international dollars; Figure 2.5). Concentrations of high values coincide with geographic areas where more data is available.

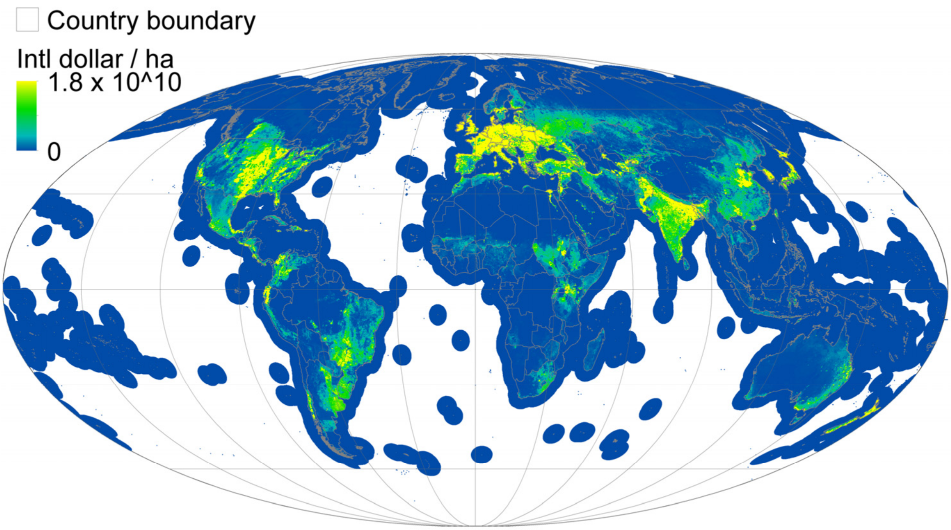


Figure 2.1 Global ecosystem services assessment value in international dollars per hectare for 2005 for Total Services. White areas are outside of the exclusive economic zone.

The Provisioning Services (Figure 2.2) accounts for almost all of the total global ES value and heavily influences the spatial pattern of the total service values. The Food Service, in turn, highly influences this category (Figure 3.2).

The Raw Service also contributes to the high valuation of the category (Figure 3.3).

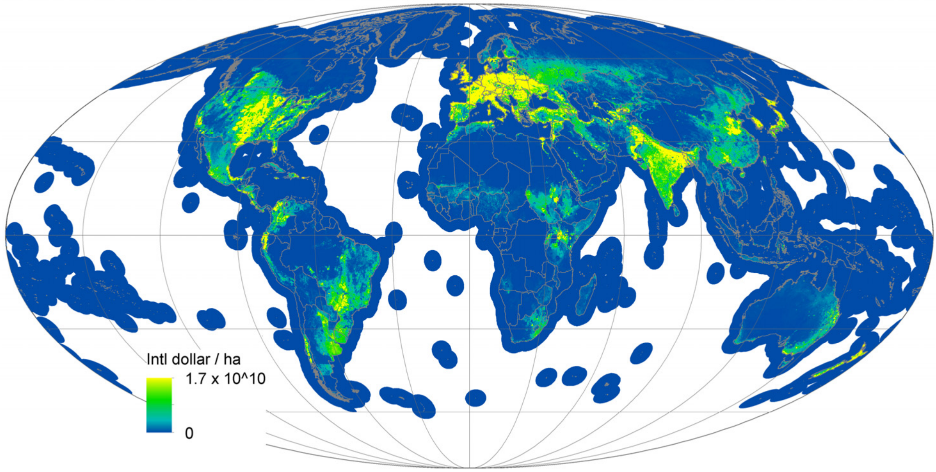


Figure 2.2 Global ecosystem services assessment for 2005 for Provisioning Services. White areas are outside the exclusive economic zone.

The Regulating Services category (Figure 2.3) reflects the spatial pattern and values from the Climate Regulating Service (Figure 3.5). High values coincide with high concentrations of carbon stock.

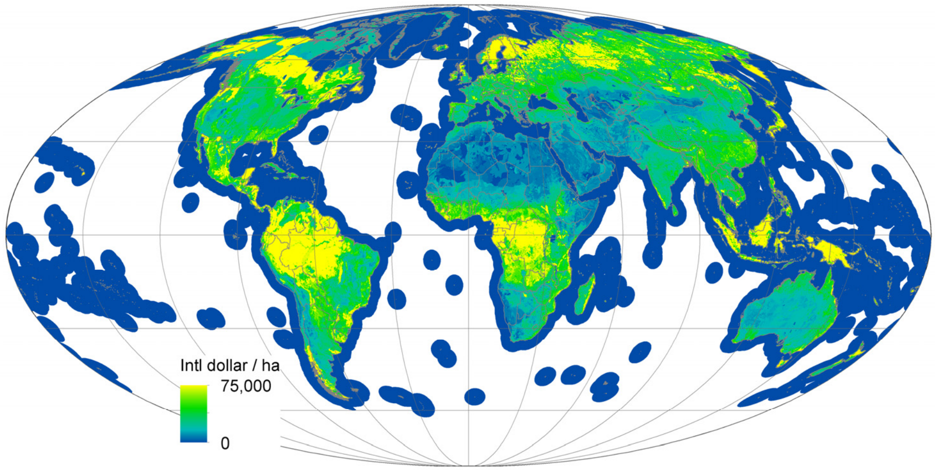


Figure 2.3 Global ecosystem services assessment for 2005 for Regulating Services. White areas are outside the exclusive economic zone.

The Habitat Services (Figure 2.4) are almost non-existent in the global valuation. However, this is due to a limited amount of data rather than a reflection of the value of the services.

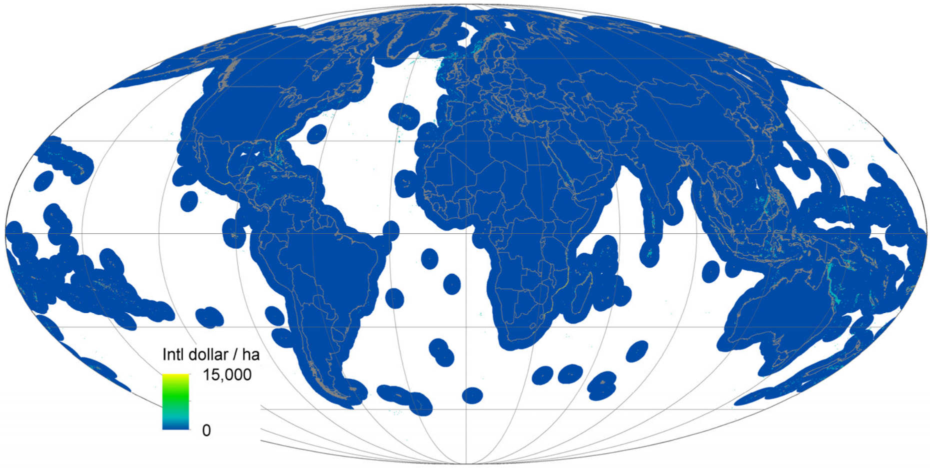


Figure 2.4 Global ecosystem services assessment for 2005 for Habitat Services. White areas are outside the exclusive economic zone.

The Cultural Services (Figure 2.5) are also almost non-existent in terms of share of total services. However, the values are much higher onshore than offshore. High valued onshore areas are those which are protected areas.

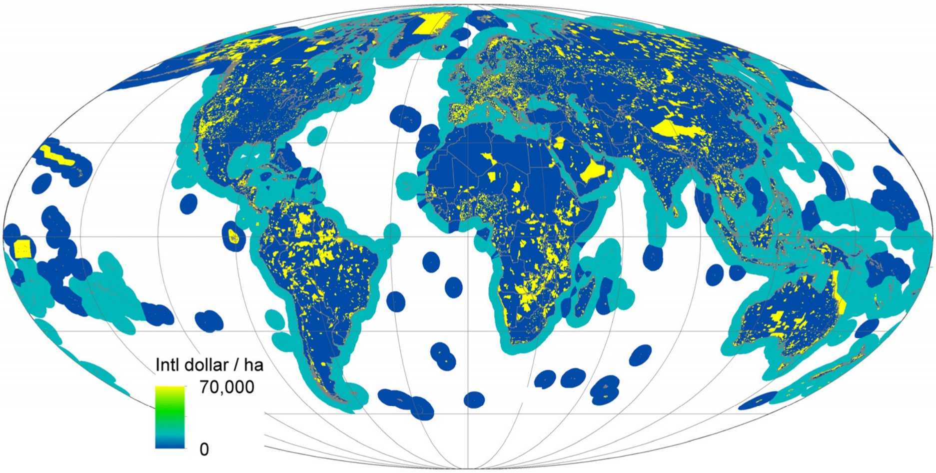


Figure 2.5 Global ecosystem services assessment for 2005 for Cultural Services. White areas are outside the exclusive economic zone.

For RCP 2.6, the agreed-upon goal of the Paris Agreement in 2016, in GCM GFDL-EM2M, one of the five GCMs in the study, KGCC changes from 2005 to 2085 reflect minor transitions in 16% of the locations to new classifications (Figure 2.6) (Wanders et al., 2015). There is little differentiation in RCP 2.6 between 2005 and 2085; however, RCP 8.5 shows more pronounced differentiation, for example, in Russia, Canada, USA, Brazil, and India. In RCP 8.5, KGCC shifts are more pronounced and occur in 34% of the world (Figure 2.6) (Wanders et al., 2015). The largest changes in climate types occur in temperate and polar regions due to increasing temperatures, decreasing precipitation, and shifts in the precipitation regime. Regions typified as tropical, desert, or snow -dominated will increase areally because of increasing temperatures. Minor climate types show significant shifts within the same major climate type moving from colder to warmer.

By 2099 in the RCP 2.6 scenario, ~17-32% of the assessed area (Figure 2.7 – row 1, column 1) will transition into a new KGCC. The newly classified area is equivalent to between ~5 x 10^7 sq. km (roughly the surface area of Asia) and ~9 x 10^7 sq. km. The KGCC transition will affect ~21-33% of the total ES value (Figure 2.7 – row 2, column 1), equaling between 4.1 x 10^{12} and 6.3 x 10^{12} international dollars. By comparison, in RCP 8.5 scenario by 2099, transitions into new KGCC will occur in ~38-54% of the assessed area, which is about 1.1 – 1.6 x 10^8 sq. km (Figure 2.7 – row 1, column 4). This scenario would affect at the minimum a surface area equal to all continental land areas except Africa and Australia to the maximum of an area equal to all continental land areas (exclusive economic zones account for half of the assessed area). Between 45 and 66% of the total ES value (Figure 2.7 – row 2) (8.5 x 10^{12} – 1.3 x 10^{13} international dollars) will have a new KGCC.

Between 2005 and 2050, the ES value affected by a shift in KGCC is approximately the same for all RCPs for each ES (Figure 2.7). The total ES value affected by a shift in KGCC falls within the range of 20-33% for all RCP scenarios for 2050 (21-32%, 21-28%, 20-26%, and 23-33% for RCP 2.6, 4.5, 6.0, and 8.5, respectively). However, around 2050 the differences between RCP scenarios become evident. The ES values affected by a shift in KGCC for RCP 2.6 plateau; in the case of RCP 4.5, the ES value affected begins to stabilize at the end of the century (circa 2090). In the two other RCP scenarios, the ES value affected continues to increase, and in RCP 8.5, the ES value affected is greater and continues to change at a greater rate than RCP 6.0 (i.e. steeper slope).

The RCP 8.5 scenario has significantly larger affected ES values than the other RCP scenarios. Every service has a larger percentage of the value affected in RCP 8.5 than in RCP 2.6. In the RCP 8.5 scenario, every service's minimum ES value affected by a shift in KGCC is greater than the service's maximum ES value affected by a shift in KGCC for RCP 2.6. For example, the maximum Food Service ES value affected in RCP 2.6 is 34%, while the minimum value affected in RCP 8.5 is 45%. The exception is for the Moderation of Extreme Events Service, which has a maximum value affected in RCP 2.6 of 19% and a minimum value affected in RCP 8.5 of 17%. The uncertainty in the ES value affected originates from the five GCMs that are used in the climate modeling and are shown by the shaded regions in Figure 2.7. This is the range in ensemble mean of the ES value. The range in ensemble mean of the ES value affected increases for each service from RCP 2.6 scenario to RCP 8.5 scenario. This is the case for each service, except for the Climate Regulation Service where both scenarios are almost equal in range (~19-38% and ~43-62%, respectively).

The transition matrix (Figure 2.8) depicts the globally summed ES value per minor KGCC shift. A summary of the transition matrix (Figure 2.9) indicates the major and minor KGCC shifts. The total ES value in the tropical KGCC (class A) will increase by 5.0×10^{11} international dollars. 3.5×10^{11} international dollars in tropical climates will undergo a minor KGCC shift by 2085 (i.e. the major climate class remains class A; blue arrow). 7.2×10^{10} international dollars in tropical climates (class A) will change to desert climates (class B, blue to orange arrow). ES values in rainforest climates (class Af) will decrease, while

ES values in monsoon climates (class Am) increase. Within the tropical climates (class A), a shift is observed from dry winters savannahs (class Aw) to dry summers (class As). Continental climates (class D) have the largest value change between major classes at 1.4 x 10^{12} international dollars. Polar climates (class E) have the smallest value change of 5.2 x 10^{10} international dollars, albeit a loss of ES values.

2.5. Conclusions

Results from this study are very valuable to study single or multiple subservices across the globe and quantify the change in ES value by the different RCP scenarios until 2099. The global ES map is also indispensable to create ES values by biome, country, continent, or at-risk areas for different hazards (e.g. earthquakes, landslides, rising sea level). Those subsets of ES values can be further analyzed for KGCC transitions. The outcome of the study provides governments with information to determine how the ES value may change and if plant or animal species, for example, will continue to survive in future KGCC.

Making a comparison of other ES assessments in order to check the ES values must be conducted with care because this ES assessment uses production values and in only few cases global values. Furthermore, this ES assessment excludes 31 services due to double-counting and conceptual incompatibility. 36 services were not included because of missing data. By making an estimate of the total value of the services missing data in this study but valued in previous studies (Costanza et al., 2014; de Groot et al., 2012) (i.e. the 36 services), this ES assessment is estimated to be undervalued by 20-22% or approximately 3.8 x 10^{12} international dollars.

It is important to note that the mapped ES values represent 2005; therefore, the values may not reflect ground truth. Even if the Paris Agreement will be maintained and countries will follow RCP 2.6 emission scenarios, more change in KGCC and ES values is still expected over the next ~30 years. If

RCP 8.5 emission scenarios are the actual reality, significant change will occur over the century.

This study does not calculate how the monetary value is impacted. The net ES value could increase or decrease and the changes might be further amplified or tempered by ecosystem adaptations to climate change. Other researchers suggest different approaches to predict changes, but these rely on input from the public (Grimm et al., 2016; Raymond and Brown, 2011); for a global study, public input would be feasible only in a multi-national research project with many resources. This study shows here a first attempt of a global, spatially distributed ES assessment with the currently available public data, which does not require the resources described above.

A better understanding of the local changes is needed in order to better prepare global economies for climate change. Incorporating uncertainty into the ES assessment is a valuable future direction of investigation and those results will better assist in decision-making because of the known errors in this ES assessment. This point should be incorporated in Action 5 of the EU Biodiversity Strategy to 2020.

This study has shown the value of ES globally (total ~1.9×10^{13} international dollars) and how much of that value will be affected by a shift in KGCC (21-33% and 45-66% for RCP 2.6 and RCP 8.5, respectively). A significant area (between 5×10^{7} sq. km and 1.6×10^{8} sq. km, depending on the scenario), somewhere between the surface area equal to Asia and the surface area of all continental land areas, will be affected by a shift in KGCC with a large impact on the local population and economies.

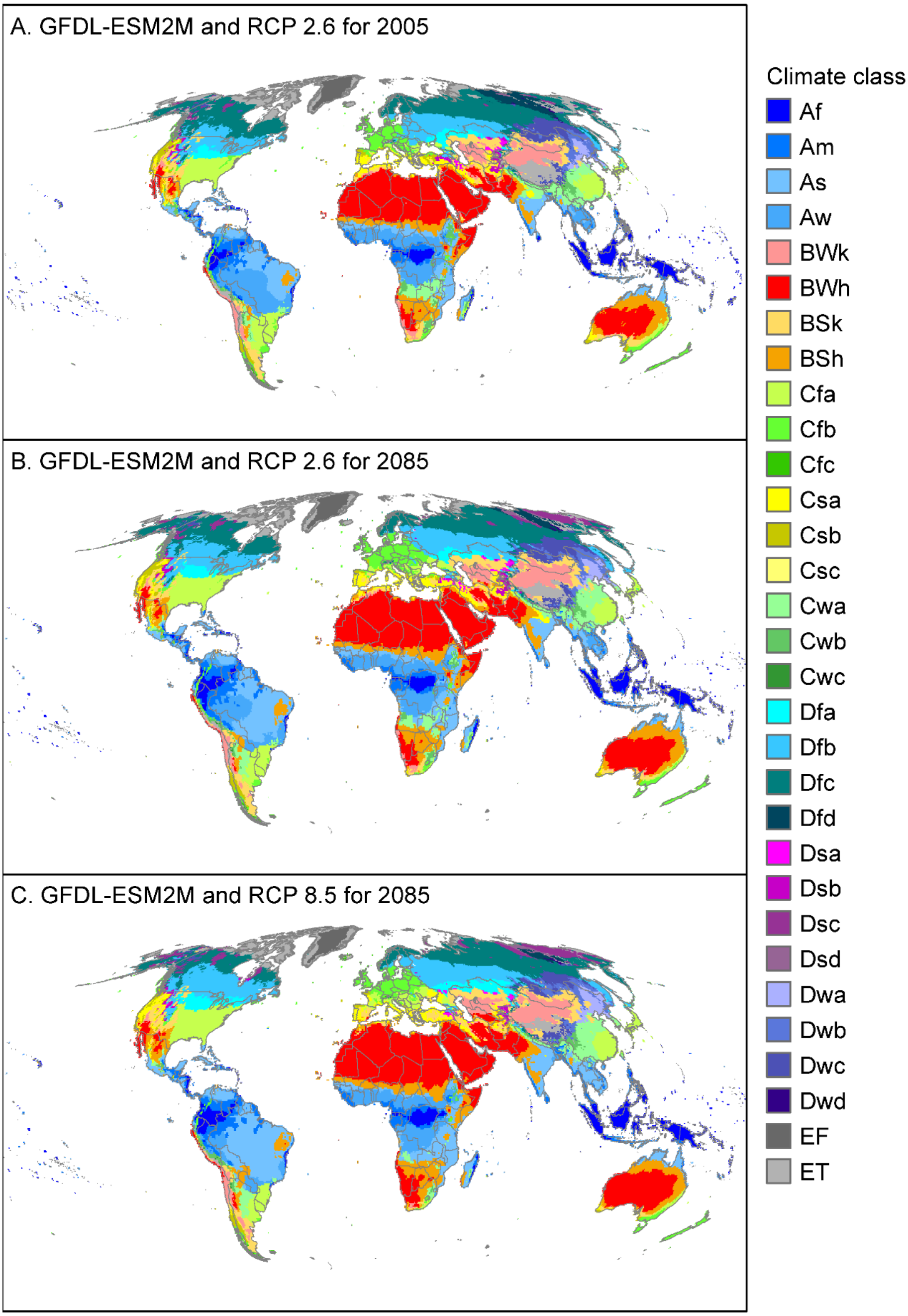


Figure 2.6 Köppen-Geiger climate classifications for GFDL-ESM2M. A. RCP 2.6 for 2005. B. RCP 2.6 for 2085. C. RCP 8.5 for 2085. Classification summary in Table 2.1.

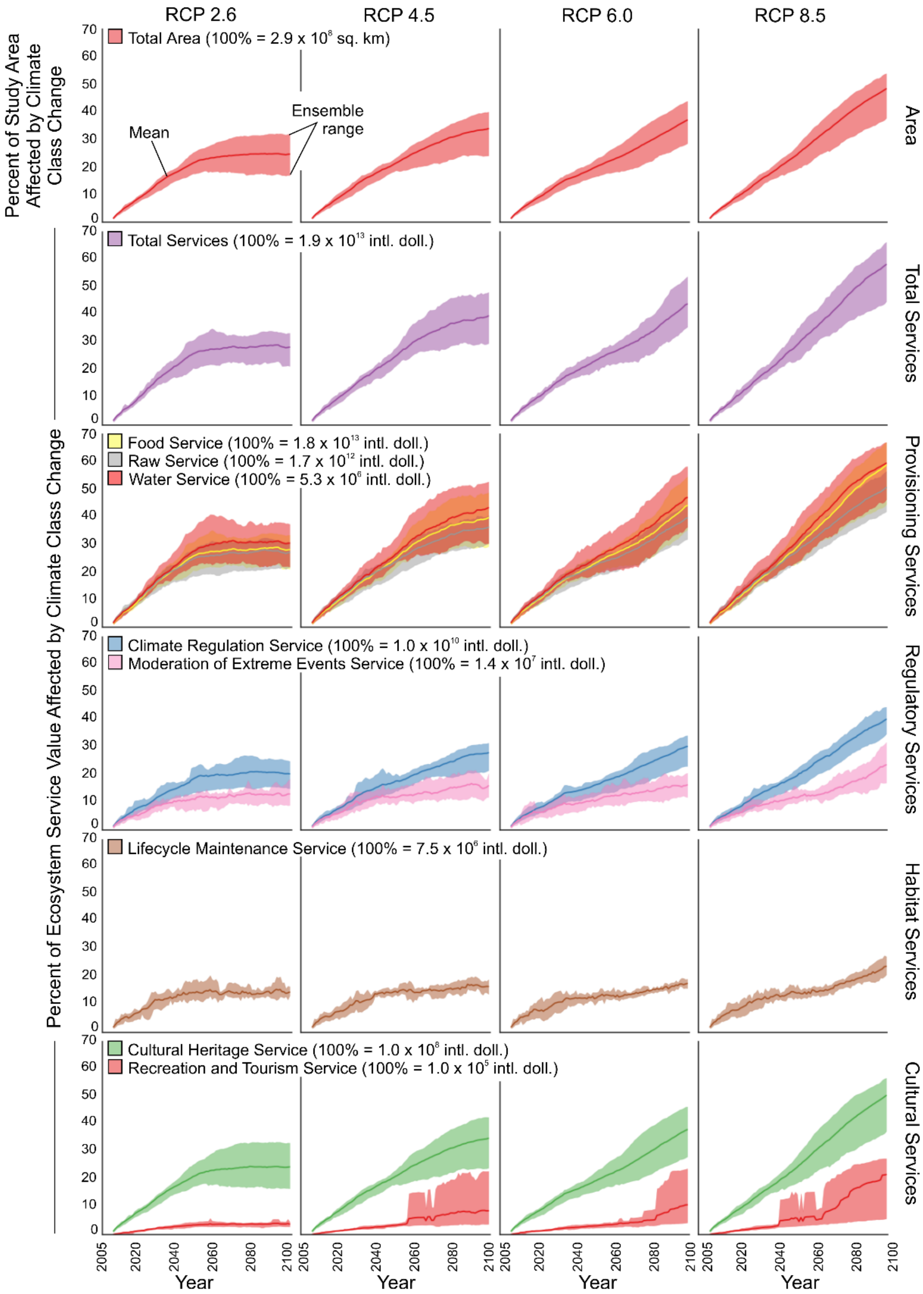


Figure 2.7 Time series of ecosystem service values affected by changes in climate class from 2000 to 2100.

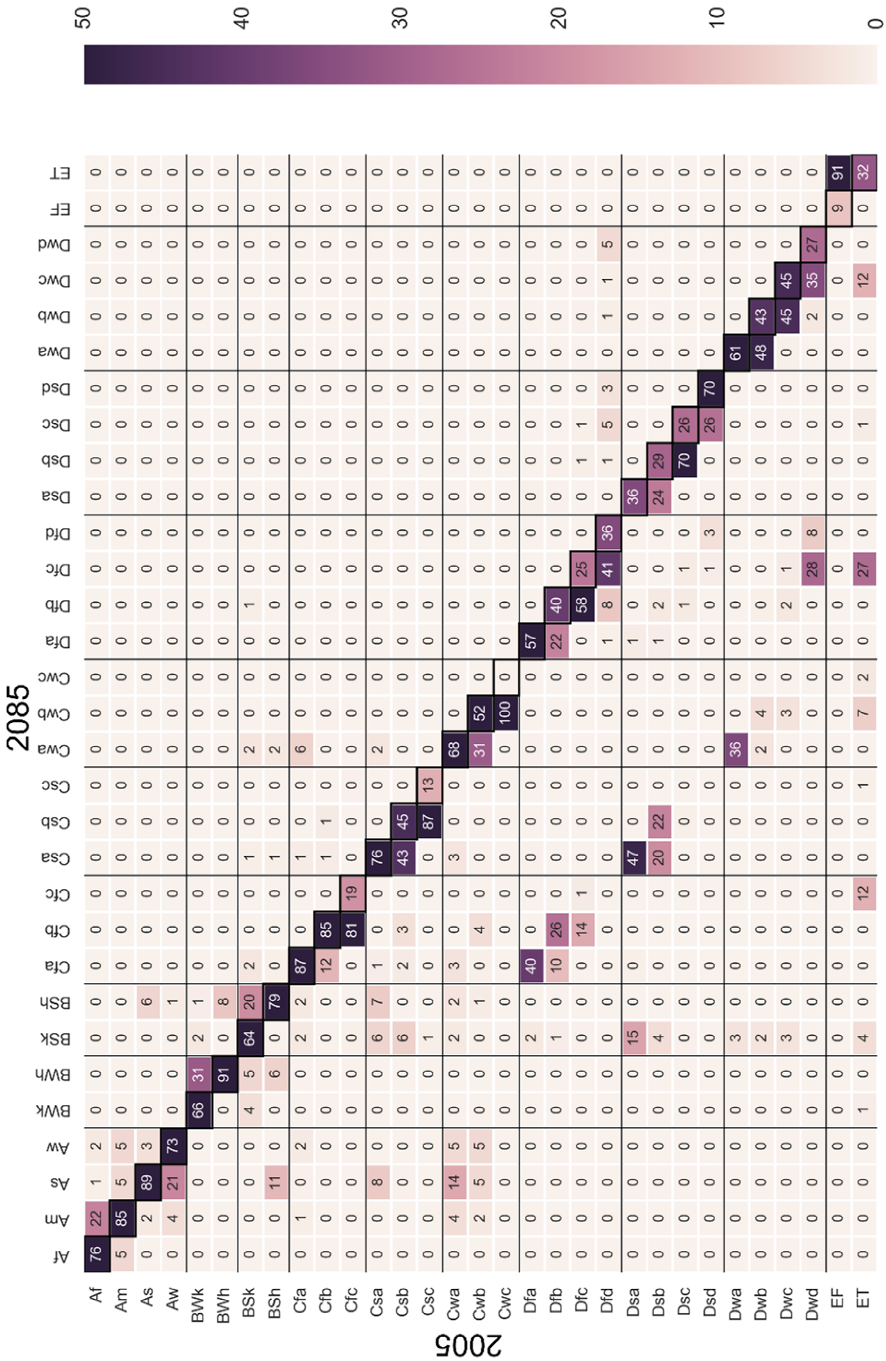


Figure 2.8 Transition matrix of percent value changed between climate classifications from 2005 to 2085 for global Total Services.

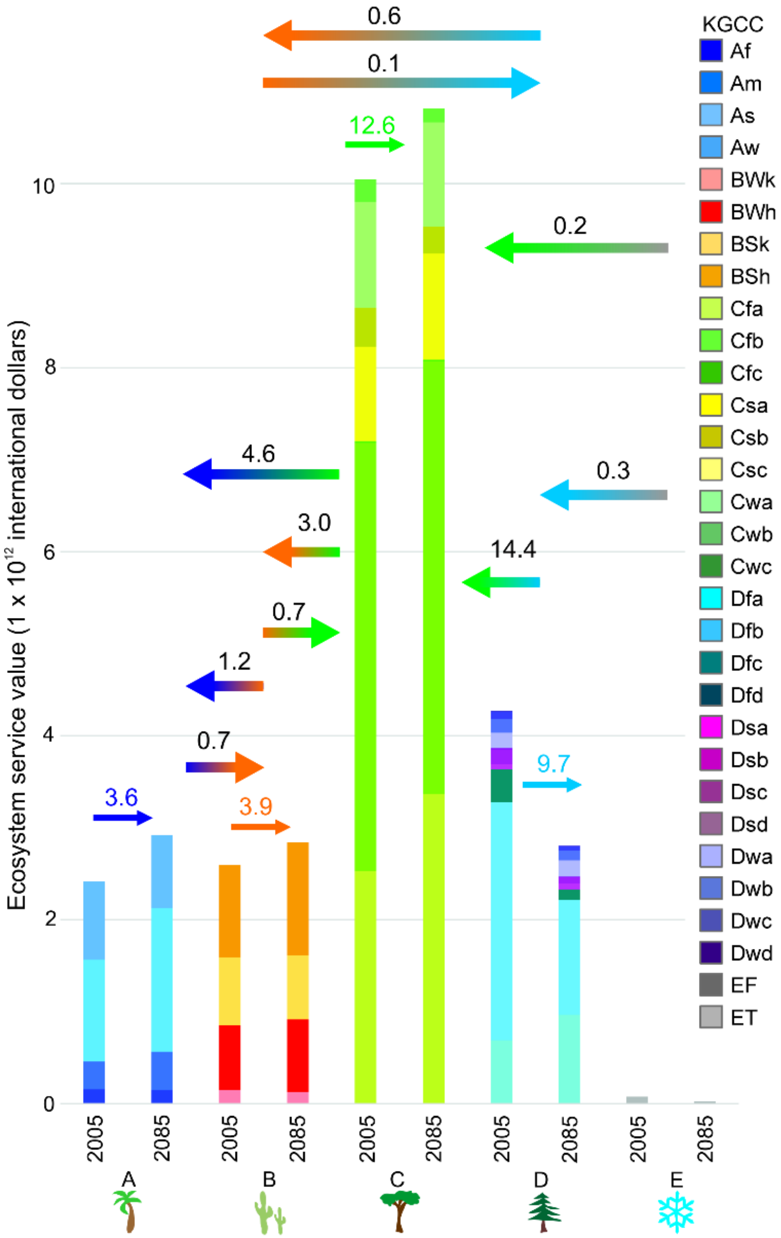


Figure 2.9 Distribution of ecosystem service values among Köppen-Geiger climate classes for 2005 and 2085. Each vertical bar represents the major class and is further divided into the minor classes. The horizontal arrows show the ecosystem service value in 1×10^{10} international dollars changing climate class from 2005 to 2085. Single-colored arrows show within major class changes and multi-colored arrows show between major class changes.

Chapter 3

Global ecosystem service assessment

This chapter is based on the appendix of paper submitted to Proceedings of the National Academy of Sciences: Watson, L., M. Straatsma, N. Wanders, J. Verstegen, S. M. de Jong, and D. Karssenberg, submitted, Supplemental information for Climate change impact on global ecosystem service values.

3.1. Introduction

Global, spatially explicit ecosystem service (ES) assessments were pioneered as a construct of valuing the environment in order to support decision-making. ES assessments calculate a monetary value for resources that are used either directly or indirectly (Costanza et al., 1997). Schägner et al. (2013) conducted a review of ES valuation papers through 2011 that map ES values and categorized the studies on topic, application, and geographic extent or scale. Of the reviewed case studies, only five studies mapped ES values at the global extent. Since the review, few studies add to the globally mapped ES values (e.g. Li and Fang, 2014). There are four main incongruences in the current state-of-the-art ES assessment research. 1) There is no consistently accepted number of services and subservices for inclusion in ES assessments (c.f. Böhnke-Henrichs et al., 2013; Costanza et al., 1997; Hattam et al., 2015; Kettunen et al., 2012; Millennium Ecosystem Assessment, 2003; van der Ploeg et al., 2010). 2) There are several variations to estimate ES values (e.g. Boumans et al., 2002; Crossman et al., 2013; de Groot et al., 2010; Li and Fang, 2014; Millennium Ecosystem Assessment, 2003; Sutton and Costanza, 2002). 3) Most publications do not present the global ES assessment spatially (e.g. Costanza et al., 2014; de Groot et al., 2012); although there are a few exceptions (e.g. Costanza et al., 1997; Li and Fang, 2014; Millennium Ecosystem Assessment, 2003). 4) While not limited to ES research, publications do not include succinct information regarding calculations or data used in the assessments, inhibiting reproduction of results for further or additional analysis (e.g. Costanza et al., 2014; Millennium Ecosystem

Assessment, 2003). Worryingly, Schägner et al. (2013) noted that 35 of 79 case studies with spatial ES maps do not include the spatial resolution.

The objective of this study is to propose a methodology for ES assessment that gives a solution to the four issues prevalent in ES literature. The research questions are:

- How can the inconsistency of included services between ES assessments be resolved?
- How can the ES be mapped on a global scale and what is an appropriate map resolution?
- How can the ES values be calculated?

This chapter first presents the methodology for reconciling the different ES assessments. Then the input data necessary for calculating the ES are discussed as well as the disaggregation methods. Next, the methodology is applied on a global scale and the ES assessment is described in detail. Afterwards, the ES value maps are presented and discussed.

3.2. Methodology

The workflow consists of the following steps:

1. An inventory of the ecosystem subservices and services in ES assessments;
2. Homogenize the inventory;
3. Reduce the inventory to those ES that are mappable and calculable;
4. Data preprocessing;
5. Spatial disaggregation; and
6. Summation of maps.

In the inventory of the ES, only those subservices are included that are conceptually compatible to the definition of an ES as providing a benefit to society (van der Ploeg et al., 2010). Those subservices determined not to benefit society are disservices, thus excluded. A comparison of five papers (Costanza et al., 1997; van der Ploeg et al., 2010; Kettunen et al., 2012;

Böhnke-Henrichs et al., 2013; Hattam et al., 2015) showed different subsets of services and subservices (Table 3.1). These papers were selected because of the ES assessment descriptions and coverages. The ES assessments all included a list of services to value for the respective studies. Costanza et al. (1997) and van der Ploeg et al. (2010) were global assessments; Kettunen et al. (2012), Böhnke-Henrichs et al. (2013), and Hattam et al. (2015) focused on local or regional areas, but the assessments could be applied to larger studies. The subservices were homogenized based on name and description because distinct names sometimes had an analogous/equivalent description.

Based on these publications, a superset of 108 ecosystem subservices was created. Each of the subservices was labelled with inclusion in the study or the reason for exclusion (i.e. included in other services, missing data, double-counting, or not used). The subservices categorized as double-counting or not used were conceptually incompatible with the proposed framework.

Table 3.1 Ecosystem services comparison of five papers and this chapter. X indicates the service was listed in the ecosystem service assessment.

Category	**Ecosystem service**	**Subservice**	**Hattam et al. (2015)**	**Böhnke-Henrichs et al. (2013)**	**Kettunen et al. (2012)**	**Costanza et al. (1997)**	**Van der Ploeg et al. (2010)**	**This chapter**	
								Included or excluded	Calculable or not
Provisioning services	Food	fish (wild and farmed)	x	x	x	x	x	Used "fish"	Calculation possible
		fresh water fishing			x				
		sea plants/vegetable food	x		x		"plants/ vegetable"	Used	Calculation possible
		livestock			x	?	"meat"	Used	Calculation possible
		reindeer herding			x	?	"NTFP" ?	Missing data	Calculation possible
		game (elk, deer, bear, other, water fowl)			x	x		Used	Calculation possible
		dairy production (traditional and organic)			x	?	"food"	Used	Calculation possible
		crops and cereals (traditional and organic)			x	x	"plants/ vegetable"	Used	Calculation possible
		fruit production (from orchards; traditional and organic)			x	x		Used	Calculation possible
		berries (non-cultivated)			x		"NTFP" ?	Used	Calculation possible
		mushrooms			x		"NTFP" ?	Used	Calculation possible
		non-timber forest product (NTFP)					x	Missing data	Calculation possible
		other					x	Not used	Unclear what this includes

Table 3.1 continued

Category	Ecosystem service	Subservice	Hattam et al. (2015)	Böhnke-Henrichs et al. (2013)	Kettunen et al. (2012)	Costanza et al. (1997)	Van der Ploeg et al. (2010)	This chapter	
								Included or excluded	Calculable or not
Provisioning services	Water supply	industrial use		x		x	x	Used	Calculation possible
		drinking water			x	x	x	Used	Calculation possible
		water other					x	Not used	Unclear what this includes
		irrigation water (unnatural)				x	x	Included elsewhere	Calculation possible
		water supply (general)					x	Not used	Unclear what this includes
	Raw materials	non-industrial aggregates (sand, rock, gravel, coral)		x		x	x	Missing data	Calculation possible
		biomass fuels				?	x	Included elsewhere	Calculation possible
		algae (non-food)		x		?		Missing data	Calculation possible
		fertilizers	x		x		x	Included elsewhere	Calculation possible
		salt		x				Missing data	Calculation possible
		timber and fiber for pulp production		x	x	x	x	Used "non-food forest products"	Calculation possible
		timber production, sustainable			x				
		energy: fuel wood		x	x	x	x		
		energy: other bioenergy			x	x		Missing data	Calculation possible

Table 3.1 continued

Category	Ecosystem service	Subservice	Hattam et al. (2015)	Böhnke-Henrichs et al. (2013)	Kettunen et al. (2012)	Costanza et al. (1997)	Van der Ploeg et al. (2010)	This chapter: Included or excluded	This chapter: Calculable or not
Provisioning services	Raw materials (cont'd.)	fodder and forage: hay			x	x	x	Included elsewhere	Calculation possible
		fodder and forage: lichens			x	?		Included elsewhere	Calculation possible
		fiber: wool			x		x	Used	Calculation possible
		fiber: leather and fur			x	x		Used	Calculation possible
		fiber: down from wild birds			x			Missing data	Calculation possible
		other					x	Not used	Unclear what this includes
	Genetic resources	plant	x	x	x	x	x	Missing data	Calculation possible
		animal		x	x		x	Missing data	Calculation possible
		general					x	Not used	Unclear what this includes
	Medical resources	biochemicals	x		x		x	Missing data	Calculation possible
		models			x		x	Missing data	Calculation possible
		test organisms					x	Missing data	Calculation possible
		bioprospecting					x	Missing data	Calculation possible
		medicinal products (natural)		x	x			Missing data	Calculation possible
		natural food supplements			x			Missing data	Calculation possible
		cosmetics			x			Missing data	Calculation possible

Table 3.1 continued

Category	Ecosystem service	Subservice	Hattam et al. (2015)	Böhnke-Henrichs et al. (2013)	Kettunen et al. (2012)	Costanza et al. (1997)	Van der Ploeg et al. (2010)	This chapter	
								Included or excluded	Calculable or not
Provisioning services	Ornamental	dyes/colorants			x	x		Missing data	Calculation possible
		decorative plants	x	x			x	Missing data	Calculation possible
		jewelry	x	x	x		"fashion"	Missing data	Calculation possible
		decorations/handicrafts	x	x	x		x	Missing data	Calculation possible
		pets/captive animals		x			x	Missing data	Calculation possible
Regulating services	Air quality	capturing fine dust potential	x	x			x	Missing data	Calculation possible
		air quality regulation	x		x (as a subservice to Biological Control)		x	Not used	Conceptually incompatible - disservice
		UVB protection				x	x	Not used	Calculation unclear
	Climate regulation	carbon sequestration	x	x	x	x	x	Missing data	Calculation possible
		gas regulation	x	x		x	x	Not used	Conceptually incompatible - disservice
		climate regulation general					x	Not used	Unclear what this includes
		microclimate regulation	?	x	x	x	x	Not used	Conceptually incompatible - disservice
		carbon storage			x			Used	Calculation possible

Table 3.1 continued

Category	**Ecosystem service**	**Subservice**	**Hattam et al. (2015)**	**Böhnke-Henrichs et al. (2013)**	**Kettunen et al. (2012)**	**Costanza et al. (1997)**	**Van der Ploeg et al. (2010)**	**This chapter**	
								Included or excluded	Calculable or not
Regulating services	Moderation of extreme events	storm protection	x	x	x	x	x	Used	Calculation possible
		flood prevention			x	x	x	Missing data	Calculation possible
		tsunami						Not used	Conceptually incompatible
		fire prevention					x	Missing data	Calculation possible
		avalanche prevention/mitigation			x			Missing data	Calculation possible
		mud flow/floods			x			Missing data	Calculation possible
		general					x	Not used	Unclear what this includes
	Water flow regulation	drainage	?	x	x	x	x	Double counting	Conceptually incompatible
		river discharge	?				x	Double counting	Conceptually incompatible
		natural irrigation			x	x	x	Double counting	Conceptually incompatible
		drought mitigation			x	x		Double counting	Conceptually incompatible
		aquifer recharge	?		x	x		Double counting	Conceptually incompatible
		coastal currents	x	x				Double counting	Conceptually incompatible
		general					x	Not used	Unclear what this includes

Table 3.1 Continued

Category	**Ecosystem service**	**Subservice**	**Hattam et al. (2015)**	**Böhnke-Henrichs et al. (2013)**	**Kettunen et al. (2012)**	**Costanza et al. (1997)**	**Van der Ploeg et al. (2010)**	**This chapter**	
								Included or excluded	Calculable or not
Regulating services	Waste treatment and water purification	water purification	x	x	x (as a subservice to Biological Control)	x	x	Not used	Conceptually incompatible - disservice
		soil detoxification	?	?		x	x	Not used	Conceptually incompatible - disservice
		abatement of noise					x	Not used	Conceptually incompatible - disservice
		water treatment general					x	Not used	Unclear what this includes
	Maintenance of soil fertility	maintenance of soil structure			x (as a subservice to Biological Control)	x	x	Double counting	Conceptually incompatible
		deposition of nutrients				x	x	Double counting	Conceptually incompatible
		soil formation				x	x	Double counting	Conceptually incompatible
		nutrient cycling				x	x	Double counting	Conceptually incompatible
		general					x	Not used	Unclear what this includes

Table 3.1 Continued

Category	Ecosystem service	Subservice	Hattam et al. (2015)	Böhnke-Henrichs et al. (2013)	Kettunen et al. (2012)	Costanza et al. (1997)	Van der Ploeg et al. (2010)	This chapter	
								Included or excluded	Calculable or not
Regulating services	Pollination	pollination of crops			x (as a subservice to Biological Control)	x	x	Double counting	Conceptually incompatible
		pollination of wild plants					x	Double counting	Conceptually incompatible
		general					x	Not used	Unclear what this includes
	Erosion prevention	erosion prevention	x	x		x	x	Double counting	Conceptually incompatible
	Biological control	pest control	x	?	x		x	Not used	Conceptually incompatible - disservice
		disease control	x	?	x		x	Missing data	Calculation possible
		seed dispersal			x (as a subservice to Life-cycle Maintenance)		x	Double counting	Conceptually incompatible
		general					x	Not used	Unclear what this includes
		resilience thru the food web	x	x		x		Missing data	Calculation possible
		population dynamics	x	x				Not used	Unclear what this includes

Table 3.1 Continued

Category	Ecosystem service	Subservice	Hattam et al. (2015)	Böhnke-Henrichs et al. (2013)	Kettunen et al. (2012)	Costanza et al. (1997)	Van der Ploeg et al. (2010)	This chapter	
								Included or excluded	Calculable or not
Habitat services	Life-cycle maintenance	nursery service	x	x	x	x	x	Used "nursery and refugia"	Calculation possible
		refugia for migratory and res. species				x	x		
		gene pool protection	x	x			"Biodiversity protection"	Double counting	Conceptually incompatible
Cultural services	Aesthetic	attractive sea/landscapes	x	x		x	x	Missing data	Calculation possible
	Recreation and tourism	recreation	x	x	x	x	x	Used "potential" tourism	Calculation possible
		tourism	x	x	x	x	x		
		ecotourism	x	x	x	x	x		
		hunting and fishing	x	x	x	x	x		
	Inspiration	artistic	x	x	x	x	x	Missing data	Calculation possible
		cultural use	x	x			x	Missing data	Calculation possible
		general					x	Not used	Unclear what this includes
	Spiritual	spiritual/religious	x	x	x	x	x	Missing data	Calculation possible
	Cognitive development	science/research	x	x		x	x	Missing data	Calculation possible
		education	x	x		x	x	Missing data	Calculation possible
		general					x	Not used	Unclear what this includes
	Cultural heritage	social and cultural values	x	x	x		x	Used	Calculation possible
	Cultural diversity	diversity	x					Not used	Unclear what this includes
	Mental well-being and health	reduction of stress			x			Missing data	Calculation possible

From the 108 subservices, nineteen are determined to be usable in the study as the ES are calculable and are conceptually compatible with the service as a benefit to society (Table 3.2).

Table 3.2 Ecosystem services assessment.

Category	Ecosystem service	Subservice
Provisioning services	Food	fish
		sea plants/vegetables
		livestock
		game
		dairy production
		crops and cereals
		fruit orchards
		berries
		mushrooms
	Water supply	industrial use
		drinking water
	Raw materials	non-food forest products
		fiber: wool
		fiber: leather and fur
Regulating services	Climate regulation	carbon storage
	Moderation of extreme events	storm protection
Habitat services	Life-cycle maintenance	nursery and refuge
Cultural services	Recreation and tourism	potential tourism
	Cultural heritage	social and cultural values

Data preprocessing included extensive research to compile data sets (Table 3.3). Compiled data had to meet certain criteria in order to be included, which are:

1. data source must be reliable (e.g. government agency or research institute);
2. data must have significant global coverage, with a preference to complete global coverage;
3. data must be used to calculate production values for as many services as possible, although exceptions can be allowed;

4. data must be for the selected year, be reasonably close temporally, or be adjustable to reflect the year (e.g. inflation); and
5. data must be mappable if not already in a GIS format.

The year 2005 was chosen based on the prevalence of global studies being available for this year, but not beyond. Some data sets were for other years and this is documented in Table 3.3.

Data preparation included resampling spatial data to a 10-km-spatial resolution, coinciding with the majority of the available global data (~0.08°). In addition, this spatial resolution was deemed fine enough for a global model but coarse enough for reasonable computational analysis.

The global spatial mapping was limited to terrestrial areas and their exclusive economic zones, excluding Antarctica, because governmental statistics for production of resources does not include international waters. It is possible that international waters could have a value associated with them, but production values may not be as reliable or continuous.

For the majority of the ESs valued, tabulated information with the lumped value for each country and spatial information to disaggregate the lumped value over the country is available. Publicly available data includes production values derived from official governmental statistics for the majority of countries for most of the services (Costanza et al., 1997; FAO, 2013, 2014, 2015; FAO and International Institute for Applied Systems Analysis, 2012; Freiwald et al., 2005; Geofabrik GmbH Karlsruhe, 2016; Hiederer and Köchy, 2012; IUCN and UNEP-WCMC, 2013; Nachtergaele and Petri, 2008; NUS Consulting Group, 2006; Ruesch and Gibbs, 2008; SADC Trade Organization, 2014; Spalding et al., 1997; Tol, 2009; UNEP-WCMC, 1999; UNEP-WCMC and Short, 2003; UNEP-WCMC et al., 2010; van der Ploeg and de Groot, 2010; VLIZ, 2012; Wada et al., 2011; World Bank, 2014). These values were supplemented with estimates when direct statistics were not available. Statistics for other years were adjusted for inflation to represent the

2005 value. Table 3.3 includes source and value information. The data is discussed in sections 3.4 – 3.8.

Table 3.3 Descriptions of subservices used in this ecosystem services assessment.

<table>
<tr><th>Category</th><th>Ecosystem service</th><th colspan="2">Subservice</th><th>Data provider</th><th>Year</th><th>Data description</th><th>Value calculation description</th><th>Sources of error</th></tr>
<tr><td rowspan="8">Provisioning services</td><td rowspan="8">Food</td><td>fish (wild and farmed)</td><td rowspan="2">fish</td><td rowspan="2">FAO (2013); VLIZ (2012)</td><td rowspan="2">2005</td><td rowspan="2">total production value including industrial, commercial, recreational, subsistence; and mariculture, aquaculture, and other farming</td><td rowspan="2">value / area</td><td rowspan="2">production may not extend the entire area; fresh water areas are not included</td></tr>
<tr><td>fresh water fishing</td></tr>
<tr><td colspan="2">sea plants/vegetable food</td><td>FAO (2013); VLIZ (2012)</td><td>2005</td><td>total aquaculture production value of aquatic plants</td><td>value / area</td><td>production may not extend the entire area</td></tr>
<tr><td colspan="2">livestock</td><td>FAO (2014, 2015)</td><td>2005</td><td>30-arc-min grid of animal density (buffalo, cattle, goat, pig, poultry, sheep); $ per live weight tonne; average weight of animal</td><td>$/tonne * #/ha * tonne/#</td><td>average animal weight; no differentiation between dairy vs meat in animal population</td></tr>
<tr><td colspan="2">game (elk, deer, bear, other, water fowl)</td><td>FAO (2015); Nachtergaele and Petri (2008)</td><td>2005; 2004-2008</td><td>game production value; land cover</td><td>value / area</td><td>production area</td></tr>
<tr><td colspan="2">dairy production (traditional and organic)</td><td>FAO (2014, 2015)</td><td>2005</td><td>Total whole milk gross production by cow, sheep, and goat by country; livestock density</td><td>value * density / population proportion</td><td>no differentiation between dairy vs meat in animal population</td></tr>
<tr><td colspan="2">crops and cereals (traditional and organic)</td><td>FAO and International Institute for Applied Systems Analysis (2012)</td><td>2000/2005</td><td>Summation of wheat, rice, maize, sorghum, millet, tuber crops, cassava and other roots, sugar beet, sugarcane, pulses, soybean, rape, sunflower, groundnut, oil palm, olive, and cotton; spatial disaggregated based on suitability of growth using rainfall, irrigation, and land agronomic capabilities</td><td>value</td><td>See Fischer et al. (2008) for details</td></tr>
</table>

Table 3.3 Continued

Category	Ecosystem service	Subservice		Data provider	Year	Data description	Value calculation description	Sources of error
Provisioning services	Food	fruit production (from orchards; traditional and organic)		FAO (2015); Nachtergaele and Petri (2008)	2005; 2004-2008	fruit production value; land cover	value / area	production area
		berries (non-cultivated)		FAO (2015); Nachtergaele and Petri (2008)	2005; 2004-2008	berry production value; land cover	value / area	production area
		mushrooms		FAO (2015); Nachtergaele and Petri (2008)	2005; 2004-2008	mushroom production value; land cover	value / area	production area
	Water supply	industrial use		Wada et al. (2011); NUS Consulting Group (2006)	2005	industrial water demand; cost of water charged to consumers	demand * value * measure conversion	prices are not available for all countries; used global average for those not available; unclear where the water originates
		drinking water		Wada et al. (2011); NUS Consulting Group (2006)	2005	domestic water demand; cost of water charged to consumers	demand * value * measure conversion	prices are not available for all countries; used global average for those not available; unclear where the water originates; all domestic demand, not just drinking water
	Raw materials	timber and fiber for pulp production	non-food forest product	FAO (2015); Nachtergaele and Petri (2008)	2005; 2004-2008	wood export value; forests	value / area	Production area; export value of wood products
		timber production, sustainable						
		energy: fuel wood						
		fiber: wool		FAO (2014, 2015)	2005	30-arc-min grid of animal density (sheep); $ per tonne wool; average weight of wool from a sheep	$/tonne * #/ha * tonne/#	Wool weight; dairy vs meat vs fiber use of animal

Table 3.3 Continued

Category	Ecosystem service	Subservice		Data provider	Year	Data description	Value calculation description	Sources of error
Provisioning services	Raw materials	fiber: leather and fur		SADC (2014); FAO (2014, 2015)	2005	price per tonne of leather; 30-arc-min grid of animal density (sheep); tonnes of hides for buffalo cattle, goat, sheep	value * density / population proportion	Hide weight; dairy vs meat vs fiber use of animal
Regulating services	Climate regulation	carbon storage		Hiederer and Kochy (2012); Ruesch and Gibbs (2008); Tol (2009)	2000	global biomass carbon map; global carbon soil map; value	carbon * value	see Hiederer and Kochy (2012); Ruesch and Gibbs (2008); Tol (2009)
	Moderation of extreme events	storm protection		Costanza et al. (1997); Spalding et al. (1997); UNEP WCMC and Short (2003)	2005	values; mangrove and seagrass coverage	value * area	value; coverage incomplete
Habitat services	Life-cycle maintenance	nursery service	nursery and refugia	UNEP WCMC (1999); UNEP WCMC et al. (2010); Costanza et al. (1997); van der Ploeg and de Groot (2010); Freiwald et al. (2005)	2005; 2010; 1999; 1997; 2007	coral reefs; turtle nesting sites	value * area	value; coverage incomplete
		refugia for migratory and res. species						
Cultural services	Recreation and tourism	recreation	potential tourism	World Bank (2014); Geofabrik GmbH Karlsruhe (2016)	2005; 2016	international tourism expenditures; lodging locations	value * tourism lodging proportion	Missing national dollars spent; beds per lodging type
		tourism						
		ecotourism						
		hunting and fishing						
	Cultural heritage	social and cultural values		FAO and International Institute for Applied Systems Analysis (2012); IUCN and UNEP-WCMC (2013); van der Ploeg and de Groot (2010)	2000; 2012; 2010	GAEZ protected sites; World Heritage Sites; TEEB cultural service general values for onshore and offshore	((GAEZ U WHS) * onshore value) + (marine area * offshore value)	Undervaluation due to global values; inclusion of man-made sites

3.3. Data disaggregation

Three different approaches are used in disaggregating the data depending on the data available (Figure 3.1). They are lumped value; quantity value; and value per hectare. For each data set, the disaggregation approach is summarized in Table 3.4 and included in the explanations in Section 3.8.

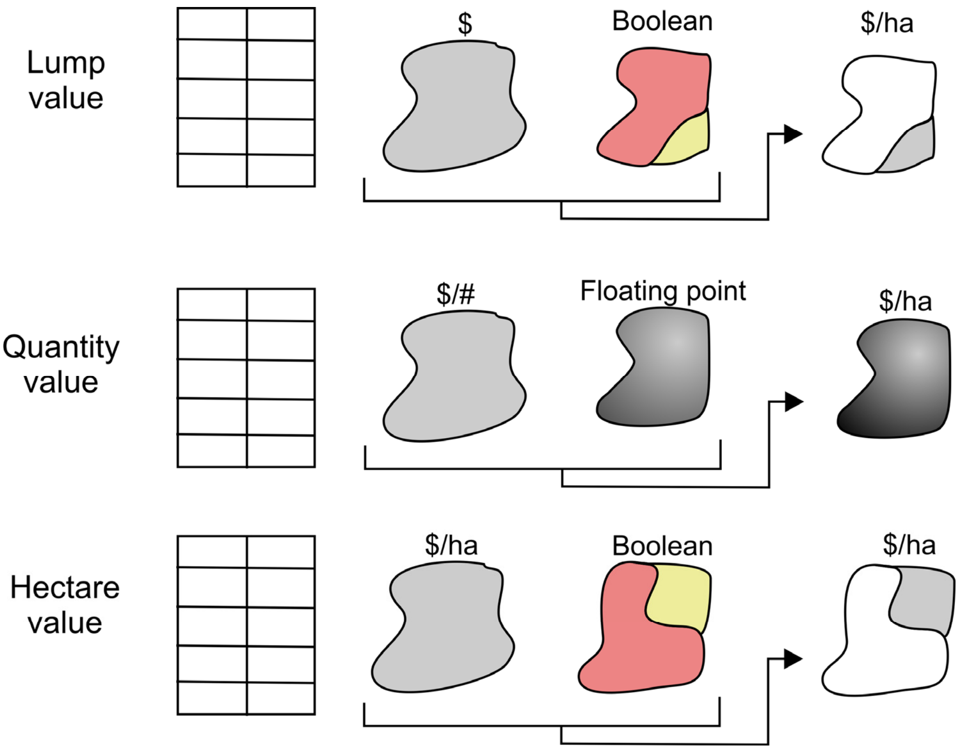


Figure 3.1 Calculation workflow. Each calculation is labeled on the far left. The workflow follows a left-to-right sequence, starting with tabular data and ending with a final value map in dollar per hectare.

The lumped value approach follows three basic steps. First, a table, which was collected externally and prepared for use, gives the ES value in international dollars for each country (Figure 3.1 – column 1) and this is assigned to the whole country (Figure 3.1 – column 2). Second, the values are disaggregated following conditional information where the ES exists inside the country and is known (Figure 3.1 – column 3). Finally, all ES values for the country are assigned to the production area and converted to a unit of international dollars per hectare (Figure 3.1 – column 4).

Table 3.4 Input data and disaggregation approach.

Table	Map	Disaggregation
Fish	Exclusive economic zone	Lump
Sea plants	Exclusive economic zone	Lump
Game	Forests	Lump
Fruit	Agricultural area	Lump
Berries	Agricultural area	Lump
Mushrooms	Agricultural area	Lump
Wood	Forests	Lump
Tourism	Lodging proportion	Quantity
Cultural Value	Protected areas	Quantity
Livestock	Animal count	Quantity
Water	Water demand	Quantity
Wool	Animal proportion	Quantity
Hides	Animal proportion	Quantity
Carbon stock	Biomass	Quantity
Dairy	Animal proportion	Quantity
-	Crops	Quantity
Mangrove	Mangrove area	Hectare
Sea grass	Sea grass area	Hectare
Coral	Coral area	Hectare
Turtles	Turtles area	Hectare

The quantity value approach also follows three basic steps (Figure 3.1). First, a table gives the ES value in dollars per quantity (e.g. per ton animal) and this value is assigned to the whole country. Second, the values are disaggregated by a map that gives for each location (grid cell) the quantity at that location (grid cell), which is spatially variable. Finally, for each grid cell, the quantity is multiplied with the dollar value per hectare, resulting in the ES map (Figure

3.1 - fourth column). This map has the same pattern as the map in the third column.

The value per hectare approach follows three basic steps that are similar to the lumped value approach (Figure 3.1). First, a table gives for each country the value of an ES (if it exists in an area) in $/ha (where it exists). This value assignment is used for the whole country (Figure 3.1 - second column). Second, a map shows where the ES actually exists. Finally, the ES service is assigned only in this area (in $/ha) and in the remaining area it is zero (Figure 3.1 - fourth column).

3.4. Double-counted data

As part of the methodology, the ecosystem services must be evaluated for double-counting (Table 3.1). Double-counted services are those ecosystem services that may be included in other calculations either directly or indirectly. In order to avoid an overestimation of the assessment, these services are excluded from the calculation. There are six services considered double-counted and therefore excluded from the assessment.

3.4.1. Provisioning Services

There are no double-counted services in the Provisioning Services category.

3.4.2. Regulating Services

In the Regulating Services, Water Flow Regulation, Maintenance of Soil Fertility, Pollination, Erosion Prevention, and Biological Control services have double-counted subservices: Drainage, River Discharge, Natural Irrigation, Drought Mitigation, Aquifer Recharge, and Coastal Currents; Maintenance of Soil Structure, Deposition of Nutrients, Soil Formation, and Nutrient Cycling; Pollination of Crops and Pollination of Wild Plants; Erosion Prevention; and Seed Dispersal, respectively. According to Verweij et al.

(2009), a supporting service that allows the existence of other services should not be separately valued or it is double-counting.

3.4.3. Habitat Services

There is only one ecosystem service in the Habitat Services category that has double-counting: Life-cycle Maintenance.

3.4.3.1. Life-cycle Maintenance Service

The service Life-cycle Maintenance contains the Gene Pool Protection subservice. This ecosystem subservice is a supporting service and seems to rely on biodiversity (Hattam et al., 2015). Biodiversity should not be calculated separately because other services rely on its existence (Verweij et al., 2009).

3.4.4. Cultural Services

There are no double-counted services in the Cultural Services category.

3.5. Incompatible data

This section goes through those subservices that are considered conceptually incompatible with the proposed framework or are not sufficiently defined in order to be calculated and consists of 25 subservices total (Table 3.1).

Under all ecosystem services categories and several services, van der Ploeg et al. (2010) suggest a subservice called Other or General (14 occurrences). It is unclear what this subservice represents and is therefore not considered.

3.5.1. Provisioning Services

Aside from the Other or General subservices, all Provisioning subservices are considered compatible.

3.5.2. Regulating Services

Within the Regulating category, there are ten incompatible subservices.

3.5.2.1. Air Quality Service

Under the Air Quality Service, Air Quality Regulation is considered conceptually incompatible because it is a disservice. Van der Ploeg et al. (2010) and Hattam et al. (2015) proposed it. Costanza et al. (1997) and van der Ploeg et al. (2010) propose the UVB Protection subservice of the same service but it is excluded because it is unclear what is required to valuate it.

3.5.2.2. Climate Regulation Service

The Climate Regulation Service contains the Gas Regulation and Microclimate Regulation subservices. These are considered disservices and are excluded. The Gas Regulation subservice can be found in all of the proposed ES assessments but it focuses on gas emissions. Methanogenesis could be calculated but the value is so small ($0.03 per hectare (Costanza et al., 1997)), it is insignificant on a global scale of millions of dollars per hectare. Of the five incorporated publications, only van der Ploeg et al. (2010) propose Microclimate Regulation.

3.5.2.3. Moderation of Extreme Events Service

The Tsunami Subservice is considered conceptually incompatible because tsunamis are not preventable and structures which would need to be large enough to mitigate or lessen destruction would likely be manmade and therefore, not an ecosystem service.

3.5.2.4. Waste Treatment and Water Purification Service

The Waste Treatment and Water Purification Service description provided in literature indicates that this ecosystem service is a disservice and calculations tend to focus on clean-up costs (e.g. Hattam et al., 2015). The service contains the Water Purification and Soil Detoxification subservices, as well as the Abatement of Noise subservice, which is not clear what it entails.

3.5.2.5. Biological Control Service

Under the Biological Control Service, the Pest Control subservice is excluded because literature indicates that this is a disservice and tends to focus on clean-up costs (Hattam et al., 2015). The Population Dynamics subservice is excluded because it is not clear what it includes.

3.5.3. Habitat Services

All Habitat Services are previously addressed.

3.5.4. Cultural Services

Under the Cultural Services category, other than the General subservices, only one service and its subservice are considered incompatible.

3.5.4.1. Cultural Diversity Service

The Diversity subservice of the Cultural Diversity Service is considered incompatible with the ES assessment because it is unclear what exactly it represents or how to calculate the value of ethnic communities (Hattam et al., 2015; Kettunen et al., 2012). The value may come from any number of combinations of: handcrafts produced, tourism visits, or education about the lifestyle of indigenous people; or the value of the land where indigenous or ethnic communities reside on protected land. However, this subservice, more than any other, seems to rely heavily on humans and human activity. If humans will be considered a part of the ES, then the ES assessment needs to be rewritten to reflect that.

3.6. Data included elsewhere

Five subservices were specifically included in another subservice. The five subservices are Irrigation, Fertilizers, Biomass Fuels, and Hay Fodder and Forage. The five subservices included elsewhere are in the Provisioning Services category and are under the Water Supply or Raw Materials services. These five subservices are included in the Food Service. The FAO food production values are "farm-gate" prices and include all production costs (FAO, 2015) and the GAEZ database includes all crops which may be used for fuels or hays (FAO and International Institute for Applied Systems Analysis, 2012). The separate value of the five subservices cannot be determined because it would involve too many assumptions in separating the values from the Food Service. However, it is known that the values of these five subservices are included in the final value.

3.7. Missing data

This section specifies those subservices that could be calculated, but data is missing. Thus, in Table 3.1, these subservices say "calculation possible". This category consists of 36 subservices (Table 3.1). Therefore, the ES assessment is undervalued by approximately 20-22% based on previous studies (Costanza et al., 2014; de Groot et al., 2012) that provided values for the subservices that this study was unable to quantify. The ES assessment could be improved considerably if all of the missing data were available on a global scale. In general, the missing subservices could be calculated using lump value disaggregation if the production in million international dollars and the production area in hectares are known.

3.7.1. Provisioning Services

The Provisioning Services category has five services that are missing data. They are the Food, Raw Materials, Genetic Resources, Medical Resources, and Ornamental services.

3.7.1.1. Food Service

In the Provisioning Services category, the Food service contains two subservices that lack data for complete calculation. The Reindeer Subservice has reindeer herding sizes and associated provinces for Norway via the Statistics Bureau of Norway, but lacks production values; reindeer production values are available for Finland via the Reindeer Herders' Association but lacks statistics on herding areas. The Non-timber Forest Product Subservice does not have production value statistics.

3.7.1.2. Raw Materials Service

In the Raw Materials Service, five subservices are lacking data. Non-industrial Aggregates (sand, rock, gravel, coral) and Salt subservices lack naturally harvested areas and production values. Algae (non-food) Subservice is not differentiated in the FAO aquaculture statistics (FAO, 2013) and it is unknown if it is included already. The Bioenergy Subservice lacks production statistics and areas for hydroelectricity or solar energy. The Down Fiber Subservice lacks information regarding production values and areas.

3.7.1.3. Genetic Resources Service

The Genetic Resources Service lacks information to calculate the Plant and Animal Subservices. It is unclear what data is required and how to value the service. Literature lists the indicators or proxies for these subservices as species for potential use or based on biodiversity (Hattam et al., 2015; Kettunen et al., 2012).

3.7.1.4. Medical Resources Service

Under Medical Resources Service, all of the subservices lack data. Biochemicals, Models, Test Organisms, Bioprospecting, and Cosmetics subservices lack clear indications of how to value the subservice and what data is required for such an evaluation. The Natural Medicinal Products and Natural Food Supplements subservices, however, are not differentiated in the Food Service. It is conceivable that items in Food (e.g. berries) are also considered Natural Medicinal Products or Natural Food Supplements; however, this is only conjecture, and it is assumed these subservices are not calculated elsewhere.

3.7.1.5. Ornamental Service

The Ornamental Service is composed of Dyes/Colorants, Decorative Plants, Jewelry, Decorations/Handicrafts, and Pets/Captive Animals. No data is available for these subservices in terms of harvest area, items, or values.

3.7.2. Regulating Services

Within the Regulating Services category, four services lack data to make a final calculation. Under the Air Quality Service, Capturing Fine Dust Subservice particularly lacks the proper function to combine data. Capturing Fine Dust should use PM10 data (van Oudenhoven et al., 2012) but these are not readily available. PM2.5 concentrations were mapped (van Donkelaar et al., 2015) and could be used as a proxy indicator but would not reflect the entire range of particulate matter. A function that intersects the PM10 concentration and a scale based on land cover type hierarchy (van Oudenhoven et al., 2012) needs to be established. A hierarchy can be postulated stating that the fine dust capture capacity depends on the land cover, land use, and woodiness of the plants (van Oudenhoven et al., 2012); therefore, forests and woody elements have the highest capacity. The capture capacity of the land cover also depends on the distance to the emission site; intersecting the mapped concentrations with the land cover should address this concept. Using LADA LUS (Nachtergaele and Petri, 2008), grade the different land cover and land uses types for the greatest potential capture capacity. Finally, a valuation for different biomes or land covers is required.

3.7.2.1. Climate Regulation Service

In the Climate Regulation Service, the Carbon Sequestration Subservice is lacking data for an accurate calculation. In order to calculate the carbon sequestration subservice with a land change, a land cover map at the beginning and end of the time-period (i.e. January and December 2005) would be required. InVEST (Natural Capital Project, 2016) is a model that combines land use/land cover maps from the current and future state, current carbon pool tables, current and future harvest maps, and a carbon price for a valuation of the carbon sequestration. There are not land use/land cover maps of the globe from the start and beginning of the year or on an annual basis. Harvest maps are also unavailable. Carbon pool tables could be calculated from Ruesch and Gibbs (2008) who produced biomass maps following IPCC 2006 guidelines (Task Force on National Greenhouse Gas Inventories et al., 2006). Carbon prices are obtainable from various sources (Tol, 2009; van der Ploeg and de Groot, 2010).

3.7.2.2. Moderation of Extreme Events Service

The Moderation of Extreme Events Service contains four subservices that lack information. The Fire Prevention Subservice requires a function that relates inland waters to land coverage and a function that relates humidity of forest areas with risk areas. This data could likely be obtained from FAO and NOAA. The Avalanche, Flood, and Mud Flow mitigation/prevention subservices require an intersection of the vegetation coverage with risk areas. Risk areas could likely be procured from nature conservancy groups or geologic research groups. The subservices would also require a valuation method as part of the function.

3.7.2.3. Biological Control Service

Under the Biological Control Service, the Disease Control and Resilience through the Food Web subservices lack data such as the extent of populations or habitat areas where disease and overpopulation, for example, are maintained by predators or other controlling species.

3.7.3. Habitat Services

The Habitat Services category does not have any services with missing data.

3.7.4. Cultural Services

Under the Cultural Services category, five services lack data that differentiate the ecosystem service areas from the Potential Tourism Subservice and the other services. The Aesthetic service contains the Attractive Sea/Landscapes subservice; the Inspiration service contains Artistic and Cultural Use subservices; the Spiritual service contains the Spiritual/Religious subservice; the Cognitive Development service contains the Research/Science and Education subservices; and the Mental Health and Well-Being Service contains the Reduction of Stress Subservice.

3.8. Available and used data

This section describes the 19 subservices that were used in the spatially distributed, global ES assessment (Table 3.2, 3.3). The script used for the modeling is available upon request.

3.8.1. Provisioning Services

The Provisioning Services are those services that provide products obtainable from the ecosystem (Millennium Ecosystem Assessment, 2003). Under the Provisioning Services category, there are three services: Food, Water Supply, and Raw Materials.

3.8.1.1. Food Service

The Food Ecosystem Service consists of nine subservices: Fish, Sea Plants and Vegetables, Livestock, Game, Dairy Production, Crops and Cereals, Fruit Orchards, Berries, and Mushrooms.

Fish Subservice

The Fish Subservice is a combination of the previously-proposed Wild and Farmed Fish and Freshwater Fish subservices. It is listed as one subservice in this ES assessment because production values do not differentiate between wild and farmed fish versus freshwater fish. This subservice was calculated following lump value disaggregation, where the fish production value for each country from FAO (2013) is disaggregated over the area of each country's marine economic zone (hectares) from VLIZ (2012). A source of uncertainty is that the fish production may not extend the entire marine economic zone thus disaggregating the production value over a larger area than where the fish are produced which may lead to lower-than-actual values per hectare in areas where there is higher fish production. The method also does not account for freshwater locations inland, as the proportion of freshwater to salt-water fishing is not specified.

Sea Plants and Sea Vegetables Subservice

The Sea Plants and Sea Vegetables Subservice follows the lump value disaggregation, where the plant aquaculture production value for each country from FAO (2013) is disaggregated over the area of each country's marine economic zone (hectares) from VLIZ (2012). A source of uncertainty is that the area of aquaculture production may not extend the entire marine economic zone, thus producing areas of lower/higher-than-actual production. The method does not account for freshwater locations inland, as the production value is not specified in this way.

Livestock Subservice

The Livestock Subservice follows value per quantity disaggregation for six indicators: buffalo, cattle, goat, pig, poultry, and sheep. The livestock production value is per live-weight ton (FAO, 2015) and varies by country; the animal population is in number per hectare (FAO, 2014); the average live-weight tonne per animal type was used as a conversion factor to disaggregate the values over the animal population. Each animal type is calculated separately. Two possible sources of uncertainty are the animal distribution as the animal density does not differentiate between those animals raised for dairy purposes versus meat purposes and the entire population was used for the calculations; and the average weight of the animals may skew the distribution of valuation. For example, the input map with poultry density does not differentiate between different bird types (e.g. geese, duck, turkey, or chicken). The average weight of chicken was used for the valuation.

Game Subservice

The calculation of the Game Subservice follows lump value disaggregation, where the game production (FAO, 2015), which varies by country, is disaggregated over the hunting area that is based on land cover types forests and grasslands (Nachtergaele and Petri, 2008). Sources of uncertainty are the assumption that game refers to hunting wild animals and birds as opposed to animals that are cultivated for that purpose, and the area is limited to non-protected forests and grasslands. However, not all of the area may be appropriate or legal for hunting purposes.

Dairy Subservice

The Dairy Production Subservice has three indicators: cattle, goat, and sheep milk. The subservice is calculated by evaluating each indicator separately following value per quantity disaggregation. The dairy production value (FAO, 2015) varies by country and is disaggregated over the population proportion calculated from animal density (FAO, 2014). A possible source of uncertainty is that not all of the animals are used for dairy production.

Crops and Cereals Subservice

The Crops and Cereals Subservice valuation map (FAO and International Institute for Applied Systems Analysis, 2012) includes both traditionally and organically farmed wheat, rice, maize, sorghum, millet, tuber crops, cassava and other roots, sugar beet, sugarcane, pulses, soybean, rape seed, sunflower, groundnut, oil palm, olive, and cotton. The data is provided already spatially disaggregated based on suitability of growth using rainfall, irrigation, and land agronomic capabilities. The values only need to be converted to million international dollars per hectare as they were provided in thousand international dollars per hectare. Uncertainties are described in the original data release (Fischer et al., 2008).

Fruit Subservice

The Fruit Orchards Subservice contains both traditionally and organically farmed apples, apricots, bananas, cherries, sour cherries, coconuts, figs, citrus fruits, grapefruits, grapes, kiwis, lemons and limes, melons, mangoes, oranges, papayas, peaches, pears, persimmons, pineapples, plantains, plums, quince, tangerines, watermelons, and fruits, pomes, stone fruits, and tropical fruits not specified elsewhere. The country-specific values (FAO, 2015) are spatially disaggregated over agricultural land use (Nachtergaele and Petri, 2008) as possible locations of orchards (lump value disaggregation). The orchard locations do not actually coincide with the full agricultural land use coverage but there are no other available limiting data.

Berry Subservice

The Berry Subservice includes both cultivated and non-cultivated production of blueberries, cranberries, currants, gooseberries, raspberries, strawberries, and berries not specified elsewhere. Because the subservice is for both cultivated and non-cultivated berries, any place where plants grow is considered an applicable disaggregation area (lump value disaggregation). Country-specific production values (FAO, 2015) and land cover (Nachtergaele and Petri, 2008) are used. A source of uncertainty is that berries do not grow equally over all arable surfaces.

Mushroom Subservice

The Mushroom Subservice follows the same valuation methodology of the Berry Subservice because country-specific production values (FAO, 2015) do not differentiate between wild and farmed mushrooms (lump value disaggregation). A cursory search shows that mushrooms can grow in a variety of environments, including the desert; therefore, the subservice is spatially disaggregated over all land cover/land use (Nachtergaele and Petri, 2008) except for urban, wetland, bare, sparse, or water areas. A source of uncertainty in the calculation is that mushrooms do not grow equally over all environments.

3.8.1.2. Water Supply Service

The Water Supply Service is made of two subservices: Industrial Use and Drinking Water. Both subservices follow the same valuation method of value per quantity disaggregation. The water value (NUS Consulting Group, 2006) is not available for all countries, so a global average was applied where the value was not defined. The water value is the amount charged to customers in million international dollars per cubic meter; the demand of water is in mm per day as calculated with a global hydrological and water resources model (Wada et al., 2011); a conversion from mm to cubic meter per hectare per year was applied. A possible source of uncertainty is the water value as it is not available for all countries. The Drinking Water subservice is actually calculated from domestic water demand and may include other purposes than human physical consumption (e.g. water used for gardens), thus this service may be overvalued.

3.8.1.3. Raw Materials Service

The Raw Materials Service is composed of the Non-food Forest Products, Wool Fiber, and Hide Fiber subservices.

Non-food Forest Product Subservice

The Non-food Forest Product Subservice is a combination of three subservices: timber and fiber for pulp production, sustainable timber production, and wood for fuel. Costanza et al. (1997) and van der Ploeg et al. (2010) propose one subservice of timber production rather than the differentiation made by Kettunen et al. (2012). These subservices were combined because FAO (2015) only reports total wood, which includes all timber products. The country-specific values were disaggregated over non-protected forest areas, which include virgin forests and forests with agricultural activities from the forest land cover (Nachtergaele and Petri, 2008). The method of disaggregation may not properly reflect where timber is actually produced, e.g. virgin forests; areas may reflect a subservice valuation where timber production does not exist. Additionally, timber production values were not available; therefore, timber export values were used instead.

Fiber subservices

The Wool Fiber and Hide Fiber subservices both follow the same valuation and disaggregation procedure of value per quantity. For the Wool Fiber, the country-specific production value per tonne of wool (FAO, 2015) is disaggregated over the population proportion of sheep from the animal density map (FAO, 2014); a global constant is used to finalize the calculation using the average weight of wool in tonnes per sheep. Possible sources of uncertainty are that the wool weight is either above or below actual produced wool weight due to a global constant and that the entire sheep population is used for wool fiber rather than a differentiation between fiber, dairy, and meat purposes.

The Hides Fiber Subservice includes hides produced from buffalo, cattle, goat, and sheep. Each hide type is calculated separately. The country-specific tonnes of hides produced (FAO, 2015) is multiplied by a single global production value in million international dollars per tonne of hides (SADC Trade Organization, 2014). This value is disaggregated over the population proportion of the animal calculated from animal density (FAO, 2014). Possible sources of uncertainty for the Hide Fiber Subservice are that the entire animal populations are used for hide fiber rather than a differentiation between fiber, dairy, and meat purposes and the production price used does not vary globally or by hide type.

3.8.2. Regulating Services

The Regulating Services category is composed of those services that provide benefits from regulating ecosystem processes (Millennium Ecosystem Assessment, 2003). There are two services included in the calculation: Climate Regulation and Moderation of Extreme Events.

3.8.2.1. Climate Regulation Service

The Climate Regulation Service contains one subservice: Carbon Storage.

Carbon Storage Subservice

The Carbon Storage Subservice is the summation of the biomass carbon and soil organic carbon. In each case, the carbon is in tonnes per hectare and multiplied by a value in dollars per tonne C (value per quantity disaggregation). This study used the data from Ruesch and Gibbs (2008) who calculated the Tier 1 biomass carbon in tonnes C based on the IPCC 2006 guidelines (Task Force on National Greenhouse Gas Inventories et al., 2006) on biomass in agriculture. It includes living above and below ground biomass. Soil organic carbon (Hiederer and Köchy, 2012) are not specified as to Tier 1 or not, but follow IPCC 2006 guidelines (Task Force on National Greenhouse Gas Inventories et al., 2006). Carbon prices are obtainable from various sources (e.g. Tol, 2009; van der Ploeg and de Groot, 2010) and vary widely depending on the kind of valuation method. The social value of carbon should be used because this is the expected damage value if the carbon is released (Natural Capital Project, 2016). The value per tonne C used in this assessment is from Tol (2009) and is the mode of all prices from a weighted, fitted distribution of social costs of carbon ($41). Possible uncertainties are those already noted by Ruesch and Gibbs (2008) such as the lack of field-verified measures and from the value of carbon due to the variation in pricing methodology.

3.8.2.2. Moderation of Extreme Events Service

The Moderation of Extreme Events contains one subservice: Storm Protection.

Storm Protection Subservice

The Storm Protection subservice is calculated using two indicators: mangroves and seagrass. These two plant species help create a natural coastline preservation system. Mangrove and seagrass coverage are from Spalding et al. (1997) and UNEP-WCMC and Short (2003), respectively; while the values in dollars per hectare are from Costanza et al. (1997) and adjusted for inflation. There is one global value for mangroves and one global value for seagrass. Each indicator is calculated separately following value per hectare disaggregation. The possible sources of uncertainty are the value because it is a single global value and the incomplete coverage for the service.

3.8.3. Habitat Services

The Habitat Services category contains those services that directly benefit the continuation of species (van der Ploeg et al., 2010). The only service calculated is Life-cycle Maintenance.

3.8.3.1. Life-cycle Maintenance Service

The Life-cycle Maintenance Service contains the Nursery and Refugia subservices. These subservices were combined because habitats may overlap between nursery and refuge sites.

Nursery and Refugia Subservice

The Nursery and Refugia Subservice includes only marine and coastal environments, but this is due only to a lack of information than a conceptual methodological decision. Three indicators are calculated separately: warm corals, cold corals, and turtle nesting sites. The calculation follows value per hectare disaggregation. The values in dollars per hectare are from Costanza et al. (1997) for corals and van der Ploeg and de Groot (2010) for turtle nesting sites; these values are global values. The area for disaggregation are the turtle nesting sites (Freiwald et al., 2005) and cold and warm corals (UNEP-WCMC, 1999; UNEP-WCMC et al., 2010). The possible sources of uncertainty are the values because they are global values and do not vary by country and the incomplete coverage for the service.

3.8.4. Cultural Services

The Cultural Services category provides nonmaterial benefits from the ecosystem (Millennium Ecosystem Assessment, 2003). This category contains two services: Recreation and Tourism and Cultural Heritage.

3.8.4.1. Recreation and Tourism Service

The Recreation and Tourism Service in this chapter combines four subservices (Recreation, Tourism, Ecotourism, and Hunting and Fishing) into one subservice: Potential Tourism. This is because of a lack of data to differentiate tourism dollars spent between different types of tourism.

Potential Tourism Subservice

Calculating the Potential Tourism Subservice follows the value per quantity disaggregation. The World Bank (2014) provides statistics on international dollars spent within a country, but does not include domestic tourism dollars or break down how or where the money is spent. The OpenStreetMap database (Geofabrik GmbH Karlsruhe, 2016) provides point data for lodging types facilitating a method to disaggregate tourism dollars. By assigning an average number of beds to each lodging type, a potential tourism proportion map was created. The number of beds attributed to each lodging type is alpine hut - 4; campsite - 30; caravan site - 60; chalet - 8; guesthouse - 3; hostel - 100; hotel - 250; motel - 150; and hotel/campsite – 50. Not all countries are represented by either the World Bank or OpenStreetMap. Two possible sources of uncertainty are the international expenditures, which creates an undervaluation of the service because of a lack of domestic dollars and the number of beds for each lodging type.

3.8.4.2. Cultural Heritage Service

The Cultural Heritage Service contains the Social and Cultural Values Subservice.

Social and Cultural Values Subservice

The Social and Cultural Values Subservice follows the value per hectare disaggregation for onshore and offshore values. The onshore value is the global median of onshore, general Cultural Heritage benefit transfer values from van der Ploeg and de Groot (2010). The onshore area is the union of GAEZ protected areas (FAO and International Institute for Applied Systems Analysis, 2012) with the UNESCO World Heritage sites (IUCN and UNEP-WCMC, 2013). The protected areas may include manmade sites. The offshore value is calculated using the marine economic zone and the marine, general Cultural Heritage benefit transfer value from van der Ploeg and de Groot (2010). The offshore and onshore values are combined for a global map. The calculation could be improved by using more spatially varied values; the value for this service is likely undervalued in some areas and overvalued in others due to a constant global value. Additionally, limiting the sites to those that are naturally occurring would represent a more "natural" service value.

3.9. Results

The total ES assessment and ES categories values were mapped (Figures 2.1-2.5). The 8 services which make up the categories were also mapped (Figures 3.2-3.9). Table 3.5 summarizes the total values of each ES.

The Food Service, under the Provisioning Services, totals 1.9 x 10^{13} and accounts for 99.8% of the total global ES value (Figure 3.2). The Food Service values are largely based on statistics from the FAO, which are reported or calculated for all countries (FAO, 2015). The Dairy Subservice is the largest influence on the output due to the cow milk top producers of USA, India, and Russia, which produce 2.5 x 10^{10}, 1.2 x 10^{10}, 9.6 x 10^{9} international dollars, respectively (FAO, 2015). These findings are significant because they indicate that transitions between KGCC will greatly influence the Food Service; however, it is not known from these results if this actually indicates a possible food shortage.

Table 3.5 Ecosystem services total mapped values.

Ecosystem category or service	Total mapped value (international dollars)	Percentage of total services
Provisioning Services	1.94E+13	99.8%
Food	*1.77E+13*	*91.0%*
Raw Materials	*1.71E+12*	*8.8%*
Water Supply	*5.33E+04*	*0.1%*
Regulating Services	1.03E+10	0.1%
Climate Regulation	*1.03E+10*	*0.1%*
Moderation of Extreme Events	*1.36E+07*	*~0.0%*
Habitat Services	7.47E+06	*~0.0%*
Life-cycle Maintenance	*7.47E+06*	*~0.0%*
Cultural Services	1.02E+08	*~0.0%*
Potential Tourism	*1.08E+05*	*~0.0%*
Cultural Heritage	*1.02E+08*	*~0.0%*

The Raw Materials service is the second largest contributor to the ES total values, accounting for 8.8% (Figure 3.3). The Hides Subservice is the greatest contributor to the Raw Materials service. It includes several hide types. The value, however, is likely overvalued as a constant global value was used for all hide types for every country.

The Water Supply Service (Figure 3.4) accounts for only 0.1% of the total global ES value. Given the importance of water, the known shortages of water due to drought, and the lack of access to clean water globally, this service is undervalued. The subservices, Domestic Water and Industrial Water, use global prices for the majority of the countries.

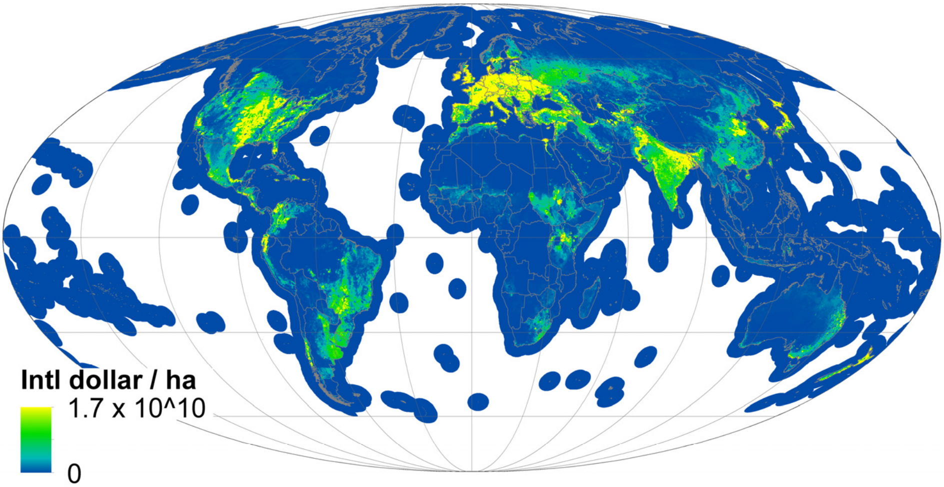


Figure 3.2 Global ecosystem service assessment: Food Service. White areas are outside the exclusive economic zone.

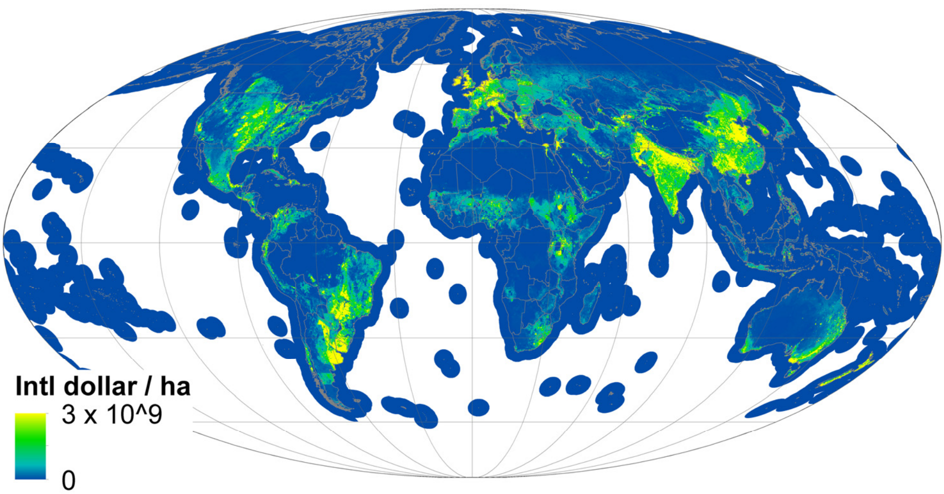


Figure 3.3 Global ecosystem service assessment: Raw Materials Service. White areas are outside the exclusive economic zone.

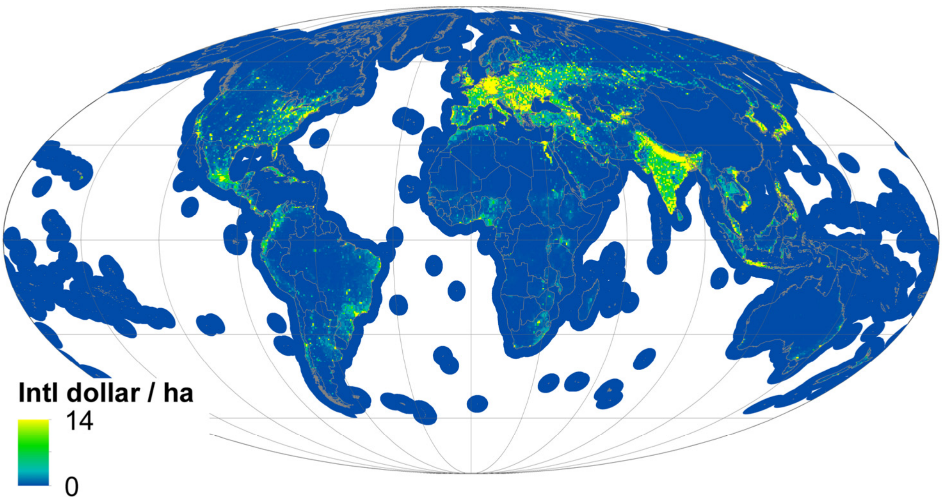


Figure 3.4 Global ecosystem service assessment: Water Supply Service. White areas are outside the exclusive economic zone.

The value of the Climate Regulation Service (1.0 x 10^{10} international dollars) represents nearly 99% of the Regulating Services category value, but only 0.1% of the total global value. High values for climate regulation correspond to tropical forests (e.g. the Amazon), where the carbon stock (i.e. Tier 1 biomass) is high, and higher latitudes (e.g. northern Canada) where the soil carbon is high (Figure 3.5). The high values reflect the high cost to society if the carbon were to be released due to deforestation or land cover change. The Climate Regulation Service value calculated in this study is on the lower end of the spectrum, because the mode of all prices from a weighted, fitted distribution of social costs of carbon values, 41 international dollars per tonne of carbon, was applied; whereas the mean is 151 international dollars per tonne of carbon (Tol, 2009). Carbon prices are obtainable from various sources (Tol, 2009; van der Ploeg and de Groot 2010) and vary widely depending on the kind of valuation method. When calculating the value of carbon, the social value of carbon should be used because this is the expected damage value if the carbon is released; additionally market prices relate to carbon sequestration and not carbon storage (Natural Capital Project, 2016).

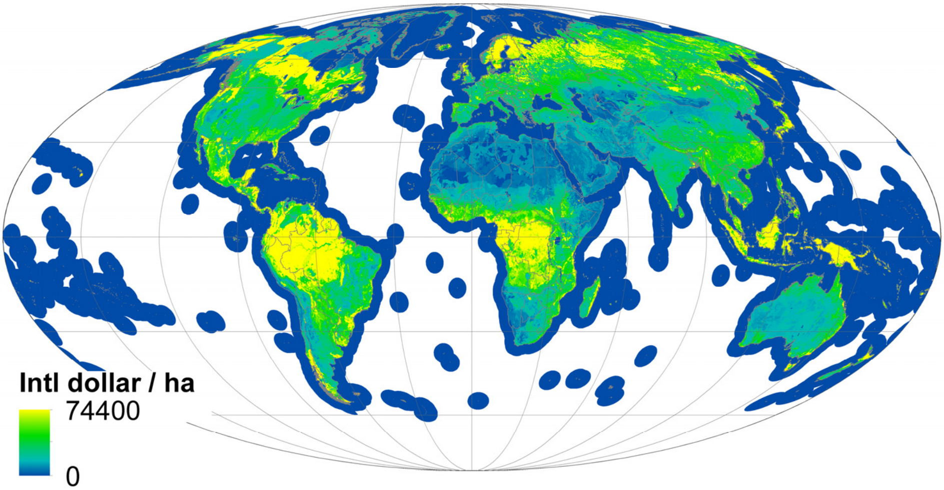


Figure 3.5 Global ecosystem service assessment: Climate Regulation Service. White areas are outside the exclusive economic zone.

The Moderation of Extreme Events Service is negligible in terms of the total global values. However, more data would certainly help to increase the value of this service (Figure 3.6). Areas with high values are in coastal areas where mangroves and seagrass are present. High concentrations are found in Nigeria, while several countries have smaller areas of high value along their coastlines (e.g. Venezuela, Guyana, Mexico, Australia, Indonesia, and Papua New Guinea).

The Life-cycle Maintenance Service is 100% of the Habitat Services because it is the only service valued in the category. However, the ES value is negligible in terms of the total global values. High value areas coincide with mapped coral and turtle nesting areas. The areas are concentrated in the Caribbean and Gulf of Mexico, the UK-Scandinavia area, the Pacific Ocean coastlines, and to a lesser degree in the Red Sea and Indian Ocean (Figure 3.7).

The Potential Tourism Service of the Cultural Services is negligible in terms of the global ES values and has little contribution to the services category. The

Potential Tourism Service map shows little spatial variation with some highly concentrated areas in Europe (Belgium and Switzerland; Figure 3.8).

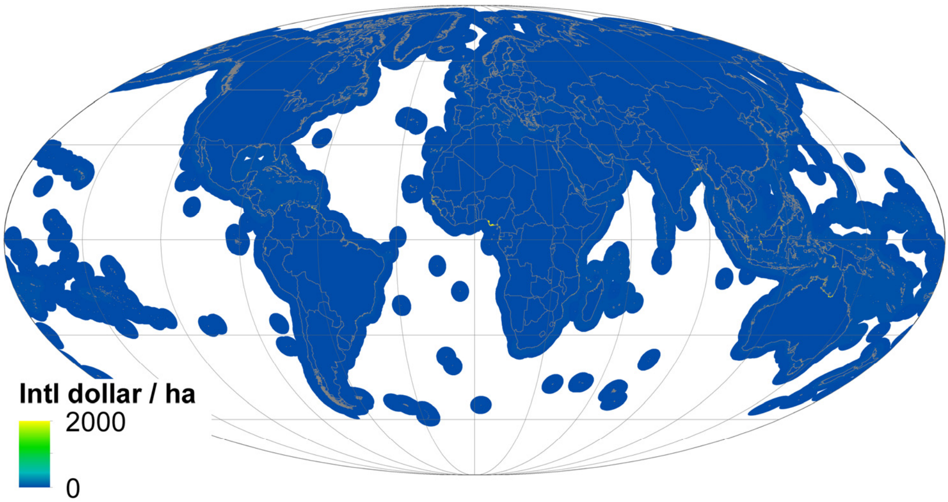


Figure 3.6 Global ecosystem service assessment: Moderation of Extreme Events Service. White areas are outside the exclusive economic zone.

Figure 3.7 Global ecosystem service assessment: Life-cycle Maintenance Service. White areas are outside the exclusive economic zone.

Figure 3.8 Global ecosystem service assessment: Potential Tourism Service. White areas are outside the exclusive economic zone.

The Cultural Heritage Service of the Cultural Services are negligible in terms of the global ES values. The Cultural Heritage Service is almost 100% of the Cultural Services total value. The Cultural Heritage Service has 3 main classes of values: offshore, protected areas, and no values (Figure 3.9).

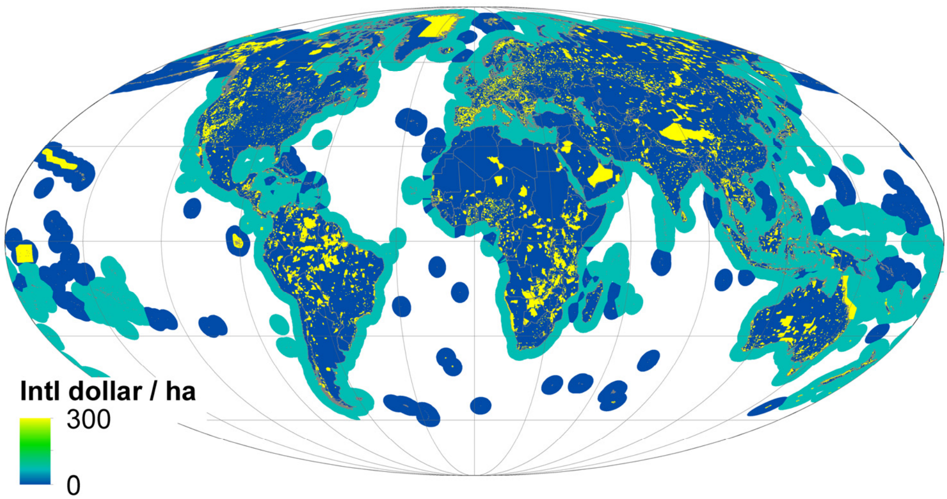


Figure 3.9 Global ecosystem service assessment: Cultural Heritage Service. White areas are outside the exclusive economic zone.

3.10. Model Verification

Making a comparison of other ES assessments in order to check the ES values must be conducted with care because this ES assessment uses production values and in only few cases global values. Many ES assessments use proxies to provide values for the services (Schägner et al., 2013). Furthermore, this ES assessment excludes 31 services due to double-counting and conceptual incompatibility. Thereby, the total number of compatible services is 77, of which the ES assessment here accounts for >25% of the services. Thirty-six services were not included because of missing data. By making an estimate of the total value of the services missing data in this study but valued in previous studies (Costanza et al., 2014; de Groot et al., 2012) (i.e. the 36 services), this ES assessment is estimated to be undervalued by 20-22% or approximately 3.8×10^{12} international dollars.

A comparison of the disaggregated values and the original reported production values shows that the summations are the same for similar significant digits (Table 3.6).

Table 3.6 Ecosystem service value check for a selection of services.

Category	Ecosystem service	Subservice	Sum from original statistics	Sum from spatial disaggregation
Provisioning services	Food	fish	8.7×10^8	8.7×10^8
		sea plants/vegetables	7.4×10^7	7.4×10^7
		game	7.2×10^7	7.2×10^7
		fruit orchards (ex. apples)	1.4×10^9	1.4×10^9
		berries (ex. strawberries)	2.1×10^8	2.1×10^8
		mushrooms	6.7×10^8	6.7×10^8
	Raw materials	non-food forest products	7.3×10^9	7.3×10^9

3.11. Discussion

Sources of uncertainty in the final valuation of the ES assessment (Table 3.3) may be classified into three categories, in addition to rasterization errors. They are originating from the published data sets, which may or may not be described; our modeling choices could use false assumptions regarding disaggregation; and constants do not represent the global spatial variation. Uncertainties are discussed with the data; however, they are not quantified in the assessment.

While the services calculated in this chapter are as complete as the data allows, several services are not accurate (e.g. Water Supply). This inaccuracy is due to the limited amount of data available rather than a systematic or probabilistic error. More data is required, therefore, in order to properly assess all of the services or to use the assessment for recommendations. Despite that weakness, this ES assessment provides a fairly complete preview of the ES values around the world.

3.12. Conclusions

Nineteen ESs were mapped globally from the four ES categories (Provisioning, Regulating, Habitat, and Cultural) and valued in monetary units (international dollar). The services were compiled from five studies (Costanza et al., 1997; van der Ploeg et al., 2010; Kettunen et al., 2012; Böhnke-Henrichs et al., 2013; Hattam et al., 2015) as no universally accepted list of ecosystem services and subservices existed. This is the first time that an ES assessment includes the full methodology applied including calculations and data sources. Based on these publications (Costanza et al., 1997; van der Ploeg et al., 2010; Kettunen et al., 2012; Böhnke-Henrichs et al., 2013; Hattam et al., 2015), a comprehensive list of ecosystem subservices was created and categorized based on inclusion in the ES assessment and if the subservice is calculable or not.

A spatially distributed ES assessment can assist in decision-making for governments in different applications. Examples are hazard assessments both for geologic and waste, urban planning and development, ecological risk, climate change, and a myriad of other studies that require an economical valuation of the environment in order to base decisions.

Future research should aim to value the missing services and quantify the uncertainty in the data.

Chapter 4

Geographic information system–based fuzzy-logic analysis for petroleum exploration with a case study of northern South America

This chapter is based on Bingham, L., R. Zurita-Milla, and A. Escalona, 2012, Geographic information system–based fuzzy-logic analysis for petroleum exploration with a case study of northern South America, AAPG Bulletin, v. 96, no. 11, pp. 2121-2142.*
**Now L. Watson.*

4.1. Introduction

The petroleum industry has increasingly incorporated geographic information system (GIS) software packages for mapping needs and database queries (Coburn and Yarus, 2000) because of its capabilities in elucidating the relationships between geological, geophysical, and topographical data inherent in the petroleum exploration process. Geographic information science (GIS) supports geoscientists who typically use many different concepts, tools, and software packages by helping them to make decisions for exploration in an organized repeatable, and data managed way, as geoscientists often work with heterogeneous (e.g. different coordinate systems or different data models) geologic data. (See Coburn and Yarus, 2000 for applications and the importance of GIS to the petroleum industry.)

Multi-criteria evaluation (MCE) is a subset of multidimensional decision and evaluation models. MCEs are essentially used to evaluate the trade-offs between alternatives with different impacts, or in other words to evaluate the outcome of combining different criteria to fulfill one or more objectives which may possibly be conflicting (Carter, 1991; Heywood et al., 2006). Different MCE methods exist; they use different criterion evaluation and score assignments. All MCE are subjective and yield different results (e.g. Heywood et al., 1995). MCE is not strictly a spatial analytical model, such as the use of analytical hierarchy process (e.g. Saaty, 1987; Andriantiatsaholiniaina et al., 2004). However, the focus of this study is MCE for spatial analysis applied to economic geology (e.g. mineral or petroleum exploration). Voogd (1983), Carver (1991), and Bonham-Carter (1994) have conducted comprehensive and in-depth studies of MCE. Malczewski (2006) provides a recent survey of literature from 1990-2004.

This study aims to create a method for MCE in a spatial environment that can be used for decision-making support in petroleum exploration by integrating data that are spatial or tabular and can be used for analysis of data; the analysis cannot be performed using interpretation software. The study proposes a data evaluation process based on a series of user-defined inputs and criteria used to show geographic areas that may be of interest for further investigation for petroleum exploration. This process differs from existing exploration processes by the incorporation of GIS analysis and combining interpretation data as well as existing petroleum field data with non-native spatial data into a reproducible analysis; the analysis can also be repeated by redefining criteria or updating input data sets. By using the results of the analysis, the geologist can support his or her reasons for requiring more or less investigation in a geographic region for future exploration. The results of the analysis are not meant to pinpoint areas for drilling wells but rather direct the interest for petroleum exploration to a geographic area and even a subsurface interval where further and more intensive investigation can be pursued. The proposed method explains how to select data and decide how influential the data are, so that there is a standard approach, but scalable for different petroleum exploration regions and adaptable depending on available data. A case study focusing on northern South America illustrates the process and outcomes; however, the proposed method is applicable to other areas as well.

4.2. Multi-Criteria Evaluation Methodologies

Table 4.1 lists several MCE publications detailing the method used and the field of application. This table does not intend to be exhaustive but to show a variety of methods and applications. Based on the sampled publications, MCE often concentrate on site evaluation problems relating to (hazardous) waste or industrial or urban planning. There are, however, several papers which relate to economic geology, the topic of interest (indicated by grey shading), which show two main types of MCE methods: Bayesian and fuzzy logic. These two methods are knowledge-driven models, meaning they rely on input from an expert or hard data. Thus, Bayesian and fuzzy logic are the most appropriate MCE for petroleum exploration (Bonham-Carter, 1994).

Table 4.1 Spatial MCE publications.

Source	MCE Method	Application
Bonham-Carter et al. (1988)	binary map analysis and Bayesian methods	mineral exploration
Aminzadeh (1994)	fuzzy logic and evidential reasoning†	petroleum exploration
An et al. (1994)	Bayesian methods (Dempster-Shafer belief theory)	mineral exploration
Wright and Bonham-Carter (1996)	fuzzy logic and Bayesian methods^	mineral exploration
Barredo et al. (2000)	weighted sum and Saaty's analytical hierarchy process	geological hazards
Tangestani and Moore (2002)	Bayesian methods (Dempster-Shafer belief theory)	mineral exploration
Dixon (2005)	fuzzy logic	geological hazards
Tounsi (2005)	fuzzy logic	petroleum exploration*
Gomez-Delgado and Tarantola (2006)	weighted sum and Saaty's analytical hierarchy process	hazardous waste site location
Aydöner and Maktav (2009)	weighted linear overlay	urban planning with respect to geological hazards

†Applied in vertical spatial context of seismic interpretation. ^Methods are not used in combination. *It is unclear from the paper if this is applied in a spatial environment.

The Bayesian method relies on a probability framework in which prior and posterior probabilities for each set of evidence is calculated (Bonham-Carter, 1994). It is appropriate for areas where well-distributed data are available. Bayesian methods are, therefore, not appropriate for areas with sparse data (i.e. frontier areas; Bonham-Carter, 1994). (Interested readers may read more about Bayesian methods in Dempster, 1968; An et al., 1994; and Bonham-Carter, 1994.)

Fuzzy logic uses five operators to combine a series of data sets for a final output map (c.f. Bonham-Carter, 1994). Each data set or criteria and subcriteria are chosen because it is considered important to evaluate the favorability of a location for a specific purpose (e.g. hydrocarbons exploration, building a house, water well drilling). Each data set is composed of data points (or objects or features) which are somewhere on the spectrum from "not favorable" to "most favorable". To each of these data points, fuzzy membership values are assigned, where $0 \leq x \leq 1$ and x is the fuzzy membership value, such that a value of 0 is unacceptable while a value of 1 is the most favorable ideal. Gradations between the two extremes reflect the expert view of either less or more favorable, respectively. After the criteria have been selected and the fuzzy membership values assigned, it is important to create a conceptual model for how these criteria and subcriteria will interact by choosing fuzzy logic operators (FLOs). The FLOs are *and*, *or*, *algebraic product*, *algebraic sum*, and *gamma operation* (Bonham-Carter, 1994). These operators act on a cell-by-cell basis of rasters that overlay each other (Figure 4.1A). The example shown in Figure 4.1 has three maps, each with four cells where the fuzzy membership value has been defined (Figure 4.1B). The graph in Figure 4.1C corresponds to the grid location in the upper left corner of each map (Column 1, Row 1; Figure 4.1). The dashed lines labeled μA, μB, and μC are the input values for each equation (4.1-4.5), corresponding to the upper left cell.

And is the FLO that selects the minimum value between two or more input maps (Equation 4.1).

$$\mu V = MIN(\mu A, \mu B, \mu C, \dots, n) \tag{4.1}$$

where μA is the membership value for Map A, μB is the membership value for Map B, μC is the membership value for Map C, MIN is the minimum value of the map inputs, and μV is the combined map value. In Figure 4.1C, the FLO *and* corresponds to the input value of μA (0.4).

Or is the FLO that selects the maximum value between two or more input maps (Equation 4.2).

$$\mu V = MAX(\mu A, \mu B, \mu C, \dots, n) \tag{4.2}$$

where MAX is the maximum value of the map inputs. In Figure 4.1C, the FLO *or* corresponds to the input value of μC (0.8). The FLOs *and* and *or* only reflect the least and greatest inputs, respectively, for each calculation at each cell location; therefore, these FLOs should be used when the end-member is the decisive factor. However, the other three FLOs use all inputs for each calculation at each cell location.

Algebraic product is a decreasive function that uses all input values. Because the input values are decimal values and the result is the product of those values, the result will always be smaller than the smallest input value (Equation 4.3).

$$\mu V = \prod_{i=1}^{n} \mu_i \tag{4.3}$$

where μ_i is the fuzzy membership function of the i^{th} map and $i=1,2,\dots,n$ maps to be combined. The example in Figure 4.1C has an *algebraic product* of 0.16. This is the smallest result possible for these data values.

Algebraic sum is an increasive function, because the result will always be larger than the largest input. It multiplies the difference between 1 and the map value for all map data sets and then subtracts this product from 1 (Equation 4.4).

$$\mu V = 1 - \prod_{i=1}^{n} (1 - \mu_i) \tag{4.4}$$

In Figure 4.1C, the output of the *algebraic sum* is 0.94, which is the highest possible result for these input values.

The FLO *gamma operation* is used as a compromise between the *algebraic sum* and the *algebraic product*. Choosing an appropriate γ (gamma) will define the outcome of the operation (Equation 4.5).

$$\mu V = (1 - \prod_{i=1}^{n}(1 - \mu_i))^{\gamma} * (\prod_{i=1}^{n}\mu_i)^{(1-\gamma)} \qquad (4.5)$$

where γ is a parameter in the range [0,1]. Figure 4.1C is a graph showing the different gamma values and the resulting fuzzy membership. The minimum value is the *algebraic product* where the gamma value is 0; while the maximum value is the *algebraic sum* where the gamma value is 1. A gamma value (0,1) will result in a value corresponding to a point along the black curve shown in the graph. In the example, gamma values [0,0.52] are decreasive while gamma values [0.91,1.0] are increasive (Figure 4.1C). These zones are found by the intersections of the *gamma operation* with the *and* operation and *or* operation, respectively. All values that result from the *gamma operation*, including the *algebraic product* that are less than the result of the *and* operation, are in the decreasive zone. All values resulting from the *gamma operation* that are greater than *or*, including the result of the *algebraic sum* are in the increasive zone. Values that result from the *gamma operation* that are greater than *and* but less than *or* are in the compromise zone. (Readers are referred to Zimmerman and Zysno, 1980 for a full mathematical explanation of the validity of the *gamma operation* as an FLO.) Because the results of the FLOs are data dependent, the graph in Figure 4.1C would be different if different values were used, for example, Column 2, Row 2.

Fuzzy logic, as presented by Bonham-Carter (1994) and supported by publications from Aminzadeh (1994), Wright and Bonham-Carter (1996), and Tounsi (2005), has been selected as the MCE method for investigating petroleum favorability in this study because:

- it is applicable for frontier areas as it does not rely on prior probabilities;
- it has been successfully used in mineral exploration, an economic geology; and

- it is acceptable for petroleum exploration in non-spatial environments.

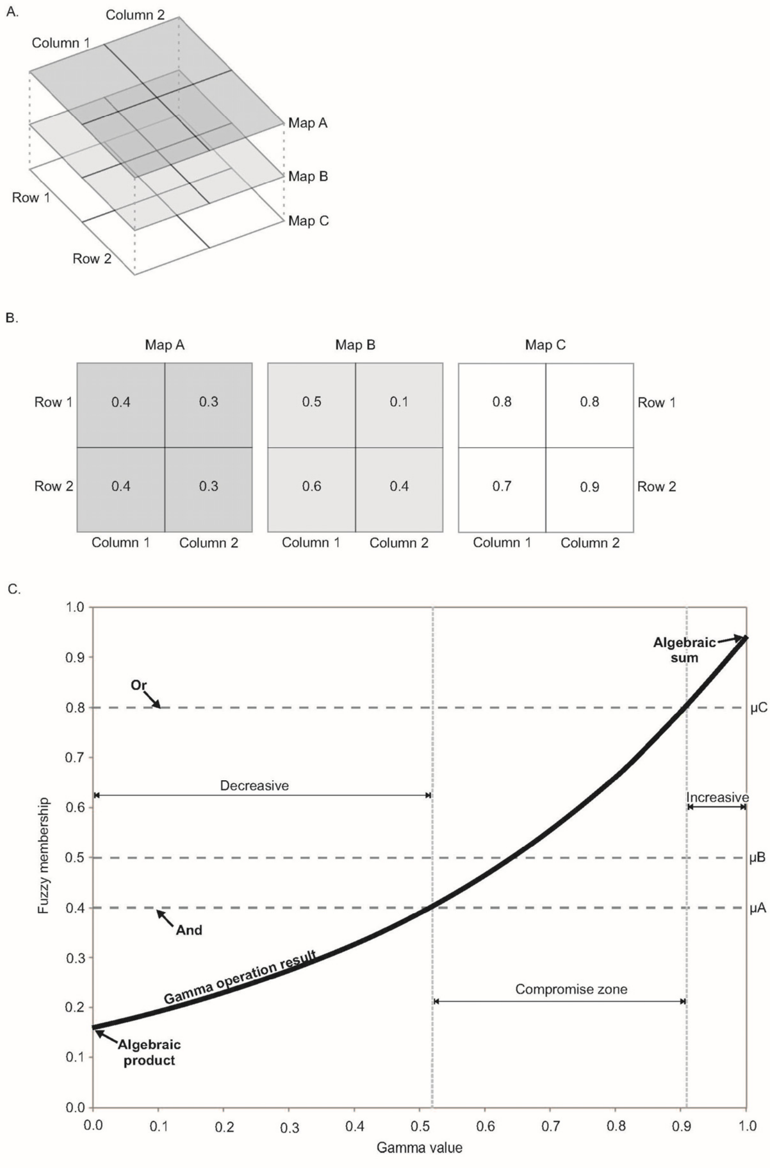


Figure 4.1 A. Depiction of three rasters that overlay each other. B. Three rasters side-by-side for assigned values to cells. C. Gamma value vs. fuzzy membership. The graph shows three values (dashed horizontal lines labeled μA, μB, and μC) and the possible results from the five fuzzy logic operators. Based on Bonham-Carter (1994). Refer to the text for discussion.

4.3. Proposed MCE Method

This section will present the process for creating a fuzzy logic MCE with appropriate criteria for either a geologic-age-specific evaluation (e.g. Cretaceous interval, Paleogene interval, etc.) by combining only the specified age data or a non-age-specific evaluation by combining all of the available data, regardless of age; in either case (age-specific or non-age-specific) the data is gradually combined by tiers. The MCE method can be described in six general steps, appropriate for any MCE methodology, shown in a workflow in Figure 4.2.

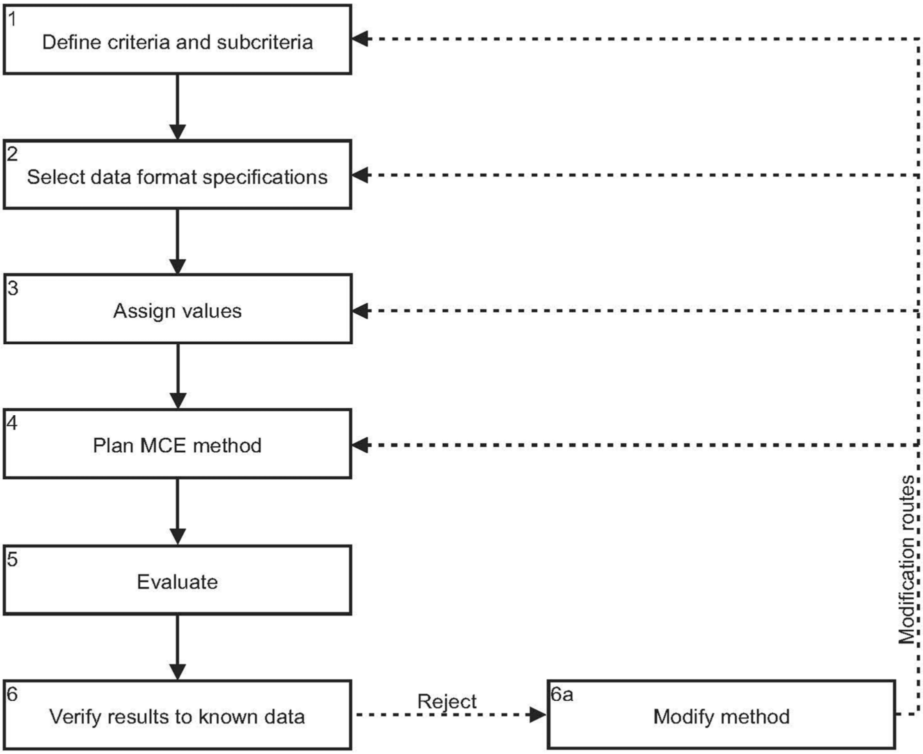


Figure 4.2 Methodology work flow.

Step 1: Defining criteria and subcriteria

With any MCE method, a listing of criteria must be established. The criteria defined here are meant to serve as a broad framework from which different petroleum companies may choose their own unique data sets for the analysis (Table 4.2). Ideally, all criteria and subcriteria will be defined and provided by the appropriate management personnel (in the case of the economic and political criteria) and the geological personnel (in the case of the remaining criteria) in any analysis. The four main criteria can be summarized as: 1) economic and political; 2) hard data; 3) seismic-derived data; and 4) other geologic features data. Constraints, which are criteria, should also be determined.

Table 4.2 Criteria for proposed MCE method.

Criteria	**Subcriteria**
Economic and Political	Costs
	Risks
	Safety
Hard Data	Geochemical analysis
	Oil and gas fields
	Oil and gas wells
	Oil and gas seeps
Seismic Derived Data	Fault interpretation
	Diapirs
	Isopachs or isochrons
	Plays
Other Geologic Features	Source rock
	Reservoir rock
	Traps
	Surface geology
	Subsurface geology
Constraints	Sedimentary basins

It is at this stage that the modeler should decide if he or she will look at non-age-specific or age-specific favorability. Non-age-specific favorability will indicate whether the area in general, regardless of possible exploration targets (age intervals of subsurface sediments), is of low to high favorability for exploration. Age-specific favorability will indicate whether an area at a specific subsurface sequence is of low to high favorability for exploration, because not all age intervals will have the same favorability in the same area (e.g. Cretaceous is low but Miocene is high for area Q).

Economic and political criteria will vary the most between different companies. Three broad subcriteria can be defined: costs, risks, and safety. Costs are the overall costs associated with the license agreement; safety refers to how safe a region is for a company's employees to work; and risk is inherent in both the costs and safety subcriteria, but also includes others such as political risks. These data are spatially and temporally dependent since changes in subcriteria favorability do not necessarily occur at political boundaries and are not necessarily constant within a political boundary; additionally, subcriteria may change over time due to changes in government and technology.

Hard data criteria are important when investigating for potential petroleum exploration sites. The considered subcriteria are geochemical analysis, oil and gas fields, oil and gas wells, and oil and gas seeps.

Petroleum exploration is highly dependent on the capture, processing, and interpretation of 2D and 3D seismic data. The subcriteria for seismic derived data are fault interpretation, diapirs, isopachs or isochrons, and plays. These data can be tied back to the seismic line or 3D volume either directly as in the cases of fault interpretation and diapirs or are a derivative of the seismic interpretation as in the cases of isopachs or isochrons and plays.

The last general criteria are other geologic features. This criterion consists of five subcriteria that have a more interpretive character than the previous (sub)criteria. They are source rock, reservoir rock, seals or traps as an areal extent, subsurface geology, and surface geology.

The final criteria to be defined are constraints. In this case, the only constraint is that hydrocarbon exploration must take place in a sedimentary basin.

Step 2: Data formats

This is a critical step as the criteria data will be available in many different data formats originating from the seismic interpretation software, the seismic interpretation analysis software, the GIS software, tables, and text documents. In general, the final format for analysis depends on two factors: the nature of the data (raster, vector) and the type of MCE analysis.

Fuzzy logic requires the use of map algebra, which is not applicable on vector datasets unless those datasets have been converted to a raster.

Most geological data is available in raster format because of interpolating data sets or to show other continuous data (e.g. isochrons). Chung and Fabbri (1993) suggest that in geological studies raster is the appropriate data format to use when comparing spatial data sets due to its "practical representation for statistical interpretation and analysis" (pg. 124). Thus, for fuzzy logic analysis, vector data should be converted to raster format where lines and polygons will be converted to a blocky pattern and point data will assume the entire cell. All tables and text documents required for the analysis must also be converted for geographic display. The subcriteria for the economic and political criteria must be converted to spatial representation if it does not already exist.

The most appropriate method for making the vector to raster conversion must be established based on the map scale of the analysis, which will influence the cell size of the raster and any vector to raster conversion methods. If the analysis is on a regional level (i.e. country extent or larger) with the purpose to show areas that are favorable for exploration, then using large cells is appropriate since the interest is focused on trends or general patterns. If the analysis is on a basinal level (i.e. one geologic basin) with the purpose to identify the "best" lease blocks for bidding or to identify the "best" locations for drilling, then using small cells is most appropriate. The modeler will need to investigate the best option for cell size keeping in mind the main purpose of the analysis.

At the end of this step, all data should be in a uniform GIS-based format with appropriate semantically consistent attributes. Furthermore, all data should be in the same projection and should have the same grid spacing (Sawatzky et al., 2009). This may mean that some data sets are generalized (data sets will lose information) which can impact the results especially in cases where outliers or small features are important, and other data sets are interpolated. Interpolated data sets will contain some amount of uncertainty and this is dependent on the method of interpolation, the sample size, the spatial distribution of sample locations, and the final area for interpolation.

Rasterization can introduce topological errors in the data set (Heywood et al., 2006). Topological errors are created when the rasterization process loses connectivity or creates false connectivity between features. This includes the loss of small polygons when the cell size chosen is too large.

Step 3: Assigning fuzzy membership values

Here, the geologist will assign fuzzy membership values to the attributes of each subcriterion. The geologist will base these values on his or her own experience and he or she will attempt to reflect the company's priorities, values, and policies as well as reflect the particular geologic phenomena of a region. Thus, it is important to note that value assignments will differ between geologists and between companies. The economic and political criteria may differ the most based on company, while the remaining criteria may differ by geologist.

Fuzzy logic uses multiplication in each of its operators (refer to Equations 4.1-4.5). If zero is used as a fuzzy membership value, the entire cell value will become zero regardless of the other inputs. Therefore, this study suggests that zero is not used for areas where no data is available. Rather, a small number, which is ideally smaller than the smallest non-zero fuzzy membership value assigned in the data set, should be used. This is because an unknown location value should not be more influential than any known location value. For instance, zero is appropriate to assign to dry wells, but it would be inappropriate to assign zero to locations where no known wells exist. In this way, unknown locations are not excluded from the analysis, which is highly important, especially in frontier exploration studies.

Step 4: Plan the Methodological Framework

The next step in the method is to determine how to connect the criteria and subcriteria with the FLOs. By using tiers or grouping the datasets, which in turn build up to submaps and are then used together for the final map, the user can identify where the different influences originate (Wright and Bonham-Carter, 1996). The method proposed in this study will use tiers of datasets to combine the subcriteria up to the criteria level.

FLOs should be chosen based on several factors:

- Should all data sets be included in the result?
- Should the result fall in the decreasive, compromise, or increasive zones of the FLOs?
- How interpretive are the data sets?

By answering these questions, the most appropriate FLO and gamma value, if the gamma operation is used, can be assigned for each of the tier combinations. For instance, if data sets are more interpretive or the source data is less certain, they should have less influence on the result, thus a decreasive or compromise FLO should be chosen. The FLOs will be chosen and supported by a brief discussion in this section.

The framework is built with large amounts of data in mind, but it is acceptable if there are some data sets missing, depending on the amount of work which has preceded the favorability mapping or what data the geologist has available. These data sets and operator combinations are simply omitted or rasters of constant cell value may be inserted. Because MCE is a subjective analysis, it will be noted that different companies will have different policies that will influence the choice of FLOs or gamma values.

The economic and political criteria relate to the lives and safety of the company employees as well as the profit of the company. The company management should be able to have flexibility in taking all subcriteria into account and to reflect the company policies of a geographic region, thus allowing for a conservative output. FLO gamma operation is used to allow the company to choose its own gamma value to determine how conservative they would like to be (Equation 4.6).

$$\mu EP = (1 - (1 - \mu c)(1 - \mu r)(1 - \mu s))^{\gamma} * (\mu c * \mu r * \mu s)^{(1-\gamma)} \quad (4.6)$$

where μEP is the combined economic and political criteria, μc is the cost subcriteria value, μr is the risk subcriteria value, μs is the safety subcriteria value, and γ = gamma value.

The hard data criteria are combined in two steps. First, the oil and gas fields, seeps, and wells will be combined using FLO *or* so that the highest value will be the most influential (Equation 4.7).

$$\mu HD1 = MAX(\mu f, \mu se, \mu w) \quad (4.7)$$

where μHD1 is the hydrocarbon data output, μf is the fields subcriteria value, μse is the seeps subcriteria value, and μw is the wells subcriteria value.

The hydrocarbon data output map is combined with the geochemical data. These data sets are the only "hard" datasets so the output should be more influential and take all data inputs into account. Thus, an increasive operator is preferred (Equation 4.8).

$$\mu HD = 1 - (1 - \mu HD1)(1 - \mu g) \tag{4.8}$$

where μHD is the hard data criteria and μg is the geochemical data subcriteria value.

Seismic derived data criteria are combined in a three-step calculation. Fault interpretation and diapirs can be directly correlated to the seismic data, called here the first seismic derivative. The interpretation may be more or less reliable depending on the experience of the interpreter; therefore, the gamma operation will be incorporated for combining these data (Equation 4.9). A larger gamma value would represent more confidence in the interpretation than a smaller gamma value.

$$\mu SD1 = (1 - (1 - \mu fi)(1 - \mu d))^{\gamma} * (\mu fi * \mu d)^{(1-\gamma)} \tag{4.9}$$

where μSD1 is the first seismic derivative, μfi is the fault interpretation subcriteria value, and μd is the diapirs subcriteria value.

The second step of combining seismic derived data is to calculate the relationship for isopachs or isochrons and plays. (Either isochrons or isopachs are used, but not both since they relate similar information.) Isopachs or isochrons and plays are the results of analyzing the first seismic derivative output, so this data is called here a second seismic derivative output. Play data represents a further analysis of data than the isopachs or isochrons; therefore, it is preferred to use the FLO *or* (Equation 4.10). This would ensure that the play data, which would have a higher value most likely, would be selected in the output data.

$$\mu SD2 = MAX(\mu i, \mu p) \tag{4.10}$$

where $\mu SD2$ is the second seismic derivative output, μi is the isopach or isochron subcriteria value, and μp is the plays subcriteria value.

The third step requires combining the values from the first and second seismic derivative maps. It is better to have a conservative value overall for the seismic data because it is interpreted and dependent on the individual interpreter. All data inputs should be reflected, so the gamma operation should be used (Equation 4.11). It is up to the modeler if the gamma value should be in the decreasive or compromise range depending on the reliability of the data. The decreasive and compromise ranges of the gamma value are data dependent; thus the data should be investigated prior to assigning a gamma value.

$$\mu SD = (1-(1-\mu SD1)(1-\mu SD2))^{\gamma} * (\mu SD1 * \mu SD2)^{(1-\gamma)} \quad (4.11)$$

where μSD is the seismic data criteria value.

The fourth map combines the subcriteria for other geologic features. The subcriteria are highly interpretive in nature; therefore, a conservative calculation is required. A small gamma value should be applied in the gamma operation so that a result is within the decreasive range (Equation 4.12).

$$\mu OG = \left(1-(1-\mu so)(1-\mu re)(1-\mu t)(1-\mu sl)(1-\mu sg)\right)^{\gamma} * (\mu so * \mu re * \mu t * \mu sl * \mu sg)^{(1-\gamma)} \quad (4.12)$$

where μOG is the other geologic features criteria value, μso is the source rock subcriteria value, μre is the reservoir rock subcriteria value, μt is the trap subcriteria value, μsl is the subsurface geology subcriteria value, and μsg is the surface geology subcriteria value.

The favorability map must then combine the four criteria maps for a combined criteria map. FLO *and* and *or* are not considered appropriate measures for this combination because they do not properly take all factors into account; while FLO *algebraic sum* and *algebraic product* do take all factors into account, they are considered extreme endpoints of the available operators. Therefore, the *gamma operation* is considered the most appropriate function (Equation 4.13).

$$\mu CC = (1-((1-\mu EP)*(1-\mu HD)*(1-\mu SD)*(1-\mu OG)))^{0.95}*(\mu EP*\mu HD*\mu SD*\mu OG)^{0.05} \quad (4.13)$$

where μCC is the combined criteria and γ = 0.95.

The choice of a gamma value is subjective, but allows the geologist to decide if the supporting data is more or less interpretive. If the geologist is more confident in the interpretation and supporting work, he or she may choose a larger gamma. However, if the geologist is less confident, he or she may choose a smaller gamma. It is suggested that the gamma value would be near 0.95 as this value will probably be increasive and reflect the decision-making process of a geologist (Bonham-Carter, 1994). Previous models used 0.95 and 0.975 for geologic models (An et al., 1991; Wright and Bonham-Carter, 1996).

The constraint is incorporated into the method using FLO and as a last step after the final gamma operation has been completed. The constraint, sedimentary basins, would have 0 where there are no basins and 1 where there are basins. Using the FLO *and* would select 0 where the sedimentary basin is not located and a non-zero value less than one where the sedimentary basin is located (Equation 4.14).

$$\mu FF = MIN(\mu Co, \mu CC) \quad (4.14)$$

where μFF is the final favorability value and μCo is the constraints criteria value.

The fuzzy logic method for petroleum exploration is shown in Figure 4.3 as a flowchart. It is designed to keep the business-related data and geologic data separate in a visual manner. The geologic data are also arranged so that it is easier to perceive the increasing interpretive character as the subcriteria progress to the right.

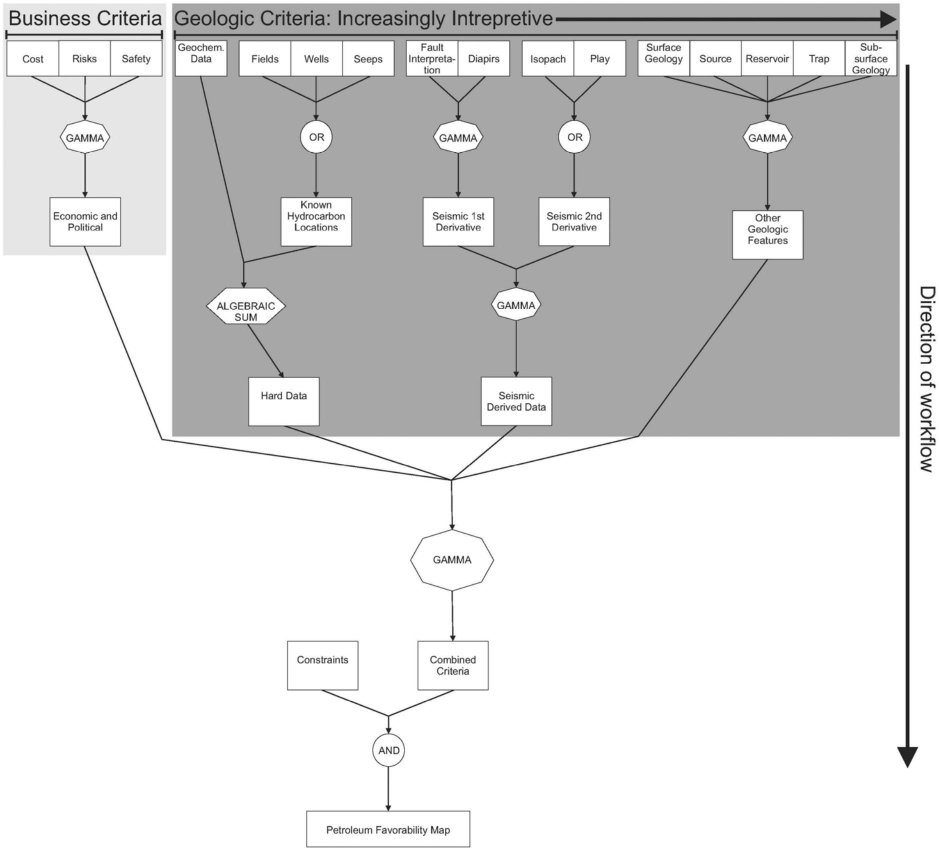


Figure 4.3 Petroleum exploration MCE method using fuzzy logic operators. The first level shows the input data sets (subcriteria) which are combined to create the criteria maps (moving from the top to the bottom following the arrows). The four criteria maps are combined with the gamma operation. The final step of the method is combining the constraints and the combined criteria map to result in the petroleum favorability map. On the left side in the light grey box are the business criteria. On the right side in the dark grey box are the geologic criteria, which are increasingly interpretive moving from the left (geochemical data) to the right (subsurface geology).

Step 5: Application

Once the criteria have been defined, the data prepared, and the framework has been planned, the method can be applied. The data sets are combined using the equations described in Step 4. The results are a series of maps showing the favorability for petroleum exploration for each criterion from the Equations 4.6-4.13. The final result, which is used for evaluation, is the map from Equation 4.14.

Step 6: Verifying outcomes

Once the final favorability map is created, it is important to verify the output and validate the method. The favorability values at known production locations are calculated as percentiles so they can be compared to each other (Wright and Bonham-Carter, 1996). By using known producing locations to see how accurate the results of the analysis are, the verification process acts as a check that known fields would be indicated with high favorability values. In the verification process, areas that are known to have no production (e.g. a dry well) should be reflected by low favorability values. After comparing the methodology results to the known locations, several modifications to the method may be initiated if there is a gross and consistent difference. These modifications may include steps 1, 2, 3, or 4 (Figure 4.2). It is possible that the area of exploration is truly frontier without known producing locations. In this case, producing locations cannot be used; however well or seep data can be used for an indication. If there are no wells drilled, whether industry or academic (such as through the Ocean Drilling Project or Deep Sea Drilling Project) and no seep locations have been identified, the verification process cannot be conducted and a sensitivity analysis should be conducted in its place. (Sensitivity analysis is beyond the scope of this chapter but the reader is referred to Saltelli and Annoni, 2010.)

4.4. Case Study: Northern South America

The proposed fuzzy logic MCE method was applied to a case study of northern South America (Figure 4.4A). The data used in this case study were provided by the Caribbean Basins, Tectonics, and Hydrocarbons industry-funded consortium (CBTH). This area was chosen because northern South America has a large amount of oil and gas that has been discovered; however, it can be considered a frontier area due to the lack of extensive exploration in the offshore areas where there are recent discoveries (Figure 4.4B, 4.4C).

The case study will look at three favorability maps for petroleum exploration. The first map will not be age-specific and will combine all data sets regardless of age, which would be used to support the overall lease block bid decision. The other two maps will be age-specific, focusing on the Cretaceous to Paleogene (145-23 Ma) and Miocene to Recent (23-0 Ma) which were chosen because they are known age intervals of hydrocarbon production in the study area (Escalona and Mann, 2011); these maps would be used to evaluate a specific interval's petroleum favorability.

4.4.1. Data sets

The data sets, 27 total, were processed and prepared for use as follows:

- Costs: data set was created by CBTH researchers based on knowledge and experience; it is a highly general map and is intended to reflect relative general costs only.
- Risks: data set was created by AON Group, Inc. (2011).
- Safety: data set was created by CBTH researchers based on knowledge and experience; it is a highly general map and is intended to reflect relative safety levels only.
- Fault interpretation: faults were interpreted from 2D seismic data and converted to lines as part of the CBTH consortium; fault interpretation is sorted by horizon level; densities are calculated by

horizon level for 10,000 square kilometers; there are 4 horizon levels (each near top of): Cretaceous, Paleogene, Miocene, and Recent.

- Diapirs: data sets were collected from several sources (Kugler, 1959; Valery et al., 1985; Brown and Westbrook, 1988; Beltran, 1993; Deville et al., 2003; DM2 Project, 2005; Sullivan, 2005; Agencia Nacional de Hidrocarburos, 2007; Duerto, 2007) and may include (remobilized) mud or shale diapirs, fields, or structures.
- Isochrons: data sets were calculated from interpolation of 2D and 3D seismic data interpretation as part of the CBTH consortium; there are three isochrons for the four horizon levels: Cretaceous-Paleogene; Paleogene-Miocene; Miocene-Recent.
- Plays: actual data are unavailable; a general map showing play risks was created by CBTH researchers based on knowledge and experience.
- Geochemical data: data set is unavailable; a general map showing total organic content was created by CBTH researchers based on knowledge and experience.
- Oil and gas wells: data sets were collected from several sources (French and Schenk, 2004; DM2 Project, 2005; Wood McKenzie, 2006; Staatsolie, 2007; Exploration and Production Information Service and Agencia Nacional de Hidrocarburos, 2008) and compared to each other to remove duplicates; French and Schenk (2004) data set was compared to Wood McKenzie (2006) fields data set as some wells were actually fields; attributes were edited to be uniform.
- Oil and gas fields: data sets were collected from several sources (DM2 Project, 2005; Castellanos et al., 2006; Wood McKenzie, 2006; Staatsolie, 2007; Exploration and Production Information Service and Agencia Nacional de Hidrocarburos, 2008) and compared to each other to remove duplicates; attributes were edited to be uniform.
- Oil and gas seeps: data sets were collected from several sources (DM2 Project, 2005; Staatsolie, 2007; Exploration and Production Information Service and Agencia Nacional de Hidrocarburos, 2008) and were compared to each other to remove duplicates; attributes were edited to be uniform.

- Source rock: source rock interpretive extents are based on several publications (Curet, 1992; Ysaccis, 1997; Di Croce et al., 1999; Sanchez, 2007; Kroehler, 2007; Yang and Escalona, 2011; and references cited therein) created as part of the CBTH database; there are two source rock data sets: Cretaceous and lower Cenozoic.
- Reservoir rock: reservoir rock interpretive extents are based on expert opinion supported by data integration created as part of the CBTH database; there are three reservoir rock data sets: Cretaceous, Paleogene, and Miocene.
- Traps: data set is unavailable; a general map showing trap presence or absence was created by CBTH researchers based on knowledge and experience.
- Subsurface geology: data sets created within CBTH consortium based on paleogeographic maps; there are three lithologic data sets: Cretaceous, Paleogene, and Miocene; lithologies included: limestone, sandstone, shale, and combinations thereof.
- Surface geology: data sets were collected from several sources (Geologisch Mijnbouwkundige Dienst, 1977; Walrond, 1987; Saunders and Snoke, 1998; Schenk et al., 1999; French and Schenk, 2004; Garrity et al., 2006; Gomez Tapias et al., 2007) and combined as set out by Bingham and Escalona (2011).
- Sedimentary basins: data set edited from Fugro Data Services, AG. (2005) to better match known data from CBTH consortium; a buffer of five kilometers was applied.

4.4.2. Data set preparation

The CBTH consortium relies on publicly available information and information provided to the project from sponsoring companies or by data sharing agreements. The data sets were collected from scales varying from 1:100,000 to 1:44,000,000.

The data sets were reprojected into a uniform projection. The study area extends from approximately 80ºW to 55ºW and 3ºN to 15ºN (Figure 4.4), is relatively close to the Equator, and has a large horizontal distance (> 2,500 km); given the type of analysis, it is deemed most important to try to preserve the relative distance and area as much as possible. Therefore, the most appropriate projection is a customized Albers projection (United States Geological Survey, 1989) with a central meridian defined as 67.5ºW; the two standard parallels are 7ºN and 11ºN; the datum used is WGS1984; and the linear unit of the projection is meters.

Given that 1) the total study area covers over 2.5 x 10^6 km^2; 2) the data sets used do not contain the kind of detail necessary for a basin or lease block analysis; and 3) the goal of the MCE is to have a general idea of favorable exploration areas rather than pinpointing drilling sites, a cell size of 25 km^2 was used to rasterize all the data sets.

4.4.3. Fuzzy membership value assignment

Using expert opinion for the region, fuzzy membership values were assigned to the subcriteria based on the attributes (Table 4.3). The median value of two attributes can be used in instances such as "medium-high" when this attribute is not present on the chart but is present in the data set. A fuzzy membership value of 0 is assigned only when the well is classified as either dry or water or to designate a non-sedimentary basin. All other less favorable minimum values are 0.1 so that the area is not nullified in the model. This is especially important for highly interpretive data sets such as reservoir rock or source rock location, but also subsurface geology. Furthermore, a non-age-specific model should not contain 0 for unfavorable attributes of age-specific data sets; although, the designation of 0 for age-specific data in an age-specific model can be justified. The fuzzy membership values may be altered for application to other regions; different geologists may prefer a different fuzzy membership scheme based on his or her experience, supporting data, or company. It is not necessary that each subcriterion has continuous fuzzy membership value ranges, especially if the nature of the data and the attribute being converted does not reflect a continuous nature.

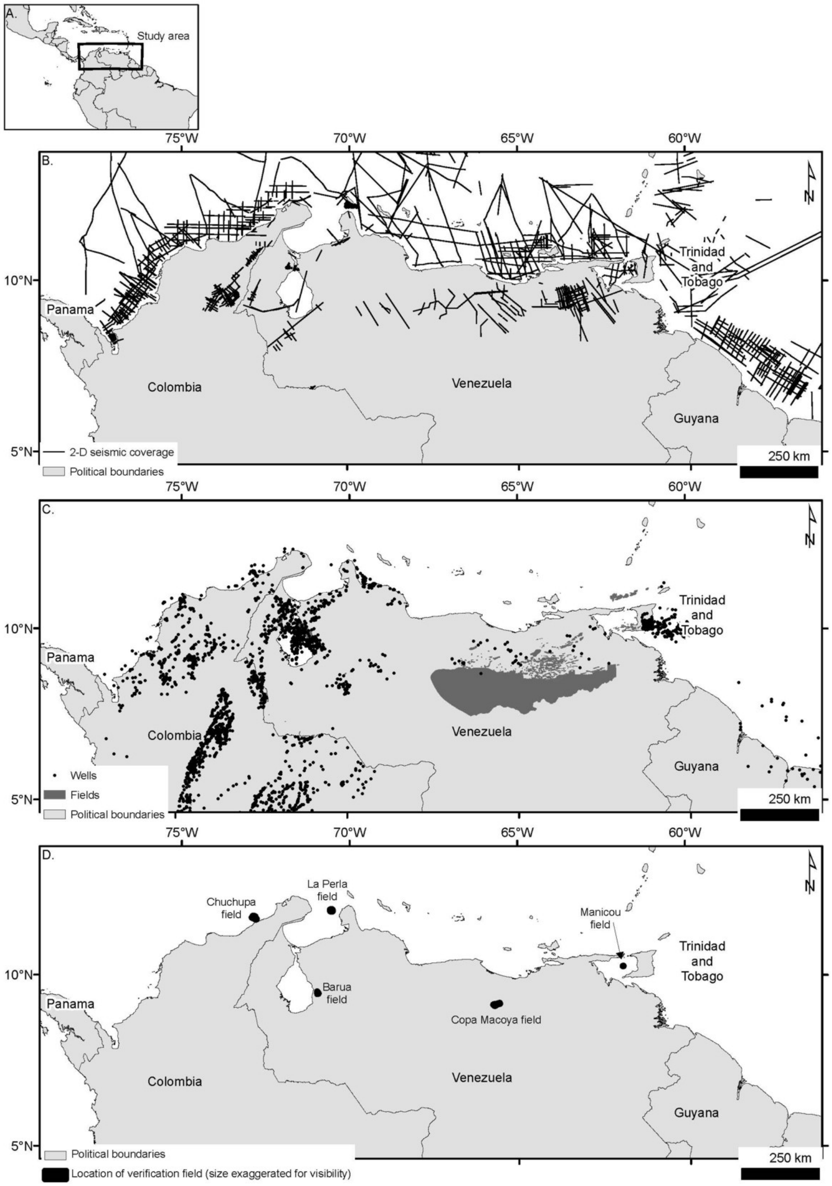


Figure 4.4 A. Central and South America showing the case study area outlined by a black heavy box. B. Case study area showing the available 2D seismic lines used. C. Case study area showing the available wells and fields used. D. Case study area showing five fields used in the verification process.

Table 4.3 Fuzzy membership values (FMV). Value applied in case study.

Subcriteria	Attribute	FMV
Costs	Very Low	1.0
	Low	0.7
	Medium	0.5
	High	0.3
	Very High	0.1
Risks	Very Low	1.0
	Low	0.7
	Medium	0.5
	High	0.3
	Very high	0.1
Safety	Very Low	0.1
	Low	0.3
	Medium	0.5
	High	0.9
	Very High	1.0
Geochemical data	Low TOC	0.1
	Medium	0.5
	High TOC	0.9
Oil and gas fields	Present	1.0
	No Data	0.1
Oil and gas wells	Dry well	0.0
	Water well	0.0
	Show	0.7
	Producing	1.0
	Other	0.1
	No data	0.1
Oil and gas seeps	Other seep	0.5
	Oil or gas	0.9
	No data	0.1
Fault density (subsurface)	0.0 – 0.02	0.1
	0.02 – 0.07	0.3
	0.07 – 0.12	0.5
	0.12 – 0.42	0.7
	0.42 +	0.9
	No data	0.1

Subcriteria	Attribute	FMV
Diapirs	Present	0.7
	Absent	0.3
Isochrons (ms TWT)	0 – 1000	0.3
	1000 – 3000	0.5
	>3000	0.7
	No Data	0.1
Plays	Low	0.9
	Medium	0.5
	High	0.2
	No Data	0.1
Source rock	Present	1.0
	No data	0.1
Reservoir rock	Present	1.0
	No data	0.1
Traps	Present	1.0
	No data	0.1
Subsurface geology	Sandstone	0.8
	Shale	0.8
	Carbonate	0.8
	No Data	0.1
	Other	0.3
	Unknown	0.2
	No deposition	0.1
Surface geology	Igneous	0.1
	Metamorphic	0.1
	Sedimentary	0.9
	Mix	0.5
Sedimentary basins	Present	1.0
	Absent	0.0
Fault density (surface)	0.0 – 0.02	0.9
	0.02 – 0.07	0.7
	0.07 – 0.12	0.5
	0.12 – 0.42	0.3
	0.42 +	0.1
	No data	0.1

4.4.4. Applying MCE method

This section demonstrates the results of combining the data at the criteria and higher levels.

Using the Spatial Data Modeller (Sawatzky et al., 2009), a model was built in ArcGIS™ 9.3.1 using the Model Builder. This step converted the conceptual model (Figure 4.3) into a working model. The working model represents all age intervals to have a regional non-age-specific favorability map. This is to support the overall lease block bid decision.

First, the economic and political criteria map will be analyzed; then the hard data criteria map will follow; after that the seismic derived data map will be explained; next the other geologic features criteria map will be shown; the combined criteria map will be shown prior to applying the constraints; finally, the petroleum favorability map will be analyzed for the non-age-specific favorability and the two age-specific favorabilities.

A conservative operation to combine the economic and political data is important when handling matters concerned with employee safety and predictable business continuity. Because the gamma operation is data dependent, the data must be analyzed for the appropriate gamma value. In much the same way as the gamma operation was explained in Figure 4.1, the choice of a gamma value is shown in Figure 4.5. The reader can imagine that the graph in Figure 4.5 is made up of two of the graphs from Figure 4.1, albeit with different input values (μA, μB, and μC). The maximum input for two data sets was 1.0 (maximum input 1 - Figure 4.5) while the third data set had a maximum input value of 0.7 (maximum input 2 - Figure 4.5). Because of the input values, it happens that several values are equal: maximum input 1 = maximum *or* = maximum algebraic sum = highest result of the maximum gamma operation; and maximum input 2 = *and* for the maximum inputs = maximum algebraic product = smallest result of the maximum gamma operation. Therefore, any gamma value will result in a compromise where no gamma value will render a decreasive or increasive output. The minimum input for one data set was 0.3 and 0.1 for the remaining two data sets. These are shown in Figure 4.5 as minimum input 1 and minimum input 2, respectively. For the minimum inputs, a gamma value less than 0.7 produces decreasive results (results are less than the smallest input value) which will produce a more conservative output. Because 0.7 is the largest gamma value, which is in the decreasive range for the minimum inputs, it was decided to use 0.5, which is an almost exact compromise for the maximum inputs. The resulting map for the economic and political criteria shows that the majority of the onshore areas are favorable (Figure 4.6A).

The hard data criteria map combines subcriteria using the *or* function and the *algebraic sum* function. The resulting map shown in Figure 4.6B shows the majority of the onshore areas are black indicating a high favorability. The light grey areas reflect low favorability; however, this does not necessarily mean "low favorability" in this instance, but rather lack of data (Figure 4.4C). The majority of the area is highly dependent on the geochemical data set, while in other areas, it is easy to identify the locations of fields, wells, or seeps (although parsing the three data is not easy). The large color swaths are due to the way in which the geochemical data set was created. This data set is appropriate for an overall indication of the hard data criteria character of the area.

The seismic derived criteria map used the gamma operation to combine the first derivative data using a gamma value equal to 0.9 resulting in an increasive output. This value was chosen based on the data inputs. In an exercise like that of the economic and political criteria, the gamma value was chosen using similar motives based on the subcriteria maximum and minimum fuzzy membership values. The gamma operation was also used to combine the first and second seismic derivative data with a gamma value equal to 0.75 resulting in a compromise output. The gamma value was chosen in the same way as the gamma value for the economic and political map and the seismic first derivative data.

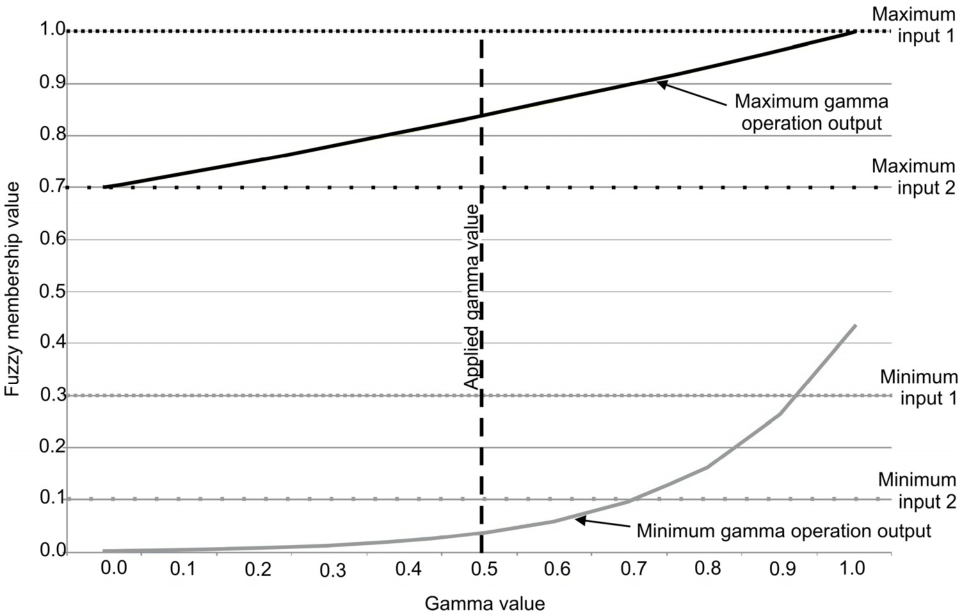


Figure 4.5 Gamma value versus fuzzy membership value for economic and political subcriteria.

Figure 4.6C shows the seismic derived data output. Light grey areas indicate lower favorability, which may be due to a lack of seismic data coverage (Figure 4.4B). However, some areas may truly have low favorability, which this distinction can be discerned through familiarity of the data and the data coverage. If the input data sets change substantially with increasing 2D seismic data, then it can be stated that a lack of data is the cause for a low favorability (Figure 4.4B). It is assumed that areas of high favorability will not decrease, but it is possible that more data will cause a reinterpretation of existing data.

The fourth criteria map, other geologic features criteria, also used the gamma operator to combine the input data sets. Following the same procedure as before, a gamma value equal to 0.8 was chosen in order to produce a conservative output. As reflected in Figure 4.6D, the highest output is 0.540. If a lower gamma value is used, this criterion will have even less influence on the final map. However, more influence could be created using a higher gamma value. Given the highly interpretive nature of the data sets, it is not considered "good" to use a higher gamma value. The input data sets had large areas of "no data" values which if defined could increase the overall favorability.

Next, the four criteria maps are combined using a gamma value equal to 0.9 as established previously and based on mineral exploration studies (e.g. Wright and Bonham-Carter, 1996; Figure 4.6E). The map has no white areas indicating that the area, overall, is favorable for petroleum exploration. However, the constraints have not been applied at this step.

Finally, sedimentary basins constrain the area for which petroleum can be explored. Once these are applied to the combined criteria map, a more complete regional, non-age-specific favorability can be analyzed. Figure 4.7A shows the final favorability map for all age intervals, thus it is not age-specific. The map shows areas marked with a white X that are in the high favorability range (a value of at least 0.7). Many of these areas may be considered potential new areas. Ideally, new exploration plays or further development of existing plays will be sought from the highest favorability areas.

Because overall favorability may not accurately reflect specific geologic age intervals, the model from Figure 4.3 was adapted to reflect two age intervals: Cretaceous-Paleogene and Miocene-Recent. First, the model was edited to exclude data sets that are age-specific and not related to the Cretaceous-Paleogene interval (i.e. Miocene data sets are excluded; non-age- specific data are included). All gamma values that were established in the first model are maintained here. The resulting favorability map shows some of the same trends as the non-age-specific map (e.g. onshore higher than offshore) but exact areas of high favorability have changed (Figure 4.7B).

Next, the model was edited for the Miocene-Recent interval in the same manner that it was also edited for the Cretaceous-Paleogene interval. High favorability areas, areas with values ≥ 0.7, are marked by a white X (Figure 4.7C). In the Miocene-Recent interval, the offshore areas are overall of higher favorability than the Cretaceous-Paleogene interval. This indicates that the offshore area is more favorable for exploration in younger sediments. Investigation of the input data shows that the Miocene-Recent interval has overall higher favorability offshore for the seismic derived data criteria and the other geologic features criteria than the Cretaceous-Paleogene interval.

4.4.5. Outcome verification

Five fields were chosen for the verification process (Figure 4.4D). The fields were chosen because they represent a variety of locations within the study area. Percentiles were calculated for a central location for each field for all 15 favorability maps (4 criteria maps and 1 final favorability map for non-age-specific and 2 ages; Table 4.4). All of the percentiles for the economic and political criteria stay constant regardless of the time interval investigated because these data are not age-dependent but rather geographic-dependent. All of the percentiles for the hard data criteria also stay constant regardless of the time interval investigated because this study does not differentiate between time-related geochemical information or the production level of the wells and fields.

All of the verification features for the non-age-specific maps are all at least in the 50th percentile; 1 field is in the 74th percentile (Chuchupa field); 1 field is in the 93rd percentile (Manicou field); and 2 fields are in the 98th and above percentiles (Barua and Copa Macoya fields). By investigating the percentiles of the criteria for each of the verification points, it can be determined that La Perla field (with overall percentile of 50) is most impacted by the economic and political criteria, due to the fact that it is located in a high cost (offshore area) and high risk area (political risk). Interestingly, the highest overall percentile is for a field in a low cost and high risk area (Barua field). There is an obvious trend between fields with lower percentiles corresponding to offshore locations and fields with higher percentiles corresponding to onshore locations. This is to be expected as there are more costs and less data for offshore areas according to the database used in the study.

The verification of the Cretaceous-Paleogene and Miocene-Recent intervals produce the same overall pattern as the non-age-specific map. That is to say, all locations are above the 50th percentile for the overall favorability; Barua field has the highest ranking percentile; La Perla has the lowest ranking percentile due to the very low economic and political criteria ranking. Based on the outcome verification, the proposed fuzzy logic MCE method can be used for general favorability analysis and for investigating specific age intervals. The results may be investigated and pursued for exploration.

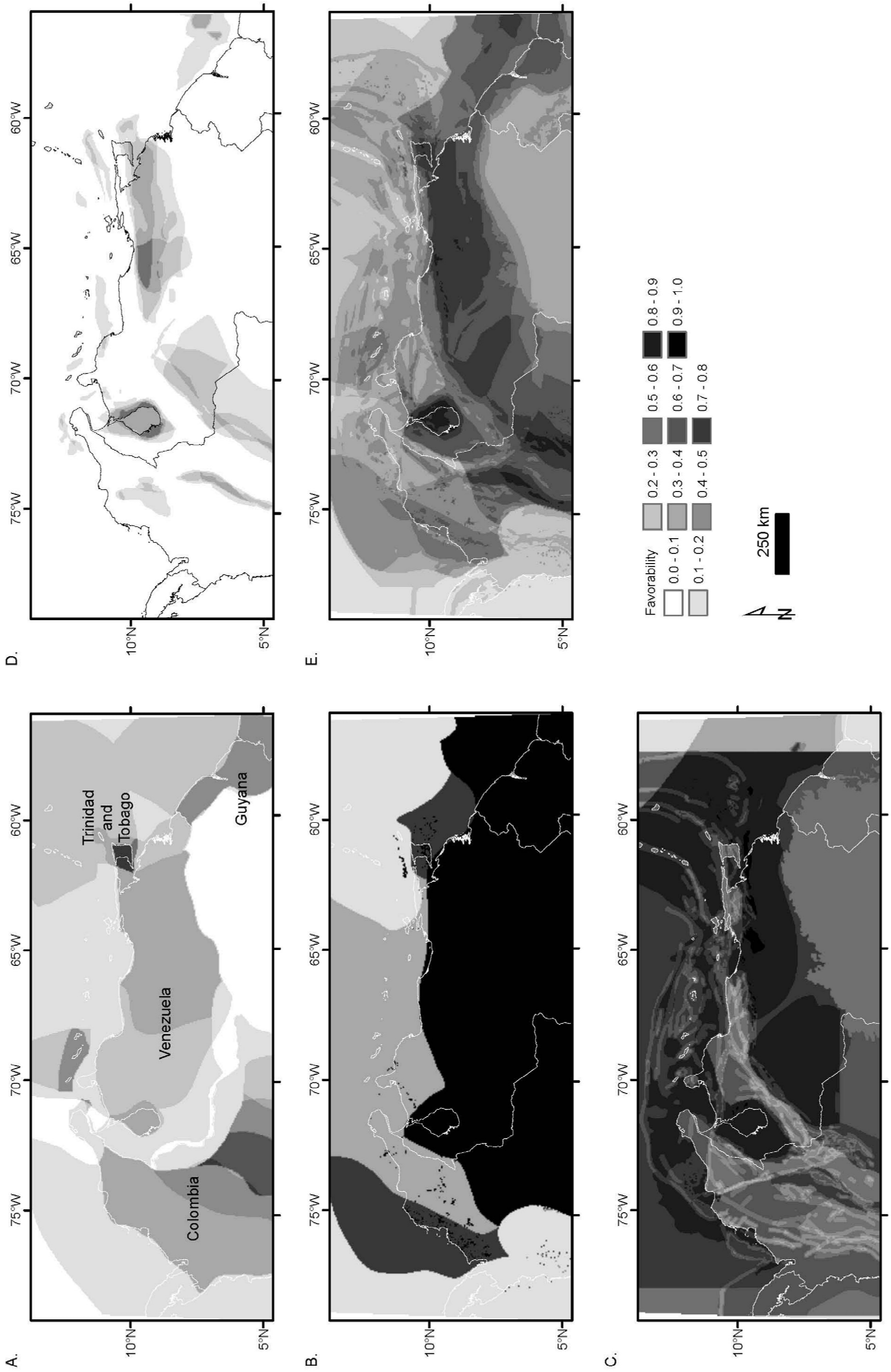
4.5. Conclusions

This study proposes the use of fuzzy logic MCE for petroleum exploration, especially in frontier areas, and in a spatial environment (GIS). A specific method for combining necessary data sets with fuzzy membership value assignments was illustrated and supported by a case study of northern South America where high favorability areas were shown as containing possible new exploration plays.

The results are dependent on the quality of the input data sets; data density; fuzzy membership values; FLOs; and gamma values. Interpretation of data and fuzzy membership value assignment will vary between geologists. Aside from the inherent subjectivity of the MCE method, like all MCE methods, the method applied here has been shown as useful for general favorability either for non-age-specific or age-specific investigations by the verification locations supporting the output.

Although it was not investigated in this study, the technological progression of spatial data infrastructures and of cloud computing offer the real possibility that MCE analysis such as the one proposed here can be performed completely online with access to data and analytical tools as a web service. This would greatly ease further petroleum exploration studies.

Figure 4.6 (following page) A. Economic and political criteria map. Resulting map from combining costs, risks, and safety subcriteria. Grey scale represents more to less favorable, where white is least favorable and black is most favorable. B. Hard data criteria map. Resulting map from combining geochemical data, fields, wells, and seeps subcriteria. C. Seismic derived data criteria map. Resulting map from combining fault densities, diapirs, isochrons, and plays. D. Other geologic features criteria map. Resulting map from combining source rocks, reservoir rocks, traps, subsurface geology, and surface geology. E. Combined criteria map. Resulting map from combining economic and political criteria, hard data criteria, seismic derived data criteria, and other geologic features criteria.



A.
B.
C.
D.
E.
75°W
70°W
65°W
60°W
10°N
5°N
Trinidad and Tobago
Venezuela
Colombia
Guyana
Favorability
0.0 - 0.1
0.1 - 0.2
0.2 - 0.3
0.3 - 0.4
0.4 - 0.5
0.5 - 0.6
0.6 - 0.7
0.7 - 0.8
0.8 - 0.9
0.9 - 1.0
250 km
N

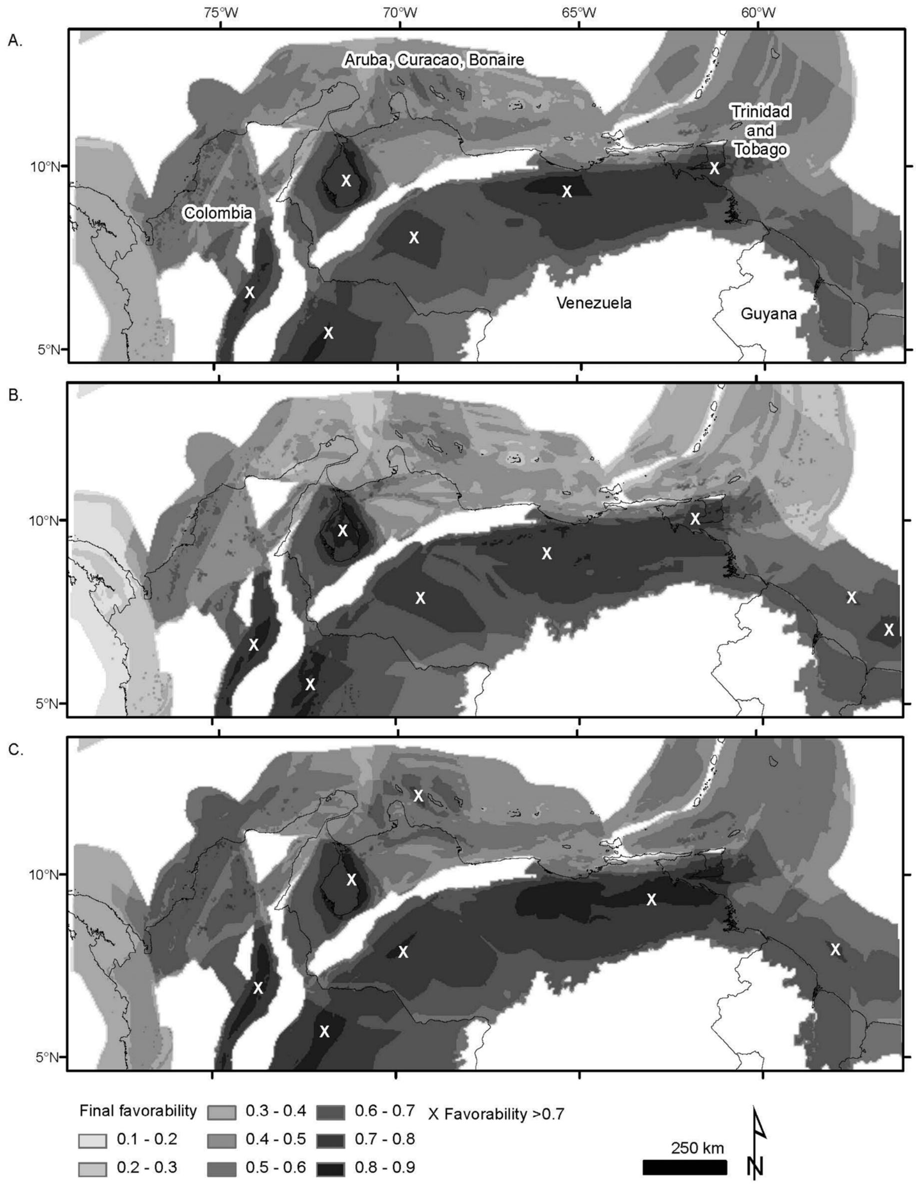


Figure 4.7 A. Final favorability map. Map resulting from applying sedimentary basins constraint to the combined criteria map (Figure 4.6E). Grey scale represents more to less favorable, where light grey is least favorable and black is most favorable. White areas were removed by the constraints. White X's indicate areas of high favorability. B. Resulting Cretaceous-Paleogene favorability map. C. Resulting Miocene-Recent favorability map.

Table 4.4 Outcome verification of five known fields.

Non-age Specific					
Field	**Economic and Political**	**Hard Data**	**Seismic Derived Data**	**Other Geologic Features**	**Overall**
Chuchupa	44	98	79	77	74
La Perla	13	98	56	65	50
Barua	76	98	98	99	99
Copa Macoya	76	98	96	96	98
Manicou	99	98	86	73	93
Cretaceous to Paleogene Interval					
Field	**Economic and Political**	**Hard Data**	**Seismic Derived Data**	**Other Geologic Features**	**Overall**
Chuchupa	44	98	56	45	59
La Perla	13	98	90	45	55
Barua	76	98	99	99	99
Copa Macoya	76	98	87	99	96
Manicou	99	98	98	62	96
Paleogene to Recent Interval					
Field	**Economic and Political**	**Hard Data**	**Seismic Derived Data**	**Other Geologic Features**	**Overall**
Chuchupa	44	98	78	86	78
La Perla	13	98	70	72	53
Barua	76	98	96	99	98
Copa Macoya	76	98	93	99	98
Manicou	99	98	86	72	92

Chapter 5

Error propagation in a fuzzy logic multi-criteria evaluation for petroleum exploration

This chapter is based on: Bingham, L., A. Escalona, and D. Karssenberg, 2016, Error propagation in a fuzzy logic multi-criteria evaluation for petroleum exploration: International Journal of Geographical Information Science, v. 30, p. 1552-1578.*
**Now L. Watson*

5.1. Introduction

Spatial multi-criteria evaluation (MCE) is useful for modeling favorable locations on a set of criteria. However, it is extremely important that the modeler and the decision-maker understand the implications of subjectivity within the method (Heywood et al., 1995) and the uncertainty related to the MCE model input, parameters, structure, and results (Thapa and Bossler, 1992; Heywood et al., 1995; Karssenberg and De Jong, 2005; Li et al., 2012). Because of the inherent subjectivity of MCE and the uncertainty both from the data and the parameters used in the MCE, there exists a need to quantify the uncertainty.

Data uncertainty is common in any spatial analysis, including MCE modeling, where the user relies on many different sources for data, especially if data is older or the original source is unknown. Model input uncertainty is generally associated with data collection or processing; data completeness for time and space; data resolution; and errors from digitizing data (Heuvelink, 1998; Heywood et al., 2006). Model parameters and structure may have some uncertainty associated with them due to the decisions made by the modeler in how to combine the data sets (Heuvelink, 1998; Heywood et al., 2006).

There are several methods for investigating uncertainty in models. Error propagation is an analysis used to investigate uncertainty and is a suitable method for calculating the uncertainty of the final output (Thapa and Bossler, 1992). The uncertainty, therefore, influences all subsequent calculations in the model. Monte Carlo simulation, used here, is an error propagation technique that calculates the model repeatedly using different input values based on an error model (Heuvelink, 1998). By interpreting the culminated results (e.g. 5th percentile, 95th percentile, and median) of hundreds or thousands of realizations, the modeler can evaluate spatial variations for further analysis (i.e. confidence level tests).

The combination of spatial MCE and error propagation is not common in publications. The closest example comes from Moon (1998), who combined spatial MCE, fuzzy logic, and error propagation; however, this was a theoretical presentation to show their importance and possible theoretical application in geosciences. The paper did not produce examples or models but an umbrella idea of applications. Davis and Keller (1997) applied fuzzy logic with Monte Carlo simulation in a spatial setting in order to investigate uncertainty related to attribute boundaries and attribute assignment for slope stability. Fernández and Lutz (2010) and Feizizadeh and Blaschke (2014) are two recent papers which focus on both spatial MCE and error propagation. Fernández and Lutz (2010) applied Taylor's series for error propagation and use a combination of defined and assumed uncertainties. Feizizadeh and Blaschke (2014) focused on comparing different MCE methods.

This chapter focuses on applying error propagation using Monte Carlo simulation to a spatial fuzzy logic MCE for petroleum exploration using geologic data and a case study from northern South America (See Chapter 4). This chapter addresses three questions:

- What are possible methods for defining uncertainty in the various components of the MCE model and can similar results be found with different methods requiring less effort?

- How do the different scenarios for defining uncertainty compare to each other?
- What is the MCE error magnitude (on average) from the defined uncertainty on the results?

The innovation of this chapter is the combination of spatial MCE, fuzzy logic, and error propagation applied to petroleum exploration. This chapter focuses only on the non-age-specific evaluation of a case study of northern South America (See Chapter 4).

5.2. Error propagation

The workflow of the uncertainty modeling follows a series of steps to create realizations for the investigated uncertainties. The following steps outline the workflow of the uncertainty modeling with Monte Carlo simulation (Heuvelink, 1998).

1. Error models are defined for each input criterion.
2. Create 2000 sets of realizations of all inputs by drawing from the probability distributions (defined by the error models in step 1).
3. Run the MCE model (Equations 4.6-4.14) for each set of realizations and store results.
4. For final favorability (Z), calculate sampling statistics over realizations.

In order to investigate systematically the sources of uncertainty, six scenarios are created and evaluated. The scenarios evaluate three basic groups of uncertainty. Group A focuses on uncertainty in observational data, specifically addressing the uncertainty related to feature attribute classification. This uncertainty addresses the possible misclassification of a feature to the wrong attribute class by either negligence or mapping error. Group B has two parts and focuses on uncertainty of weighting of evidence with a component of observational data. The two parts are fuzzy membership assignment (weighting of evidence) and boundary transition zone (observational data). The uncertainty of the fuzzy membership assignment is related to the expert opinion that a specific attribute should be assigned a specific fuzzy membership value. The boundary transition zone is the uncertainty that the boundary between two classified areas is geographically mislocated either due to mapping errors, classification errors, or rasterization processes. Group C focuses on changing model parameters (i.e. fuzzy logic operators, FLOs). The different scenarios combine the groups in a successive manner. Scenarios 1-3 focus on Group A; Scenario 4 combines groups A and B; Scenario 5 combines groups A and C; and Scenario 6 combines all groups. The results of the different scenarios are evaluated by comparing two different threshold values (0.5, 0.7) and two different confidence levels (60%, 95%). Scripts used for evaluating the scenarios are available upon request.

Scenario 1: "Simple" uncertainty

Scenario 1 acts as the base case of the six scenarios. It assumes that all input data set feature classifications (i.e. Group A) have an uncertainty probability of 0.1 for being misclassified. This value was chosen as most appropriate based on informed expert knowledge. In Scenario 1, this uncertainty is formally represented as follows: class numbers are defined i=1, …, N with N, the total number of classes. X is a discrete random variable representing the class of a feature. The probability of the originally mapped class i=k is:

$$\Pr(X = k) = u \qquad (5.1)$$

The probability of the remaining classes i≠k is:

$$\Pr(X = i) = (1 - u)/(N - 1) \text{ , for all } i \neq k \qquad (5.2)$$

The purpose of this simple scenario is to evaluate the necessity of a more detail-oriented expert-defined uncertainty, i.e. are similar results possible with less effort. Its significance is to compare the analysis results of increased resources and more in-depth modeling. The originally defined classification is assigned a probability of 0.9 (i.e. u = 0.9). A probability of 0.1 is distributed equally among the remaining classes as described by Pr(X=i). For example, for subcriterion geochemical (TOC), polygon 964 was originally classified as high TOC by an expert (Figure 5.1D). Scenario 1 models with 0.1 probability that the area included in polygon 964 is not classified correctly and may be one of the other classifications (none, low, low-medium, medium, medium-high). A 0.1 probability is distributed equally among these five classifications (Figure 5.1A). Polygons 963, 968, 969, 970, and 971 were originally noted as "unknown TOC" (Figure 5.1D); therefore, these areas are equally probable as being one of the six classifications: none, low, low-medium, medium, medium-high, and high (Figure 5.1A).

Scenario 2: Expert-defined uncertainty spread across neighboring classes

Scenario 2 aims to be slightly more complex than Scenario 1 in order to evaluate the difference of a detailed expert-defined uncertainty and a limitation to possible misclassification. Just like Scenario 1, it focuses on Group A uncertainty only; groups B and C uncertainties are ignored. In this scenario, a geological expert with experience in the case study area defined the uncertainty of each input data set by reviewing the attribute classification and the geographic location of the features. Every feature in every data set was assigned a probability that the feature classification is incorrect. A probability distribution is created using this assigned value. The probability that the feature is misclassified is split equally between the class neighbors. The number of class neighbors is defined i=1, …, N with N the total number of classes. X is a discrete random variable representing the class of a feature. The probability of the originally mapped class i=k is:

$$\Pr(X = k) = u \qquad (5.3)$$

The probability of the class neighbors i=k+1 and i=k-1 is:

$$\Pr(X = k - 1) = \Pr(X = k + 1) = \frac{1-u}{2} \qquad (5.4)$$

The probability of the remaining classes is zero.

For example, polygon 965 was originally classified as "medium-high" TOC (Figure 5.1D). The expert-defined uncertainty is a probability of 0.5 that the area is either "medium" or "high" TOC (Figure 5.1B) and is split equally between the two classes (i.e. 0.25 medium, 0.5 medium-high, 0.25 high, because i=2). In the case of polygon 964, the uncertainty is a probability of 0.1 that the area is not "high" TOC (Figure 5.1D); however the classification "high" is an end-member and in this case "medium-high" classification is assigned a probability 0.1 because i=1 (Figure 5.1B). Polygons 963 and 968-971 are treated the same as in Scenario 1 because the original classification was "unknown" TOC; thus each attribute is equally likely (i.e. i=N) (Figure 5.1B, D).

Scenario 3: Expert-defined uncertainty in pseudo-normal distribution

Scenario 3 continues to focus only on Group A uncertainty like scenarios 1 and 2. It uses expert-defined uncertainty like Scenario 2. However, unlike Scenario 2 where reclassification is limited, Scenario 3 distributes uncertainty among all of the classes in a pseudo-normal distribution.

Class numbers are defined i=1, …, N with N the total number of classes. X is a discrete random variable representing the class of a feature. The probability of the originally mapped class i=k is:

$$\Pr(X = k) = u \qquad (5.5)$$

The remaining probability 1-u is distributed over all the remaining classes i≠k. The probability distribution was created with expert opinion to follow a smooth, bell-curve-shape taken from Gaussian distribution sigma values (1σ=0.341, 2σ=0.136, 3σ=0.21, 4σ=0.001); hence called "pseudo-normal distribution" as the originally classified attribute will disrupt the normal bell curve (Figure 5.1C). The classes nearer to the originally assigned class will be more probable than those classes further away and all classes will have some probability of being the correctly assigned classification. In situations where the class is unknown, the probability distribution follows a normal distribution fitted to N.

Figure 5.1C shows the probability distribution of the geochemical subcriterion. For example, polygon 964 has a probability of 0.1 of being misclassified, which is divided among the classes in a pseudo-normal distribution. The polygons as well as the uncertainty are labeled in the map (Figure 5.1D). All uncertainty probability distributions can be found in Appendix I.

Scenario 4: Expert-defined uncertainty over pseudo-normal distribution with fuzzy membership assignment and boundary transition zone

Scenario 4 builds on the uncertainty modeling of Scenario 3 by using the same input data uncertainty and probability distributions. Scenario 4 additionally investigates the uncertainty effects of fuzzy membership assignment and a boundary transition zone of 10 km. This scenario combines Group A and Group B uncertainties. Fuzzy membership uncertainty is represented using a stochastic fuzzy membership value. The fuzzy membership values originally assigned to each feature are $j \in g$, $g = [0,1]$; j may be different for each feature. In order to represent uncertainty, each of these values is replaced by a stochastic variable j_Y, derived from the original fuzzy membership value as:

$$j_Y = j + Y \tag{5.6}$$

In Equation 5.6, Y is a Gaussian distributed random variable with a mean 0 and a standard deviation 0.1. In each Monte Carlo realization, a random variable is drawn from j_Y.

Input data sets were assigned a boundary transition zone of 10 km because of the scale of the map and cell size. This means that for every neighboring area, the actual boundary may be shifted up to 5 km into one area or another as the boundary transition zone is bisected by the original boundary. The boundary transition zone is randomly reassigned a class membership between the two neighbors (Figure 5.2), having equal probability of occurrence of 0.5. Boundary transition zones are not applicable to all input data sets (Table 5.1). Examples of exceptions are where the boundary is already certain or the original format is point data.

Table 5.1 Error propagation parameters.

Subcriteria	**Border classification**	**Fuzzy membership assignment**
Costs (C)	Yes	Yes
Safety (S)	Yes	Yes
Risks (R)	No+	Yes
Geochemical (G)	No‡	Yes
Fields (F)	No‡	Yes
Wells (W)	No‡	Yes
Seeps (W)	No‡	Yes
Fault density (U)	No‡	Yes
Diapirs (A)	Yes	Yes
Isochrons (I)	No†	Yes
Plays (P)	Yes	Yes
Surface geology (Q)	Yes	Yes
Source rock (X)	Yes	Yes
Reservoir rock (V)	Yes	Yes
Traps (T)	Yes	Yes
Subsurface lithology (L)	Yes	Yes
Sedimentary basin (N)	Yes	No*

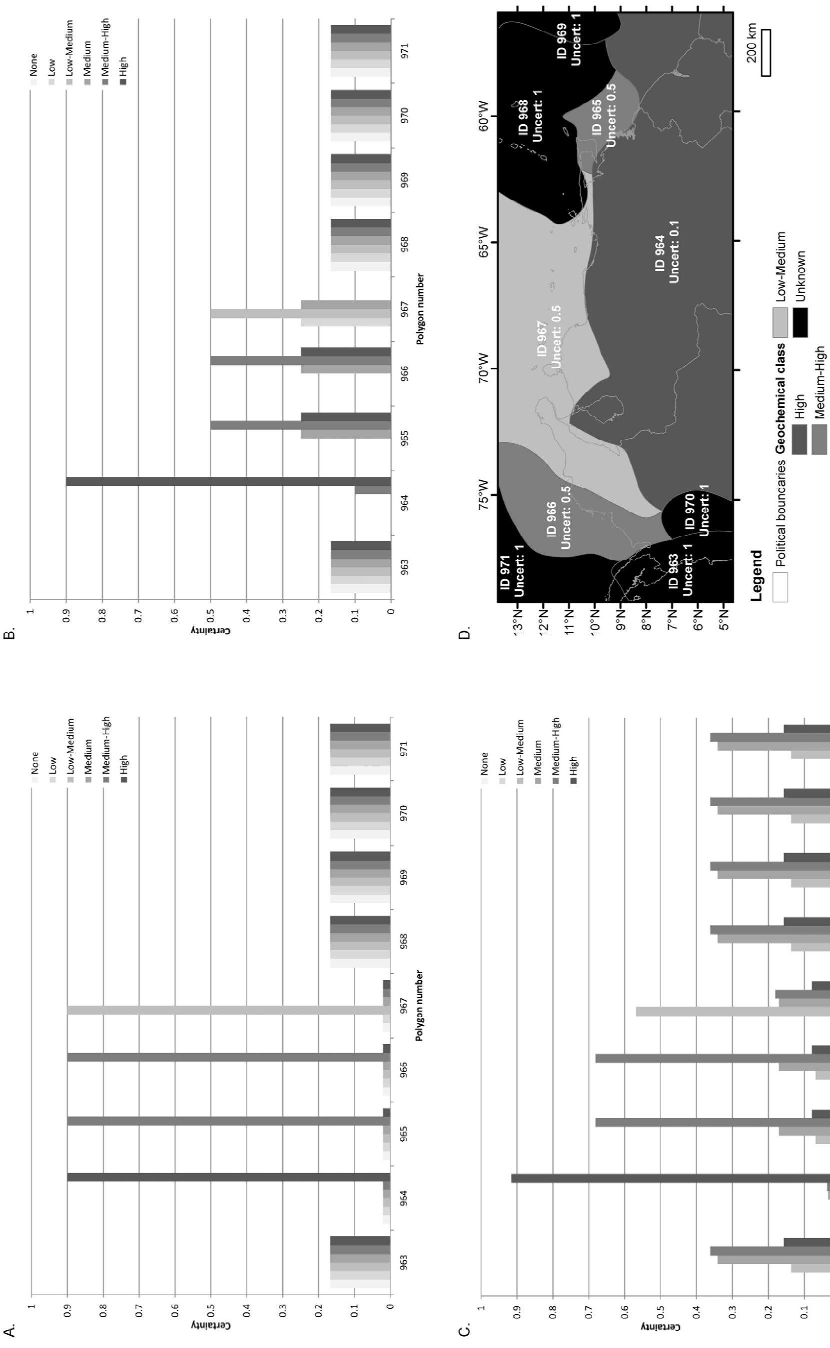
+Risks were not included in the border classification error because the boundaries follow the accepted political and economic zone boundaries.

‡These data sets were not included because the random error model was applied.

†The isochrons were not included because it is a continuous data set and has no borders.

*Sedimentary basins are not included in fuzzy membership assignment or error modeling because value is not uncertain; either the location is a sedimentary basin or it is not and this is well-established information.

Figure 5.1 (on the following page) A. Graph showing the discrete probability distributions representing uncertainty in the geochemical subcriteria following Scenario 1. The x-axis is the polygon ID shown in D. The y-axis is the probability of a class. Each polygon number shows the distribution of six classes. B. Graph showing the uncertainty distribution of the geochemical subcriteria following Scenario 2. Each polygon number shows the distribution of two, three, or six classes as the case may be. C. Graph showing the uncertainty distribution of the geochemical subcriteria following scenarios 3 through 6. Each polygon number shows the distribution of six classes. D. Map showing the geochemical subcriteria. Each feature polygon is colored by class and labeled with the polygon ID and expert-assigned uncertainty. Appendix I provides the probability distributions of other input variables.



A.
B.
C.
D.
Certainty
Polygon number
None
Low
Low-Medium
Medium
Medium-High
High
963
964
965
966
967
968
969
970
971
ID 971
Uncert: 1
ID 966
Uncert: 0.5
ID 963
Uncert: 1
ID 970
Uncert: 1
ID 967
Uncert: 0.5
ID 964
Uncert: 0.1
ID 968
Uncert: 1
ID 965
Uncert: 0.5
ID 969
Uncert: 1
200 km
Legend
Political boundaries
Geochemical class
High
Medium-High
Low-Medium
Unknown

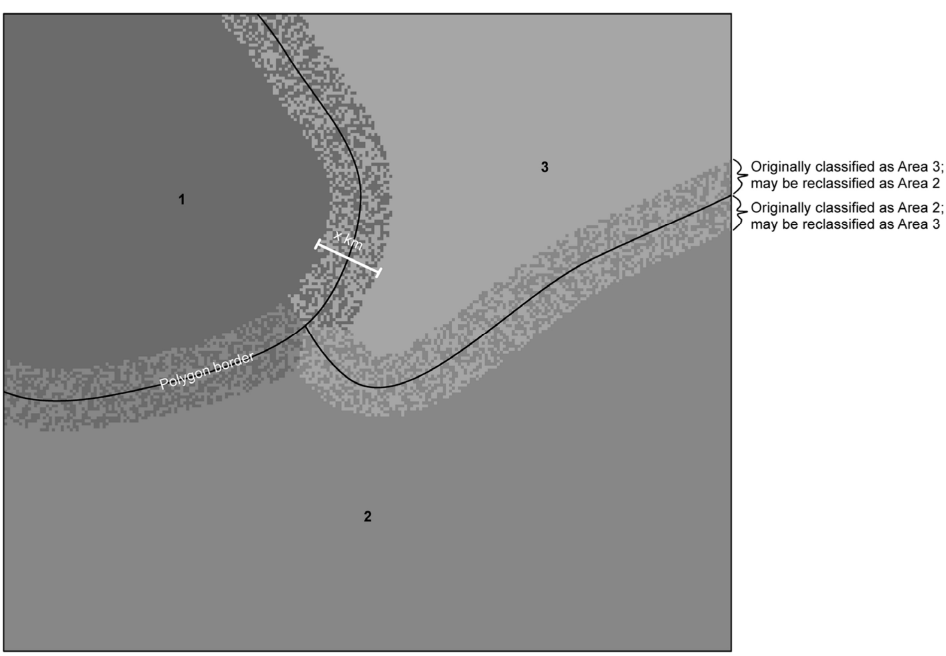


Figure 5.2 Boundary transition zone example. The polygon border may shift between neighboring areas. The cells within the transition zone are randomly reassigned.

Scenario 5: Parameter investigation

Scenario 5 builds on Scenario 3 ignoring Group B uncertainty, but Scenario 5 introduces Group C uncertainty (model structure uncertainty). Scenario 5 changes all of the FLOs to the gamma operator.

The FLO *gamma operation* applies a γ (gamma), where different gamma values result in different favorabilities (Equation 5.7).

$$\mu V = \left(1 - \prod_{i=1}^{n}(1-\mu_i)\right)^{\gamma} * \left(\prod_{i=1}^{n}\mu_i\right)^{(1-\gamma)} \tag{5.7}$$

where μ_i is the fuzzy membership function of the i^{th} map and i=1,2,…,n maps to be combined, γ is a parameter in the range [0,1], and μV is the combined favorability value. This FLO takes all input into account, while other FLOs are either more restrictive (*and*, *or*) or result in extreme values (*algebraic product*, *algebraic sum*). Chapter 4 discusses the FLOs in more detail.

Gamma values are $q \in g$, $g=[0,1]$. q_z is a random variable representing the gamma value, q is the originally assigned gamma value, and Z is a Gaussian random variable with mean zero and standard deviation 0.2 (Equation 5.8).

$$q_z = q + Z \tag{5.8}$$

Scenario 6: parameters with fuzzy membership uncertainty and boundary transition zone

Scenario 6 builds on Scenario 5 adding fuzzy membership uncertainty and a boundary transition zone. This scenario takes all sources of uncertainty of an MCE into account. It addresses groups A, B, and C uncertainties; thus, it applies equations 5.5-5.8.

Confidence levels and thresholds

This section does not intend to give a complete review of statistical theory behind confidence levels and threshold values, however it is deemed necessary for a brief overview and application in order that the reader is sure to understand the presentation of results and the discussion. Confidence levels are used when the most effective way to describe the error associated with an event cannot be precisely determined. A confidence level provides "an interval and a probability that the unknown value falls within the interval" (Isaaks and Srivastava, 1989, p. 494). Geoscience applies confidence levels on events that do not necessarily repeat over time (i.e. a well is only drilled once), but over space (i.e. multiple wells may be drilled in a prospect). However, it is further understood that the data collected (e.g. from wells) are skewed towards a bias of good outcomes (Isaaks and Srivastava, 1989; Goovaerts, 1997). The confidence intervals are calculated using the percentiles from the Monte Carlo simulation.

Figure 5.3 shows a graph illustrating two different confidence intervals. The area within the confidence interval is shaded grey. By changing the confidence level from 1-α_1 to 1-α_2, the confidence level is lower. In this study, 95% and 60% confidence levels are calculated and compared. A confidence level of 95% is used because of the conventional use of the interval as well as the lower risk associated with the outcomes; 5% risk is considered exceptional for petroleum exploration. Because the data used in the study is not industry-grade (i.e. data available for university research and public use) and to allow for comparison in a high-risk fashion, a confidence level of 60% is presented for comparison.

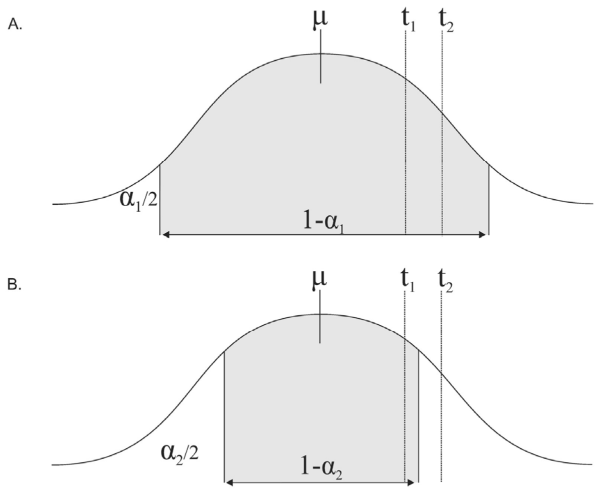


Figure 5.3 Confidence interval graphs with mean μ. Two thresholds are shown by dashed lines (t_1 and t_2). A. Boundaries of confidence interval a_1 shown with solid black lines. B. Boundaries of confidence interval a_2 shown with solid black lines.

The concept of a threshold value is such that it is an indicator of a critical behavior (Isaaks and Srivastava, 1989). Figure 5.3 shows two threshold values, t_1 and t_2. In the case of this study, the threshold value indicates the required favorability for petroleum exploration. The favorability value chosen to indicate possible exploration is 0.7 because the fuzzy membership values have this value as a medium-high qualitative description. A lower favorability value of 0.5 is presented for comparison based on the favorability values, because of the contextual relationship of 0.5 to "medium" quality outcomes. It is assumed that less than "medium" quality outcomes are not preferred for exploration decisions.

The confidence level is combined with the threshold value to indicate three different classifications of locations. Those areas that are: (1) confident to be above the threshold value; (2) confident to be below the threshold value; or (3) ambiguous (i.e. it is unknown if the location is above or below the threshold and no decision can be made). Figure 5.3 illustrates how the confidence level and threshold value may restrict the results. The interval for a level of 1-α_1 straddles t_1 and t_2 and is therefore ambiguous (Figure 5.3A); the interval of 1-α_2 straddles t_1 and is ambiguous (Figure 5.3B). However, 1-α_2 is completely below t_2, so it is confident to be below the threshold (Figure 5.3B).

5.4. Results

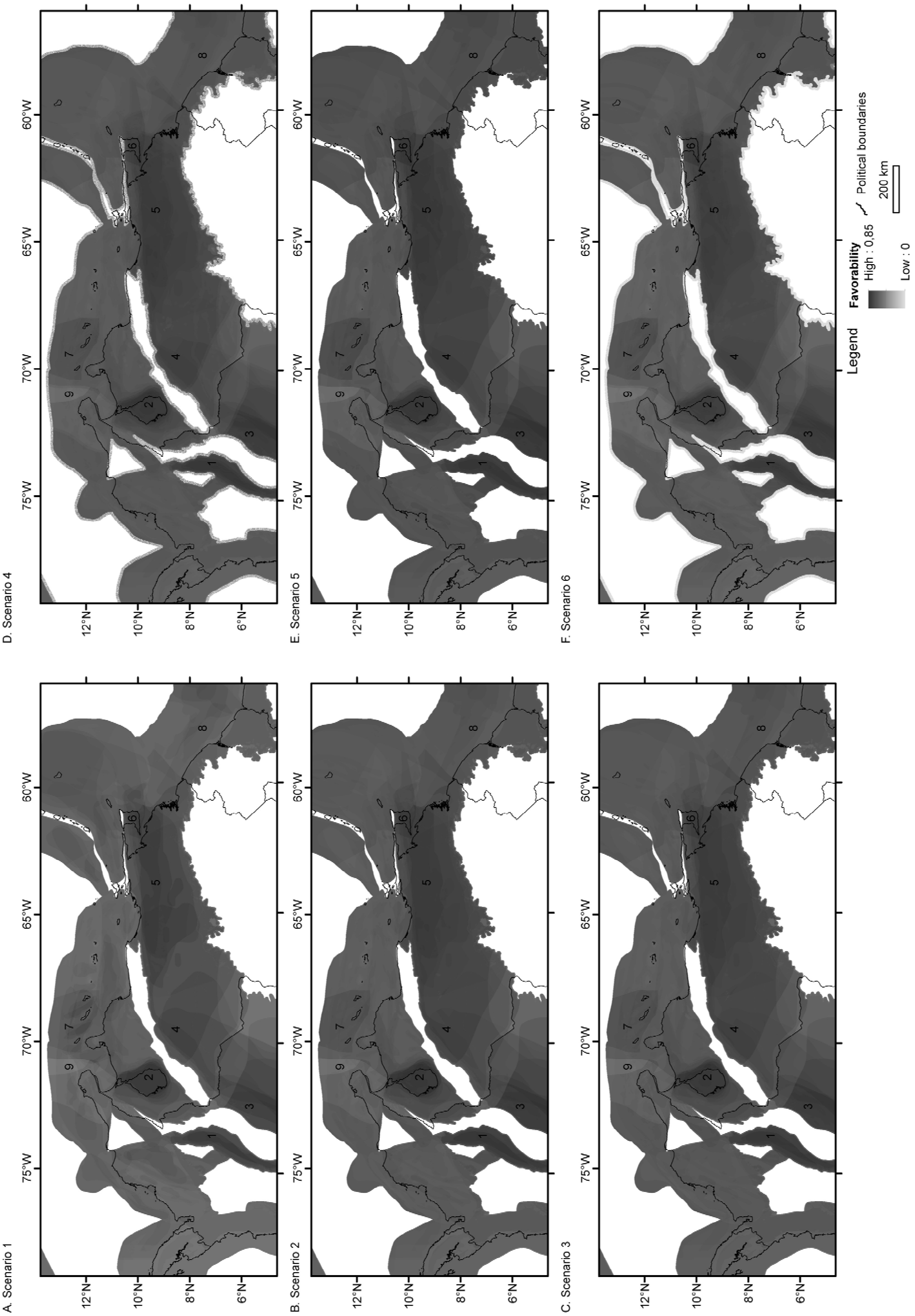
The median values of the realizations for all scenarios are shown in Figure 5.4. Areas in white are excluded from the results because the areas are not sedimentary basins, thus not appropriate for petroleum exploration activities. Scenario 3 (Figure 5.4C) has higher favorability in areas of known production in the Magdalena Valley basin, Llanos basin, Maracaibo basin, Guárico subbasin, Eastern Venezuelan basin, and Trinidad. Relatively high values are also shown in Aruba, Curaçao, and Bonaire, which are not producing areas, and offshore Guyana where there has been a recent oil discovery (Liza-1; Rosati and Carroll, 2015) after several unsuccessful attempts of exploration. A comparatively low area is just northeast of Guajira Peninsula. All scenarios reflect similar spatial patterns of favorability trends, i.e. higher favorability onshore than offshore and higher favorability in the nine mentioned areas. Scenarios 1, 2, 3, and 5 have similar ranges of favorability from ~0.4 to ~0.8. Scenario 4 has favorability range from ~0.1 to ~0.8 and Scenario 6 has a range from ~0.0 to ~0.8. However, there are two identifiable ranges of values that appear more often – one ranging from ~0.0 to ~0.1 and a second ranging from ~0.5 to ~0.8 for both scenarios (4 and 6). Scenarios 4 and 6 include low favorability, likely dominating the lower value range histogram, in the boundary transition zone between the sedimentary and non-sedimentary basins.

The standard deviation of the final favorability Z was calculated for each scenario and is shown in Figure 5.5. Scenario 3 (Figure 5.5C) has an overall low standard deviation ranging from 0.02 to 0.09. There is a small area in Guyana near the border to Suriname that has a standard deviation ~0.3 because of the uncertainty related to various data sets overlapping there. Disregarding the non-sedimentary basins (shown with cross hatch marks), the lowest standard deviation is onshore and increases towards the offshore because of increased uncertainty; however, there is not much variation between the two regions. Scenarios 2 and 4 exhibit similar spatial trends and ranges of standard deviation to Scenario 3 with the exception of the border region in Scenario 4, which has high standard deviation due to the boundary transition zone. Scenario 1 has high standard deviation between 0.15 and 0.24 with higher values concentrated onshore and in areas of known hydrocarbon production. Scenarios 5 and 6 exhibit similar spatial trends to each other and have similar ranges from ~0.20 to ~0.40. These scenarios also show the greatest amount of spatial variation within the map results.

Following Scenario 3 through the changes in thresholds and confidence intervals (Figures 5.6- 5.10), some general results can be related to the other five scenarios. A threshold value of 0.7 and a confidence interval with a confidence level of 95% results in 41% of the cells being either above or below the threshold; 59% of the cells cannot be used to support decisions (Figures 5.6C; 5.7). By narrowing the confidence level to 60%, the number of cells that can be used for decision-making increases to 67% (Figures 5.7; 5.8C). By increasing the acceptable risk of making a wrong decision (i.e. by decreasing the confidence level of the confidence interval), the number of cells meeting the criteria increases. By lowering the threshold value to 0.5 and using a confidence level of 95%, the total area available for decision-making increases;

85% of the cells are either above or below the threshold (Figures 5.7; 5.9C). Accepting more risk by reducing the confidence level to 60%, the total area available for decision-making increases and most cells are either above or below the threshold (Figures 5.7; 5.10C). In general, all of the scenarios follow the same pattern: narrowed confidence level and lowered threshold value increases the total area available for decision-making (Figures 5.6-5.10).

Figure 5.4 (on the following page) Median favorability of final favorability of all realizations. A. Scenario 1. B. Scenario 2. C. Scenario 3. D. Scenario 4. E. Scenario 5. F. Scenario 6. 1: Lower Magdalena Valley basin; 2: Maracaibo basin; 3: Llanos basin; 4: Guárico subbasin; 5: Eastern Venezuela basin; 6: Trinidad; 7: Aruba, Bonaire, and Curaçao; 8: Guyana; 9: northeast of Guajira Peninsula.


A. Scenario 1
B. Scenario 2
C. Scenario 3
D. Scenario 4
E. Scenario 5
F. Scenario 6
12°N
10°N
8°N
6°N
75°W
70°W
65°W
60°W
1
2
3
4
5
6
7
8
9
Legend
Favorability
High : 0,85
Low : 0
Political boundaries
200 km

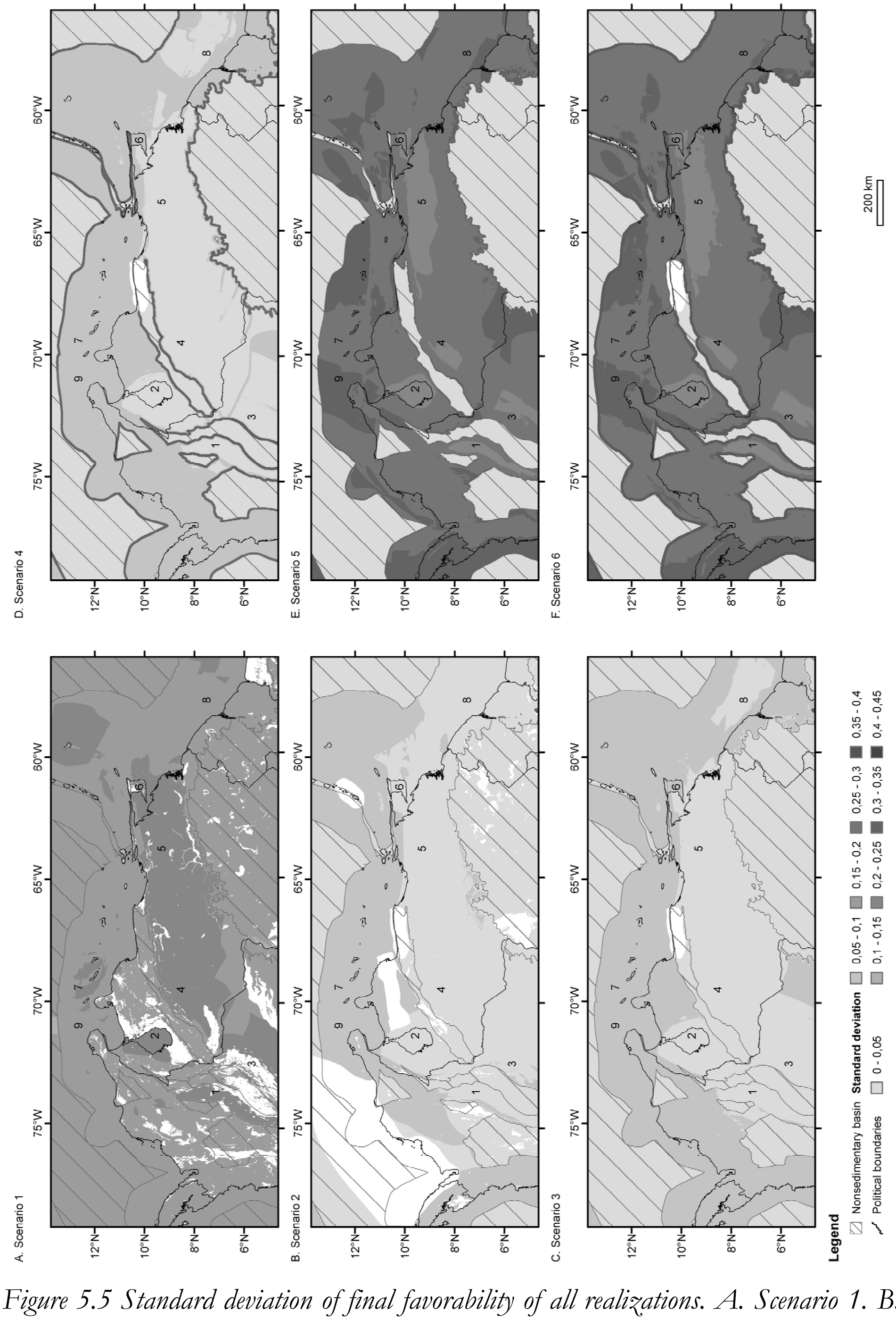


Figure 5.5 Standard deviation of final favorability of all realizations. A. Scenario 1. B. Scenario 2. C. Scenario 3. D. Scenario 4. E. Scenario 5. F. Scenario 6. See Figure 5.4 for labels 1-9.

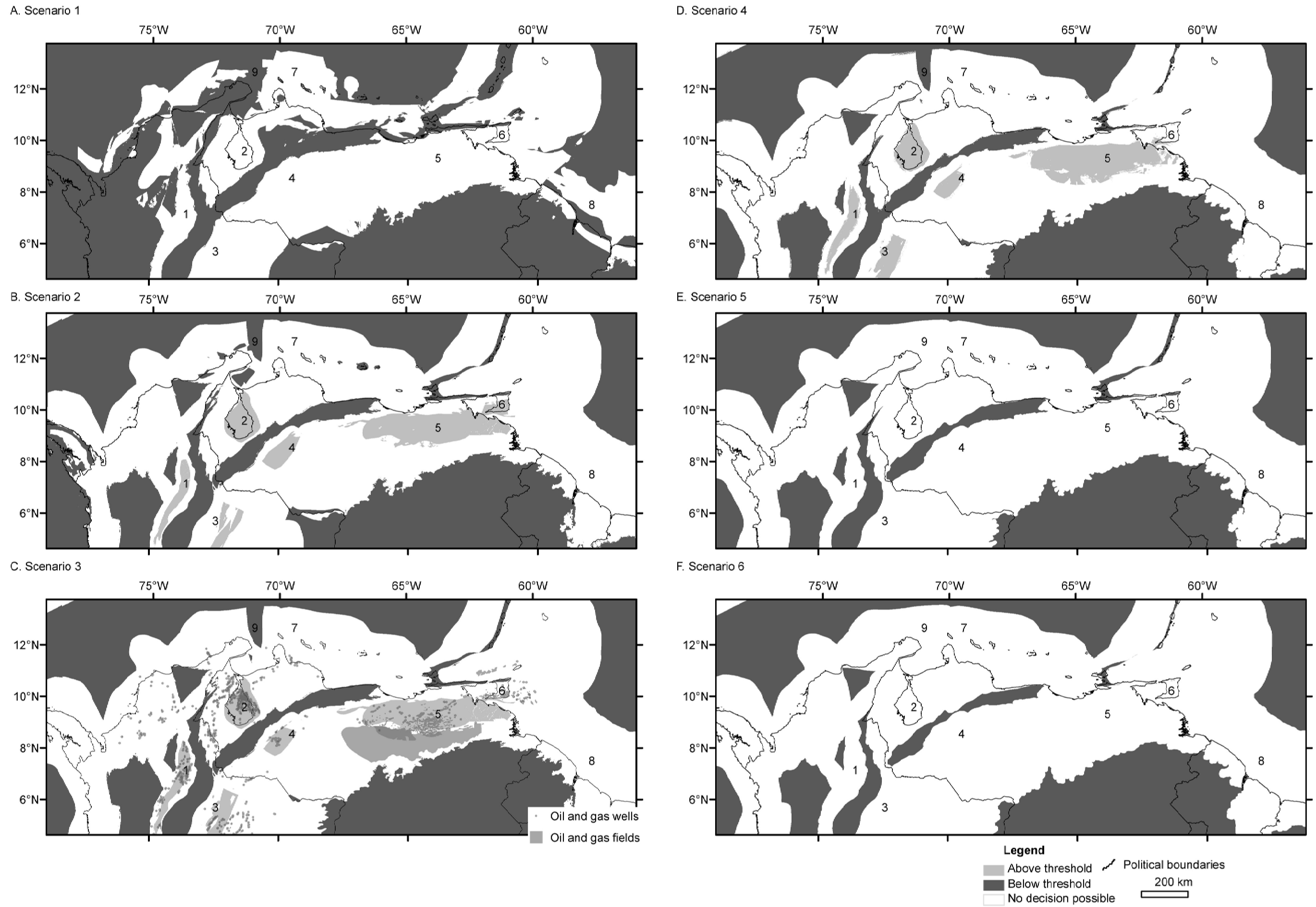
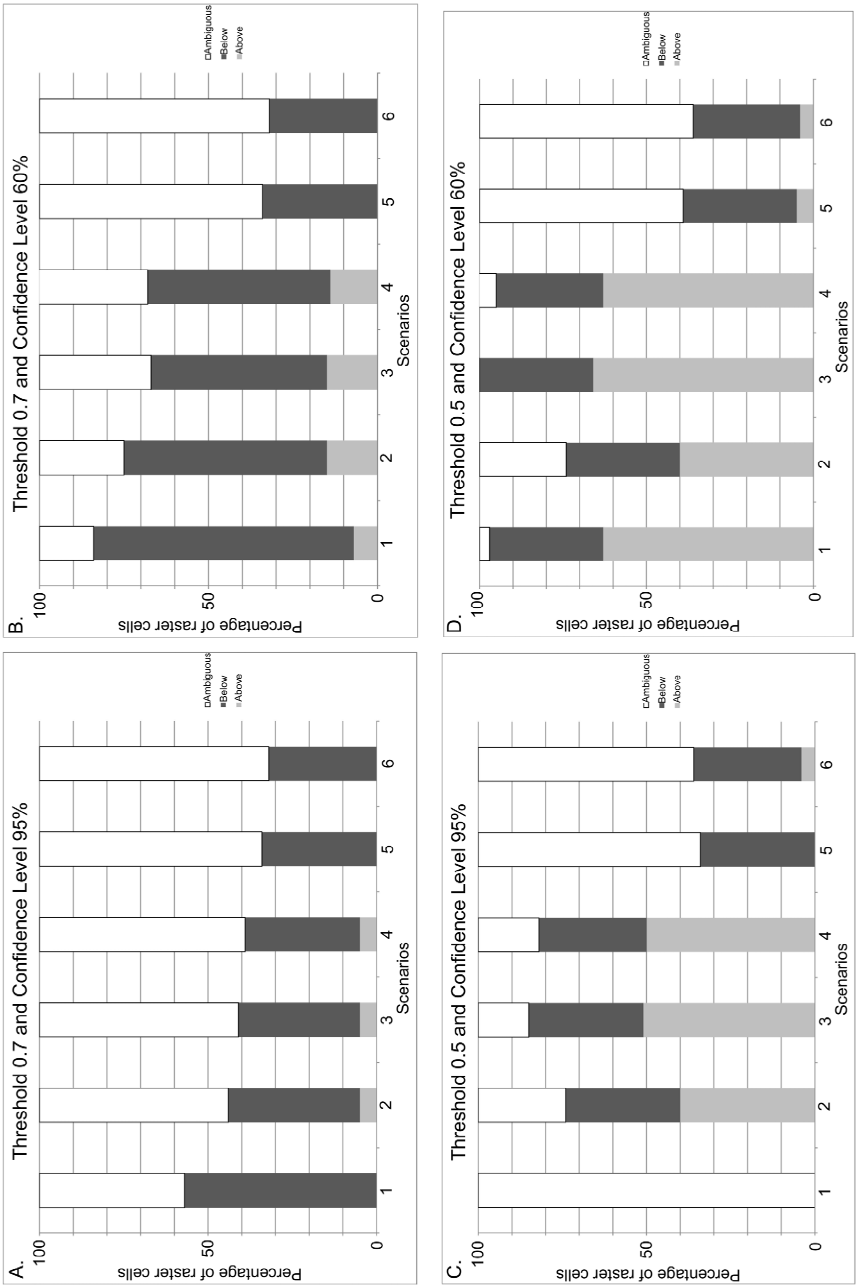

A. Scenario 1
B. Scenario 2
C. Scenario 3
D. Scenario 4
E. Scenario 5
F. Scenario 6
75°W
70°W
65°W
60°W
12°N
10°N
8°N
6°N
1
2
3
4
5
6
7
8
9
Oil and gas wells
Oil and gas fields
Legend
Above threshold
Below threshold
No decision possible
Political boundaries
200 km

Figure 5.6 (on the previous page) Threshold value 0.7 and confidence interval 95%. A. Scenario 1. B. Scenario 2. C. Scenario 3. Medium Grey areas are oil and gas wells and fields. D. Scenario 4. E. Scenario 5. F. Scenario 6. White represents ambiguous (i.e. no decision possible); dark grey represents above the threshold; light grey represents below the threshold. 1: Lower Magdalena Valley basin; 2: Maracaibo basin; 3: Llanos basin; 4: Guárico subbasin; 5: Eastern Venezuela basin; 6: Trinidad; 7: Aruba, Bonaire, and Curaçao; 8: Guyana; 9: northeast of Guajira Peninsula.

Figure 5.7 (on the following page) Graph summarizing all scenario results for threshold value and confidence level combinations. A. Threshold value 0.7 and confidence level 95%. B. Threshold value 0.7 and confidence level 60%. C. Threshold value 0.5 and confidence level 95%. D. Threshold value 0.5 and confidence level 60%. Light grey bars show the percentage of the map with the lower boundary of the confidence interval above the threshold value; dark grey bars show the percentage of the map with the upper boundary confidence interval below the threshold value; white bars show the percentage of the map where it is ambiguous (confidence interval straddles threshold).


A.
Threshold 0.7 and Confidence Level 95%
B.
Threshold 0.7 and Confidence Level 60%
C.
Threshold 0.5 and Confidence Level 95%
D.
Threshold 0.5 and Confidence Level 60%
Percentage of raster cells
100
50
0
Scenarios
1
2
3
4
5
6
Ambiguous
Below
Above

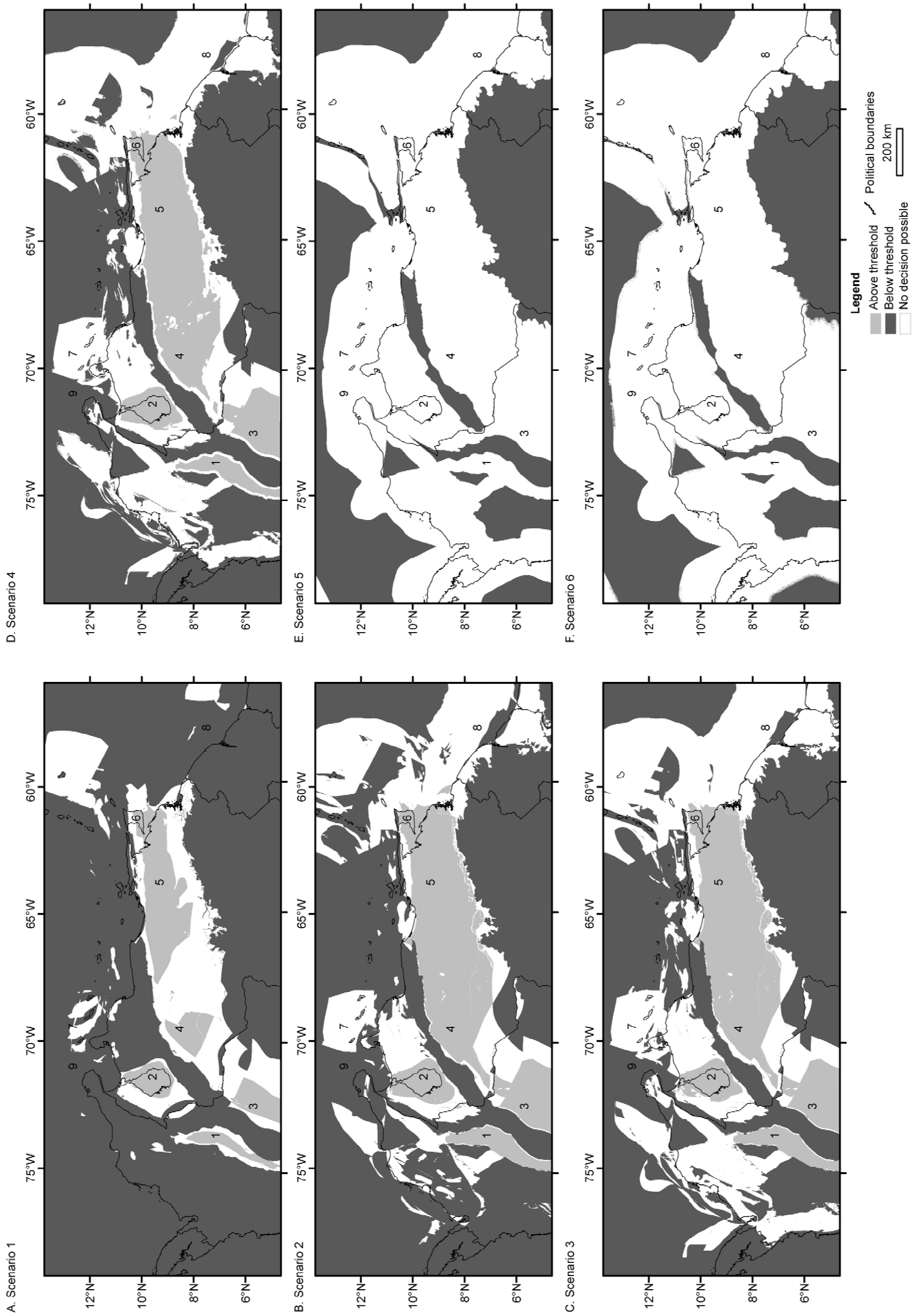
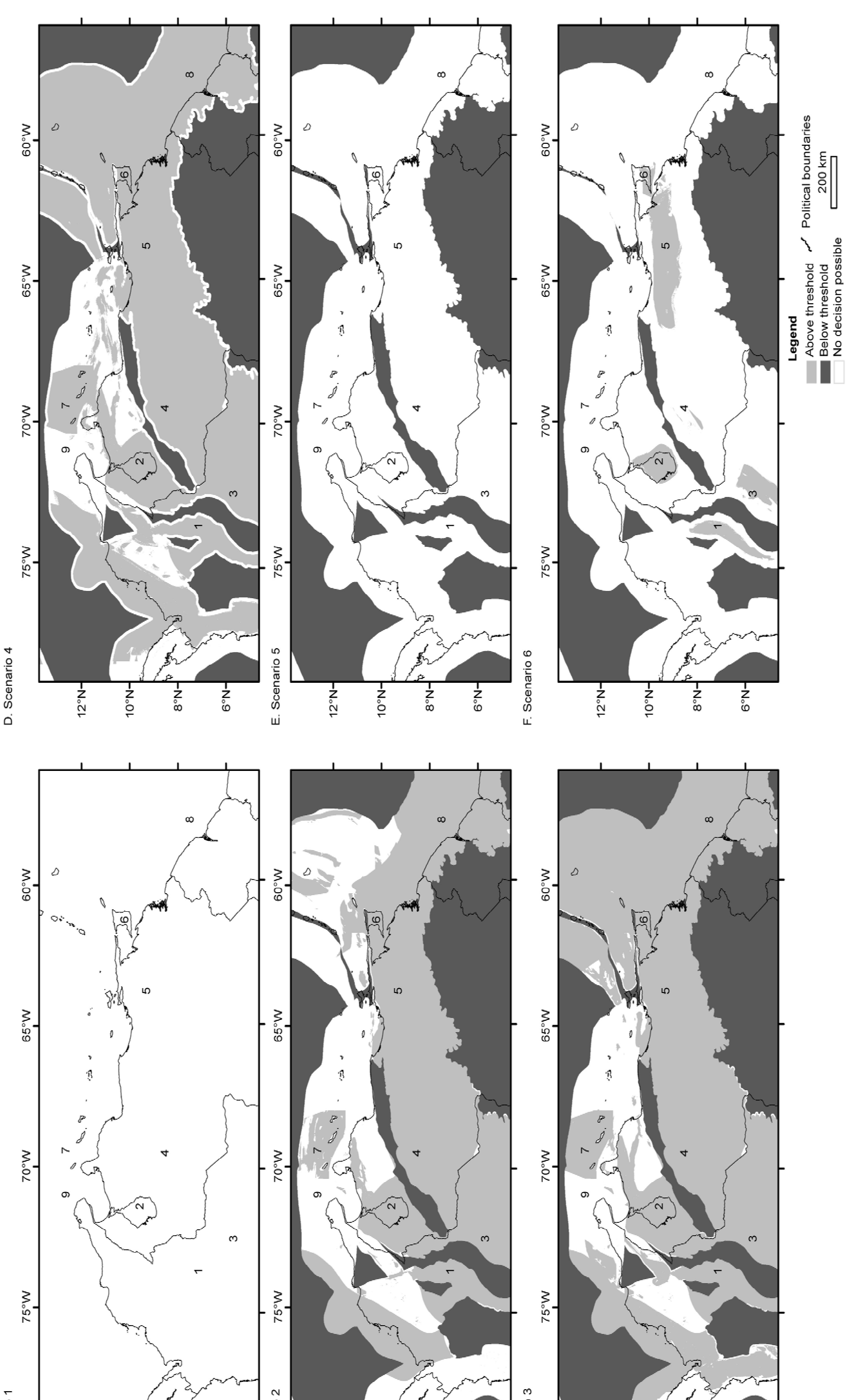
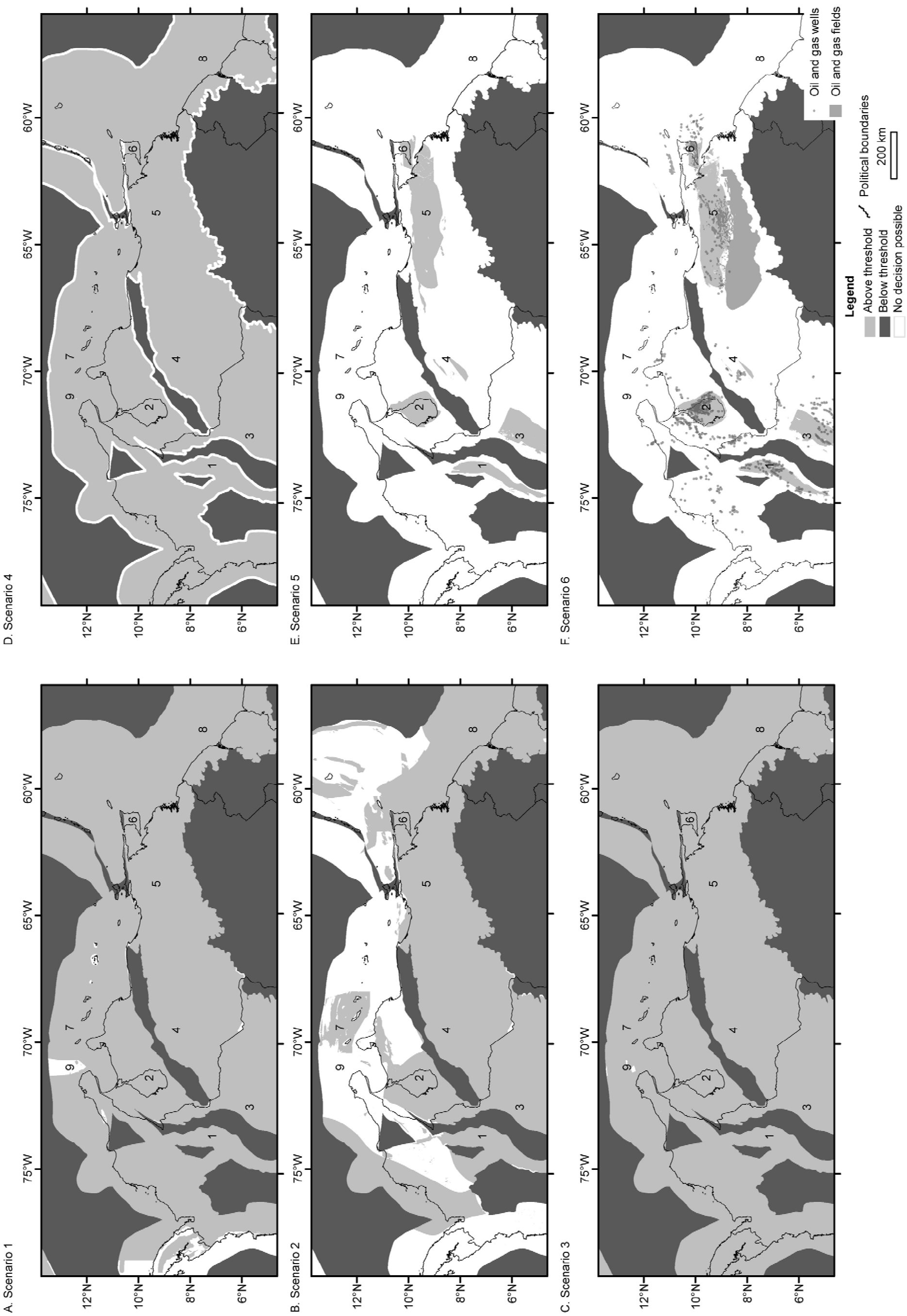

A. Scenario 1
B. Scenario 2
C. Scenario 3
D. Scenario 4
E. Scenario 5
F. Scenario 6
12°N
10°N
8°N
6°N
75°W
70°W
65°W
60°W
Legend
Above threshold
Below threshold
No decision possible
Political boundaries
200 km

Figure 5.8 (on the previous page) Threshold value 0.7 and confidence interval 60%. A. Scenario 1. B. Scenario 2. C. Scenario 3. D. Scenario 4. E. Scenario 5. F. Scenario 6. White represents ambiguous (i.e. no decision possible); dark grey represents above the threshold; light grey represents below the threshold. 1: Lower Magdalena Valley basin; 2: Maracaibo basin; 3: Llanos basin; 4: Guárico subbasin; 5: Eastern Venezuela basin; 6: Trinidad; 7: Aruba, Bonaire, and Curaçao; 8: Guyana; 9: northeast of Guajira Peninsula.

Figure 5.9 (on the following page) Threshold value 0.5 and confidence interval 95%. A. Scenario 1. B. Scenario 2. C. Scenario 3. D. Scenario 4. E. Scenario 5. F. Scenario 6. White represents ambiguous (i.e. no decision possible); dark grey represents above the threshold; light grey represents below the threshold. 1: Lower Magdalena Valley basin; 2: Maracaibo basin; 3: Llanos basin; 4: Guárico subbasin; 5: Eastern Venezuela basin; 6: Trinidad; 7: Aruba, Bonaire, and Curaçao; 8: Guyana; 9: northeast of Guajira Peninsula.


A. Scenario 1
B. Scenario 2
C. Scenario 3
D. Scenario 4
E. Scenario 5
F. Scenario 6
75°W
70°W
65°W
60°W
12°N
10°N
8°N
6°N
Legend
Above threshold
Below threshold
No decision possible
Political boundaries
200 km



A. Scenario 1
B. Scenario 2
C. Scenario 3
D. Scenario 4
E. Scenario 5
F. Scenario 6
12°N
10°N
8°N
6°N
75°W
70°W
65°W
60°W
Legend
Above threshold
Below threshold
No decision possible
Political boundaries
200 km
Oil and gas wells
Oil and gas fields

Figure 5.10 (on the previous page) Threshold value 0.5 and confidence interval 60%. A. Scenario 1. B. Scenario 2. C. Scenario 3. D. Scenario 4. E. Scenario 5. F. Scenario 6. Medium grey areas are oil and gas wells and fields. White represents ambiguous (i.e. no decision possible); dark grey represents above the threshold; light grey represents below the threshold. 1: Lower Magdalena Valley basin; 2: Maracaibo basin; 3: Llanos basin; 4: Guárico subbasin; 5: Eastern Venezuela basin; 6: Trinidad; 7: Aruba, Bonaire, and Curaçao; 8: Guyana; 9: northeast of Guajira Peninsula.

5.5. Discussion

From the uncertainty applied to the data sets in this study, the results, in general, show that lowering the confidence level from 95% to 60% results in more cells for decision-making. Changing the threshold value from 0.7 to 0.5 results in more cells that are considered more favorable (i.e. number of cells above the threshold increase). With a threshold value of 0.7 and confidence level of 95% (Figures 5.6; 5.7), regardless of the scenario, the majority of the results either do not support exploration or are inconclusive. In the case that accepts the most uncertainty in the results with threshold value of 0.5 and confidence level of 60%, more areas are above the threshold and support exploration than in previous cases (Figures 5.7; 5.10). However, it is not necessarily good that all of an area could be explored because it is not probable that petroleum exists in the entire study area. In the same case, if all of the uncertainty sources are taken into account (Scenario 6), there are few areas where exploration is supported (Figures 5.7; 5.10F). By overlaying known oil and gas wells and fields, it is shown that many existing production areas are in the ambiguous areas (Figure 5.10F), although new areas are also predicted. In many of the cases, depending on the sources of uncertainty taken into account, decisions are not possible. Because of this conundrum, it is difficult to choose only one case for making decisions. It would most likely suit the realistic situation that areas are further classified for decision-making and that all four cases are used for a specified scenario. In short, areas would be given a grade based on the threshold value and confidence interval.

Group A (uncertainty of observational data with respect to attribute classification) with expert-defined uncertainty in either scenarios 2 or 3 yield overall similar spatial results with local variation and have lower standard deviation than Scenario 1 (Figure 5.7). Scenario 2 has more cells available for decision-making when the threshold value is 0.7 regardless of the confidence interval, and Scenario 3 has more cells available for decision-making when the threshold value is 0.5 regardless of the confidence interval (Table 5.2). Because scenarios 2 and 3 yield similar results and rely on expert opinion, they are favored over Scenario 1, which produces very different results.

Scenario 4 combines groups A (uncertainty of observational data with respect to attribute classification) and B (uncertainty of weighting of evidence with respect to fuzzy membership assignment and observational data with respect to boundary transition zones) uncertainties and presents more uncertainty in its results as expected since more uncertainties are quantified. However, fuzzy membership and border transition uncertainty (Group B) contribute less to the output uncertainty than the uncertainty of the attribute classification in the input data sets (Group A). It is concluded that there is more uncertainty related to the input data set attribute classification rather than the fuzzy membership values for the defined uncertainties, because the addition of Group B uncertainty has little impact on the results of Scenario 4 compared to Scenario 3. It is possible that differently defined uncertainties for either Group A or Group B could yield different results.

Group C uncertainty (model uncertainty of FLOs) overshadows the other uncertainties defined in groups A or B. Scenarios 5 and 6 have similar spatial patterns and values both in the standard deviation and threshold results. The results of scenarios 5 and 6 verify that changes in the gamma value have large impacts on the results. This confirms the known subjectivity and uncertainty related to MCE models and reinforces the necessity to construct models based in logical grounding of the real-world phenomena and data evaluation of an expert. This is a sensitive aspect of the model.

The weaknesses in this approach are the subjectivity related to every aspect of the analysis: the input data, the MCE methodology, the fuzzy membership values, the defined uncertainties, the accepted threshold value, and the acceptable confidence level. All of these aspects of the analysis may change depending on the expert opinion or depending on the company policy that an exploration geologist would refer to for decisions. However, every aspect of the analysis would not necessarily change or change drastically.

Table 5.2 Comparison of different scenarios and different threshold value and confidence level cases.

Scenario	***Threshold value 0.7***					
	Confidence level 95%			***Confidence level 60%***		
	Above	*Below*	*Ambiguous*	*Above*	*Below*	*Ambiguous*
1	0%	57%	43%	7%	77%	16%
2	5%	39%	56%	15%	60%	25%
3	5%	36%	59%	15%	52%	33%
4	5%	34%	61%	14%	54%	33%
5	0%	34%	66%	0%	34%	66%
6	0%	32%	68%	0%	32%	68%

Scenario	***Threshold value 0.5***					
	Confidence level 95%			***Confidence level 60%***		
	Above	*Below*	*Ambiguous*	*Above*	*Below*	*Ambiguous*
1	0%	0%	100%	63%	34%	3%
2	40%	34%	26%	40%	34%	26%
3	51%	34%	15%	66%	34%	0.05%
4	50%	32%	18%	63%	32%	6%
5	0%	34%	66%	5%	34%	61%
6	4%	32%	64%	4%	32%	64%

When comparing known locations of oil and gas wells and fields (Figures 5.6C; 5.10F), it may be concluded that the uncertainties are underestimated for some subcriteria. The coverage of the oil and gas wells and fields data set is not complete; however, it can be used as a guide for validation. Some areas where petroleum exists coincide with the ambiguous zone. In Figure 5.6C, the confidence level of 95% means that 5% of the cells are incorrectly classified as either above or below the threshold value. In Figure 5.10F, 40% of the cells are incorrectly classified as being above or below the threshold. While not all of the existing wells and fields are shown to be in the confidence levels and above the threshold value, some validation is shown. Further work is needed therefore to better constrain the defined uncertainties in order to better reflect known production information. Despite the weaknesses, statistical information is given that can be used to support decisions which would not be present otherwise. Additionally, the MCE and Monte Carlo simulation could be repeated for age-specific analysis and validation of producing fields may reflect better the reality of production information.

5.5. Conclusions

This chapter applies a Monte Carlo simulation to a fuzzy logic MCE to determine the best scenario for defining uncertainty in the input data and model structure. It addresses three groups of uncertainty sources (attribute classification – scenarios 1-3; fuzzy membership assignment and boundary transition – Scenario 4; FLO – Scenario 5), combines the uncertainty sources in different ways (scenarios 4-6), and proposes three methods for defining input data attribute classification uncertainty (scenarios 1-3). It finds that similar results can be obtained in either of the two expert-defined uncertainty scenarios (scenarios 2 and 3) and thus are the favored uncertainty definition approaches. Uncertainty from fuzzy membership assignment did not affect the results as much as attribute classification uncertainty (Scenario 4 vs. scenarios 1-3). Changing FLOs to gamma and changing the gamma values significantly changed the output, indicating that the choice of FLO and gamma value must be chosen in a clear and logical manner (Scenario 5).

Threshold values and confidence levels need to be predetermined prior to analyzing the results to prevent bias in the interpretation; however, the most useful interpretation may include several cases (i.e. multiple thresholds or multiple confidence levels) which grade the locations. Future work may better constrain uncertainties in order to match known production locations better and to focus on age-specific evaluations. By incorporating the uncertainties of the subcriteria and defining them within the provided MCE framework, the uncertainty analysis can be incorporated in forecasts used for decision-making.

Chapter 6

Synthesis

6.1. Introduction

Oftentimes decision-makers, whether they are politicians, managers, or practitioners, ignore uncertainty in spatial data and analysis results. Generally, uncertainty remains in the realm of researchers and academia (Fisher, 2009; Heuvelink, 1998). By not including or recognizing the uncertainty related to spatial data and analyses, decision-makers neglect a very important aspect of their decisions – namely the reliability of those decisions based on the data and results at hand. The need to define and communicate uncertainty in geographic information science is well documented, spanning decades (e.g. Brodaric, 1992; Hauck et al., 2013). Various approaches for defining and communicating uncertainty range from basic verbal expressions to fuzzy set approaches to error propagation (McMaster, 1991; Aminzadeh, 1965; Heuvelink et al., 1989, respectively). In particular, continental to global scale GIS data necessitate the defining of uncertainty because of the scale of the data and the number of data sets combined. This thesis has addressed the issues of combining data sets for large areas and including uncertainty about the data and results. By using two case studies from two different geoscience disciplines, some of the challenges and possible solutions are described and proposed.

6.2. Climate impacts on ecosystem services

The importance of climate change is a highly-charged topic socially and politically; however, in the scientific community the conversation is focused not on if it is occurring, but mainly on how the environment will be affected by changes in climate. Various studies look at different aspects of climate change from assessing how species react to changes (e.g. Okazaki et al., 2016) to how microclimates change (e.g. Kelly and Adger, 2000). This thesis has focused on the ecosystem services (ES) that are exposed to climate change.

The first research question was: *what is the suitable methodology for valuing and mapping global ES so that the spatial pattern and values of the ES assessment are transparent and consistent*? Because there is no consistent approach or methodology currently available in literature, a compiled ES assessment was proposed in order to establish a consistent valuation methodology and consistent ESs (Chapter 3). This assessment used five studies (Costanza et al., 1997; van der Ploeg et al., 2010; Kettunen et al., 2012; Böhnke-Henrichs et al., 2013; Hattam et al., 2015) to organize a list of ES that could be calculated. All of the data were presented and three spatial disaggregation methods were described. Each disaggregation method was assigned to the matching ES based on the input data available. The final global ES value is 1.9 x 10^{13} international dollars in the year 2005. However, 36 ecosystem services could not be calculated because of missing data. Therefore, the total value is greater than calculated here. A point of improvement to the ES assessment will be to gather the data for the missing ES to calculate fully the global spatial ES value.

Uncertainty in the data falls into one or more of the following four categories: undefined or unquantified uncertainty; coverage completeness (e.g. data gaps or topological errors from rasterization); attribute completeness (e.g. global values); and temporality (e.g. seasonal or migratory activity). Due to a lack of quantified uncertainty definitions from service providers, the uncertainty for the data was not calculated. Some data sets did not have any indication of the reliability of the data. In other cases, it is known that there is some uncertainty in the data, especially from rasterized data sets such as land cover, but the uncertainty is not quantified.

On the other hand, some of the data sets included probabilistic errors that can be used for analysis (e.g. animal density grids). Yet still, other data sets included a verbal description of reliability. For example, all of the FAO production statistics were graded on an ordinal and descriptive scale of reliability; to quantify the scale requires access to the original data and/or collaboration with FAO or other knowledgeable entities. Although the uncertainty in the data is not completely known and not defined, it was the best available and assumed to be reliable enough to use in the ES assessment due to the provenance of the data from research institutes, government agencies, or trade organizations.

The ES assessment was calculated at a global scale. The data were either already provided at or were generalized to a resolution of approximately 100 sq. km. If the results should be used at the local level, higher resolution data sets will need to replace the global data sets. While obvious, some ES may not be applicable to some localized areas (e.g. Fish Subservice in a desert environment), and some localized areas may benefit from ES for the locality in much the same way that the Reindeer Subservice is applicable for Arctic regions.

Another point of data uncertainty originates in the disaggregation of the values. The uncertainty that was not quantified stems from the assumptions related to data coverage and completeness. While the disaggregation methods themselves are straightforward, there is some unknown uncertainty due to the use of spatial attributes for disaggregation (e.g. all agricultural areas for fruit production). Disaggregation of some ES values could be more detailed and use more than general land cover and land use maps.

The uncertainty in the data and model influenced the resulting ES values and their disaggregation. The uncertainty associated with the assessment was communicated qualitatively in order to show where the assessment could be improved and uncertainty decreased. However, the uncertainty was not quantified and there was no analysis to support the robustness of the ES assessment results. This is a weakness in the assessment and was not addressed for the input or model assumptions. Quantifying the uncertainty of the input data and model are a valuable future direction of research that will require collaboration with experts or various institutions. Although possibly timeconsuming, the results of the ES assessment would be better supported. A minimal effort would provide a range of values for each ES.

The strengths and uniqueness of the approach in this thesis, however, was the showcase of a global spatial ES assessment that was calculated from publically sourced data at a good spatial resolution. It did not require much computational efforts, expert opinion, or specialized software. In fact, the entire process used open-source software (PCRaster) with open-source libraries (e.g. Python, GDAL, seaborne). The computational framework is open and can be easily extended, as well as reproduced (Scripts available upon request). The methodology provided here, especially in its completeness of data and disaggregation methods used, enables decision-makers from all levels of government access to the means of personalized ES assessments for their communities, given they have data at the appropriate scale.

Future pathways for research include:

- including missing ES;
- quantifying the uncertainty in the input data; and
- reducing the number of assumptions.

Second, the thesis asked: *how much of ES values are impacted by a transition in KGCC and how can the effected value be mapped taking into account the uncertainty regarding climate change models?* This study modeled climate class transitions and assessed the valued ES that were in a different climate class at the end of the 21st century. Climate change was derived from five Global Circulation Models (GCMs) and four climate change scenarios (RCP 2.6, 4.5, 6.0, and 8.5). It was characterized by the change in Köppen-Geiger climate class (KGCC) on an annual basis. KGCC were chosen because of the relation to ecosystems and the environment. Until 2050, 20-30% of the ES value is exposed to a KGCC transition, independent of the selected RCP scenario. After 2050, however, the ES value exposed to climate change strongly depends on the RCP scenario, where RCP 2.6 has the least changes and 8.5 has the greatest.

Uncertainty in the ES data propagates to the ES values exposed to KGCC shifts. Where there are spatial uncertainties, those continue in the KGCC transition modeling and forecasting in the future. The spatial distribution of the ES values may change depending on the improvement of the area for disaggregating the values (e.g. apple orchards over all agricultural land versus apple orchards in actual orchard areas); this may change the ES value in different KGCC at the end of the 21st century. The reliability of the ES values in new KGCC after climate change scenarios is unknown. It is, however, acceptable given the data providers (e.g. Food and Agriculture Organization of the United Nations). Improvements in the ES assessment will make the ES transitioned values more robust.

Wanders et al. (2015) extracted the KGCC from the GCM output and addressed the uncertainty in the GCMs. The climate change modeling was performed on a 0.5° grid, while the ES assessment was at ~0.08° grid. This means there is considerable generalization in the ES value transition statistics. This could mean that the ES values in a KGCC transition are actually less or more than what is stated.

Uncertainty in the results and model were only communicated as a range of ES values that were classified in a different KGCC over time (Fig. 3.2). If an ES assessment with included uncertainty were used in the KGCC transitions, then a more reliable range of values for each GCM and RCP could be calculated.

Although there is uncertainty in the ES values in KGCC transitions, this is a new perspective of climate change and ecosystem services. The sheer proportion of ES area in a KGCC transition, regardless of the value of the ES, is frightening, to put it lightly. This study indicates that climate change is having and will have impacts on society and that not only mitigation plans but also adaptation plans are required. This study did not investigate specifically how ES may be affected by climate change, such as analyzing which ES will no longer exist in a specific region or which ES will find new niche areas. While this is important, the scope of such a study on a global scale requires an international effort.

Future research pathways that would improve the study are:

- improving the ES values;
- applying an error propagation analysis; and
- applying a spatial uncertainty analysis specifically to address topological errors.

6.3. Decision support in oil exploration

While governments and industries make moves to be less reliant on fossil fuels to meet international agreements intended to mitigate risks and increase adaptation due to climate change, petroleum exploration will continue to be an important industry to help supply the world with oil and gas for fuel, electricity, and plastics, for example. Spatial decision support systems (SDSS) in GIS can strengthen and support decision-making in petroleum exploration for several reasons. One, is to lessen the effects of movement of people between companies or departments by providing a repeatable and consistent methodology for choosing where to explore for oil. Second, SDSS enable the combination of multi-criteria evaluation (MCE) and GIS. Third, SDSS facilitates the quantification of interpretive data and combining it with hard data.

In Chapter 4, this thesis asked: *what is a methodology of spatial MCE that supports petroleum exploration and how can the resulting maps be used to support petroleum exploration*? Applying fuzzy logic in an MCE that incorporates hard data to interpreted data mimics the geologist's assessment. The mapped results show areas coded in a range between not favorable to favorable. These favorability maps can be used to assist in further exploration. A basic test was made to verify if the model would show favorable areas for existing fields and there were mixed results depending on the criteria evaluated. This test introduced the need for a more thorough analysis of the uncertainty in the results.

The proposed MCE requires 17 data sets for an evaluation. The number of data sets and the data required should pose no problem for a petroleum company, as the data sets are required for prospecting. However, the company may not have the same resolution of all the data sets, especially in areas where the company has had no exploration experience before.

The methodology can be applied using specialist GIS software (e.g. Esri and spatial analyst tools) or open-source software with some programming support (e.g. Python in PCRaster). It is hard to conclude if a company would implement the methodology or not because the only hurdle to implementation would be the motivation of geologists and GIS engineers. The economic and political criteria, however, are probably least likely to be incorporated because companies likely have other internal decision-making processes to address issues related to costs, risks, and safety.

Future research pathways for this study would be to:

- compare the fuzzy logic MCE to other MCE methods;
- apply the methodology in another case of different scale; and
- to evaluate the realistic implementation in a petroleum company.

The need for uncertainty to be incorporated in the MCE for petroleum exploration leads to the research question of Chapter 5, which is: *how can the proposed spatial MCE methodology for petroleum exploration be assessed for uncertainty and what is the uncertainty*? It was determined that evaluating different scenarios for defining data and model uncertainty with the use of error propagation using Monte Carlo simulation would provide a thorough analysis of the uncertainty. By assessing the results of the error propagation through confidence level maps, a more robust verification of the prediction of results could be made. It was determined that the fuzzy logic MCE and error propagation analysis focusing on attribute classification and fuzzy logic operators would provide the best support for decision-making.

Although uncertainty was defined for all of the input data sets both in terms of originally classified attributes and associated fuzzy logic membership, the case study determined that the uncertainty needs to be decreased or better-defined. The uncertainty was defined using expert opinion and in some cases the data was created using expert opinion. The modeling results would be greatly improved by using more hard data and few interpretive data sets. The model uncertainty is likely not to be decreased because of the nature of fuzzy logic MCE. By changing any of the parameters, the output is changed significantly. The uncertainty was communicated using confidence level maps that could be used in the decision-making process.

This study combines spatial-based fuzzy logic MCE and error propagation for predicting favorable areas for petroleum exploration. This combination has not been performed before. It is a straightforward approach facilitating adoption easily and is adaptable for different regions, scales, and available data.

A possible future research pathway from this study could be to include a grading system to further classify areas based on confidence level and threshold values in order to better rate possible areas of interest based on the uncertainty of the modeling results.

6.4. Uncertainty assessment

Maps have uncertainty associated with them. Sources, definitions, and evaluations of uncertainty in spatial data vary and have influence on analyses and eventually decisions made from resulting maps. Because of the need for decision-makers and modelers to understand the uncertainty in the data and results used, this thesis asks: *how can uncertain information be defined and modelled for global scale studies*? Each of the chapters presents a solution to this problem depending on the case. Table 6.1 summarizes a list of requirements that an ideal study would include and maps the research of this thesis onto these requirements.

Table 6.1 Transparency checklist.

Requirement	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Data is publicly available	*Yes*	*Yes*	*Partial*	*Partial*
Data provenance is provided	*Yes*	*Yes*	*Yes*	*Yes*
Data uncertainty is quantified	*Descriptive*	*Descriptive*	*No*	*Yes*
Calculations for combining data is clear	*Yes*	*Yes*	*Yes*	*Yes*
Uncertainty for combinations is defined	*Descriptive*	*Descriptive*	*No*	*Yes*
Assumptions are declared	*Yes*	*Yes*	*Yes*	*Yes*
Input uncertainty is propagated to output	*No*	*Partial*	*No*	*Yes*

First, using publicly available data in continental or global assessments enables other researchers to access the same data for either replication of results or further analysis. It also creates added-value to existing research by government agencies, research institutes, or other researchers. The majority of the data used in this thesis is publicly sourced. In Chapter 4 and Chapter 5, data associated with seismic interpretation was proprietary. However, petroleum companies would have their own database and likely most petroleum exploration researchers will have similar data sets.

Second, the data provenance should be known. Such information facilitates replication of results as well as further analysis based on previous work. Having the provenance of data enables modelers to update specific data sets, as they are improved or updated. This thesis was thorough in its regard to defining the sources and provenance of all data used.

Third, the uncertainty in the data inputs should be defined. Ideally, the uncertainty will be quantified for numerical analysis; however, this is not always possible or feasible. In this thesis, the uncertainty in the data was descriptive in one case and quantitatively defined in another. Data uncertainty may focus on different characteristics: completeness (either attributes or geographic), resolution, scale of maps, mapping non-spatial, scale of map versus decision-making, and scientific credibility (Hauck et al., 2013).

Fourth, calculations for combining data must be clearly presented either as part of the main methodology or in supplementary information if scripts or programs were used. This facilitates replication of results, application of the methodology to other case studies, and updates to methodologies, especially in scripts, where technology provides improvements. This thesis clearly provided the disaggregation methods and mathematical equations as well as the scripts used for modeling (refer to digital appendices).

Fifth, the uncertainty related to the combinations of data should be defined. As the same reasoning for the data uncertainty, quantitative definitions enable numerical analysis. If quantitative definitions are not feasible or known, qualitative definitions (e.g. assumed, estimated, or reported values) can be used to help with the decision-making process.

Sixth, any assumptions that were made during the modeling process not otherwise included in the data or modeling uncertainty need to be declared. Assumptions may indicate uncertainty or errors in the data or methodology. It may be as basic as the modeler not fully understanding a relationship between two variables in the study; however, a basic assumption can have severe effects on the results. Assumptions that were made in the case studies are stated as clearly as possible.

The final requirement will be to explain the total uncertainty in the results. This is likely the most time intensive and difficult requirement because the uncertainty needs to be accounted for in all aspects of the study. Essentially, this requirement will be fulfilled with an error propagation study as in Chapter 5, but it could also be fulfilled by providing a minimum-maximum output of results as in Chapter 3.

This thesis did not completely meet the ideal for each model, although the final model meets the ideal situation of uncertainty analysis of input and model, and presentation.

6.5. Recommendations for future research

This thesis proposed a complete methodology for calculating ecosystem services assessments thereby facilitating a valuation of ES in KGCC transitions resulting from climate change and a methodology for predicting areas of favorable petroleum exploration with defined uncertainty. In both of the case studies, the implementation of modeling complex ideas and relationships was straightforward. Uncertainty is a major aspect of these studies given the complex relationships of the data that are modeled. Including more quantitative data with quantitative uncertainty will create more reliable model results to support decision-making as compared to the subjectivity of qualitative uncertainty descriptors. This is because trying to create quantitative indicators to qualitative descriptors is subjective (e.g. applying probability to qualitative frameworks).

Ecosystem services assessments and climate change have implications for human health and the environment. While the scope of the thesis was not to address what may happen to agriculture and other symbiotic relationships in the environment due to the large ecosystem services value changing climate classes, the implications for the future are grim.

Recommendations for future work in terms of the methodological approach of the ES and climate change studies include:

- defining quantitative uncertainty of data;
- quantifying missing ES;
- reducing assumptions in the data and model;
- applying error propagation;
- reducing topological errors; and
- assessing adaptation of ES in KGCC transition areas.

The use of a spatial-based fuzzy logic multi-criteria evaluation for petroleum exploration is promising as a decision-support tool. Recommendations for future work include:

- applying the methodology in another case study of a different scale;
- evaluating the implementation of the methodology in a petroleum company;
- improving input data; and
- reducing uncertainty associated with input data.

The results of analyses used by decision-makers, whether they be managers or politicians, need to have easily understandable uncertainty definitions. It is recommended that confidence level maps are used, because these can clearly show to the decision-maker where decisions based on the results are confidently supported and where they are not. This would facilitate a more transparent decision-making process.

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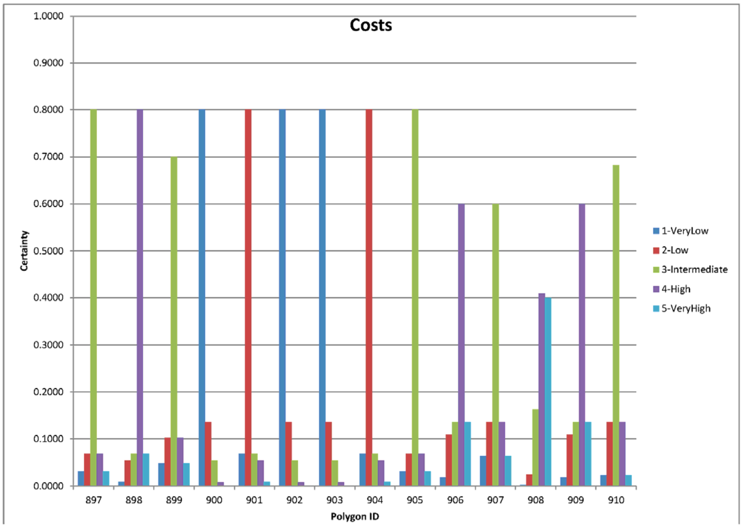
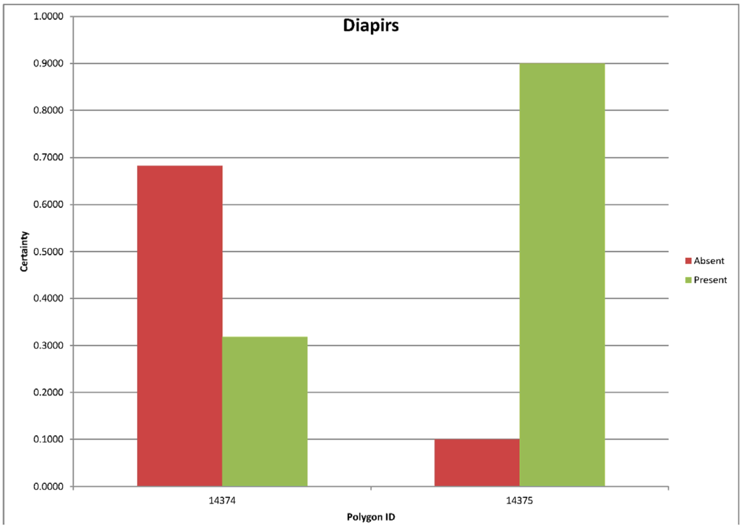
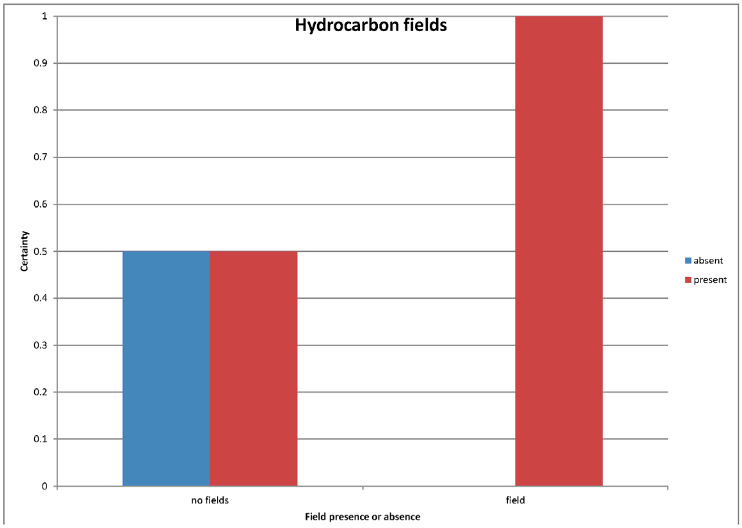
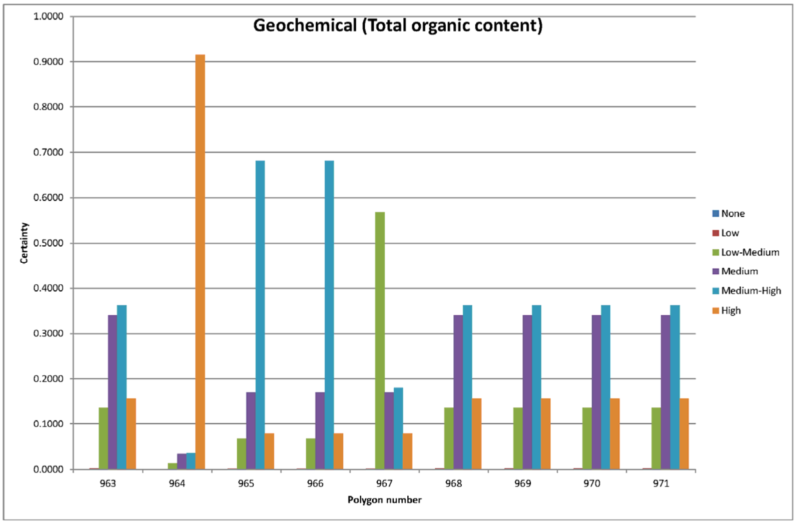
Appendix I: Probability distribution tables.

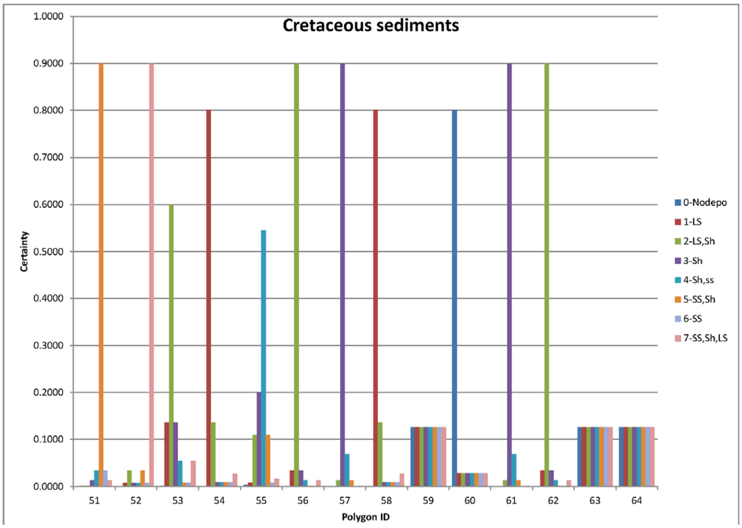
Uncertainty probability distribution graphs for all input data sets for Scenario 3 in Chapter 5.

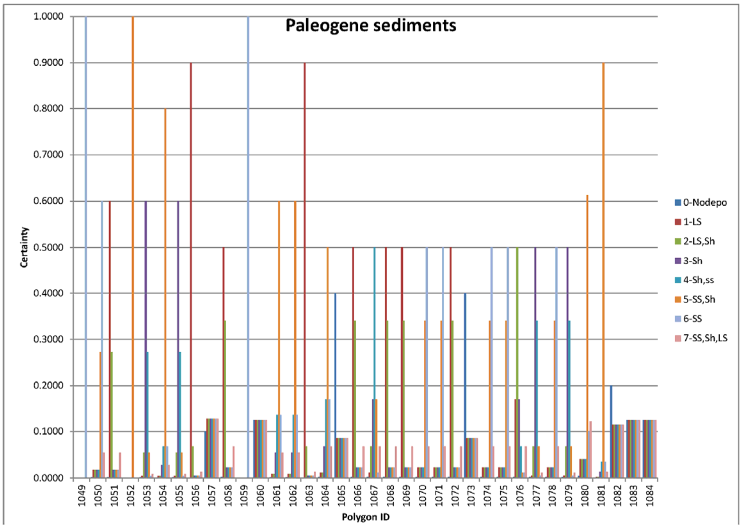


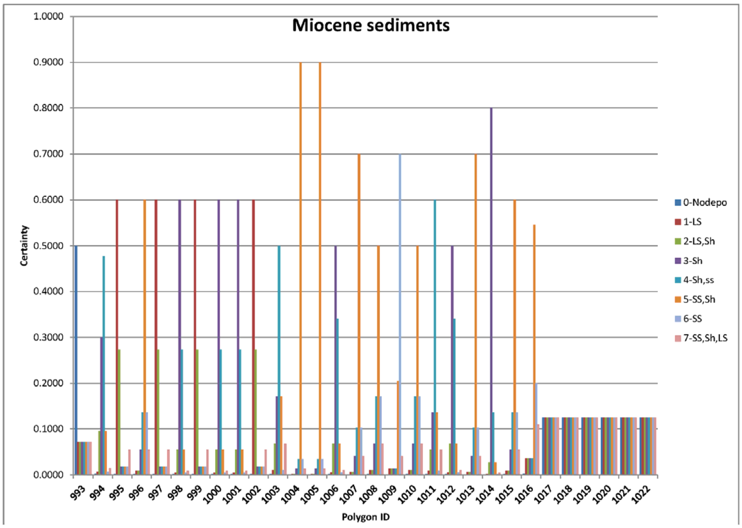

Diapirs
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
Certainty
14374
14375
Polygon ID
Absent
Present

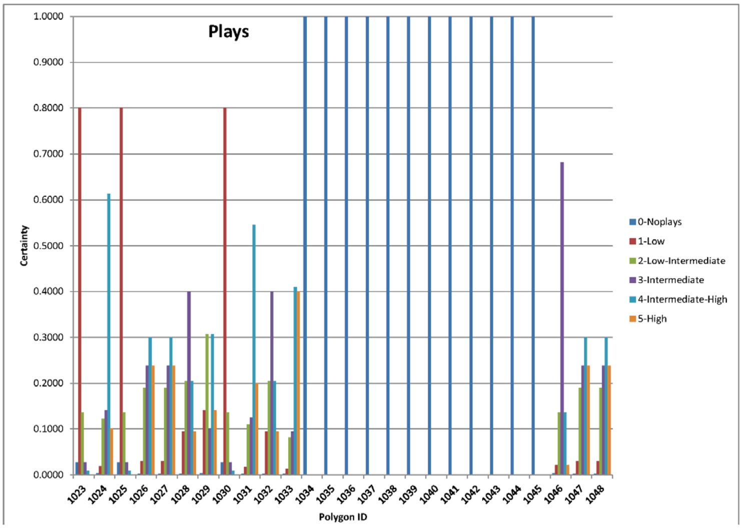

Hydrocarbon fields
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Certainty
no fields
field
Field presence or absence
absent
present

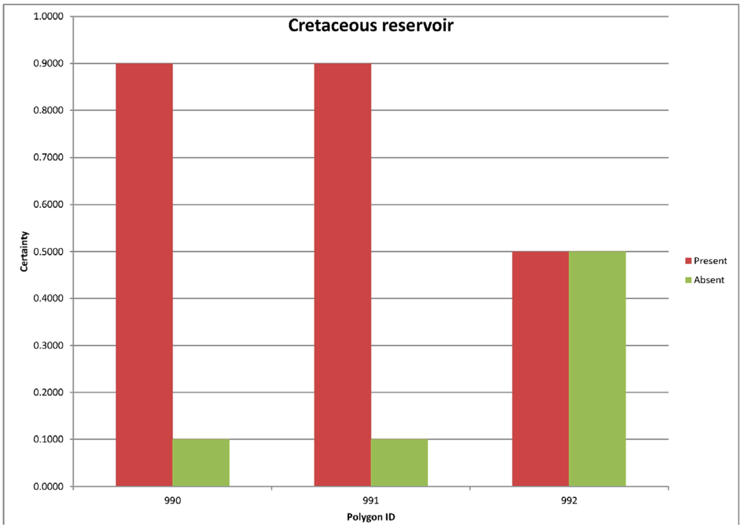

Geochemical (Total organic content)
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
963
964
965
966
967
968
969
970
971
Polygon number
None
Low
Low-Medium
Medium
Medium-High
High

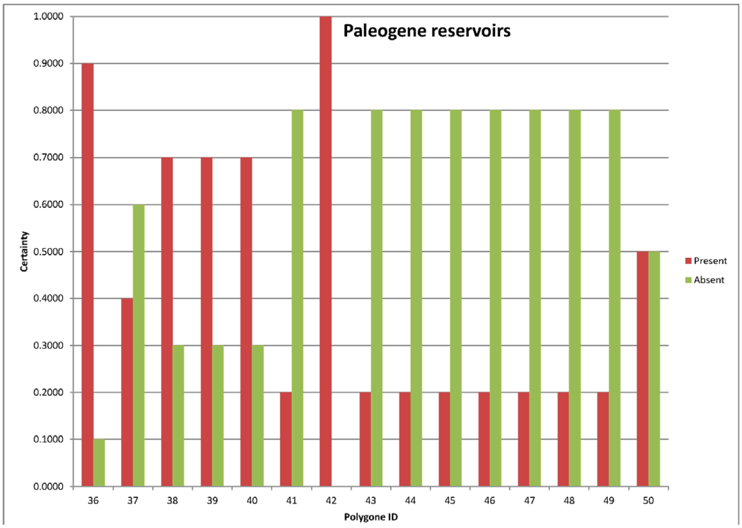

Cretaceous sediments
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
51
52
53
54
55
56
57
58
59
60
61
62
63
64
Polygon ID
0-Nodepo
1-LS
2-LS,Sh
3-Sh
4-Sh,ss
5-SS,Sh
6-SS
7-SS,Sh,LS

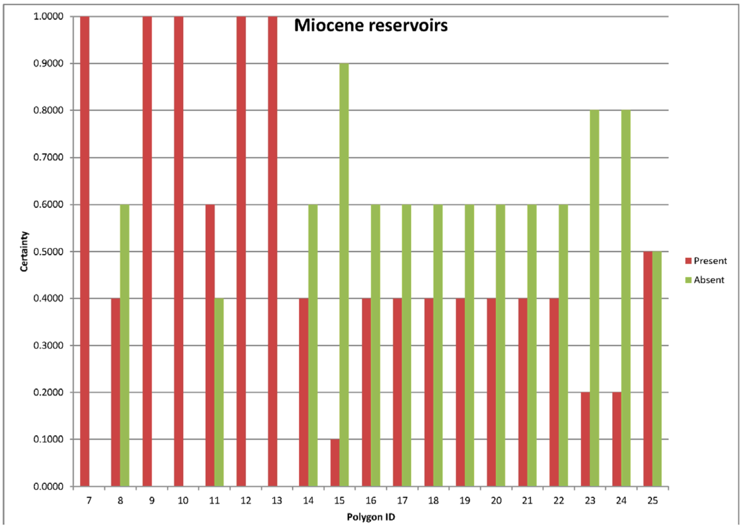

Paleogene sediments
Certainty
Polygon ID
0-Nodepo
1-LS
2-LS,Sh
3-Sh
4-Sh,ss
5-SS,Sh
6-SS
7-SS,Sh,LS

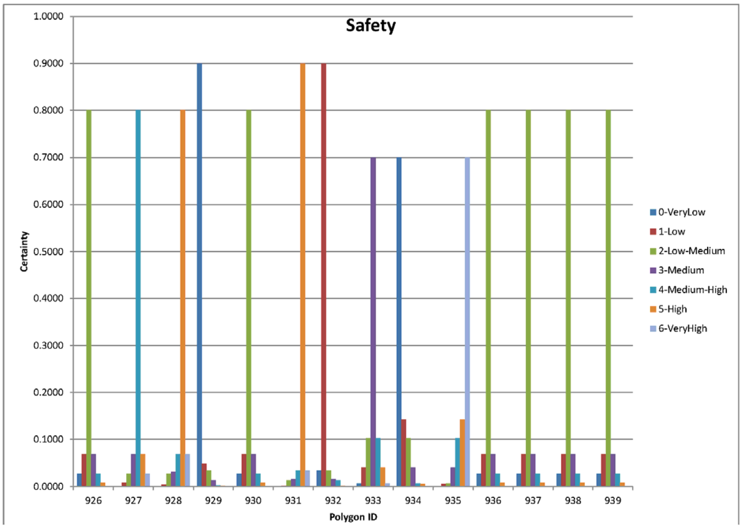

Miocene sediments
Certainty
Polygon ID
0-Nodepo
1-LS
2-LS,Sh
3-Sh
4-Sh,ss
5-SS,Sh
6-SS
7-SS,Sh,LS

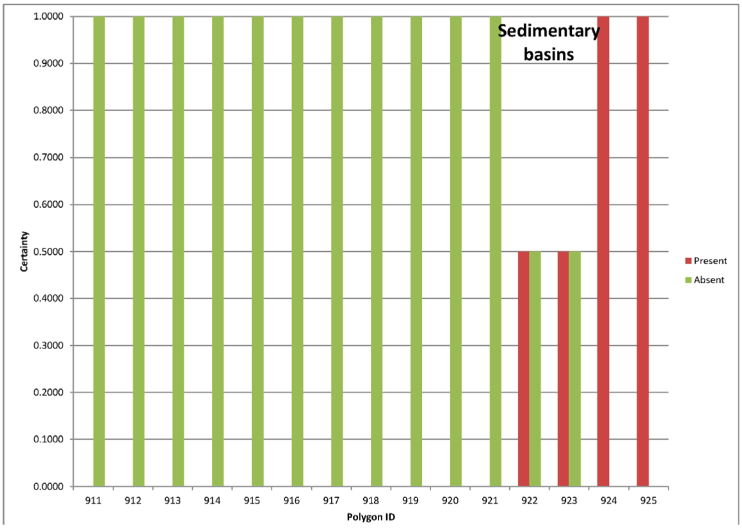

Plays
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
1023
1024
1025
1026
1027
1028
1029
1030
1031
1032
1033
1034
1035
1036
1037
1038
1039
1040
1041
1042
1043
1044
1045
1046
1047
1048
Polygon ID
0-Noplays
1-Low
2-Low-Intermediate
3-Intermediate
4-Intermediate-High
5-High

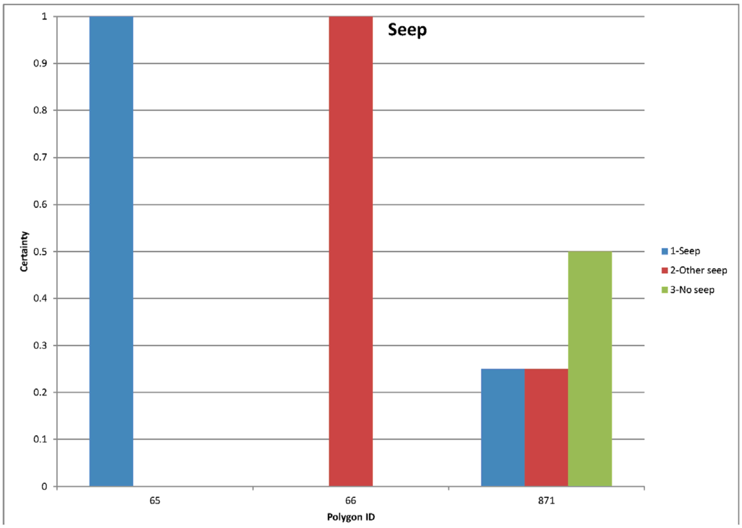

Cretaceous reservoir
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
990
991
992
Polygon ID
Present
Absent

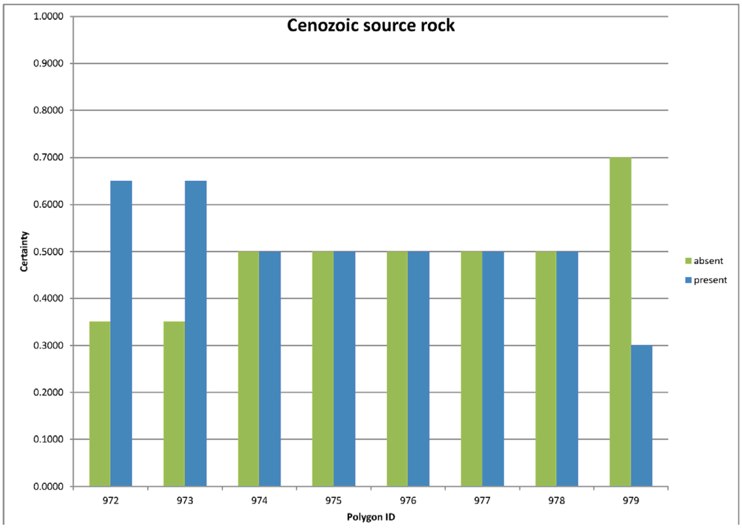

Paleogene reservoirs
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
Polygone ID
Present
Absent

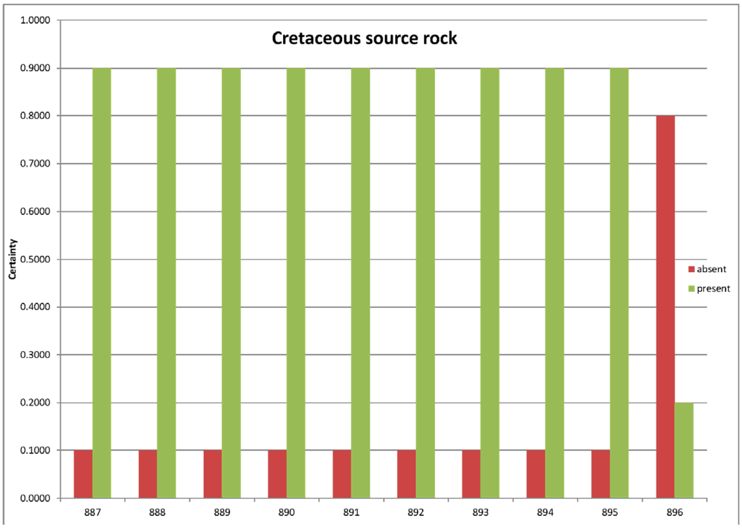

Miocene reservoirs
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
Polygon ID
Present
Absent

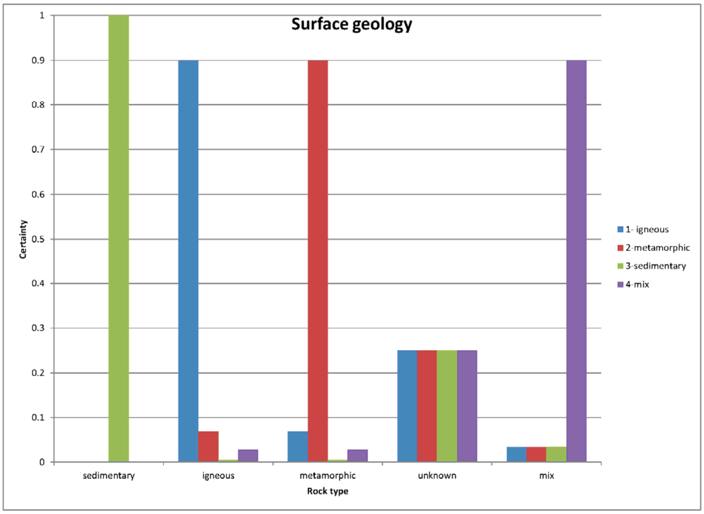

Safety
Certainty
Polygon ID
0-VeryLow
1-Low
2-Low-Medium
3-Medium
4-Medium-High
5-High
6-VeryHigh

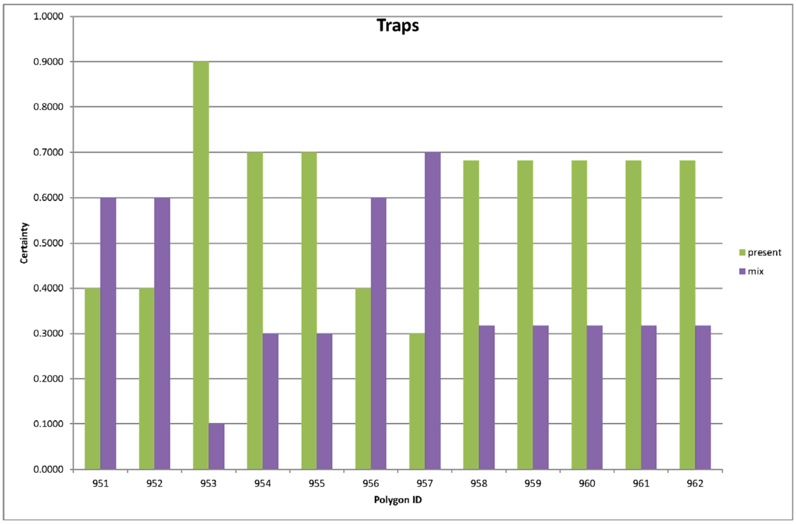

Sedimentary basins
Certainty
Polygon ID
Present
Absent

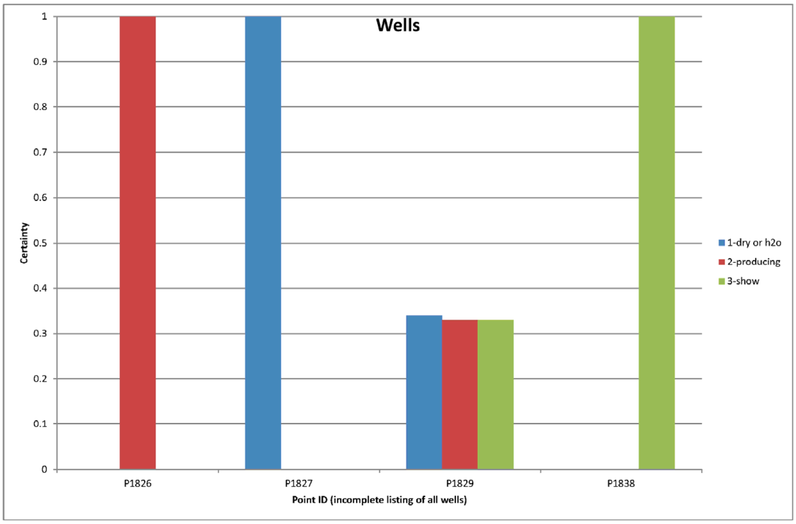

Seep
Certainty
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
65
66
871
Polygon ID
1-Seep
2-Other seep
3-No seep

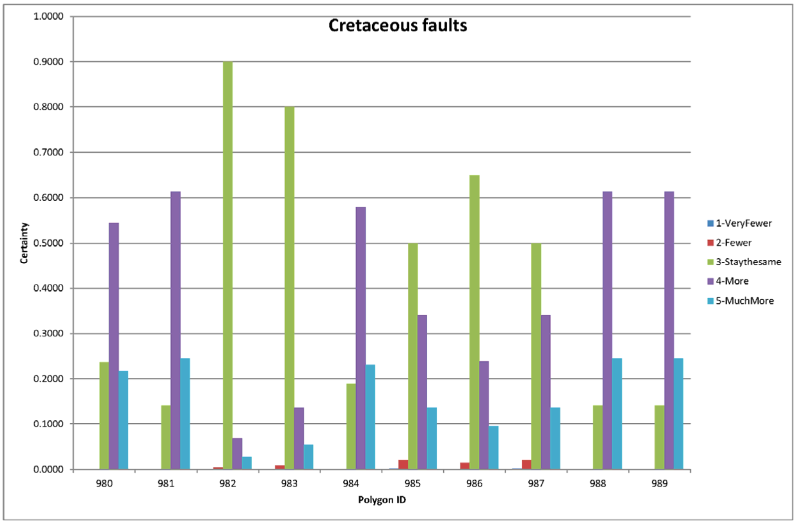

Cenozoic source rock
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
972
973
974
975
976
977
978
979
Polygon ID
absent
present

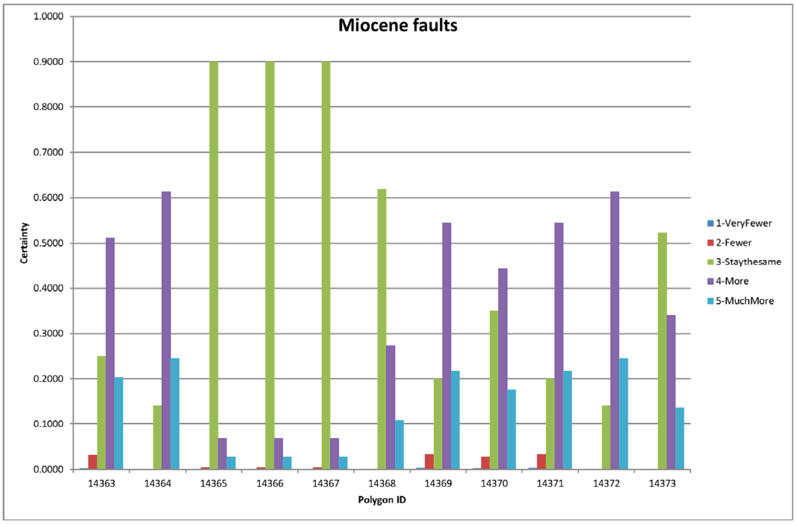

Cretaceous source rock
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
887
888
889
890
891
892
893
894
895
896
absent
present

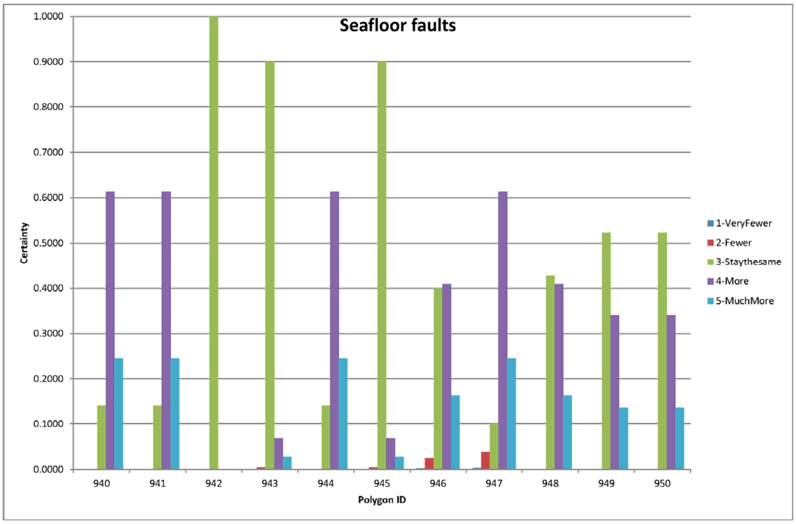

Surface geology
Certainty
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
sedimentary
igneous
metamorphic
unknown
mix
Rock type
1- igneous
2-metamorphic
3-sedimentary
4-mix

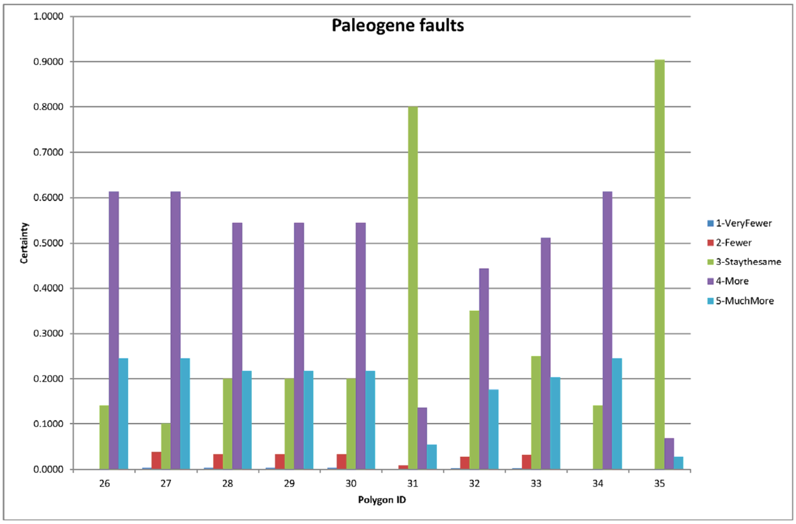

Traps
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
951
952
953
954
955
956
957
958
959
960
961
962
Polygon ID
present
mix


Wells
Certainty
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
P1826
P1827
P1829
P1838
Point ID (incomplete listing of all wells)
1-dry or h2o
2-producing
3-show


Cretaceous faults
Certainty
Polygon ID
1-VeryFewer
2-Fewer
3-Staythesame
4-More
5-MuchMore
980
981
982
983
984
985
986
987
988
989


Miocene faults
Certainty
Polygon ID
1-VeryFewer
2-Fewer
3-Staythesame
4-More
5-MuchMore
14363
14364
14365
14366
14367
14368
14369
14370
14371
14372
14373


Seafloor faults
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
940
941
942
943
944
945
946
947
948
949
950
Polygon ID
1-VeryFewer
2-Fewer
3-Staythesame
4-More
5-MuchMore


Paleogene faults
Certainty
1.0000
0.9000
0.8000
0.7000
0.6000
0.5000
0.4000
0.3000
0.2000
0.1000
0.0000
26
27
28
29
30
31
32
33
34
35
Polygon ID
1-VeryFewer
2-Fewer
3-Staythesame
4-More
5-MuchMore

Summary

Access to natural resources is a problem that current and future generations will need to overcome. To better understand potential changes in access for society due to impacts on the environment, global spatio-temporal modeling of data is required. However, the spatial data for global assessments have uncertainty, and decision making can still be problematic especially in regards to combining data. The basic problem associated with combining data for global assessments is the data's heterogeneous nature in terms of source, type, quality, uncertainty, and accuracy.

These problems contribute uncertainty and that uncertainty needs to be communicated. The overarching research question of this thesis is: *how can uncertain information be defined and modelled for global scale studies*? This thesis focuses on the application of GIS for solving spatial questions that require the combination of several data sets that cover large geographical areas, come from many different data providers, and have varying quality with known and unknown uncertainty. The thesis uses the combined spatial data set for decision-making related to petroleum exploration and climate change. The thesis has two major sections.

The first section focuses on using geographic information systems for the spatial understanding of climate class change on ecosystem services. An ecosystem service assessment valuation composed of 19 criteria is proposed based on previous studies. A case study focusing on a global, spatial valuation is calculated by combining the values of empirical data from 23 databases where some are spatial and some are non-spatial. The global value presented is far less than previous studies; however, this study excludes several criteria (31) from other previous publications and was unable to reliably quantify all of the criteria (36). Uncertainty in the input data are described but not quantified. Using five general circulation models and four representative

concentration pathways, the Köppen-Geiger climate classification transitions were modeled from 2005 to 2099. The ecosystem service value was then evaluated to quantify how much would be in a new climate class. Depending on the representative concentration pathway, between 25-66% of the ecosystem service value will be affected by a climate class change. Uncertainty in the results are presented as a range of values.

The second section focuses on the use of geographic information systems, multi-criteria evaluation, and error propagation for petroleum exploration. The first part proposes a fuzzy logic multi-criteria evaluation by combining 16 criteria comprised of 26 data sets. Because of the nature of petroleum exploration, the data sets are empirically defined and expert-based. The use of fuzzy logic is meant to mimic the traditional approach by a geologist evaluating the data but provides a framework for consistency, repeatability, and evaluation for uncertainty. A case study focusing on northern South America and combining data sets from publically available and consortium-based sources predicts new areas for exploration between Curacao and Aruba and offshore Guyana and Suriname. Uncertainty is first described and then quantified in the second half of the study. After the multi-criteria evaluation is applied, the attribute classification, fuzzy logic memberships, and the multi-criteria evaluation calculations are subjected to an error propagation analysis in order to quantify the uncertainty. The error propagation analysis showed that attribute classification using expert-defined uncertainty was the preferred approach over a constant defined uncertainty. Further, attribute classification uncertainty affected the results more than the fuzzy membership uncertainty, which could therefore be omitted; uncertainty related to the multi-criteria evaluation calculations heavily influenced the results and thus require care when selecting.

In the concluding remarks, a data and model transparency checklist is provided based on what may be considered appropriate points in a study to quantify or describe the uncertainty in a model. While the two sections are viewable as opposing societal goals, creating a robust petroleum exploration decision-making support tool and understanding how ecosystem service values are affected by climate class transitions are important for society.

Samenvatting

De beschikbaarheid van voldoende natuurlijke hulpbronnen zoals water, voedsel en energie is een urgent probleem met grote implicaties voor de lange termijn. Om goed in te kunnen schatten welke natuurlijke hulpbronnen in de toekomst beschikbaar zijn en wat dat betekent voor onze samenleving en het milieu is het nodig om op de beschikbaarheid te kwantiferen. Door de toegenomen mondialisering is het noodzakelijk om die kwantificering uit te voeren op mondiaal schaalniveau. Dat kan alleen met ruimtelijke modellen. In dit proefschrift ligt de nadruk op modellen voor wereldwijde ecosysteemdiensten en voor exploratiegeologie. Het modelinstrumentarium bestaat uit ruimtelijke modellen met een tijdscomponent, waarin een grote diversiteit aan invoergegevens wordt verwerkt met mathematische vergelijkingen tot informatie die relevant is voor het nemen van maatregelen. De invoergegevens komen uit diverse bronnen, en verschillen in ruimtelijk detail en nauwkeurigheid, waardoor de voorspellingen van de modellen ook kunnen variëren en een tot nu toe onbekende onzekerheid bevatten.. Deze modelonzekerheden moeten gekwantificeerd worden en gecommuniceerd naar degene die modeluitkomsten gebruiken voor beleid.

De overkoepelende onderzoeksvraag van dit proefschrift is: hoe kan onzekerheid in ruimtelijke data beschreven en gekwantificeerd worden voor studies op mondiaal schaalniveau? De nadruk ligt in deze studie op het gebruik van Geografische Informatiesystemen (GIS) en ruimtelijk-dynamische modellen met als invoer omvangrijke, mondiale datasets van wisselende kwaliteit en de onzekerheid die daaruit voortvloeit. Aan de hand van twee casussen wordt dit probleem uitgewerkt. De eerste casus gaat over de modellering van ecosysteemdiensten en kwantificeert welk deel van die diensten worden beïnvloed door de wereldwijde klimaatverandering. De tweede casus beschouwt en analyseert ruimtelijke datasets die nodig zijn voor het bepalen van de verkenning van vindplaatsen voor aardolie.

In de eerste casestudy van dit proefschrift wordt berekend hoe de mondiale klimaatzones zullen verschuiven in de komende decennia. Als basis zijn de Köppen-Geiger klimaatzones gekozen en zijn er 19 typen ecosysteemdiensten beschouwd afkomstig uit 23 verschillende wereldwijde databestanden. Deze mondiale studie bevat minder detail dan regionale studies die meer criteria in beschouwing nemen maar het voordeel van deze studie is dat het een wereldwijd overzicht biedt van ecosysteemdiensten en de toekomstige veranderingen daarin. Onzekerheden in de invoergegevens en in de modellen zijn kwalitatief beschreven en meegenomen maar konden niet in detail kwantitatief worden uitgedrukt. Onzekerheid in het toekomstige klimaat is gekwantificeerd door gebruik te maken van vijf klimaatmodellen gebruikt en vier klimaatscenario's (RCP: Representative Concentration Pathways). Aggregatie van de neerslag- en temperatuurgegevens uit deze klimaatmodellen vormde de basis voor de bepaling van de verschuiving van de Köppen-Geiger klimaatzones tussen 2005 en 2099. Voor de locaties waar een verschuiving in klimaatzones wordt verwacht is de waarde van de ecosysteemdiensten bepaald. De resultaten laten zien dat, afhankelijk van het klimaatscenario, tussen de 25 tot 66% van de huidige waarde van ecosysteemdiensten blootgesteld is aan een verschuiving. Naast de presentatie van deze verschuivingen is de onzekerheid ten gevolge van het gebruik van klimaatmodellen bepaald.

De tweede casestudy van dit proefschrift richt zich op het gebruik van complexe, ruimtelijk datasets voor het bepalen van geschikte gebieden voor de exploratie van aardolie. Er wordt gebruikt gemaakt van GIS, ruimtelijke multi-criteria analyses en foutenvoortplantingstechnieken. Een fuzzy logic multicriteria-analyse wordt toegepast gebruikmakend van 16 kenmerken voor aardolie-exploratie afkomstig uit 26 verschillende gegevensbronnen. Gegeven de complexiteit van aardoliebeschikbaarheid zijn de gegevens zowel gebaseerd op empirisch onderzoek en als op interpretaties van deskundigen. Het gebruik van semiautomatische fuzzy logic technieken bootst feitelijk de traditionele werkwijze na van een geoloog die alle gegevens beschouwt en interpreteert. De hier gebruikte methode is echter consequent, objectief, herhaalbaar en biedt kwantitatieve mogelijkheden voor onzekerheidsanalyse. Eén casestudy werd uitgewerkt voor het noordelijk deel van Zuid-Amerika, waarbij publiek beschikbare gegevens gecombineerd zijn met door bedrijven beschikbaar gestelde gegevens tot nieuwe, veelbelovende gebieden voor aardolie-exploratie nabij Curaçao, Aruba en voor de kust van Suriname. Onzekerheid in de analyse is eerst kwalitatief beschreven en daarna kwantitatief beschouwd. Deze onzekerheidsanalyse toont aan dat de interpretatie van de gegevens door een deskundige tot betere resultaten leidt dan een uniforme onzekerheidstoekenning aan de analysestappen. De diverse gebruikte rekenmethoden in de multi-criteria analyse dragen in grote mate bij aan de totale onzekerheid en dienen dus zorgvuldig gekozen te worden.

Het proefschrift sluit af met de bespreking van een transparant datamodel en een controlelijst hoe om gegaan kan worden met onzekerheden in modellen en datasets en hoe die uiteindelijk gepresenteerd kunnen worden. De twee casestudy's zouden beschouwd kunnen worden als tegenstrijdig: de analyse van ecosysteemdiensten en klimaatverandering versus de analyse voor optimale locaties voor aardolie-exploratie, maar beide toepassingen zijn van groot belang voor onze maatschappij.

About the author

Lisa Jean Watson was born in Edmond, Oklahoma, United States of America in 1979 to Gerald R. and Terri D. Watson. Lisa began her undergraduate studies at the University of Texas at Dallas and continued until graduation at the University of Texas at Austin, where she received a Bachelor of Arts in Liberal Arts. Her studies focused on Archaeology and Geosciences. Particular interest focused on Mycenaeans in Ancient Greece and Geology. While a student in the Jackson School of Geosciences at the University of Texas at Austin, Lisa began working as an undergraduate research assistant for Dr. Fred Taylor and Dr. Paul Mann at the Institute for Geophysics. Here, she was introduced to geographic information systems. Through a long-term project led by Dr. Paul Mann and Dr. Alejandro Escalona, she learned more about the technology and applications and continued working at the Institute for Geophysics after graduation. In 2009, Lisa attended the Geographic Information Management and Applications MSc program via Utrecht University. At this same time, she moved to Norway to work at the University of Stavanger. In 2011, Lisa received her MSc degree and continued working at the University of Stavanger. Following graduation, Lisa continued a dialogue with Dr. Derek Karssenberg and began a collaboration, eventually turning into the basis of this PhD that formally started in 2014. Upon graduation, Lisa will begin a permanent position as an associate professor at the University of Stavanger.

List of publications and conference presentations

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L. Bingham now L. Watson