ENVIRONMENTAL DECISION SUPPORT INTEGRATING SCIENTIFIC INPUT, MODELS, ECONOMIC VALUATION, AND STAKEHOLDER PARTICIPATION

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

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ABSTRACT

This dissertation presents and demonstrates three novel decision support tools aimed at assisting government and private organizations in tackling complex decisions involving multiple parties, affecting ecosystems and economies, and including choices made more difficult by significant uncertainty in relevant scientific knowledge.

The first tool integrates the economic input-output approach of life cycle assessment with environmental fate, exposure and risk assessment to estimate the spatial distribution of air toxic health risks due to sector-specific economic activity in the US. The model is used to relate the economic activity and exposure potential (population density and meteorology) associated with point source emissions of the heavy metal and carcinogen, hexavalent chromium, or Cr(VI), on a county basis. The results indicate that linking economic activity, emission estimates, and fate and transport models for air toxics can inform both life cycle impact and comparative health risk assessments, allowing us to better target emission reductions to minimize hot-spots of risk.

The second tool is a framework for science-based assessment and multi-stakeholder deliberation. The framework combines attributes of existing tools for environmental assessment and management, such as multiple criteria analysis, integrated assessment, and uncertainty analysis. It consists of two parts: a *DPSIR* (Drivers-Pressures-States-Impacts-Responses) analysis to identify the important causal relationships among anthropogenic environmental stressors, processes, and outcomes; and a *Decision Landscape* analysis which aims to ensure that relevant legal, institutional, and social factors affecting a decision, as well as the knowledge, values, and decision making of participants in the various elements of the DPSIR process, are recognized

and considered. The framework is applied to coral reef protection and restoration in the Florida Keys National Marine Sanctuary, focusing on anthropogenic stressors, such as domestic wastewater. A structured elicitation of values and beliefs conducted at a coral reef management workshop held at Key West, Florida is used to develop information for an integrated DPSIR/Decision Landscape framework. The framework identifies key DPSIR relationships, current scientific understanding, and stakeholder perceptions, which can be used together to predict the outcomes of management options and to identify future research needed to resolve conflict among stakeholders over scientific understanding and preferred management options.

The third tool is aimed at identifying where additional scientific research may be needed to support better informed decisions and resolve possible conflicts over preferred management actions. The method combines and builds on aspects of multiple stakeholder deliberation, multiple criteria analysis, Bayesian Belief Networks, and value of information analysis. The method is applied to coral reef protection and restoration in the Guánica Bay Watershed, Puerto Rico, focusing on assessing and managing anthropogenic stressors, such as sedimentation and pollution from inland sources such as sewage, agriculture, and development. Structured elicitations of values and beliefs conducted at a coral reef management workshop held at La Parguera, Puerto Rico are used to develop information for demonstrating the method. Beliefs and preferred management options are examined for whether they exhibit greater coherence between stakeholders when informed by plausible study results. The results indicate that new scientific research is likely to bring people who initially disagree to agree. However, there can be situations where prior beliefs may be too different from the study results to shift perspectives and bring people to agreement. Though preliminary these results suggest that the method can provide useful insights on the social implications of a research program.

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CHAPTER 1. INTRODUCTION

PROBLEM AND THESIS STATEMENT

Government and private organizations regularly confront complex decisions that involve multiple parties, affect ecosystems and economies, and include choices made more difficult by significant uncertainty in relevant scientific knowledge. Decisions are often made without appropriate consideration of scientific information and without representation of multiple stakeholder objectives. This is often due to a mismatch between available knowledge about these topics and the needs of agencies, businesses, and individuals making critical decisions that affect the environment. Decision support tools exist for addressing some of these needs (often separately) as is described in the "Current Approaches" section below. However, improved decision support methods are needed that integrate these needs, and that provide decision makers with the following seven capabilities:

1. predicting human health, ecosystem, natural resource, and economic impacts;
2. economic valuation of the above impacts;
3. assessment of impacts at various spatial scales, including national, regional and local;
4. generation of management alternatives for environmental problems;
5. sensitivity and uncertainty analysis of impact and valuation estimates, including scenario analysis, expert elicitation, and probabilistic risk analysis;
6. decision analytic evaluation of management alternatives considering uncertain costs and environmental impacts, based on multiple attributes and multiple stakeholders; and

7. determination of the value of information associated with new monitoring, experiments, studies, and research, considering improvements in the expected value of preferred management alternatives and increases in the likelihood that conflicting stakeholders will come to agreement about their decision preferences.

STRUCTURE OF THE DISSERTATION

This dissertation describes several decision support tools that were developed during the course of my graduate education for better addressing these needs. It is composed of the three studies or publishable works described below. Here each study's contribution to the field of environmental decision support is summarized and the way in which each tool delivers desired capabilities mentioned in the thesis statement is described.

Study I: Economic Sources and Spatial Distribution of Airborne Chromium Risks in the U.S.

This study is about a decision support tool for assessing spatial variation in health risk due to air toxics in response to changes in economic activity, and links economic input-output analysis, air quality modeling, and human health exposure and risk assessment. This tool aims to offer the first four capabilities desired by decision makers mentioned in the thesis statement.

Study II: A Decision Support Framework for Science-Based, Multi-Stakeholder Deliberation: A Coral Reef Example

This study describes a decision support framework for incorporating ecosystem services valuation, scientific input, and multiple stakeholder preferences and beliefs. The framework is based on the concept of decision analysis and combines attributes of existing decision support tools for environmental assessment and management, such as: MCA, integrated assessment, and uncertainty analysis. This tool aims to offer the first six of the capabilities desired by decision makers mentioned in the thesis statement.

Study III: The Role of Scientific Studies in Building Consensus Among Stakeholders in Environmental Decision Making: A Coral Reef Example

This study demonstrates a decision support method for identifying where additional scientific research may be needed to support better informed decisions and resolve possible conflicts over preferred management actions. The method combines decision analysis, multiple stakeholder deliberation, and value of information analysis. This tool aims to offer all seven of the capabilities desired by decision makers mentioned in the thesis statement.

CHAPTER 2. ECONOMIC SOURCES AND SPATIAL DISTRIBUTION OF AIRBORNE CHROMIUM RISKS IN THE US[1]

ABSTRACT

We present a model that integrates the economic input-output approach of life cycle assessment with environmental fate, exposure and risk assessment to estimate the spatial distribution of air toxic health risks due to sector-specific economic activity in the US. The model is used to relate the economic activity and exposure potential (population density and meteorology) associated with point source emissions of the heavy metal and carcinogen, hexavalent chromium, or Cr(VI), on a county basis. Total direct annual airborne emissions of Cr(VI) in the US were 44 tonnes in 2002, with 97% from facilities in four major sectors: power generation, wood, plastics, and chemicals, metals, and scientific services. These include 6 tonnes of Cr(VI) emitted in the supply chains of these sectors. A highly variable national distribution of lifetime cancer risk is predicted, with a population-weighted mean of 2.7×10^{-7}, but with hot-spot counties with lifetime risks as high as 6×10^{-6}. Furthermore, high exposures and risks tend to occur in more highly populated counties. In particular, the population of Los Angeles County is exposed to the highest level of risk in the country and almost three quarters of the total predicted cancer incidence due to inhalation of airborne Cr(VI) emissions. This finding can be attributed largely to the use of Cr(VI) as a corrosion inhibitor by the scientific services sector facilities in the County, the use of shorter facility stacks, and their siting within a highly populated area. These results indicate that

[1] The contents of this chapter have been published as: Rehr, A.P., M.J. Small, H.S. Matthews, and C.T. Hendrickson (2010). Economic Sources and Spatial Distribution of Airborne Chromium Risks in the U.S. Environ. Sci. Technol. 44 (6), pp 2131–2137.

linking economic activity, emission estimates, and fate and transport models for air toxics can inform both life cycle impact and comparative health risk assessments, allowing us to better target emission reductions to minimize hot-spots of risk.

INTRODUCTION

In recent years significant efforts have been made to link insights from the fields of life cycle assessment and environmental health risk assessment (Cowell, Fairman et al. 2002; Matthews, Lave et al. 2002). Life cycle assessment (LCA) has traditionally been used to evaluate the environmental impacts of industrial products from production to consumption, including air pollutant emissions. Separately, health risk assessment has been used to evaluate the exposure and health risk associated with emissions. In particular, human health exposure and risk estimates are often a critical component of life cycle impact assessment (LCIA) (Udo de Haes, Jolliet et al. 1999; Bare, Norris et al. 2003; Jolliet, Margni et al. 2003; Pennington, Potting et al. 2004; Bare and Gloria 2006; De Schryver, Brakkee et al. 2009). However, few studies have assessed the impact of economic inputs and environmental discharges on human health and the environment in a geographically disaggregated manner (Cicas, Hendrickson et al. 2007). Such studies are important since they allow control strategies to focus in areas where they are needed most and many decisions by local or regional policy makers would be better informed by data and model results that are local or regional in context.

We develop an economic-spatial risk model for the US to predict how changes in economic activity for various sectors will impact county level health risks due to point source emissions of air toxics. We estimate the relative contributions of industrial point source emissions of air pollutants from different and model the fate, human exposure, and associated health risks of these emissions. We gauge the effect of supply chain economic activity on total emissions by using economic input-output life cycle assessment (EIO-LCA) to estimate emissions. This study advances existing environmental impact models by disaggregating health risks by economic sector and by source and receptor locations, to allow for the creation of better-targeted air quality and economic policies.

In the LCA field, material flow analysis (MFA) and EIO-LCA have been used to estimate the impacts of alternative industrial products and processes. MFA has been used to track the movement of materials, such as heavy metals, through industrial processes, use, disposal, and release to the environment, but it does not typically model the fate and associated risk of these releases (Johnson, Schewel et al. 2006; Higgins, Matthews et al. 2007). Johnson et al. (2006) assessed material flows of chromium at the national and global aggregate level including environmental releases, but did not model their fate and subsequent exposure and risk.

EIO-LCA has been used to estimate changes in emissions due to changes in economic demand, in most cases using national aggregate data, and does not translate emissions into localized health risk (Hendrickson, Lave et al. 2006). Hawkins et al. (2006 and 2007) and Higgins et al. (2007) combine a national input-output model with a model based on physical flows of cadmium and lead to forecast the effect of changes in economic activity, but do not estimate health risks.

In the health risk assessment field, the US EPA has done significant research into modeling and assessing the fate, transport and associated risk of toxic air pollutants at a locally disaggregated level. One of these assessments is the National-Scale Air Toxics Assessment (NATA) produced in 1996, 1999, and 2002 (released in June 2009) (U.S. Environmental Protection Agency 2006; U.S. Environmental Protection Agency 2007; U.S. Environmental Protection Agency 2009). The EPA conducts the NATA every three years to produce nationwide estimates of toxic air pollutant emissions from various sources and resulting ambient concentrations, human exposures, and cancer and non-cancer risks for use as a screening tool for prioritization of air toxics and locations with the highest risks. A limitation of the NATA is that it does not include disaggregated exposure and health risks by economic sector or by emissions source locations. However, the most recent Human Exposure Model (HEM III) produced by EPA, which is used by the Agency, local agencies, and industry to estimate health risks that may result from air pollutant emissions from an industrial facility or a cluster of facilities located near one another, does allow for modeling of exposure and health risks of pollutants by economic sector (Palma 2007; U.S. Environmental Protection Agency 2007). HEM III incorporates the atmospheric dispersion model, AERMOD, to produce ambient air toxics concentrations and an exposure model, HAPEM, to provide estimates of population exposure to air toxics from outdoor emission sources by accounting for population time-activity budgets, such as the time spent outside, indoors, and commuting to and from work. A limitation of HEM III is that it is typically not intended for nationwide assessments (Palma 2007).

A recent development among LCA and health risk assessment practitioners has been to use the concept of intake fraction, or the ratio of the mass of pollutant intake to the mass of pollutant emitted, to express and interpret emissions source and exposure relationships in place of the dispersion/exposure model paradigm for greater simplicity and transparency (Bennett, McKone et al. 2002; Greco, Wilson et al. 2007; Levy, Wilson et al. 2003). Additionally, in place of risk and cancer cases as endpoints, many studies now use disease burden, which is recommended by the UNEP-SETAC life-cycle initiative, typically measured as disability adjusted life-years, (DALYs) (McKone, Kyle et al. 2006).

Our economic-spatial risk model uses AERMOD to estimate ambient concentrations and a unit risk factor to estimate exposure and resulting cancer risk, which is used as the endpoint for human health characterization because we are trying to capture spatial variation in both sources and receptors and also for its regulatory significance (U.S. Environmental Protection Agency 2006). In our case, from an LCA perspective, it would follow that the average lifetime risk of cancer increases incrementally by economic activity ($) in a sector. As such, our model can be generally applied to air toxics or criteria pollutants using appropriate cancer and non-cancer endpoints.

Thus, our model builds on MFA, EIO-LCA, the NATA and HEMIII to support a nationwide assessment of the economic sources and distribution of health impacts due to air pollutants in the US. There are advantages to assessments and models that locally disaggregate environmental impacts like NATA and HEM instead of using national averages like MFA and EIO-LCA. For example, by estimating localized disaggregated risks across the US our model can be used to avoid policy responses that lower overall average risk but create isolated areas of high risks. Likewise, there are advantages to models like MFA and EIO-LCA that disaggregate environmental impacts by economic sector and direct vs. supply chain sources, including the ability to evaluate the impacts of a product over its entire life cycle. Additionally, there are advantages to a model that disaggregates environmental impacts by emissions source locations, such as the ability to regulate production in the areas that contribute the most to health risks. We discuss uncertainties in the model we have developed (due to limited ground truth data and other factors) in the Results section.

Here we use the model to explore spatial variation in health risk and how it relates to variations in economic activity and exposure potential around associated toxic air emissions of hexavalent chromium, or Cr(VI). Cr(VI) is a good candidate for this analysis because it is a prevalent industrial heavy metal and a human carcinogen in air causing lung cancer (Kimbrough, Cohen et al. 1999; U.S. Environmental Protection Agency 2007). Additionally, Cr(VI) emissions are not ubiquitous, but instead tend to be concentrated at a small number of facilities across the country, and they also have a relatively short transport range, which results in most observed levels being locally generated, so Cr(VI) as a hot-spot pollutant should tend to show significant spatial resolution in both emissions and impacts. An earlier assessment in 1999 (results for Cr(VI) for the most recent NATA in 2002 were not available) showed that Cr(VI) emissions from facility, area, and mobile sources contributed 4% to an EPA-estimated average lifetime cancer risk of 4.2×10^{-5} from all air toxics in the US or approximately seven annual cancer cases (See the Supporting Information for a breakdown of the predicted contribution from all toxic air pollutants) (Palma 2007). The current assessment for 2002 is expected to produce a similarly small number; however, targeted reductions of Cr(VI) emissions may still be warranted if hot-spot communities are identified. Additionally, because Cr(VI) emissions are produced primarily as a result of industrial activity (Kimbrough, Cohen et al. 1999; Palma 2007), there is an opportunity to improve human health by reducing emissions due to direct economic and supply chain activity. Reducing emissions of Cr(VI) will also likely lead to reductions in the risks due to co-emitted pollutants, since these are often affected by the same control measures.

METHOD AND DATA SOURCES

Our economic-spatial risk model calculates the change in cancer risk in each county in the US that would result from a change in output for an economic sector or sectors (Figure 1). First an economic component allows a change in demand to be input into an economic sector. The change in demand in a sector is equal to the change in producer value (in $) of a product or fraction of the total industry output based on the most recent data for economic sectors from the US Economic Census for the year 2002 (U.S. Census Bureau 2007). The change in demand is translated into a proportional change in output and subsequently of emissions (emissions per unit demand) and risk resulting from facilities in that sector. This assumes a linear relationship between outputs, emissions, ambient concentrations, exposures, and risks in a sector.

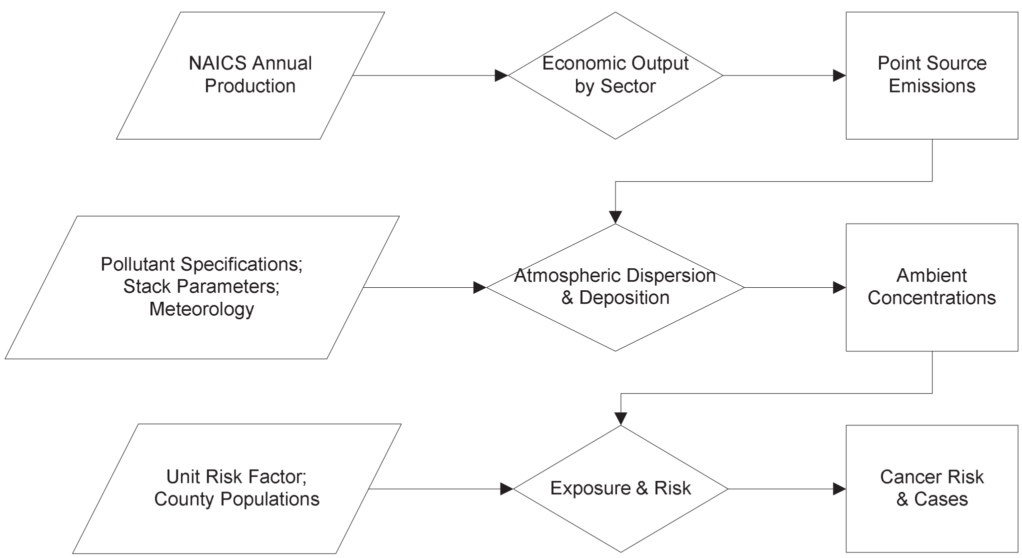

Figure 1. A flow diagram of the model including the inputs and outputs into the three major model components (economic output by sector, atmospheric dispersion and deposition, and exposure and risk).

To model annual average ambient concentrations resulting from point sources, several parameters are input into EPA's AERMOD atmospheric dispersion model (U.S. Environmental

Protection Agency 2006) (See the Supporting Information for a full description of the dispersion model). These include annual emissions per unit demand and pollutant parameters from specific stacks at facility locations based on the most recent data (2002) from the EPA National Emissions Inventory (U.S. Environmental Protection Agency 2006); EPA-processed hourly weather station data from the National Weather Service for the year 1991 including default specified values for surface characteristics (U.S. Environmental Protection Agency 2006), and pollutant specifications from the literature, which are discussed in more detail below. Each source is assigned to only the nearest weather station. Time-averaging of resulting hourly ambient concentrations is handled internally by AERMOD. Annual average ambient air concentrations are then estimated at affected county centroids using interpolation. Next for each county the model then estimates human exposure, lifetime individual risk and cancer incidence resulting from the simulated ambient air concentrations using EPA unit risk factors based on default exposure factors and cancer slope factors (U.S. Environmental Protection Agency 2007; U.S. Environmental Protection Agency 2007), and county population data from the US Census Bureau for the year 2002 (U.S. Census Bureau 2007). The resulting risk and cancer cases are disaggregated by NAICS (North American Industry Classification System) sector codes and the emissions source counties and risk receptor counties.

We also estimate the degree to which changes in economic activity lead to changes in supply chain activity and corresponding nationwide facility emissions using EIO-LCA (Carnegie Mellon University Green Design Institute 2008). We multiply supply chain economic activity for each of the major Cr(VI)-emitting sectors (the sum of supply chain activity due to related Cr(VI)-emitting subsectors) by an emissions factor based on the corresponding sector's facility emissions and total annual economic output in that sector. However, we cannot model supply chain impacts with any spatial resolution because the data is at the industry level and thus, does not show specific product locations.

For example, to estimate the effect of raising national electrical output by 10% (corresponding to $30 billion demand into NAICS 2211), the model 1) Increases economic output in this sector by 10%; 2) Increases emissions released from each of the facilities in this sector by 10% (and increases corresponding emissions produced due to purchases by this sector and its chain of suppliers from other sectors); 3) Estimates the resulting ambient concentrations due to point source emissions based on AERMOD; 4) Finds the ambient concentration at the centroid of affected counties using interpolation; 5) Calculates human exposure and cancer risk due to the ambient concentration in each county keeping track of the contributing economic sectors and emissions source locations; and 6) Displays the impacts of emissions in terms of the distribution of risk of cancer or number of cancer cases among populations, for example on a map showing risk by county or with a cumulative distribution function (cdf) showing population-weighted risk by county.

MODELING CR(VI) POINT SOURCE AND SUPPLY CHAIN EMISSIONS

Cr(VI) is one of three valence states of the heavy metal, chromium. The others are chromium metal, Cr(0), and trivalent chromium, Cr(III), an essential nutrient. Cr(VI), however, is a human carcinogen in air causing lung cancer (Kimbrough, Cohen et al. 1999; U.S. Environmental Protection Agency 2007). Cr(VI) air emissions are produced primarily as a result of industrial activity (Kimbrough, Cohen et al. 1999; Palma 2007). Cr(VI) air emissions can be particle-bound or dissolved in droplets (due to its extremely high boiling point, chromium is rarely found in the gas phase). Cr(VI) stack particles from heating processes such as smelting, combustion systems and electroplating are found to have diameters less than 10 μm with most particles in the fine mass range (0 to 2.5 μm) (Kimbrough, Cohen et al. 1999). Fine particulate matter containing Cr(VI) can travel distances over 100 km from their sources. Its transport range is limited due to major sinks, such as dry and wet deposition, and its reduction to Cr(III) in the atmosphere according to a half-life ranging from 16 hours to 5 days due to the presence of reducing agents such as vanadium and acidity (Kimbrough, Cohen et al. 1999). However, Cr(VI) can be introduced or reintroduced into the atmosphere by wind resuspension.

Pollutant specifications input into AERMOD for Cr(VI) include deposition and half-life. Both wet and dry deposition are accounted for assuming 100% of airborne particles are fine mass (less than 2.5 μm diameter) and have an average diameter of 2 μm. This assumption is based on the literature for Cr(VI) particle emissions (Kimbrough, Cohen et al. 1999) as well as characteristics of lead particle emissions from stacks, because stack particles of different pollutant types are generally similar (Goyal, Small et al. 2005). The model can take into account the atmospheric half-life of the pollutant to address chemical transformations other than deposition. The upper bound estimate of half-life for reduction from Cr(VI) to Cr(III) of 5 days is used. Exposure and cancer risk is modeled using an inhalation unit risk factor for Cr(VI) of 1.2×10^{-2} $(\mu g/m^3)^{-1}$, which is based on an inhalation cancer slope factor of 41 mg/kg-day, assuming exposure 24 hours per day over a 70-year lifetime (U.S. Department of Energy 1997).

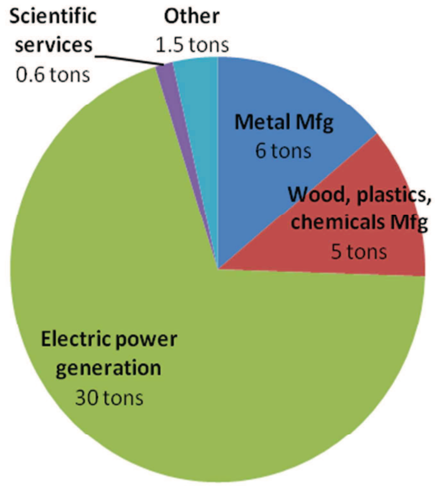

Figure 2. Reported 2002 Cr(VI) Air Emissions from Point Sources for the US by Economic Sector (2-Digit NAICS).

For this analysis of Cr(VI) we focused on four major economic sectors that produced the bulk (97%) of emissions in 2002: electric power generation (70%), metal manufacturing (14%), and wood product manufacturing, plastics and rubber manufacturing, chemical manufacturing, and printing (12%), and professional, scientific, and technical services (1%).

NEI point source emissions data for Cr(VI) for the US for 2002 are from nearly 9200 stacks at 970 facilities. Of these emissions sources approximately 1500 are electric power utility stacks that emit a total of 30 metric tons (tonnes) of Cr(VI), 1250 are metal manufacturing stacks that emit a total of 6 tonnes of Cr(VI), about 2750 are wood and other manufacturing stacks that emit a total of 5 tonnes of Cr(VI), about 350 are stacks from scientific services facilities that emit a total of 0.6 tonnes of Cr(VI), and about 3300 are stacks from 15 other sectors that emit a total of 1.5 tonnes of Cr(VI) (See Appendix A for Table S1 in the Supporting Information for a breakdown of all Cr(VI) data by sector) (U.S. Environmental Protection Agency 2006) (Figure 2).

Figure 3 shows facility locations and their relative emissions overlaid on a map of population by county.

Electric power utilities emit Cr(VI) during combustion of chromium-containing fossil fuels, such as coal and oil (Kimbrough, Cohen et al. 1999). In this situation the chromium is not originally hexavalent, but the high temperatures involved in the process result in oxidation that converts the chromium to its Cr(VI) state. Metals manufacturing plants emit Cr(VI) when metals, including chromium, are combined and heated, such as in stainless steel, or when Cr(VI)-containing acid is electroplated onto metal parts in a bath to provide a decorative or protective coating, such as in chrome plating. The scientific services sector emits Cr(VI) during chrome plating for research and development of defense vehicles, landing gear, etc. NEI point source emissions of Cr(VI) from chrome plating are typically measured directly (Takemoto 2009). Wood, plastics and rubber, and chemical manufacturing emit Cr(VI) during the processes of adding Cr(VI)-containing compounds to wood to provide pest resistance, to dyes, paints, inks, and plastics to provide pigmentation, and to paints and primers to provide corrosion resistance.

For the four major Cr(VI)-emitting sectors, Cr(VI) emissions may also be associated with the other sectors in their upstream supply chain production. For example, to make stainless steel, the metal manufacturing sector purchases energy from power utilities and materials, such as metal and wood, from manufacturers to create the final product, and in the process these different sources generate waste and Cr(VI) emissions.

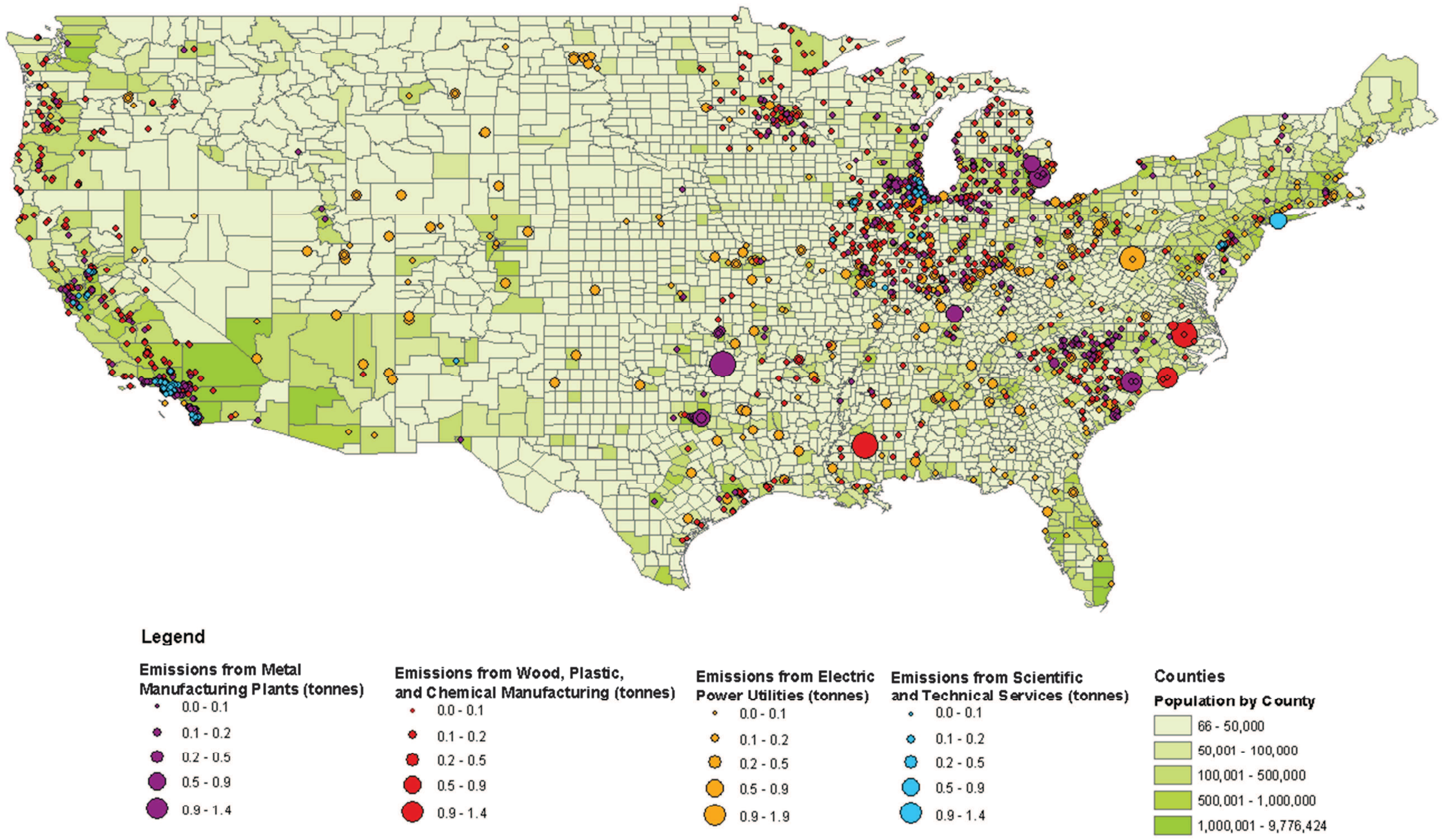

Figure 3. Facility locations that reported emissions of Cr(VI) (in tonnes) in 2002 and population by county.

RESULTS

Distribution of Chromium Risks by County and Economic Sector

We predict a highly variable national distribution of lifetime individual cancer risk (LIR) due to emitted ambient Cr(VI), with a population-weighted mean of 2.7×10^{-7}, but with hot-spot counties with lifetime risks as high as 6×10^{-6}. Figure 5. Predicted Lifetime Individual Cancer Risk of Cr(VI) due to Point Source Emissions from Current Production of NAICS 2211 Power Generation, NAICS 32 Wood Product Manufacturing, Chemical Manufacturing, Plastics and Rubber Manufacturing, and Printing, NAICS 33 Combined Metal Manufacturing Sectors, and NAICS 54 Professional, Scientific, and Technical Services.5 shows the combined estimated LIR on a map for the sectors evaluated (See the Supporting Information for maps of estimated lifetime individual risk by sector). Cumulative distribution functions of risk by county (ranked and population-weighted, respectively) are shown in Figure 4. These indicate that 37% of the counties and 20% of the population have minimal LIR (less than 10^{-11}), with high exposures and risks tending to occur in more highly populated areas. The top 10% or 30 million people face an average risk of 8×10^{-7} and the top 5% or 15 million people face an average risk of 2×10^{-6}.

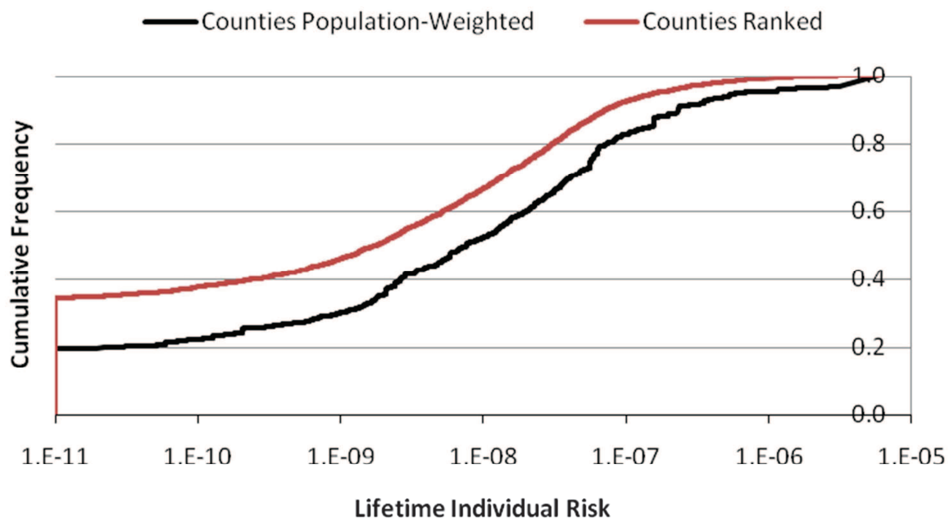

Figure 4. Cumulative distribution functions of risk of cancer due to Cr(VI) in 2002 by county (ranked in red and population-weighted in black).

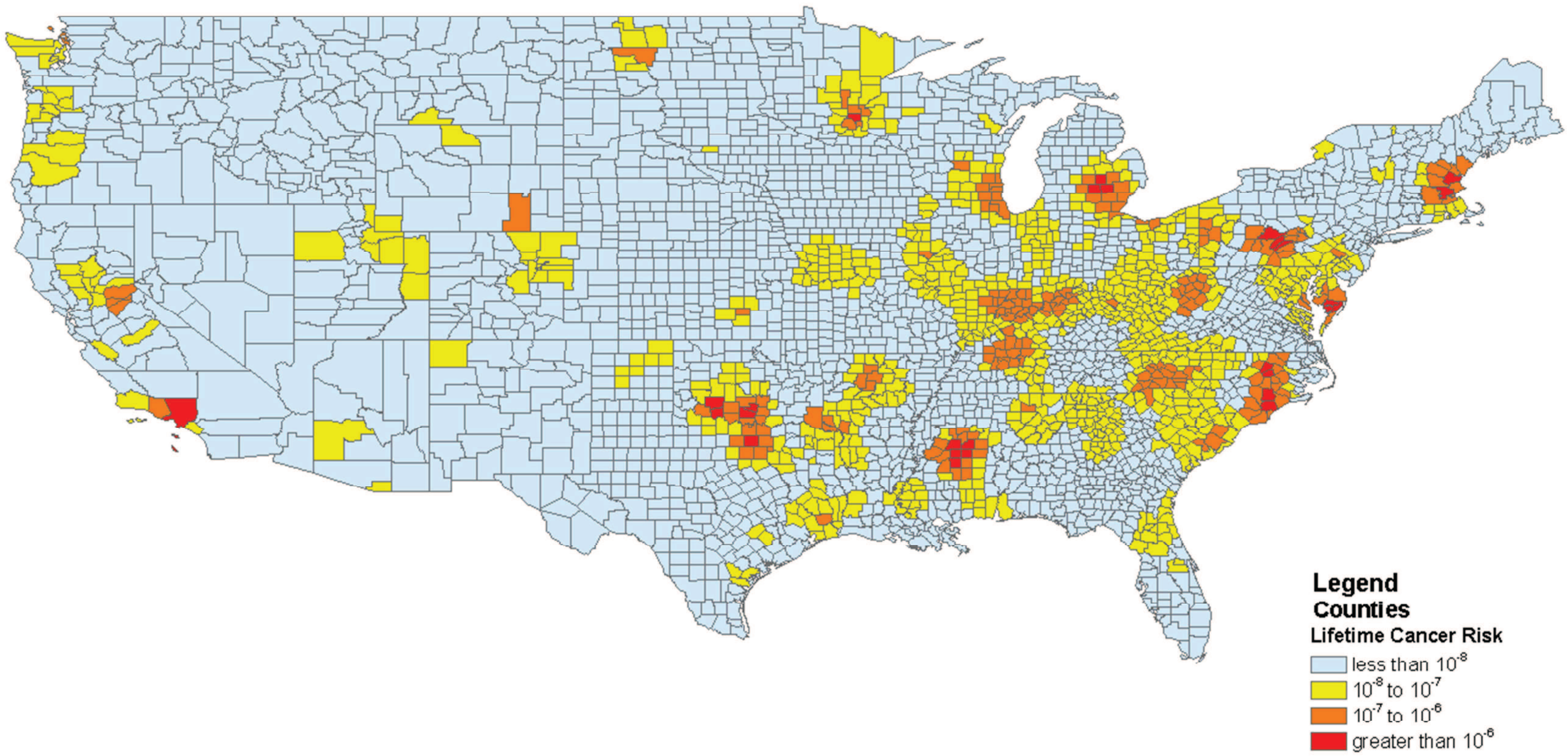

Figure 5. Predicted Lifetime Individual Cancer Risk of Cr(VI) due to Point Source Emissions from Current Production of NAICS 2211 Power Generation, NAICS 32 Wood Product Manufacturing, Chemical Manufacturing, Plastics and Rubber Manufacturing, and Printing, NAICS 33 Combined Metal Manufacturing Sectors, and NAICS 54 Professional, Scientific, and Technical Services.

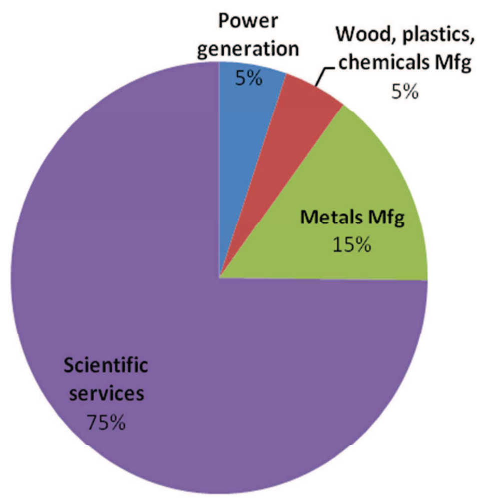

Figure 6. Breakdown of cancer incidence by economic sector associated with a lifetime average risk of 2.7 x 10-7 due to Cr(VI) point source air emissions in 2002.

As with many single-compound air toxics risk estimates, the total predicted US annual cancer incidence associated with this lifetime average risk is small, 1.1 (expected cases over a lifetime due to annual exposure), just slightly higher than the NATA estimate for 1999 of about 0.7 (See the Supporting Information). However, this number will be larger when area and mobile sources are added and it will add to other risk factors in hot-spot communities. Table S4 in the Supporting Information shows the top ten receptor counties, or hot-spot communities, with regard to cancer incidence, the associated risk exposure and population, and the economic sectors and emissions source counties contributing to them. The scientific services and the metals manufacturing sectors were responsible for the bulk of incidence (0.8 and 0.2 cases, respectively) (Figure 6). Three of the counties were predominantly responsible for their own risk, while seven of the counties had computed risks predominantly associated with emissions from one or more neighboring counties. Six of the counties had predicted risk due to only one sector while the others had significant risk contributions from two or more sectors.

Los Angeles County was exposed to and was also responsible for the highest risk level and almost three quarters of cancer incidence due to Cr(VI). This can be attributed largely (99%) to emissions from its scientific services facilities. Responsible facilities include various aeronautical, defense and space vehicle contractors including Northrop Grumman, Lockheed, Vought Aircraft, Boeing, McDonnell Douglas, and their associated suppliers who use Cr(VI) to plate various airplane, missile or rocket parts for corrosion resistance. Other hot-spot counties include Middlesex County, Massachusetts, which is impacted by another defense contractor, Lawrence Ripak, located about 350 km away in Suffolk County, New York; Calhoun, IL, which is impacted by metals manufacturing and electric power utilities from other counties; and Denton County, Texas, which is impacted by metal manufacturing and other facilities in neighboring Dallas County, Texas.

The relative risk of emissions from different economic sectors can be gauged using a risk-emissions ratio, or population-weighted average risk to kilograms of Cr(VI) emissions (See Table S3 in the Supporting Information). The risk-emissions ratio for power generation and wood and chemical manufacturing sectors was lower than the overall average, for metals manufacturing it was the same as the overall average, and for scientific services it was 49 times higher than the overall average, another indicator that this sector's emissions occur in locations where they do the most harm. Cr(VI) emissions in the supply chains from each of these sectors were computed, totaling 6 tonnes, or approximately 14% of facility emissions (See the Supporting Information). However, since these emissions cannot be localized, their risk implications are not pursued further.

Discussion of Uncertainties

There are uncertainties and limitations concerning model data and methods, including those in the NEI Cr(VI) emissions, the atmospheric transport model (AERMOD) assumptions (such as linearity), the processed meteorological data, pollutant specifications, using the county centroid to represent risk across a county, exposure assumptions, including the unit risk factor, and Census Bureau economic output data and EIO-LCA modeling. These concerns are addressed in the Supporting Information in a discussion for the scientific services sector in Los Angeles County, since it emerges as a major driver of risk. We also compare model results with external datasets. Our findings are summarized as follows:

- Emissions inventories are likely to underestimate total emissions due to omitted sources (Harris and Davidson 2005), however, emissions estimates for included sources can be either high or low (U.S. Environmental Protection Agency 2006);
- For the scientific services sector in Los Angeles County, where chromium emissions result primarily from plating applications, NEI point source emissions estimates of Cr(VI) are typically measured directly by facilities through stack tests, according to the local pollution control agency, California Air Resources Board (CARB) (U.S. Environmental Protection Agency 2006; Takemoto 2009);
- The assumption that emissions respond directly to economic sector output most likely overestimates the elasticity of emissions, due to capacity and regulatory constraints on source facilities;

- The AERMOD atmospheric dispersion model is applied with a number of simplifications, though overall errors are likely to be only moderate given the annual averaging period employed (See the Supporting Information);

- Significant errors can occur in selected counties as a result of the use of county vs. average of census track centroids for exposure calculations (in Los Angeles County exposures were underestimated by nearly a factor of 10 using the coarser vs. the finer spatial resolution) (See the Supporting Information);

- Simulated annual average concentrations for chromium compounds compare favorably to reported values in the 2002 NATA (results for Cr(VI) were not available) (See the Supporting Information); the NATA tends to underestimate measured values by a factor of 2-3 (Logue 2009);

- In many areas ambient concentrations of Cr(VI) will likely be dominated by other factors, such as mobile sources or highways and soil and dust resuspension from naturally occurring sources, or from historic chromium emissions deposited to the land surface, roadways, and buildings (total exposure and risk are thus underestimated, recognizing that our estimates are limited to the exposures and risks associated with current emissions to the air) (Harris and Davidson 2005);

- Moderate errors in exposure estimates occur due to the use of ambient (vs. both outdoor and indoor) concentrations and due to the assumption that individuals spend their entire life in a single county (proper consideration of the latter would lessen the variance of the national population distribution of exposure and risk) (Marshall, Granvold et al. 2006);

- The cancer unit risk factor Cr(VI) is derived from conservative assumptions based on an upper confidence limit (U.S. Environmental Protection Agency 2007).

While we believe that errors associated with these uncertainties could result in a net shift in the absolute risk associated with current ambient emissions of Cr(VI) either upward or downward, most apply in a similar manner across all locations. As such, the relative magnitudes of the Cr(VI) risks predicted for different counties (i.e., those shown in Figure 4) are likely more robust. Furthermore, we are not aware of any estimates at this time that are more accurate or precise.

DISCUSSION

The results of this analysis suggest that the use of economic activity as an input into fate and transport models and the level of spatial variation in emissions sources and impacts produced offer important lessons for LCA and health risk comparative assessments. First, inhalation exposure and cancer risk are not proportional to emissions from different economic sectors due to differing plant locations (e.g., relative to downwind populations), characteristics (e.g., stack heights), and meteorology (e.g., wind speed and direction). In 2002, the scientific services sector produced a fifth of the estimated point source emissions of Cr(VI) in Los Angeles County, but were responsible for over ninety percent of the predicted cancer risk there due to the use of lower stacks (averaged 7 meters tall compared to 35 meters for other stacks), and meteorology that concentrates exposure in the metropolitan area. Other studies have found that various factors not considered here also tend to increase exposure to Cr(VI) emissions in the Los Angeles area (Marshall, Granvold et al. 2006). Additionally, the scientific services sector did not produce any emissions in Middlesex County, Massachusetts, but due to meteorology that carries pollution northeast from Suffolk, New York to the populated area, the County is predicted to be a hot-spot location for Cr(VI) exposure.

Second, location relative to large population centers is clearly important. In 2002, electric power generation produced 70% of US point source emissions of Cr(VI), but was responsible for only 5% of predicted cancer incidence due to the use of higher stacks, which disperses particles further, and siting generally far away from population areas; whereas the scientific services sector produces only 1% of point source emissions of Cr(VI), but is estimated to be responsible for 75% of cancer incidence due to the use of lower stacks and siting in higher population areas. Consideration of these lessons in LCA and comparative health risk assessments can allow for better targeted reductions of emissions in areas that are hot-spots for exposure and risk.

Future work includes: 1) Investigating the contribution to air pollutant exposure from other heavy metals (e.g. mercury, lead, and PCBs) and due to other exposure pathways (e.g., ingestion) and considering how they act in combination for use in evaluating multi-pollutant tradeoffs and policy decisions; 2) Implementing the model as a website for use by consumers, companies and local governments; and 3) Disaggregating supply chain emissions by locality to account for spatial variation in risk due to impacts over the full life cycle of a toxic material.

CHAPTER 3. A DECISION SUPPORT FRAMEWORK FOR SCIENCE-BASED, MULTI-STAKEHOLDER DELIBERATION: A CORAL REEF EXAMPLE[2]

ABSTRACT

We present a decision support framework for science-based assessment and multi-stakeholder deliberation. The framework consists of two parts: a *DPSIR* (Drivers-Pressures-States-Impacts-Responses) analysis to identify the important causal relationships among anthropogenic environmental stressors, processes, and outcomes; and a *Decision Landscape* analysis to depict the legal, social, and institutional dimensions of environmental decisions. The Decision Landscape incorporates interactions among government agencies, regulated businesses, non-government organizations (NGO), and other stakeholders. It also identifies where scientific information regarding environmental processes is collected and transmitted to improve knowledge about elements of the DPSIR and to improve the scientific basis for decisions. We discuss application of the decision support framework through examination of coral reef protection and restoration in the Florida Keys National Marine Sanctuary, focusing on anthropogenic stressors, such as domestic wastewater. A structured elicitation of values and beliefs conducted at a coral reef management workshop held at Key West, Florida is used to develop information for an integrated DPSIR/Decision Landscape framework, and to show the

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[2] The contents of this chapter has been submitted for publication as: Rehr, A. P., M. J. Small, P. Bradley, W.S. Fisher, A. Vega, K. Black, and T. Stockton. (*Submitted* 2010). "A Decision Support Framework for Science-Based, Multi-Stakeholder Deliberation: A Coral Reef Example." Environmental Management.

role that further scientific information and research might play to populate the framework and better inform decisions.

INTRODUCTION

Government and private organizations regularly confront complex decisions that involve multiple parties, affect ecosystems and economies, and include choices made more challenging by unknown certainty of relevant scientific knowledge. Decisions are often made without appropriate consideration of scientific information, without knowledge of the uncertainty of the scientific information, without full representation of different stakeholder objectives, and without consideration of the value of ecosystem services (Costanza, Andrade et al. 1999; Lynam, de Jong et al. 2007; McNie 2007; Cowling, Egoh et al. 2008). We describe a decision support framework and methodology to better address these shortcomings. The proposed decision support framework is based on the concept of decision analysis, which provides a course of action when there are conflicting desires and uncertainty in the consequences of alternative decisions (Gregory, Keeney et al. 1992; Keeney 1992; Clemen 1996). The proposed framework draws from and expands on existing decision support tools for environmental assessment and management.

Much progress has been made in recent years to advance scientific understanding of ecosystems, including responses to stressors, value to human wellbeing, and sustainable delivery of goods and services. However, there is often a mismatch between scientific knowledge and the needs of agencies, businesses, and individuals making critical decisions that affect the environment. Improved decision support methods can be used to bridge this gap to: 1) guide scientists in the selection of targeted research studies and models responsive to the needs of decision makers and stakeholders; and 2) provide decision makers with the tools needed to interpret scientific results, understand uncertainties, draw relevant inferences regarding the decision problem, and identify further data collection and research needs. An existing tool for incorporating scientific information into a decision process is integrated assessment. Integrated assessment incorporates knowledge from two or more domains into a single framework, often using numerical models, in order to inform public policy (Rubin, Small et al. 1992; Dowlatabadi and Morgan 1993; Turner, Georgiou et al. 2003; Matthies, Giupponi et al. 2007). Integrated assessment can be used to combine information from the environmental, social, and economic contexts.

A better understanding of uncertainty in a decision problem will allow decision makers to either take action or target additional research needs. Uncertainty can include variability in current resource conditions or incomplete scientific knowledge regarding the causal relationships between management options and current resource conditions. Probabilistic techniques and expert elicitation are existing tools for analyzing uncertainty in a decision (Morgan, Henrion et al. 1990; Cullen and Frey 1999; Cullen and Small 2004).

A decision support framework that encourages multi-stakeholder participation and deliberation can be used to build agreement around a preferred management action, especially among multiple decision makers and stakeholders who have differing objectives and beliefs regarding a problem (Cohen 1997; DeKay, Small et al. 2002; Renn 2006; Reed 2008). The NRC (National Academy of Sciences National Research Council 1996) described this democratization of risk and environmental policy decisions as an analytic-deliberative process, requiring a combination of *analysis* (input from physical and social sciences) and *deliberation* (input from stakeholders).

An existing tool for including multiple stakeholder objectives is multi-criteria decision analysis (MCDA), sometimes called multi-criteria decision making. MCDA is aimed at helping to evaluate the relative importance of multiple, possibly conflicting criteria in a decision scenario (Makowski, Somlyody et al. 1996; Belton and Stewart 2001; Cohon 2004; Kiker, Bridges et al. 2005; Messner, Zwirner et al. 2006). These criteria determine the basis for one particular choice or course of action over another. Often, management decisions must consider a wide range of criteria, especially when consensus is needed across groups with widely disparate interests.

A decision support framework that incorporates the value and sustainability of ecosystem services could help to promote decisions that achieve a better balance between resource use, depletion or degradation, and preservation. Including ecosystem services in environmental decision making presents a way to incorporate benefits of the environment that may otherwise be overlooked (Costanza, d'Arge et al. 2002; Hein, Koppen et al. 2006; Boyd and Banzhaf 2007; Turner, Morse-Jones et al. 2010). Valuation of natural resources and environmental quality can be approached from a number of perspectives, including market and non-market measures of willingness-to-pay and contingent valuation (Bockstael, Freeman III et al. 2000; Farrow, Goldburg et al. 2000; Hanley, Shogren et al. 2007). For a variety of social, economic, and behavioral reasons, common environmental resources tend to be under-valued (Hassan, Scholes et al. 2005). As a result, land and resource use decisions have often been made to increase short-term economic opportunities with little attention to the long-term effects on goods and services, including human health, that are derived from natural ecosystems.

In this paper an initial decision support framework for assessing and managing coral reef stressors in the Florida Keys is developed by combining: 1) an analysis to identify causal relationships among anthropogenic environmental stressors, processes, and outcomes with 2) an analysis to depict the legal, social, and institutional dimensions of environmental decisions. A management plan for the National Oceanic and Atmospheric Administration Florida Keys National Marine Sanctuary (NOAA FKNMS) was developed in 2007. A scoping study of preferences for future environmental and economic outcomes and beliefs about scientific relationships between management options and outcomes was completed by volunteers participating in a coral reef management workshop held at the NOAA FKNMS in June 2009. The decision support framework described herein is initially derived by integrating information drawn from this management plan and scoping study.

BACKGROUND: CORAL REEF MANAGEMENT IN THE FLORIDA KEYS

The Florida Keys are a chain of 822 low-lying islands from Biscayne National Park south of Miami to the Dry Tortugas (Figure 7). The coral reef tract extends nearly continuously along the 356 km shallow offshore waters of the Keys. Most of the reef tract lies within the boundaries of the 9,800 sq km FKNMS. The FKNMS contains the third largest barrier reef in the world.

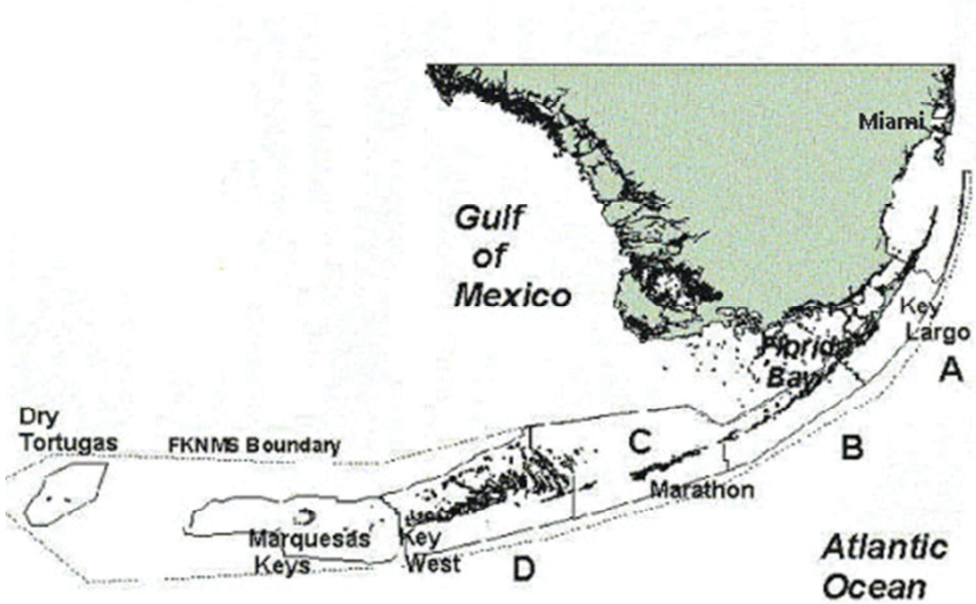

Figure 7. Map of the Florida Keys National Marine Sanctuary (National Oceanic and Atmospheric Administration)

Coral reefs provide important ecosystem services including regulating processes (shoreline protection, water quality maintenance, climate regulation), provisioning resources (fish, pharmaceuticals, and other marine natural products and chemicals), cultural benefits (tourism, recreation), and ecological support systems (nutrient cycling, habitat, nursery areas) (Hassan, Scholes et al. 2005). According to the United Nations Environmental Programme (UNEP) coral reefs provide a total of \$100,000 - \$600,000 in ecosystem services per sq km per yr (UNEP 2006). Based on an approximately 2000 sq km hardbottom reef area in FKNMS, this amounts to over one billion dollars per yr. This is likely true in Florida Keys, which support a commercial fishing industry worth several millions of dollars per year (NOAA 2010) and a tourism industry based mainly on marine resource-based activity worth one billion dollars per year (Leeworthy and Bowker 1997; Wheaton, Jaap et al. 2001).

A number of threats to coral reefs in the FKNMS have been identified, including ocean warming and acidification associated with increasing atmospheric carbon dioxide (Orr, Fabry et al. 2005; Doney, Fabry et al. 2009); regional and local water pollution from sources such as municipal wastewater and agricultural runoff (Hallock and Schlager 1986); altered freshwater flow regimes from the nearby Florida Everglades (Porter and Porter 2002); harmful fishing practices and overfishing (Chiappone, Dienes et al. 2004); and adverse physical contact and sediment resuspension from diving and boating activities (Jaap 2000; Shivlani and Suman 2000; Rouphael and Inglis 2002). In Florida about 60 percent of the coral reefs are threatened. Live coral cover in the FKNMS has decreased by nearly 40 percent from 1996 to 2000 (Wheaton, Jaap et al. 2001), and observations of coral disease have increased (Holden 1996; Santavy, Summers et al. 2005). In the past 20 years, coral bleaching has become more frequent, lasted longer, and been responsible for dramatic declines in coral cover in the FKNMS (Burke and Maidens 2004). The loss of coral in the Florida Keys has led to a decline in ecosystem services, including economic benefits from tourism and fisheries.

Given these threats, a wide range of decision makers and stakeholders now recognize the priority and urgency for actions to protect and restore Florida's coral reefs (Harwell 1998). The FKNMS management team crafted a plan to protect its natural resources, including coral reefs, seagrass, and mangroves. The FKNMS management plan (NOAA 2007) is implemented in collaboration with parties such as the US Environmental Protection Agency, Florida Department of Environmental Protection, Florida Department of Health, Florida Department of Community Affairs, the US Army Corps of Engineers, municipalities, and counties, each with differing authority and perception of environmental issues. Together, these agencies must consider options, such as marine zoning, restoration of damaged reefs, and stormwater management, to address the threats (NOAA 2007). These options will require economic sacrifices by the Florida Keys community and likely tradeoffs with economic development. There will be conflicting views among these parties and among their stakeholders on the severity of different threats, the potential to manage those threats, which actions should be taken, and their anticipated environmental and socioeconomic outcomes.

DECISION SUPPORT FRAMEWORK

The emerging decision support framework initiates the decision analysis process. The first part decomposes the issue into identifiable steps and illustrates potential outcomes, intended or unintended, of different alternatives. It is achieved through application of a *DPSIR* (Driving Forces-Pressures-States-Impacts-Responses) conceptual approach (Figure 8), which has been used to link ecological and socioeconomic factors and to scope the important causal elements of environmental decision-making (Brouwer, Georgiou et al. 2003; UNEP 2007). The DPSIR framework provides a logical structure to house scientific information on relevant environmental and socioeconomic relationships. Scientific knowledge in the form of monitoring data, scientific studies, predictive models, or expert judgment can inform the relationships between components of the DPSIR framework (Figure 8, orange boxes).

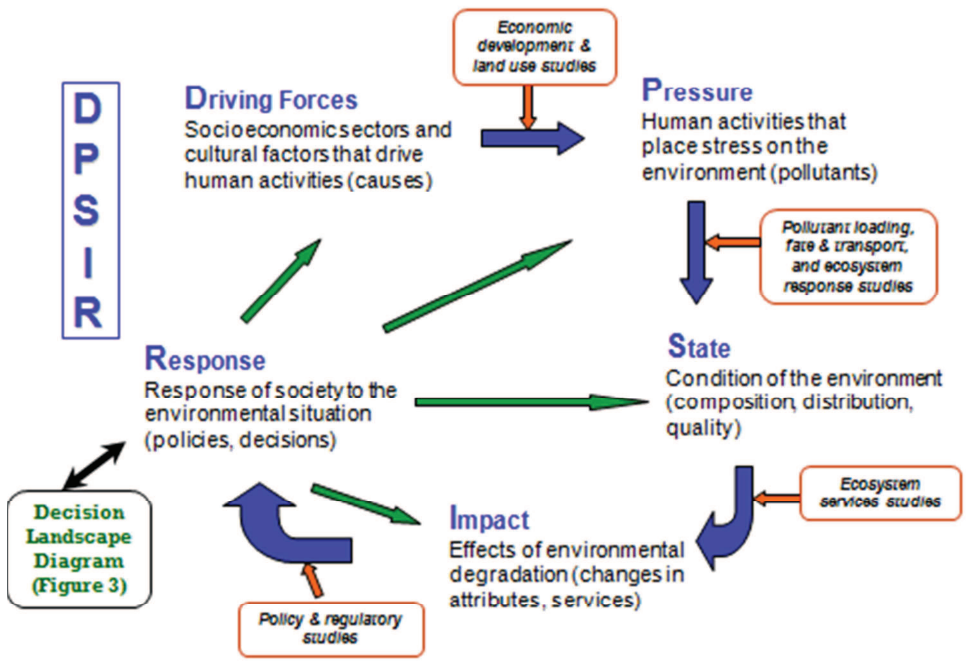

Figure 8. The elements of DPSIR including links to scientific input (orange boxes) and the Decision Landscape (adapted from (Fisher 2009; Bradley, Fore et al. 2010)

The second part of the decision support framework clarifies the decision situation and objectives and organizes management options. This is achieved through development of a *Decision Landscape* (Figure 9), which builds on previous conceptual approaches to describe the relationships between environmental and social components in an environmental decision problem (Tonn, English et al. 2000; Pyke, Bierwagen et al. 2007). The Decision Landscape analysis ensures that relevant legal, institutional, and social factors affecting a decision are recognized and considered. It addresses the knowledge, values, and decision making of participants in the various elements of the DPSIR process (Figure 8, bottom left-hand corner). It informs stakeholders regarding decision makers and decision options (Figure 9, components in green), system behavior and potential outcomes. It also identifies where scientific information regarding environmental processes is collected and transmitted to help improve knowledge about elements of the DPSIR and to support an improved scientific basis for decisions (Figure 9, components in orange).

Together, DPSIR and the Decision Landscape provide a robust framework (DPSIR/DL framework) to incorporate relevant scientific knowledge, to weigh perceived and real environmental outcomes, to evaluate differences in ecosystem services and values, to recognize uncertainties in the assessments and even to identify monitoring or research projects to reduce that uncertainty.

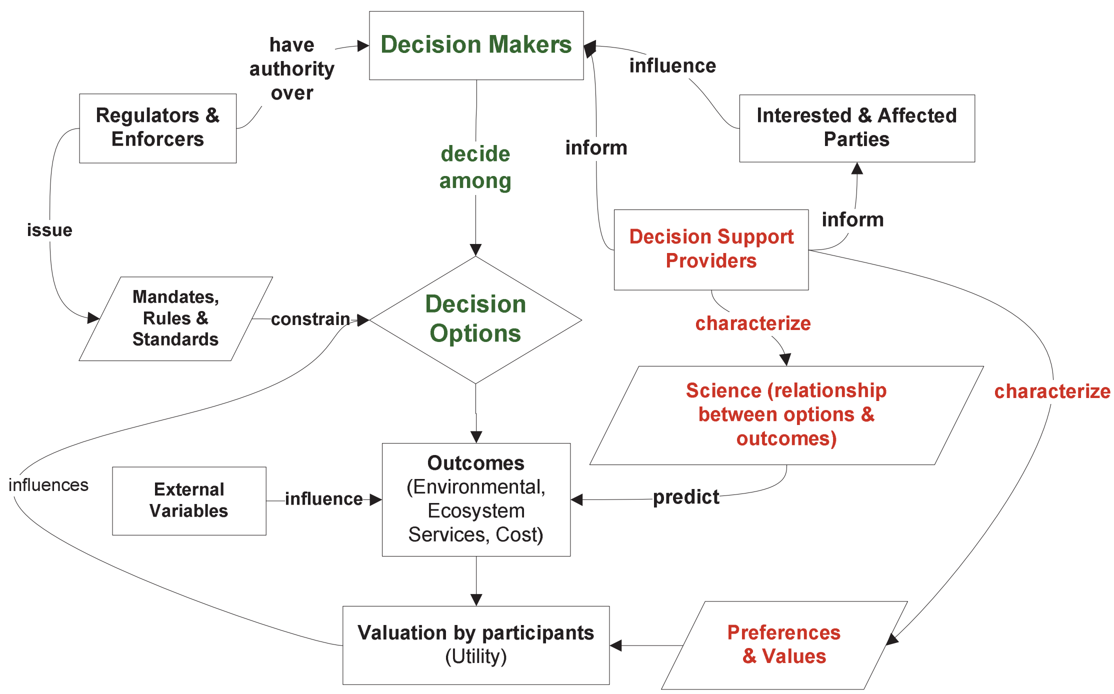

Figure 9. Components and Key Relationships in an Environmental Management Decision Landscape

INFORMING AND APPLYING THE FRAMEWORK

Information from various sources can be used to inform the DPSIR/ DL framework. In the examples presented here, ideas and concepts were collected from the FKNMS management plan (NOAA 2007) and from discussions at a Coral Reef Decision Support Workshop held at the FKNMS in 2009. Presented below are: 1) preliminary DPSIR and Decision Landscape analyses of one portion - the water quality portion - of the FKNMS management plan; 2) a scoping study of preferences and beliefs elicited from ten volunteers at the workshop regarding coral reef management and research needs in the FKNMS; and 3) an overview of a proposed DPSIR/DL framework based on the results of the study that can be used to assist future planning for coral reef management in the FKNMS.

Coral Reef DPSIR and Decision Landscape Analyses

Drawing from the management plan, the DPSIR analysis for the water quality action plan included delineation of important drivers, pressures, "abiotic" (physical-chemical) and "biotic" (biological) states, and impacts on ecosystems services. For each of the DPSIR elements, variables, existing knowledge and future research needs could be identified (Table 1 illustrates an example for domestic wastewater discharges). Development of the Decision Landscape included delineation of important management actions, decision makers, and legal mandates that constrain decision options (Table 2 outlines important institutional components for the water quality action plan). Stakeholders in the water quality strategies include environmental, fishing, and business and trade groups. Decisions are made by a variety of institutions (Table 2) and decision support is provided by institutions that prepare monitoring results, models, studies that link pollutants and impacts, and news reports (e.g., EPA, FDEP, NOAA FKNMS, National Coral Reef Institute, University of Miami, Miami Herald).

Table 1. Variables, Current Knowledge and Research Needs for Domestic Wastewater Discharges Organized in the DPSIR Framework Derived from Management Plan

	Variables	**Current Knowledge**	**Research Needs**
Drivers	• Population Growth • Land Use • Economic Activity – Industry – Agriculture – Recreation/tourism • Waste Disposal	• Census data • USGS land use/GIS data • Bureau of Econ. Analysis/ Census economic data – Water, energy, material use (e.g., fertilizer)	• Scenario Development – Future Population – Future economic activity – Land use/land cover projection model
Pressures	• Water use, diversion • WW discharge rates – N, P, BOD, TSS, toxics • NPS loading rates • Impingement – Boating, diving, etc.	• Inventories – Cesspits, onsite systems, package plants, municipal plants • NPDES permit data – Compliance monitoring	• Scenario Development – Water use – Wastewater loading rates – NPS loading rates – Impingement projections
State (Abiotic)	• Freshwater flow rates • Ambient WQ – N, P, Algal, DO, TSS, toxics	• USGS flow monitoring • Fed/state WQ data • Habitat assessments	• Biotic-Abiotic interactions • Uncertainties – Climate change – Variable rain patterns
State (Biotic)	• Coral cover/health • Fish Species Presence and Abundance	• Coral reef monitoring – Fed/State programs – Academic, NGO and volunteer programs	• Stressor-response studies linking human activity to changes in coral condition • Reef persistence modeling • Linkage of coral reef attributes to ecosystem services
Impacts (Eco. Serv.)	• Recreation/tourism • Fisheries • Shoreline protection	• Socioeconomic monitoring program • Recreation and Tourist Uses, Values, Attitudes and Perceptions study (NOAA)	• Improved quantification of ecosystem services • Improved quantification of social preferences

Terms: USGS=U.S. Geological Survey; GIS=Geographic Information Systems; WW=wastewater; N=Nitrogen; P=Phosphorus; BOD=Biochemical Oxygen Demand; TSS=Total suspended solids; NPS=non-point source (pollution); NPDES=National Pollutant Discharge Elimination System; WQ=water quality

Table 2. Decision Options, Decision Makers, and Legal Mandates in the Decision Landscape for the Water Quality Strategies Portion of the FKNMS Management Plan

Decision Options	**Decision Makers** **(and Regulators/Enforcers)**	**Legal Mandates (Rules/Standards)** **(constraints)**
Domestic Wastewater Strategies	Monroe County, Key Largo Wastewater Treatment District, FKAA, EPA, FDEP, FDCA, municipalities, FDOH, and City of Islamorada	• FL Sec 6 (Ch 99-395) which covers treatment and disposal standards • Governor's Executive Order 96-108 (elimination of cesspits)
Stormwater Strategies	Monroe County, local municipalities, FDEP, FDOT, and SFWMD	• 40 CFR 122- The National Pollution Discharge Elimination System permitting and related regulations • Best Management Practices
Florida Bay/External Influence Strategies	FKNMS: • EPA, FDEP, and NOAA Everglades/Florida Bay: • NPS, SFWMD, USACE, FDCA, USFWS, and Monroe County	• FL Sec 62-043 Surface Water Improvement and Management Act • Sec 403.021 of the Florida Statutes • Sec 62-302 Surface Water Quality Standards • Sec 62-303 Identification of Impaired Surface Waters • PL 101-605 Florida Keys National Marine Sanctuary and Protection Act • 15 CFR 922, 929 & 937 Florida Keys National Marine Sanctuary Regulations, Final Rule • 16 USC 6401 Coral Reef Conservation Act • 33 USC 1251 Clean Water Act • PL 106-541 Water Resources Development Act of 2000
Marina and Live-Aboard Strategies	FWC, Monroe County, local municipalities, EPA, and NOAA	• Florida Clean Vessel Act of 1994 • Sec 327.53 of the Florida Statutes • No-Discharge Zones (City, State)
Landfill Strategy	Monroe County, FDEP, U.S. Navy, and EPA	• 40 CFR 240-299 RCRA Regulations
Hazardous Materials Strategies	USCG, FDEP, NOAA, Monroe County, and FDCA	• 40 CFR 240-299 RCRA Regulations • 49 CFR 100-185 HAZMAT Regulations
Mosquito Spraying Strategy	FDA, Consumer Services (FDACS), and FDCA	• 40 CFR 150-189 FIFRA Regulations
Canal Strategy	Monroe County, FDCA, SFWMD, EPA, FDEP, and municipalities	• Same as applicable to Florida Bay/ External Influence Strategies above

Terms: FKAA=Florida Keys Aqueduct Authority; EPA=Environmental Protection Agency; FDEP=Department of Environmental Protection; FDCA=Florida Department of Community Affairs; FDOT=Florida Department of Transportation; SFWMD=South Florida Water Management District;

NOAA=National Oceanic and Atmospheric Administration; NPS=National Park Service; USACE=U.S. Army Corps of Engineers; RCRA=Resource Conservation and Recovery Act; USCG=U.S. Coast Guard; FDACS=Florida Department of Agriculture and Consumer Services; HAZMAT=Hazardous Materials; FIFRA= Insecticide, Fungicide and Rodenticide Act

Scoping Study to Inform a DPSIR/Decision Landscape Framework

Ten volunteer respondents at the Coral Reef Decision Support Workshop were elicited for their preferences regarding different environmental and ecosystem services outcomes; beliefs regarding pressure-state-impact relationships for Florida's coral reefs; identification of alternative decision options; and research needed to reduce uncertainties related to environmental outcomes (See Appendix B for a blank elicitation form). The respondents included decision makers, decision support providers, and interested and affected parties. Eight were affiliated with or funded by NOAA, NMS, or FKNMS, four of whom held PhD degrees, and two of whom held academic appointments. Of the two other respondents, one held a PhD and had an academic appointment and one worked for a non-government organization. Given the small sample size, no statistical analyses of the results were made. Rather, the elicitation results are used to provide an initial scoping of preferences and beliefs, to identify points of possible consensus, and to provide a basis for the construction of a DPSIR/DL framework.

Respondents were asked to weight the relative (%) importance of four outcomes for the FKNMS region: coral reef health; water quality; tourism and economic growth; and fisheries health and vitality. Preferences for different outcomes (Figure 10) were highest for good coral reef health (average of 34.5%), followed by good coastal water quality and good fisheries health and vitality (averages of 27.5% and 27% respectively), and finally high tourism and economic growth (average of 11%).

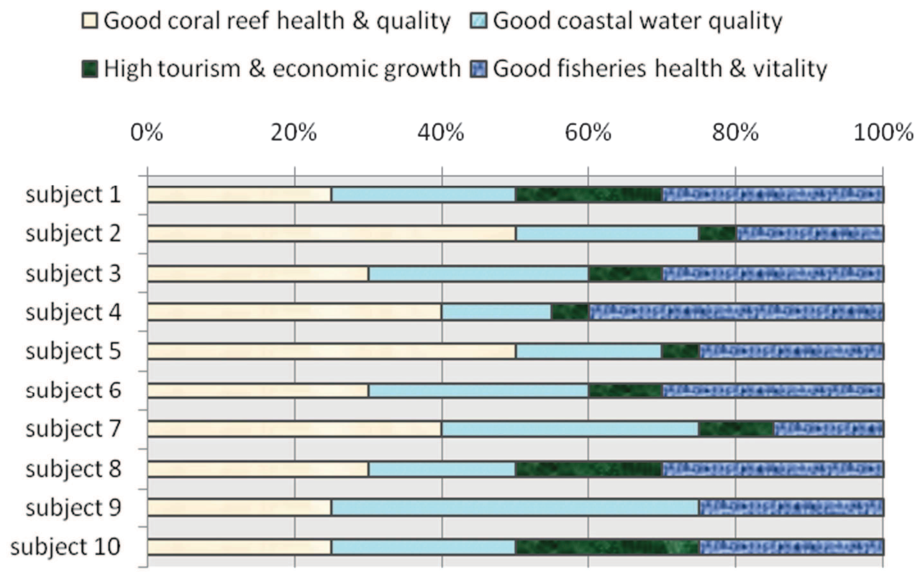

Figure 10. Respondent preferences (relative weights) for different outcomes in the FKNMS region

The volunteers were also elicited regarding their beliefs about relationships between various pressures and environmental state in the FKNMS. They were asked to estimate the probability of good coral reef health given different scenarios of water quality, climate change and fishing practices; these responses indicate the perceived uncertainty between Pressure and State in the DPSIR framework (Figure 11). The average of participant responses indicates a belief that coral reef health will improve with higher water quality, less climate change and stronger fishing restrictions. This occurs despite a wide range of beliefs about the likelihood of good coral reef health. Differences could result from different notions regarding coral reef health, the relative importance of different stressors, or the potential for any environmental change to make a substantive difference. As a group the respondents believed that improvements in water quality would have the largest impact on coral reef health, followed by improvements in climate-related conditions. However, the largest predicted increase in the likelihood of good coral reef health occurred when all three conditions were favorable.

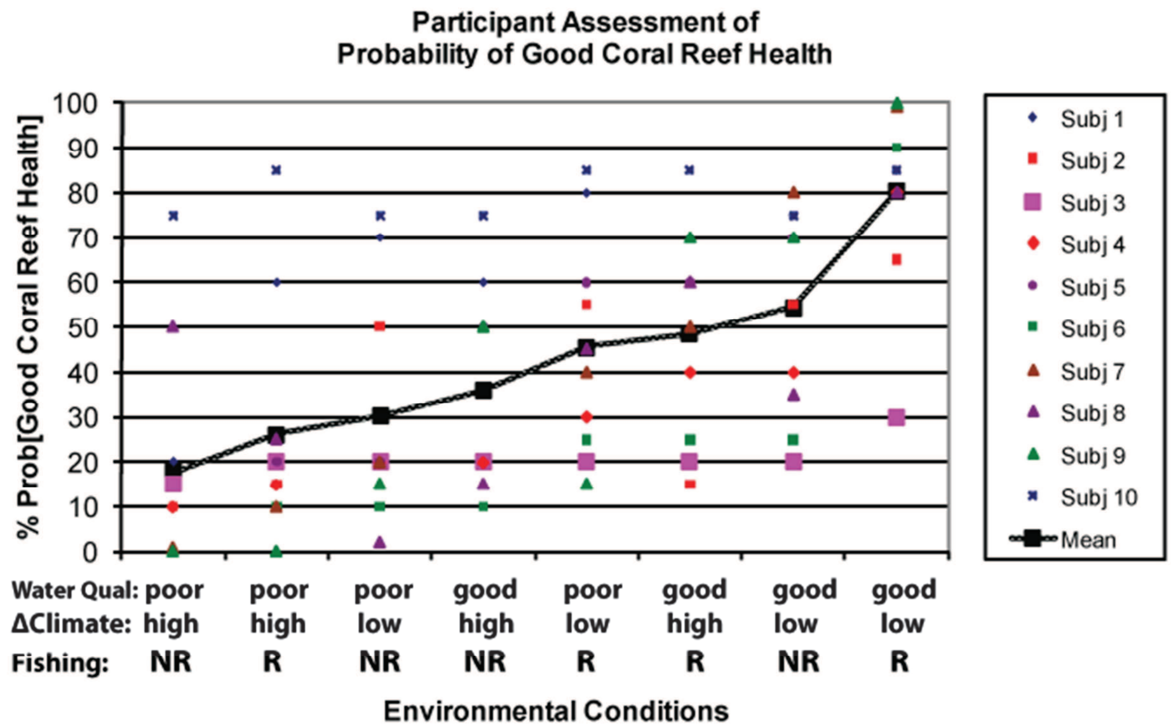

Figure 11. Ratings of ten respondents (subj) regarding the probability (%) of good coral reef health based on various environmental scenarios involving (good/poor) local water quality, (high/low) potential for climate change (ocean warming and acidification), and restricted (R) or unrestricted (NR) fishing.

The same ten volunteers were also asked to identify critical uncertainties in any factor affecting environmental quality and economic wellbeing in the Florida Keys, particularly those that limit the ability to identify effective management options. The critical uncertainties and research needs (Table 3) included studies to better standardize metrics of coral reef health, to assess current reef conditions in the FKNMS, to better understand causes of coral reef decline and conditions that promote effective restoration and recovery, to integrate water quality monitoring and modeling, and to study of the effect of educational efforts on attitudes and preferences.

Table 3. Critical Uncertainties and Suggested Research Studies to Reduce Uncertainties Identified by Workshop Participants

Critical Uncertainties	**Suggested Research Studies**
1. The need for consistent, quantitative metrics to assess coral reef "health".	The reef science and management communities should actively pursue agreement on quantitative measures of reef ecosystem processes that relate to reef ecosystem "health."
2. Current baseline information on reef condition in the FKNMS	Mapping and monitoring of reef ecosystems throughout the Florida Keys
3. Causes of coral reef decline	
A. Causes of "regional pandemic" coral diseases	Study to track the spatial distribution and conditions associated with coral bleaching and disease events
B. Mechanisms of coral disease transmission and spread, including probiotic vs. disease responses among corals	Probiotic/antibiotic studies to determine what makes some coral susceptible to disease and others resistant.
C. Improved understanding of coral spawning, recruitment and settlement.	Field studies of coral spawning, recruitment and settlement
D. Relationships between coral reef health and nutrient concentrations, algae, zooplankton, and higher food chain biota, such as fish	Laboratory and field studies of coral reef health under different conditions
4. Effectiveness of proposed reef protection and restoration strategies	
A. Effect of no-take areas on fish populations and coral reef health	Long-term monitoring of fish populations, catch, and coral reef health at and near designated no take zones
B. Effect of ecotourism (vs. current tourism practices) on coral reef health	Long-term monitoring of areas where coral reef contact is limited and ecotourism practices are maintained
C. Long-term success of reef restoration projects	Long-term monitoring of reef restoration sites
5. Causal relationships between human activity and water quality in the Florida Keys	Integrated assessment of nutrient loads associated with agriculture, urban development, and wastewater, and the impact on water quality in the Florida Keys, conducted by biophysical and social scientists
6. Impact of education on preferences for coral reef protection and preservation of other ecosystem services	Study of response to information on coral reefs and ecosystem services presented to different segments of the population

Development of an Integrated DPSIR/ Decision Landscape Framework

Based on the management plan and the elicitation, exercises and deliberations of the workshop, an integrated DPSIR/DL framework for FKNMS began to emerge (Table 4). The framework identifies key DPSIR relationships, current scientific understanding, and stakeholder perceptions, which can be used together to predict the outcomes of management options and to identify future research needed to resolve conflict among stakeholders over scientific understanding and preferred management options. As these aspects of the framework evolve the ability to project future outcomes improves. A wide range of information and research is needed to provide comprehensive decision support for coral reef management in the FKNMS. As yet, an integrated model capable of linking human activities, water quality, coral reef health, fisheries, and ecosystem services does not exist for the region.

Wastewater treatment strategies proposed in the FKNMS management plan should reduce nutrient discharges and improve water quality, with probable benefits for coral reef health and delivery of ecosystem services such as fisheries, and tourism. However, given other stresses on the system, the cost of nutrient reduction and the loss of other economic opportunities, enhanced wastewater treatment may not be justified. No decision is without tradeoffs, but information provided in an organized framework could better inform what those tradeoffs will be.

Table 4. An Overview of Scientific Understanding, Stakeholder Perceptions, and Research Needs for Predicting Outcomes of Management Options Organized in the DPSIR Framework

	Scientific Understanding	**Stakeholder Perceptions**	**Research Needs**
Drivers →Pressures	• Increased population and human activity leads to increased water use and pollutant loadings	• Disagreement regarding the type and intensity of effects of population growth on coral reefs and economic growth	• Economic input-output models • Hydrologic and hydrodynamic non-point source pollution models • Models to evaluate different decision scenarios
Pressures →Abiotic State	• Sediment and nutrient discharges throughout the watershed add to pollutant loads reaching coral reefs and the coastal environment	• Disagreement regarding the sources of pollutants in aquatic systems and the means to control them	• General ambient water quality model • Models to evaluate different scenarios
Abiotic State ←→ Biotic State	• Multiple water-borne physical and chemical stressors lead to increased algae, decreased coral cover, and imbalance in number and diversity of fish	• Disagreement regarding effects of pollutants on the condition of the coral reef community; effects of water-borne stressors relative to climate change stressors and damage by physical contact • General agreement that coral condition can be improved by reduction of environmental stressors	• Indicators explicitly sensitive to human disturbances • Coral health/fisheries model • Model to link water quality to ecological attributes • Models to evaluate different scenarios
Biotic State →Ecosystem Services	• Changes in the amount and condition of coral reef ecosystems (coral, fish and other inhabitants) and delivery of ecosystem services	• Disagreement on what constitutes an ecosystem service, what provides the service, the value of the service and how ecological state affects the delivery of the service	• Rate functions that quantify ecosystem services • Economic model to predict value of services from corals and fisheries • Models to evaluate different scenarios • Methods to incorporate stakeholder values
Integrated Assessment	• Activities to fulfill basic human needs result in use and alteration of coral reef ecosystems and services	• Disagreement regarding quantifiable linkages among interacting human activities and consequent effects on coral reef ecosystem services	• Development of an integrated model • Educating and engaging stakeholders

DISCUSSION

The development of effective decision support for complex multiple stakeholder problems, such as coral reef protection and management, is a demanding and often thorny challenge. A broad range of pressures, management options, scientific information, and conflicting objectives must be aligned for a strategic delivery of relevant knowledge and information. Organizing the existing scientific research, associated uncertainties and research needs into the DPSIR framework facilitates the ability to forecast system responses and uncertainties. A Decision Landscape ensures that relevant constraints and flows of authority and information are recognized in the development of preferred management options.

The integrated DPSIR/DL framework has advantages over existing methods for environmental decision making and assessment. While an MCDA can help to evaluate the relative importance of multiple, possibly conflicting criteria in a decision scenario, the DPSIR/DL framework builds on that by incorporating multiple stakeholder beliefs about scientific relationships between various aspects of a decision problem, such as management options, anthropogenic stressors, environmental processes, and economic outcomes, which can provide more validity to a preferred management option. While integrated assessment can be used to incorporate knowledge from the environmental, social, and economic contexts, the DPSIR/DL framework builds on that by incorporating the multiple stakeholder context for beliefs about scientific relationships and preferences for future environmental and economic outcomes, which can help to identify points of conflict and possible consensus. The DPSIR/DL framework improves on existing methods by identifying monitoring or research projects to reduce uncertainties, and by considering the value of ecosystem services impacted by a decision. The DPSIR/DL framework also takes into account the iterative nature of the decision process and thereby conforms to the need for adaptive resource management. Adaptive management is a strategy to continually check the performance of selected options and adjusting policy as needed (Holling 1978; National Research Council 2003). Adaptive management is enhanced by formal analysis and optimization methods (Williams 2001) and by broad stakeholder participation (Schindler and Cheek 1999). The DPSIR/DL framework can provide a platform through which adaptive management activities can be identified, implemented and tracked.

Elicitations and discussions at a Coral Reef workshop were used to scope preferences for outcomes, beliefs regarding pressure-outcome relationships, and the research needed to reduce important uncertainties in these relationships. Not surprisingly, the ten workshop respondents who were mainly resource managers and not in business or commerce, most highly valued coral reef health, followed by water quality, fisheries health and vitality and lastly, by tourism and economic growth. In agreement with existing studies, they believed as a group that coral reef health will improve with higher water quality, less climate change and stronger fishing restrictions, despite a wide range of beliefs about the likelihood of good coral reef health. They expressed belief in some synergy among the environmental factors needed to enable good coral reef health, as evidenced by the high mean probability of good coral reef health when all three factors represent higher environmental quality. This indicates a belief as a group that a broad-based management strategy would be more acceptable than a focus on only one or two of the environmental pressures. The respondents reported on many critical uncertainties and research needs that limit the ability to identify effective management options. Whereas each uncertainty and suggested research area has validity, it is unlikely that any one organization, such as FKNMS and its collaborators, can mount a research strategy that addresses all the critical issues.

Mechanisms for coordinating activities across a broad range of scientific researchers in the Florida Keys are thus needed, and plans for enabling these were also discussed at the Workshop.

Elicitation results and workshop sessions were used to develop an initial DPSIR/DL framework for particular FKNMS coral reef management issues. The initial constructs will be built upon and expanded in the future with the intent of contributing to a process that strategically incorporates critical scientific knowledge into local and regional decisions.

CHAPTER 4. THE ROLE OF SCIENTIFIC STUDIES IN BUILDING CONSENSUS AMONG STAKEHOLDERS IN ENVIRONMENTAL DECISION MAKING: A CORAL REEF EXAMPLE

ABSTRACT

We present and demonstrate a new decision support method called the Expected Consensus Index of New Research (ECINR) for identifying where additional scientific research may be needed to support better informed decisions and resolve possible conflicts over preferred management actions. The method combines and builds on aspects of multiple stakeholder deliberation, multiple criteria analysis, Bayesian Belief Networks, and value of information analysis. We apply ECINR to coral reef protection and restoration in the Guánica Bay Watershed, Puerto Rico, focusing on assessing and managing anthropogenic stressors, such as sedimentation and pollution from inland sources such as sewage, agriculture, and development. Structured elicitations of values and beliefs conducted at a coral reef management workshop held at La Parguera, Puerto Rico are used to develop information for demonstrating ECINR. An initial analysis showed that the final study group of seven stakeholders, consisting of resource managers and scientists, preferred the management options of establishing marine protection areas and restoring a lagoon (their first and second choices, respectively). Since they were already in agreement for their top choices, we based the ECINR analysis on the next set of decision options, which were reducing loadings from each of sewage, agriculture, and development, for which they were not in agreement. The scenario assumed that loadings would be reduced incrementally from each source through a series of management steps, which would be ranked in order of maximizing anticipated benefits. We then examined whether beliefs

exhibited greater confidence and coherence between stakeholders when informed by plausible study results. Generally, we find that new scientific research is likely to bring people who initially disagree to agree. Seventy-five percent of the possible research results are projected to lead to more agreement among the stakeholders. However, we find that there can be situations where prior beliefs may be too different from the study results to shift perspectives and bring people to agreement. There were also a few cases where results actually led to more conflict among stakeholders. Overall, stakeholders believed before the research was conducted that research to determine sewage loadings and agriculture loadings would bring about the largest change in agreement (ECINR = 0.2 as an average of the stakeholder perspectives). Research to determine development loadings was thought to produce neither more agreement nor more conflict on average (ECINR = 0.0). The effect of a combined research study to determine loadings from all three sources is in preparation and the predicted ECINR is expected to be higher than that of each individual research programs and probably less than the sum of that of the individual research programs. In terms of prioritizing a research agenda to reduce uncertainty and resolve conflicts, stakeholders would pursue determining loadings from agriculture and sewage, and would likely forego research to determine loadings from development since it is not predicted to make a difference. If stakeholders wished to choose only one research program, and assuming they are conflict-averse, trends in the individual research outcomes of the programs would lead them to opt for sewage loadings research. Though preliminary these results suggest that ECINR can provide useful insights on the social implications of a research program. Future work involving a larger and more diverse sample group, more detailed information about stakeholder trust in the science, additional outcomes that create more realistic tradeoffs between the environment and economy, cost information for management options and research studies, and automation of the method, would help to clarify these results.

INTRODUCTION

Environmental decision making frequently involves issues over which individuals and groups disagree regarding critical scientific underpinnings and the degree of uncertainty that is acknowledged. As an environmental risk is acknowledged and further studied, the associated uncertainty also tends to be amplified as new data or events expose previously unrecognized aspects of the problem. While people may agree that management decisions require sufficient information to justify a response strategy, those who favor a rapid management response may argue that enough information is already known, whereas those who favor a delay argue that further study is needed (Cullen and Small 2004).

In these environmental decision making problems involving uncertainty, Bayesian statistical inference can be used to assess probabilities or degrees of belief (e.g., about relationships between management options and resource conditions) and how they are updated with evidence or new information. (Ellison 1996). Bayesian statisticians and their critics disagree over whether peoples' degree of belief, which may be different initially, will tend to move closer together as new evidence is obtained. Critics say when people hold widely different worldviews initially they can remain the same despite repeated evidence (Jaynes 2003). In the case of multi-stakeholder environmental decision making this suggests that new studies and information that reduce uncertainty may not resolve conflicts in all cases. In this study, we test this on a real multi-stakeholder environmental decision problem.

Due of the complexity of decision problems involving multiple stakeholders, who may differ in their preferences for outcomes, their beliefs about science and uncertainty, and their trust in the objectivity and quality of proposed studies, there is not currently a clear way to estimate the effect of these studies on consensus building. These cases would benefit from a unique method to prioritize research agendas to support the decision process. In this study, we present and demonstrate a new method to solve this problem. The new method combines and builds on aspects of existing tools, such as multiple stakeholder deliberation, multiple criteria analysis (MCA), Bayesian Belief Networks (BBNs), and value of information (VOI) analysis.

First, the new method recognizes the importance of encouraging multi-stakeholder participation and deliberation to build agreement around a preferred management option, especially among multiple decision makers and stakeholders who have differing objectives and beliefs regarding a problem (Cohen 1997; DeKay, Small et al. 2002; Renn 2006; Reed 2008). MCA is often used in decision making contexts that involve multiple stakeholders, such as in participatory management of natural resources. MCA is a tool aimed at helping to evaluate the relative importance of multiple, possibly conflicting criteria in a decision scenario (Makowski, Somlyody et al. 1996; Belton and Stewart 2001; Cohon 2004; Kiker, Bridges et al. 2005; Messner, Zwirner et al. 2006). It is important to note that there can be shortcomings to requiring agreement or consensus for decisions, including the possibility that it will be too difficult get everyone to agree and that management responses will be delayed unnecessarily (Coglianese and Allen 2004) .

Second, the new method recognizes that these decisions involve choices made more difficult by significant uncertainty in relevant scientific knowledge. Uncertainty can include variability in current resource conditions or incomplete scientific knowledge regarding the causal relationships between management options and resulting resource conditions. Probabilistic techniques and expert elicitation are existing tools for analyzing uncertainty in a decision (Morgan, Henrion et al. 1990; Cullen and Frey 1999; Cullen and Small 2004; Hoffman, Fischbeck et al. 2007; Hoffman, Fischbeck et al. 2007). A BBN, or graphical network for modeling probabilistic interrelationships between events, presents an effective way to represent uncertainty in environmental decision problems. BBNs can be used to estimate the probabilities that various decision options will have particular outcomes of interest, and corresponding stakeholder valuations of these outcomes. A BBN is especially useful when individual nodes of the network will be updated with evidence or new information to see how these change the preferred management strategy (Stiber, Pantazidou et al. 1999; Borsuk, Clemen et al. 2001).

Third, the new method recognizes that reducing uncertainty with new information in multiple stakeholder decision contexts needs to take into consideration stakeholders' differences in preferences and beliefs about uncertainty and trust in the science. VOI analysis is used in decision analysis to assess the expected impact of proposed tests, monitoring or research for reducing uncertainties *that matter* to a pending decision (Yokota and Thompson 2004). The VOI is the expected increase in value of the optimal decision informed by the knowledge, compared to the choice made under the pre-information state. It is important to note that information can only have value if it has the potential to change the prior (without information) decision. However, most VOI studies assume: 1) a single decision maker with known prior beliefs regarding the probability of different environmental and economic outcomes associated with each decision options; 2) a known utility for different outcomes; and 3) a known likelihood function for scientific studies that inform the probabilities in step 1) reducing the uncertainty associated with some or all of the decision options.

To compute the VOI for reducing uncertainty and resolving conflicts in a multi-stakeholder environmental decision, we propose a new method called the Expected Consensus Index of New Research (ECINR). ECINR recognizes that decision support is needed as part of an iterative analytical-deliberative process involving scientific studies, assessments and negotiations among stakeholders. It assumes that two or more stakeholders currently prefer different decision options. ECINR is calculated by taking the probability before new research is conducted that a scientific study will lead to a result that allows these different stakeholders to come to agreement (consensus) on the preferred decision option.

In this study we demonstrate the ECINR method for assessing and managing coral reef stressors in Guánica Bay, Puerto Rico. We use it to examine whether beliefs can be expected to exhibit greater confidence and coherence between stakeholders when informed by plausible study results. We suggest how these results can be used to identify priorities for new research. We use information obtained from a written elicitation of preferences for future environmental and economic outcomes and beliefs about associated scientific relationships and detailed face-to-face elicitations completed by volunteers participating in a coral reef management workshop held at La Parguera, Puerto Rico in April 2010.

We expect the participants will move to agreement over preferred management options based on science that reduces key uncertainties. However, in cases where prior beliefs regarding the outcomes of decisions are too disparate, agreement may not be achieved, or could even be reduced by study results. Therefore, the value of the information for supporting the decision process will be greater when the uncertainty being reduced matters in a similar manner across stakeholders. We also expect the value to be greater when research results are more certain.

METHOD AND DATA SOURCES

In this study we combine a conceptual model with information elicited regarding an environmental decision problem within a BBN. We then apply the ECINR method described above to identify where additional scientific research may be needed to support better informed decisions and resolve possible conflicts over preferred management actions. The environmental decision problem addressed major coral reef stressors in Puerto Rico, which include land-based sources of pollution, over fishing, and global climate change. We used the recent Coral Reefs Decision Support Workshop in Puerto Rico in April 2010 as an opportunity to elicit preferences and beliefs regarding the efficacy of proposed regulations for coral reefs protection.

The conceptual model used to structure our written elicitation exercise was the DPSIR/DL framework, which covers the relevant components of a multi-attribute environmental decision making problem, and which we demonstrated previously for the case of managing coral reef stressors in the Florida Keys (Rehr, Small et al. *Submitted* 2010). The DPSIR/DL framework integrates the *Driving Forces, Pressures, States, Impacts, and Responses* model (which aims to identify the important causal relationships among anthropogenic environmental stressors, processes, and outcomes); and the *Decision Landscape* model (which aims to ensure that relevant legal, institutional, and social factors affecting a decision, as well as the knowledge, values, and decision making of participants in the various elements of the DPSIR process, are recognized and considered).

Study Area: Guánica Bay Watershed, Puerto Rico

Our study site is the Guánica Bay Watershed located on the southwestern side of Puerto Rico near La Parguera (Figure 12). Coral reefs in this area have the highest abundance of living corals in Puerto Rico and are considered to be an example of "healthy reefs," since they have more than 20 percent total coral cover (Morelock, Ramírez et al. 2001). The coral reef tract in Puerto Rico extends up to 15 km offshore and covers an area of approximately 2000 sq km (UNEP-WCMC and NOAA) (Burke and Maidens 2004).

Figure 12. Map of the study site (Ramos-Scharron 2009)

Based on area Puerto Rico's coral reefs are estimated to be worth over one billion dollars per yr in ecosystem services (i.e., shoreline protection, water quality maintenance, climate regulation, fish, pharmaceuticals, tourism, recreation, nutrient cycling, habitat, and nursery areas (Hassan, Scholes et al. 2005) - according to a United Nations Environmental Programme (UNEP) estimate that coral reefs provide a total of \$100,000 - \$600,000 per sq km per yr (UNEP 2006). This is likely true in Puerto Rico, which supports a tourism industry based partially on marine resource-based activity worth 3.5 billion dollars (Burke and Maidens 2004).

The abundance and cover of coral reefs in Puerto Rico have declined over the past 30 years due to local stressors associated with rapid population growth, which has led to increased development, deforestation for agriculture, and increased discharge of sewage. Some of the consequences include high sediment influx, increased nutrient levels, overfishing and habitat modification, which, when combined, threaten 90% of reefs (Burke and Maidens 2004). On top of local stressors, there are global stressors, including ocean warming and acidification. Coral disease and bleaching have been observed. The loss of coral in Puerto Rico has led to a decline in ecosystem services, including economic benefits from fisheries, which decreased by 70% from 1970-1990) (Burke and Maidens 2004). Despite the fact that Puerto Rico's coral reefs are under government jurisdiction, effective management is limited by a lack of laws regulating fishing activities and recreation.

A wide range of decision makers and stakeholders now recognize the priority and urgency for actions to protect and restore Puerto Rico's coral reefs. These options may require economic sacrifices by the Puerto Rico community and likely tradeoffs with economic development, such as agriculture and development. There will be conflicting views among these parties and among their stakeholders on the severity of different threats, the potential to manage those threats, which actions should be taken, and their anticipated environmental and socioeconomic outcomes.

Data Sources: Written Elicitation Exercise and Face-to-Face Elicitation

Data for our analysis were collected through an elicitation exercise filled out by participants prior to and during the workshop, and then by subsequent open interviews designed to populate prior and conditional probabilities in formal influence diagrams (BBNs) for each participant (See Appendix C for the attached blank elicitation form and the list of face-to-face elicitation questions; and Figure 13 for an example of a BBN for Participant A showing prior beliefs before implementation of new research and management options). Note that the exercises and subsequent elicitations are *not* intended to provide a representative sample of scientific or popular opinion on the issue of interest. Rather, they are intended to reflect the range of values and beliefs held by particular participants in a decision problem (those asked to participate in the workshop as a result of their prior and ongoing managerial, scientific and community experience and expertise).

We collected three kinds of data from stakeholders in the exercise: 1) preferences – indicating their weights placed on different resource outcomes or objectives; 2) their current beliefs about scientific relationships (including associated uncertainty) between elements in an environmental system, such as between management options, stressors, and outcomes; and 3) their beliefs regarding the efficacy of possible new research and data collection programs for reducing key uncertainties and improving resulting management decisions. Some beliefs about implementation cost and the value of affected ecosystem services were also captured, but not enough to use this information in a benefit-cost analysis.

Eighteen participants filled out the exercise prior to the workshop. We asked stakeholders to fill it out again after the discussion so we could see the effect of learning during workshop, which included new research results, to see how this would change responses, but it was difficult to get them to do this, and very few changed their written answers. Thus, the written elicitation provided more of an inquiry into the key issues of importance to stakeholders. Based on the results of the exercise and discussions throughout the workshop, we designed a template BBN based on key issues of importance to stakeholders that included management options, outcomes (and their valuations), and research studies to reduce key uncertainties.

On the final day we conducted seven face-to-face elicitations to produce the final individual BBNs for the analysis, including: 1) a relative rating of references for outcomes (coral reef health, tourism, fisheries); 2) beliefs about science including a breakdown of loadings from sewage, agriculture, and development; the probability that restoration of a Lagoon upstream from Guanica Bay would be effective at filtering nutrients and sediments, and probabilities that different combination of stressors (Marine Protection Areas (MPAs), water quality and climate change) will produce outcomes of interest. Our final study group consisted of one natural resource manager, four scientists, and two resource conservation specialists who worked at local non-profits.

Design of BBNs

Our BBN was designed to represent the current situation of coral reefs stressors and management in the Guánica Bay Watershed from the viewpoint of stakeholders (See Appendix C for a full explanation of each node of the BBN). The network depicts that loadings from agriculture, sewage and development are polluting inland water quality and Bay water quality, which in turn, affect coral health, and the fisheries and tourism that depend on them, the benefits that people care about. Natural resource managers can implement management options, which include reducing loadings from different sources, restoring the Lagoon, which when implemented, adds a node, Lagoon water quality, which changes depending how effective the lagoon is believed to be, and finally implementing MPAs, which when implemented, enhances coral health and fisheries. Ocean warming/acidification is included as an external variable that affects coral health and can be set at low or high or left to chance. Research can then be carried out by activating research nodes and results (for loadings, coral effects, fisheries, and ecosystem services) and then their effect on management option preferences determined.

The total pollution load, *Total load*, is a represented by a function of the individual sources and their associated hypothetical reductions (management options) as shown in Eq. 1:

$$Total\ Load = SewLoad \times \left(1 - \frac{SewRed}{100}\right) + AgLoad \times \left(1 - \frac{AgRed}{100}\right) + DevLoad \times \left(1 - \frac{DevRed}{100}\right)$$

Loadings distributions were computed over the low, medium, high, and very high in a manner that minimized variance based on stakeholders' prior beliefs. Loadings values included in the model are relative (and therefore unitless) though roughly scale to mg/L concentrations of suspended solids in unpolluted source waters (very low = 0-25; low = 25-50), moderately polluted source waters (moderately low = 50-125; moderately high = 125-250) and highly polluted source waters (high = 250-500; very high = 500-750). The range of values used for *TotalLoad* of 0 to 750 was thought to allow for a more realistic distribution (with six intervals from low to very high) than would a smaller range. Since the analysis is of a comparison of benefits, the actual units used are not important.

The BBN was designed to be used for computing the preferred management option based on maximizing benefits and then for performing a comparative benefits assessment (between without- and with-information conditions). *Benefits* are computed as shown in Eq. 2:

$$Benefits = A \times Tourism + B \times Fisheries + C \times Coral\ Health \times Ecosystem\ Services$$

Where, A, B, and C are weightings of the importance of the outcomes, relative to *Ecosystem Services*, given by the volunteers. *Netica,* a commercially available BBN software package, is used to build and run the BBNs. To examine the effect of plausible new study results as described earlier, *Netica* uses probabilistic inference (the probability of some event given the occurrence of some other event) to adjust beliefs based on the new evidence, i.e., Bayes' theorem. Bayes' theorem adjusts probabilities given new evidence by calculating a posterior probability (*H* given *E*) as shown in Eq. 3:

$$P(H|E) = \frac{P(E|H)\,P(H)}{P(E)}$$

Where, *H* represents a specific hypothesis; *P*(*H*) is the *prior probability* of *H* that was inferred before new evidence, *E*, became available; *P*(*E* | *H*) is the *conditional probability* of seeing the evidence *E* if the hypothesis *H* happens to be true (it is also a *likelihood function* when it is considered as a function of *H* for fixed *E);* and *P*(*E*) is the *marginal probability* of *E*: the *a priori* probability of witnessing the new evidence *E* under all possible hypotheses calculated as the sum of the product of all probabilities of any complete set of mutually exclusive hypotheses and corresponding conditional probabilities as shown in Eq. 4:

$$P(E) = \sum P(E|H_i)P\,(H_i)$$

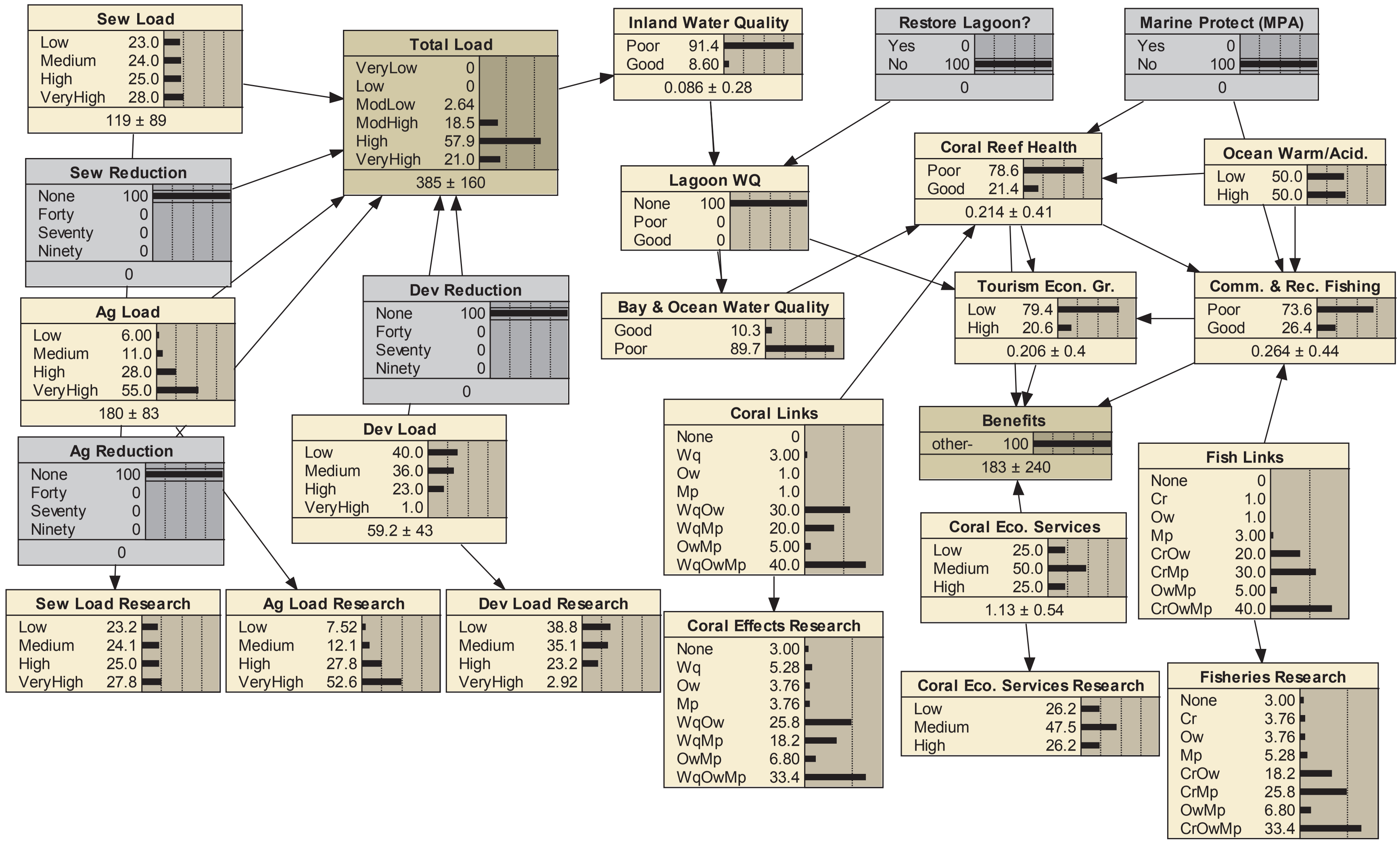

Figure 13. Bayesian Belief Network showing prior beliefs for Participant A (gray nodes represent management options)

ECINR Analysis

An initial analysis showed that all of the stakeholders preferred the management options of establishing marine protection areas and restoring the lagoon (their first and second choices, respectively). Since they were already in agreement for their top management choices, the ECINR analysis was based on the next set of decision options, which includes reducing loadings from sewage, agriculture, and development, for which they were not in agreement. The scenario assumed that loadings would be reduced incrementally from each source by 40%, 70% and 90%, which would amount to nine management options in total (Table 5).

Table 5. Set of nine alternative management options for reducing loadings from sources

Reduction (%)	**Ag**	**Sew**	**Dev**
40	1	2	3
70	4	5	6
90	7	8	9

Based on their prior (without new information) beliefs about the contribution of loadings from different sources, their stepwise ranking of the nine management options was determined. Next three hypothetical new research programs (on each of agriculture, sewage, and development loadings) were added to clarify the contribution to total loadings of each source. The degree to which each of the proposed study findings is predicted to promote agreement (consensus) around options at each step in their stepwise ranking, CI_{step}, was computed as shown in Eq. 5:

$$CI_{step} = \frac{\#\ of\ management\ option\ selections\ with\ concurrence}{\#\ of\ option\ selections\ undertaken}$$

Where it can be defined further in Eq. 6:

$$CI_{step} = \frac{(\#\ management\ options\ to\ which\ all\ agree)\ x\ (\#\ stakeholders)}{(\#\ of\ sequential\ management\ steps) x\ (\#\ stakeholders)}$$

An example of how the agreement index is computed at each step for two stakeholders is shown in Table 6. In ties, it is assumed that the option selected first is the one that leads to more agreement at that step and then the other option is automatically selected in the next step. The agreement index is cumulative considering all management options up to and including the given step. A limitation of the analysis due to the assumption made for handling ties is that the option automatically selected second may not always be the one that would lead to the most agreement at the given decision step.

Table 6. Example of computing agreement for two stakeholders in a hypothetical decision

Steps	Stakeholder 1	Stakeholder 2	Consensus Index
1	1	2	0/2 = 0
2	4	5	0/4 = 0
3	7	8	0/6 = 0
4	2	1,3 (1)	4/8 = 0.5
5	5	1,3 (3)	6/10 = 0.6
6	3	4,6 (4)	9/12 = 0.75
7	8	4,6 (6)	13/14 = 0.93
8	6	7,9 (7)	16/16 = 1.0
9	9	7,9 (9)	18/18 = 1.0

Then the value of each of the study results (after the research is conducted) at each step, $CINR_{step}$, was computed as the change in agreement between the with- and without-information conditions. Finally, the individual stakeholder perspectives that a particular study will bring stakeholders to agreement (before the research is conducted) (Expected CI or ECI) at each management step was computed as shown in Eq. 7:

$$ECI_{step} = \sum_{outcome=1}^{n} (CI_{step})_{outcome} \ x \ Preposterior\ Probability_{outcome}$$

Where an *outcome* is one of the various ways that the research can turn out; and the *Preposterior Probability* is the probability before the research is conducted that a result will come out a given way, with associated implications for decision preferences. Then the value of each of the research programs (before the research is conducted) at each step, $ECINR_{step}$, was computed as the expected change in the agreement between the with- and without-information conditions.

The study assumed that stakeholders share the same beliefs about the accuracy of the research (the likelihood functions or false+/false- rates) and that the new research is nearly perfect, with the probability that the correct inference is made equal to 94%.

The following examples illustrate in tabular form how we identified preferred management options under the cases of 1) prior beliefs and 2) research outcomes, using the BBN for Participant A.

Identifying preferred management options under prior beliefs and research outcomes

In Table 7 the baseline case (for the BBN in Fig. 2) is shown with initial probabilities of good coral reef health, high tourism, good fisheries, and their respective associated benefits. Next the effects and associated benefits of implementing the preferred management options of MPAs and the Lagoon are shown. Our analysis assumes that these strategies have already been implemented. Next an example of the method used for selecting preferred options in the stepwise ranking of management options to reduce loadings is shown for steps 1 and 2 (an AgRed of 40% and an AgRed of 70%, respectively) of each of the possible selections are compared and the option with the highest benefits is selected (and bolded). In Table 8, the complete stepwise ranking of all nine management options is shown for Participant A based on prior beliefs. This ranking shows that Particpant A initially favors reductions in agriculture followed by sewage and then development. In Table 9, the stepwise ranking is repeated after knowledge of a research finding that loadings from agriculture are in fact low (AgLow). This ranking shows how changing beliefs from agricultural loadings being high to agricultural loadings being low also changes preferences for reductions from agriculture versus other options (now Participant A favors reductions in sewage followed by development and then agriculture). Table 10 is a comparison of the stepwise rankings of management options under prior beliefs vs. under new research finding of AgLow. Reductions in sewage and development have risen in the stepwise ranking (the old and new positions are connected with orange arrows), while reductions in agriculture have fallen (the old and new positions are connected with blue arrows).

Table 7. Example of the baseline without management options, the effects of implementing MPAs and Lagoon (the baseline for the analysis), and the strategy for selecting steps 1 and 2 in the stepwise ranking of alternatives for reducing loadings for Participant A.

	MPAs	Lagoon	SewRed	AgRed	DevRed	P(GoodCorals)	P(HighTourism)	P(GoodFisheries)	Benefits	ΔBenefits
Baseline →	No	No	None	None	None	21%	26%	20%	183	-
W/mgmt	**Yes**	No	None	None	None	40%	41%	60%	320	137
options →	No	**Yes**	None	None	None	46%	31%	35%	292	109
Baseline$^{\mathbf{analysis}}$ →	**Yes**	**Yes**	**None**	**None**	**None**	**74%**	**57%**	**71%**	**474**	**291**
	Yes	Yes	40%	None	None	74%	58%	71%	476	2
Step 1 →	**Yes**	**Yes**	**None**	**40%**	**None**	**74%**	**58%**	**71%**	**477**	**3**
	Yes	Yes	None	None	40%	74%	57%	71%	475	1
	Yes	Yes	40%	40%	None	75%	59%	71%	480	6
Step 2 →	**Yes**	**Yes**	**None**	**70%**	**None**	**75%**	**59%**	**71%**	**481**	**7**
	Yes	Yes	None	40%	40%	75%	59%	71%	479	5

Table 8. Example of a stepwise ranking of management alternatives to reduce loadings based on prior beliefs for Participant A.

Mgmt Steps	MPAs	Lagoon	SewRed	AgRed	DevRed	P(GoodCorals)	P(HighTourism)	P(GoodFisheries)	Benefits	ΔBenefitss
Baseline analysis →	Yes	Yes	None	None	None	74%	57%	71%	474	-
1	Yes	Yes	None	**40%**	None	74%	58%	71%	477	3
2	Yes	Yes	None	**70%**	None	75%	60%	71%	481	7
3	Yes	Yes	None	**90%**	None	76%	61%	72%	487	13
4	Yes	Yes	**40%**	40%	None	76%	63%	72%	493	19
5	Yes	Yes	**70%**	70%	None	77%	65%	72%	500	26
6	Yes	Yes	70%	90%	**40%**	78%	68%	73%	508	34
7	Yes	Yes	**90%**	90%	40%	79%	71%	73%	516	42
8	Yes	Yes	90%	90%	**70%**	80%	73%	73%	522	48
9	Yes	Yes	90%	90%	**90%**	81%	74%	73%	527	53

Table 9. Example of a stepwise ranking of management alternatives to reduce loadings based on a research finding of AgLow for Participant A.

Mgmt Steps	MPAs	Lagoon	SewRed	AgRed	DevRed	P(GoodCorals)	P(HighTourism)	P(GoodFisheries)	Benefits	ΔBenefits
Baseline analysis →	Yes	Yes	None	None	None	74%	57%	71%	474	-
AgLow →	Yes	Yes	None	None	None	75%	60%	71%	483	9
1	Yes	Yes	**40%**	None	None	76%	61%	72%	487	15
2	Yes	Yes	**70%**	None	None	76%	63%	72%	492	18
3	Yes	Yes	70%	None	**40%**	77%	65%	72%	498	24
4	Yes	Yes	70%	None	**70%**	78%	67%	72%	505	31
5	Yes	Yes	**90%**	None	70%	78%	68%	73%	509	35
6	Yes	Yes	90%	**40%**	70%	79%	71%	73%	516	42
7	Yes	Yes	90%	**70%**	70%	80%	73%	73%	523	49
8	Yes	Yes	90%	70%	**90%**	81%	75%	73%	528	54
9	Yes	Yes	90%	**90%**	90%	81%	76%	74%	532	58

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Table 10. A comparison of the stepwise rankings of management options under prior beliefs vs. under new research finding of AgLow

Steps	Under Prior Beliefs	Under New Research =AgLow
1	Ag 40%	Sew 40%
2	Ag 70%	Sew 70%
3	Ag 90%	Dev 40%
4	Sew 40%	Dev 70%
5	Sew 70%	Sew 90%
6	Dev 40%	Ag 40%
7	Sew 90%	Ag 70%
8	Dev 70%	Dev 90%
9	Dev 90%	Ag 90%

RESULTS

Prior Beliefs about the Contribution of Loadings from Different Sources

The seven volunteers' elicited prior beliefs about the contribution from Agriculture, Sewage, and Development to total loadings are shown in Figure 14. Three volunteers believed that Sewage had the largest contribution (at 50%). Two volunteers believed that agriculture had the largest contribution (at 60% and 50%). All volunteers believed that Development did not have the largest contribution. Two believed that all of the sources contributed equally. As a group, they believed that Sewage contributed the most to total loadings (average of 40%), followed by Agriculture (average of 37%), and finally Development (average of 24%).

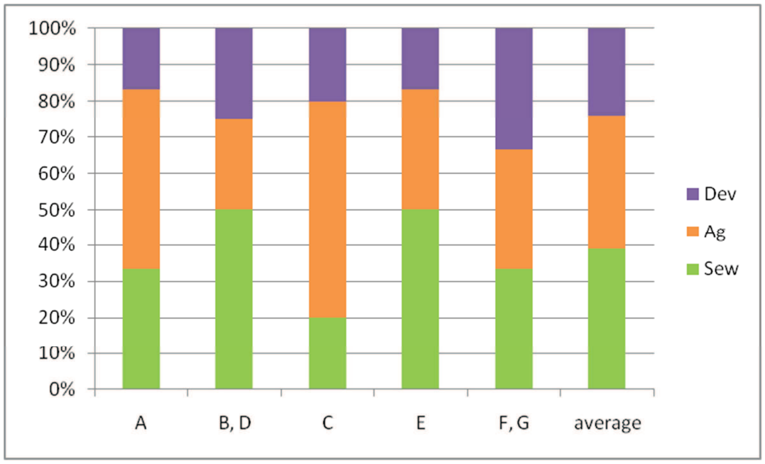


Figure 14. Prior (w/o research) beliefs about the contribution of different sources to total pollution loadings

Change in Agreement among Stakeholders over Preferred Options due to Study Results

Depending on the results of the proposed new research programs, we predict variable trends in the change in agreement (CINR) among stakeholders regarding preferred management options across the management steps. Predicted agreement at each management step in response to each new study result compared to the No Research alternative is shown in Figure 15. The incremental change in agreement at each management step with each new piece of information is shown in Fig. 6. Most of the research results (9 out of 12, or 75%, which include all results except for Ag Low, Ag Med, and Dev V High) were predicted, on average, to lead to an increase in agreement among stakeholders across the management steps (Figure 16). Therefore, the value of the research results in terms of bringing stakeholders to agreement was generally positive. In fact, the change in agreement in response to four of the research results (Ag V High, Sew High, Sew V High, Dev Med) was monotonically increasing across the management steps (Figure 16 part b). These research results were most consistent with the stakeholders' prior beliefs. The other five results that led to more agreement among stakeholders, on average, were found to have incremental changes in agreement that were non-monotonic across the management steps (Figure 16 part c). Three of those results (Ag High, Sew Low and Dev High) produced more agreement at more of the management steps than they produced less agreement, one result (Sew Med) produced neither more nor less agreement, and one result (Dev Low) resulted in less agreement more often than not. These research results tended to be somewhat consistent with the stakeholders' prior beliefs. However, the three study results that appeared to be the most different from any of the stakeholders' prior beliefs (Ag Low, Dev V High, Ag Med) had negative value in terms of bringing stakeholders to agreement across the management steps (Figure 15). In fact, the incremental change in agreement in response to these results was monotonically decreasing (Figure 16 part d). In these cases the posterior probabilities on the levels of loadings in response to research results were not large enough to fully shift perspectives and bring stakeholders to agreement.

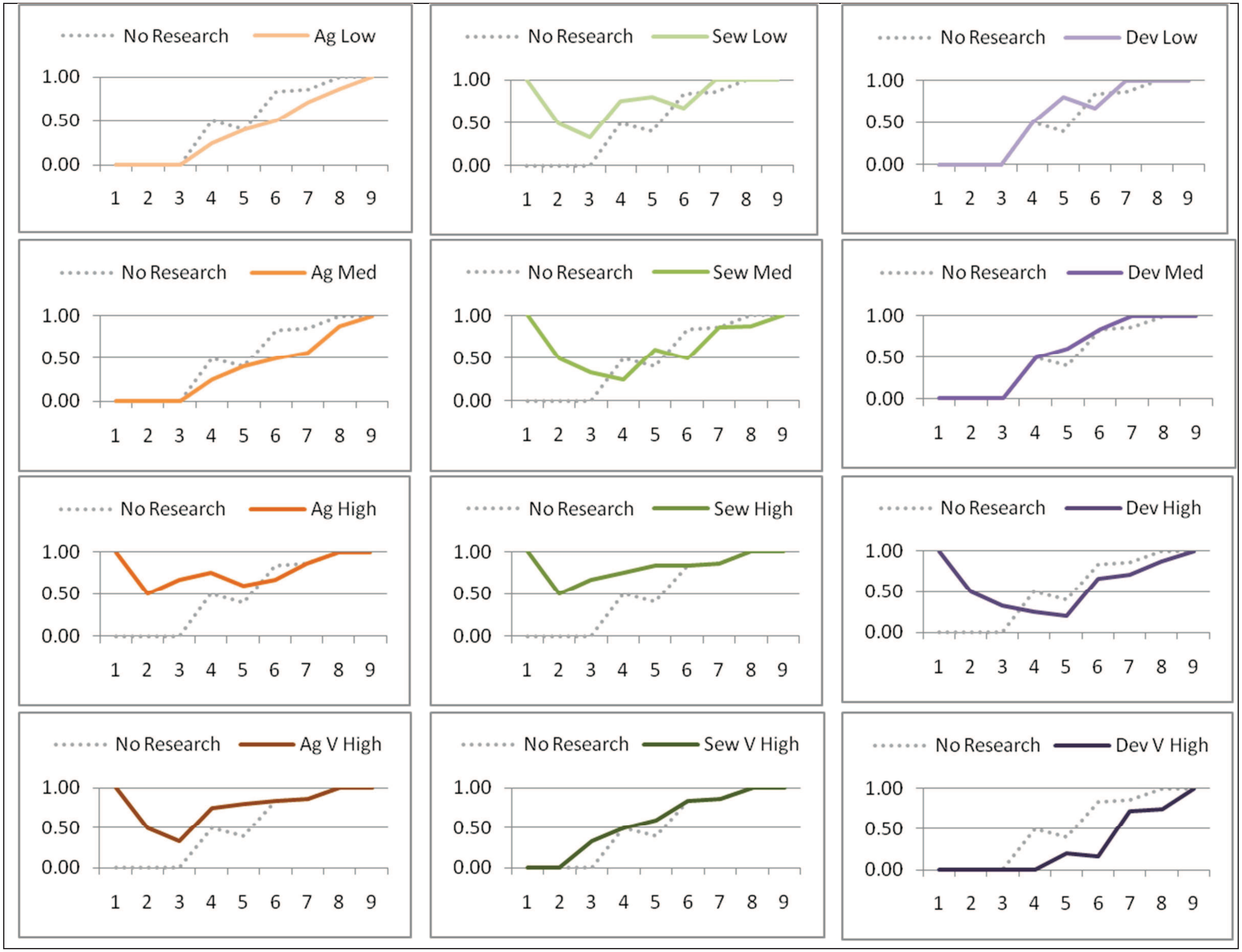
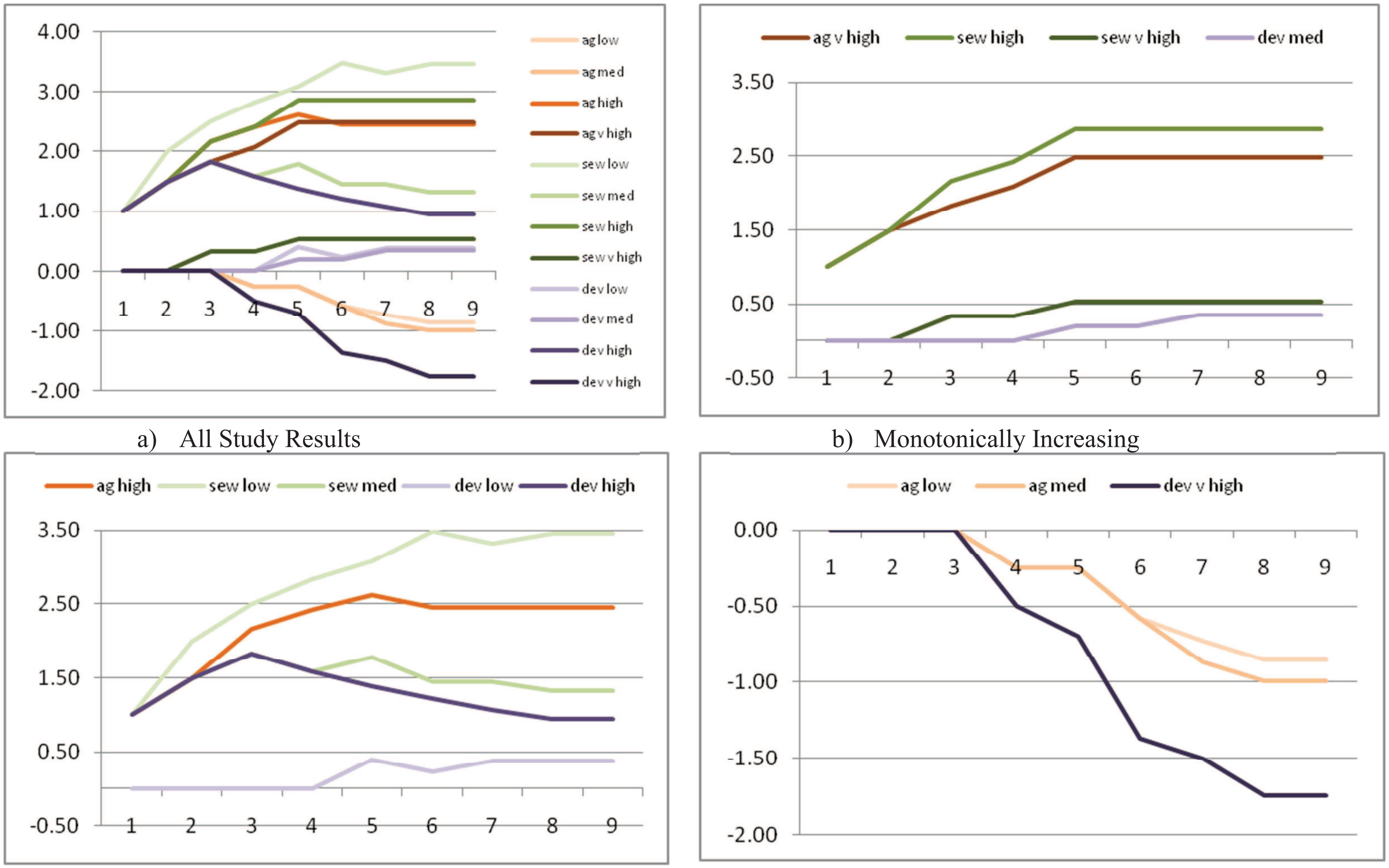


Figure 15. Agreement among stakeholders (CIstep) (y-axis) for study results vs. no research alternative across the management steps (x-axis) (All results lead to more agreement, on average, except for Ag Low, Ag Med, and Dev V High)



a) All Study Results

b) Monotonically Increasing

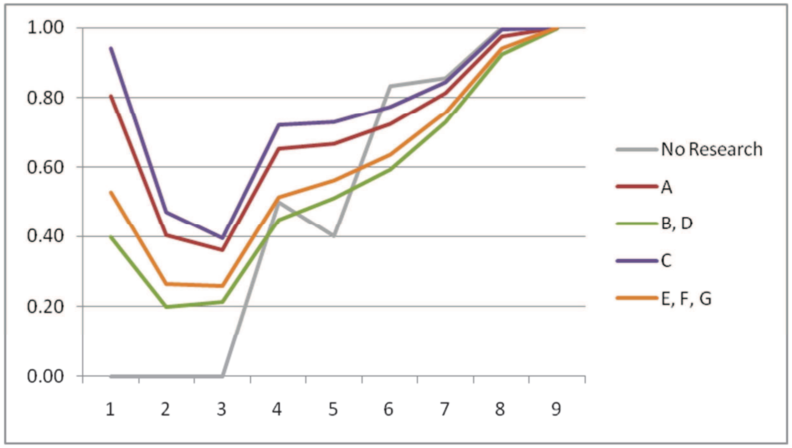
c) Non-monotonic

d) Monotonically Decreasing

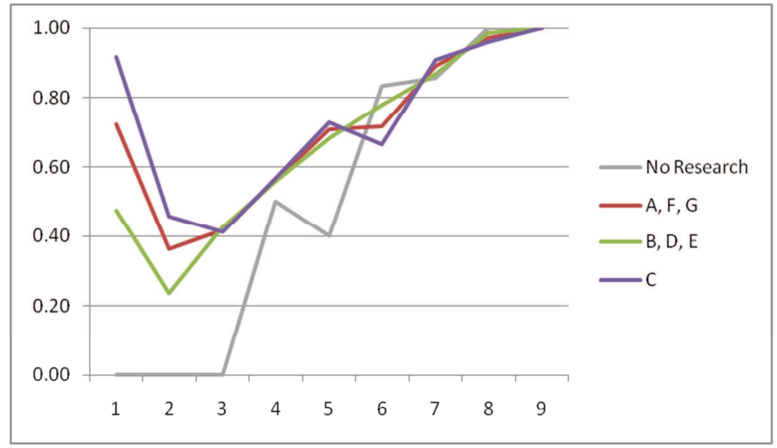
Figure 16. Incremental change in agreement (CIstep) (y-axis) across the management steps (x-axis) with each new piece of information

Stakeholder Expectations that Research Studies will Lead to Agreement (ECINR)

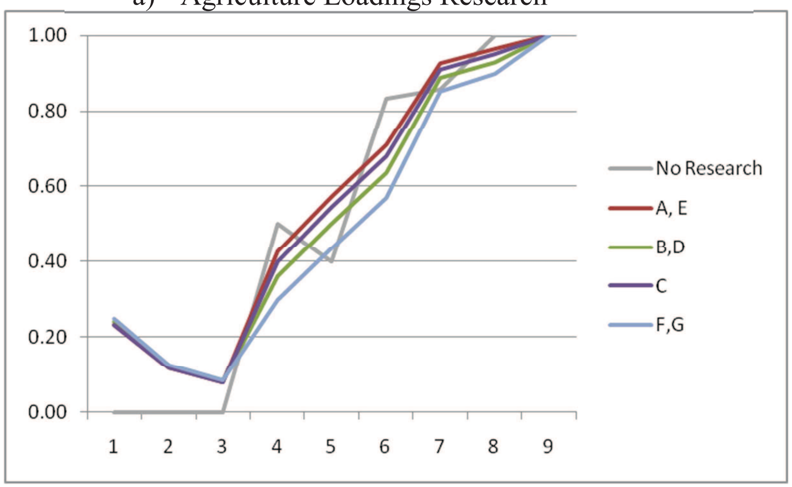
Depending on the different research programs, we predict variable trends among the individual stakeholders in their expectations about whether the programs will lead to agreement about preferred management options. Beliefs of individual stakeholders before the research is conducted about the degree to which each of the individual research studies and a combined study will lead to agreement compared to under the no research alternative (change in agreement adjusted by preposterior probabilities = ECINR) are shown in Figure 17. Stakeholders believed on average before the research was conducted that research programs to determine sewage loadings and agriculture loadings would tend to promote agreement most of the three research programs on average (ECINR for each of the two programs is 0.2 averaged across the management steps) (Figure 17 parts a and b). Research to determine loadings from development was expected to produce neither more agreement nor conflict on average (ECINR is 0.0 averaged across the management steps) (Figure 17 part c). The effect of a combined research study to determine loadings from all three sources is in preparation and the predicted ECINR is expected to be higher than that of individual research programs and probably less than the sum of that of the individual research programs (to go in Figure 17 part d). Thus, in terms of prioritizing their research agenda to reduce uncertainty and resolve conflict, these results suggest that stakeholders would first conduct research to determine loadings from sewage and agriculture, and they would forego research to determine loadings from development since it is not predicted to change their decisions to a degree which would allow them to come to agreement. Now if stakeholders wished to choose only one research program to implement, and assuming they are conflict averse, the trends in the individual research outcomes shown in Figure 16 would lead them to opt for sewage loadings research. The incremental changes in agreement across the management steps for two of the outcomes of the agricultural loadings research program (AgLow and AgMed) were zero or negative (with more conflict produced at each step) (Figure 16 part d); whereas the incremental changes in agreement across the management steps for all of the outcomes of the sewage loadings research program were likely to be positive (with more agreement produced at each step) (parts b and c).



a) Agriculture Loadings Research



b) Sewage Loadings Research



c) Development Loadings Research

d) Combined Research Program (*in prep.*)

Figure 17. Stakeholder expectations that research studies will lead to agreement over preferred management options (ECINRstep) (y-axis) compared to no research alternative across the management steps (x-axis)

DISCUSSION

We presented and demonstrated a new decision support method for identifying where additional scientific research may be needed to support better informed decisions and resolve possible conflicts over preferred management actions. As we expected the participants tended to move to agreement over preferred management options based on science that reduces key uncertainties. However, we found that there can be cases where prior beliefs may be too different from the study results to shift perspectives and bring people to agreement. Therefore, our results lend support to the Bayesian statisticians' argument. However, in statistical distributions there may be outliers, so there is some truth to the critics' argument as well. A larger and more diverse sample group would help to clarify these results. Though preliminary these results suggest that ECINR can provide useful insights on the social implications of a research program.

Different from what we had expected, differences in preferences for outcomes (values) did not influence the degree of agreement in this particular study. Had we included outcomes that presented some realistic tradeoffs between the environment and economy, such as agricultural and development economic health, and had stakeholder groups, such as farmers and developers (who would have likely held conflicts of interest with management options to reduce loadings from agriculture and development), participated in the workshop and elicitations, then there may have been more conflicts over preferred management options due to inherent values. Including cost information for management options and research studies, which we were not able to obtain because the information was not known by workshop participants, would have also created more realistic tradeoffs. Additionally, we were not able to show here that ECINR would have increased when research results are more certain and when stakeholder beliefs about the meaning of the study results are not too different. Varying these factors may lead to more realistic conflicts over the research findings among stakeholders.

Additionally, using Netica alone to undertake powerful calculations, such as to determine ECINR for larger number of stakeholders and for multiple combinations of research results proved cumbersome. Furthermore, in calculating agreement over preferred management options without a more powerful program, we made the assumption in tie situations that after selecting the half of the tie that would bring the most agreement at its step, to select the second half of the tie automatically after that; however, this may not always be the one that would lead to the most agreement at its step. Perhaps automating the method by interfacing with Netica through another program would allow for more powerful calculations that would reduce these limitations and improve results.

Thus, future work on ECINR is needed to clarify the results of this preliminary study. That could involve using a larger and more diverse sample group, eliciting more detailed information about stakeholder trust in the science, including additional outcomes and cost information to provide more realistic tradeoffs between the environment and economy, and automating the method to allow for more powerful calculations.

CHAPTER 5. SUMMARY AND CONCLUSIONS

This dissertation presented and demonstrated three novel decision support tools aimed at assisting government and private organizations in tackling complex decisions that involve multiple parties, affect ecosystems and economies, and include choices made more difficult by significant uncertainty in relevant scientific knowledge. This dissertation provided examples of how the tools can be useful for the real world situations on which they were demonstrated.

Now that the tools have been developed, how can they be made accessible to real world decision makers and be thought of as useful in their eyes? Making this happen will require ongoing discussions and multiple updates on the tools. The field of creating new decision support tools to address complex environmental problems becomes challenging for this reason. Working effectively with decision makers presents numerous challenges, such as how to clearly communicate science to audiences that will not consist of scientists, how to ensure that participants fill out questionnaires for testing the decision support tools, and how to determine what real world decision makers would like to use and are able to use.

Our published papers and workshops present opportunities to get feedback on the tools developed. Preliminary feedback from resource managers, scientists, and citizens has been generally positive in that they believe the tools will be useful in their work. Based on the ES&T publication on the chromium tool, a news story was written in the UK's Emerging Health Threats Forum: "US model flags chromium emission hotspots: People living in Los Angeles are at highest risk for cancer linked to chromium exposure, model suggests" (Else 2010). It contained the following comment by an expert epidemiologist: 'Park says the model is a good way to study the cancer risks of exposure to emissions of hazardous chemicals and should be used to also assess the risks from airborne mercury. Robert Park, a specialist in occupational disease epidemiology, says that at the individual level these risks are very low. By comparison, 100,000 smokers in every million are at risk of developing cancer. Nevertheless, he acknowledges that the estimate of cancer risk for Los Angeles County is six times higher than the level the EPA deems acceptable: one case in every million people. Within the County there are probably small pockets where the risk due to Cr(VI) exposure could be 100 times higher than this, or more, adds Park.'

The results of the workshop evaluation in Puerto Rico indicated that most of the participants believed that the DPSIR tool would be useful to them in their work and a little more than half of them believed that a tool (like ECINR) aimed at prioritizing research agendas based on the ability of research to reduce uncertainty and resolve conflicts would be useful to them in their work. While participants thought the ECINR tool sounded nice, the evaluation also showed that participants did not understand the presentation about the science behind the tool. Additionally, participants felt that it was unclear how they would implement such a tool, with limited time and funds. Participants have said if the tools were implemented as websites for use by consumers, companies and local governments - as are EIOLCA (Carnegie Mellon University Green Design Institute 2008) and the EPA's DASEES (Decision Analysis for a Sustainable Environment, Economy, and Society), which is being developed to house tools such as DPSIR, Decision Landscape, and perhaps, ECINR – then they would be able to test them. Thus, based on the feedback about the decision support tools described in this dissertation, many challenges still exist to make meaningful tools that are accessible and useful to real world decision makers.

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APPENDIX A. SUPPORTING INFORMATION FOR “ECONOMIC SOURCES AND SPATIAL DISTRIBUTION OF AIRBORNE CHROMIUM RISKS IN THE US”

Contents:

A. Parameters Used in Model Calculations

Symbol	Definition (units)	Value
Dispersion Model		
NEI Data		
	Stack emissions (ton/yr converted to g/s)	
	Stack height (ft converted to m)	
	Exit velocity (ft/s converted to m/s)	
	Exit temperature (F converted to K)	
	Stack Diameter (ft converted to m)	
	Gas flow (ft/s converted to m/s)	
Weather station data (some values are specified)		
	Year	
	Month	
	Day of month	
	Julian day	
	Hour of day	
	Heat flux (W/m^2)	
	Surface friction velocity (m/s)	
	Convective velocity scale (m/s)	
	Lapse rate above mixing height (m)	
	Convective mixing height (m)	
	Mechanical mixing height (m)	
	Monin-obukhov length (m)	
	Surface roughness length (m)	0.25
	Bowen ratio	1
	Albedo	1.0 (day); 0.25-0.5 (night)
	Reference wind speed (m/s)	
	Reference wind direction (degree)	
	Reference height for wind (m)	
	Ambient temperature (K)	
	Reference height for temperature (m)	
	Precipitation code (0-45)	
	Precipitation rate (mm/hr)	
	Relative humidity (%)	
	Surface pressure (mb)	
	Cloud cover (tenths)	

Symbol	Definition (units)	Value
Dispersion Model (cont'd)		
Distance (x,y) from each facility to the nearest weather station		
x	Distance (west-east) (m)	
y	Distance (south-north) (m)	
$latitude_{centroid}$	Latitude of county centroid (degree)	
$longitude_{centroid}$	Longitude of county centroid (degree)	
$latitude_{facility}$	Latitude of facility (degree)	
$longitude_{facility}$	Longitude of facility (degree)	
Model specifications (for Cr(VI))		
	Fraction of particles in fine mass	1
	Average diameter of particle (μm)	2
	Half-life (days)	5
	Grid size	-150 km by +300 km (west-east); 250 km by +300 km (south-north)
Output		
	Annual average air concentration (ng/m^3 converted to μg/m^3)	
Exposure and Risk Model		
LIR	Lifetime individual risk	
C_E	Air concentration (μg/m^3)	
URF	Unit risk factor (μg/m^3)	1.2×10^{-2} (μg/m^3)$^{-1}$
I	Number of cancers per year	
P	Population of county	
T	Lifetime (years)	70

B. Tables and Figures

TableS1. Cr(VI) emissions data by economic sector

2-Digit NAICS	Name	Number Facilities	%	Emissions (metric tons)	%
22	Utilities	1486	16%	30	70%
33	Primary Metal Manufacturing	1250	14%	6	14%
32	Wood Product Manufacturing	2763	30%	5	12%
54	Professional, Scientific, and Technical Services	337	4%	0.6	1%
21	Mining	1189	13%	0.54	1%
92	Public Administration	860	9%	0.35	1%
48	Transportation and Warehousing	202	2%	0.25	1%
31	Manufacturing	394	4%	0.11	0.30%
56	Administrative and Support and Waste Management and Remediation Services	72	1%	0.07	0.20%
81	Other Services (except Public Administration)	178	2%	0.06	0.10%
42	Wholesale Trade	28	0%	0.008	0.02%
61	Educational Services	110	1%	0.007	0.02%
81	Other Services	51	1%	0.007	0.02%
62	Health Care and Social Assistance	121	1%	0.004	0.01%
71	Arts, Entertainment and Recreation	33	0%	0.002	0.00%
11	Agriculture, Forestry, Fishing and Hunting	58	1%	0.002	0.00%
23	Construction	35	0%	0.0009	0.00%
44	Retail Trade	12	0%	0.0004	0.00%
53	Real Estate and Rental and Leasing	8	0%	0.00009	0.00%
Total		9187	100%	44	100%

Table S2. Chromium compound emissions data by economic sector

2-Digit NAICS	Name	Number Stacks	%	Emissions (tons)	%
33	Primary Metal Manufacturing	11056	26%	225	42%
22	Utilities	6289	15%	143	27%
32	Wood Product Manufacturing	12521	29%	123	23%
31	Manufacturing	2587	6%	10	2%
21	Mining	2560	6%	10	2%
56	Administrative and Support and Waste Management and Remediation Services	455	1%	9	2%
92	Public Administration	2156	5%	7	1%
61	Educational Services	1144	3%	2	0%
62	Health Care and Social Assistance	1068	2%	0	0%
48	Transportation and Warehousing	825	2%	2	0%
54	Professional, Scientific, and Technical Services	785	2%	1	0%
81	Other Services (except Public Administration)	434	1%	2	0%
42	Wholesale Trade	224	1%	0.03	0%
11	Agriculture, Forestry, Fishing and Hunting	152	0%	0.01	0%
23	Construction	98	0%	0.02	0%
53	Real Estate and Rental and Leasing	90	0%	0.02	0%
51	Information	86	0%	0.01	0%
71	Arts, Entertainment, and Recreation	71	0%	0.00	0%
44	Retail Trade	65	0%	0.01	0%
49	Transportation and Warehousing	57	0%	0.01	0%
45	Sporting Goods, Hobby, Book, and Music Stores	32	0%	0.02	0%
52	Finance and Insurance	17	0%	0.00	0%
72	Accommodation and Food Services	9	0%	0.00	0%
Total		42781	100%	535	100%

Table S3. Risk-Emissions Ratio by Sector (population-weighted average risk/kg Cr(VI) emissions)

Sector	Risk-Emissions Ratio	Ratio to Overall Average
Overall	**6.5×10^{-6}**	**-**
Power Generation	4.5×10^{-7}	0.07
Wood/Chemical Mfg	2.6×10^{-6}	0.4
Metals Mfg	6.5×10^{-6}	1.0
Sci/Tech Svs	3.2×10^{-4}	49

Table S4. Economic Sectors and Emissions Sources Contributing to Airborne Chromium Risks in the US in 2002 for the Top 10 Receptor Counties by Predicted Cr(VI)-Related Cancer Incidence

Rank	Receptor County	Population (Millions)	Lifetime Individual Risk (Rank)	Source County(ies)	Contributing Sector(s)
1	Los Angeles, CA	9.8	6×10^{-6} (1st)	>95% Los Angeles, CA	92% Sci Svs, 5% Metals Mfg, 2% Wood/Chem Mfg
2	Middlesex, MA	1.5	1×10^{-6} (21st)	>95% Suffolk, NY	>95% Sci Svs
3	Calhoun, IL	5.4	2×10^{-7} (161st)	68% Cook, IL, 10% Will, IL, 7% Lake, IN 10% from 5 others	61% Metals Mfg 32% Power Gen 5% Other
4	Denton TX	0.5	2×10^{-6} (13th)	>95% Dallas, TX	69% Metals Mfg, 31% Other
5	Ingham MI	0.3	3×10^{-6} (6th)	>95% Lapeer, MI	>95% Metals Mfg
6	Wayne, MI	2.0	4×10^{-7} (83rd)	>95% Macomb, MI	>95% Metals Mfg
7	Rockingham, NH	0.3	2×10^{-6} (8th)	>95% Suffolk, NY	>95% Sci Svs
8	Hennepin, MN	1.1	5×10^{-7} (57th)	93% Hennepin, MN, 2% Scott, MN	92% Sci Svs, 5% Metals Mfg, 2% Wood/Chem Mfg
9	Oakland, MI	1.2	5×10^{-7} (62nd)	83% Macomb, MI, 7% Oakland, Mi, 8% Lapeer, MI	>95% Metals Mfg
10	Dallas, TX	1.3	2×10^{-7} (125th)	>95% Dallas, TX	>95% Metals Mfg

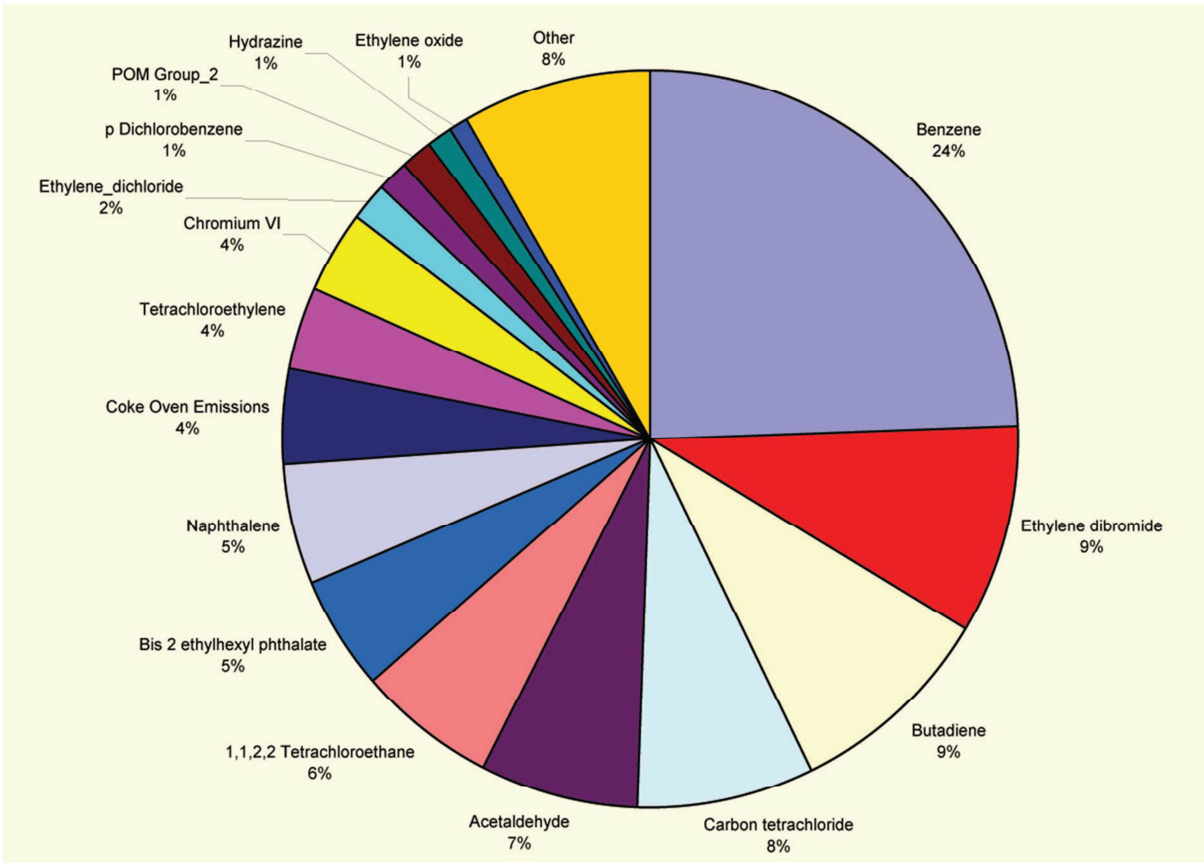
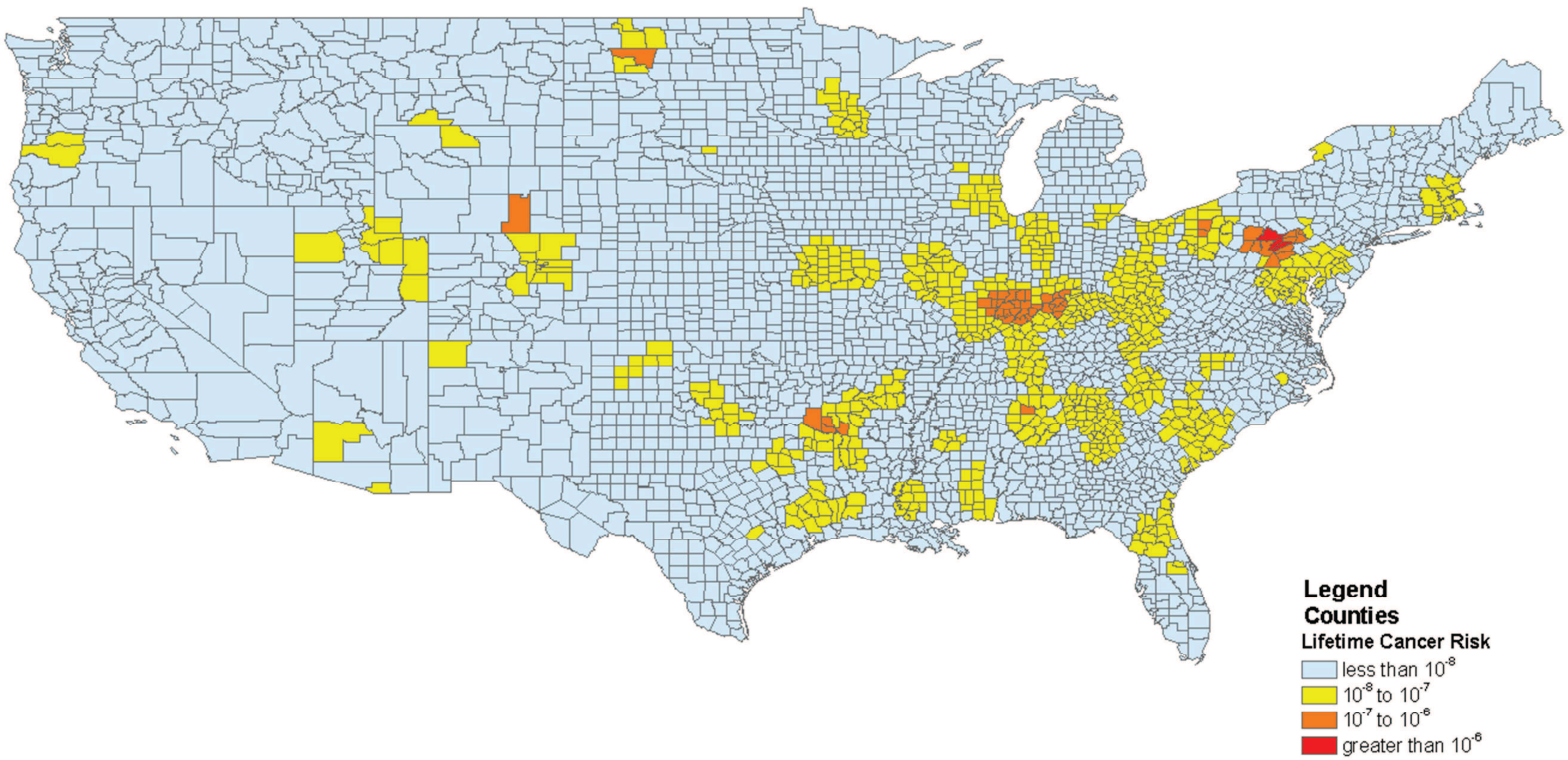


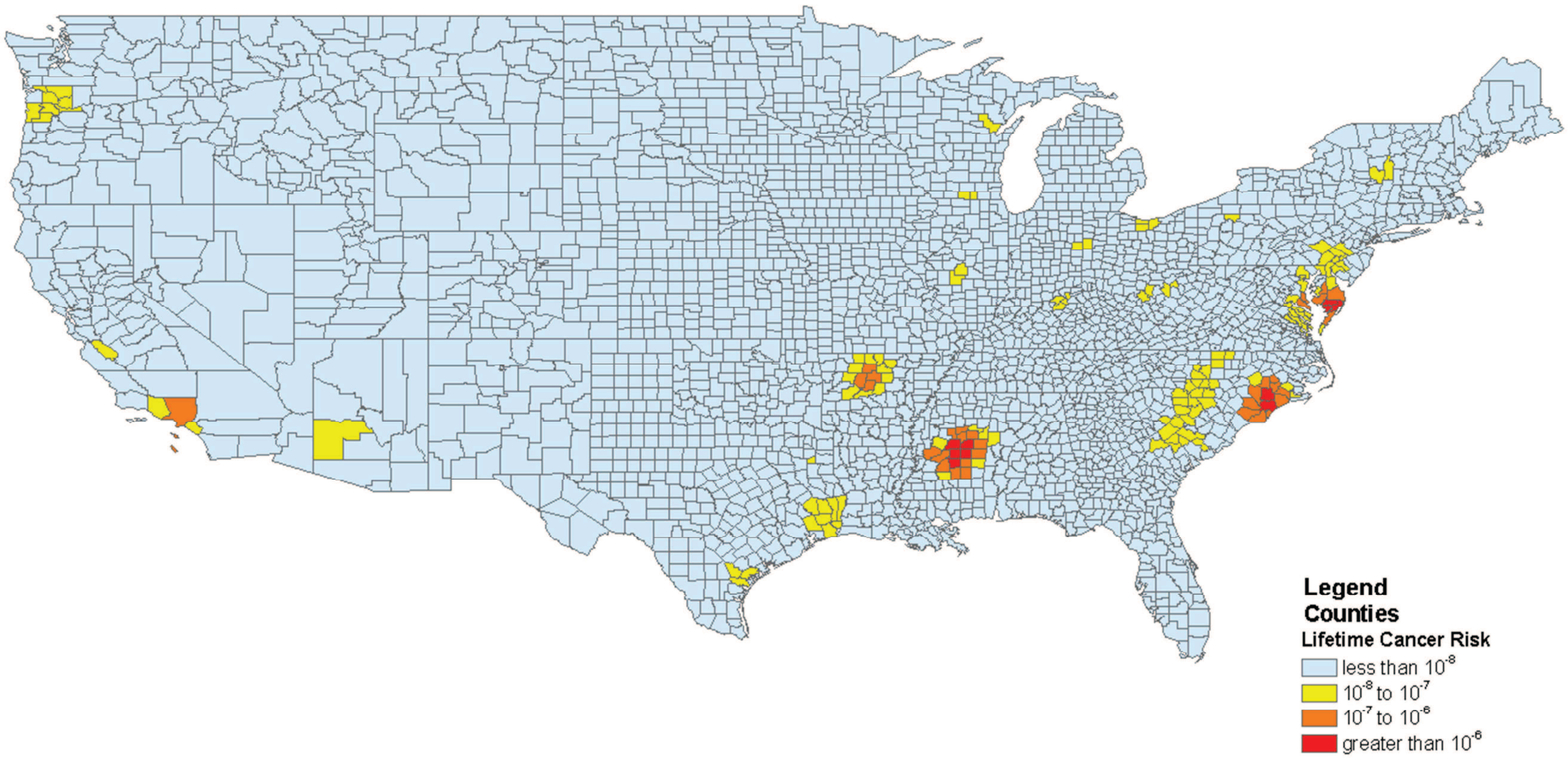
Figure S1. Compound Specific Contributions to Average Risk in US due to Air Toxics (Total estimated risk equals 4.2 x 10^{-5}) (based on the 1999 National Scale Air Toxics Assessment) (Palma 2007)

Figure S2 (Below). Maps of Estimated Lifetime Cancer Risk Resulting from Emissions by Sector

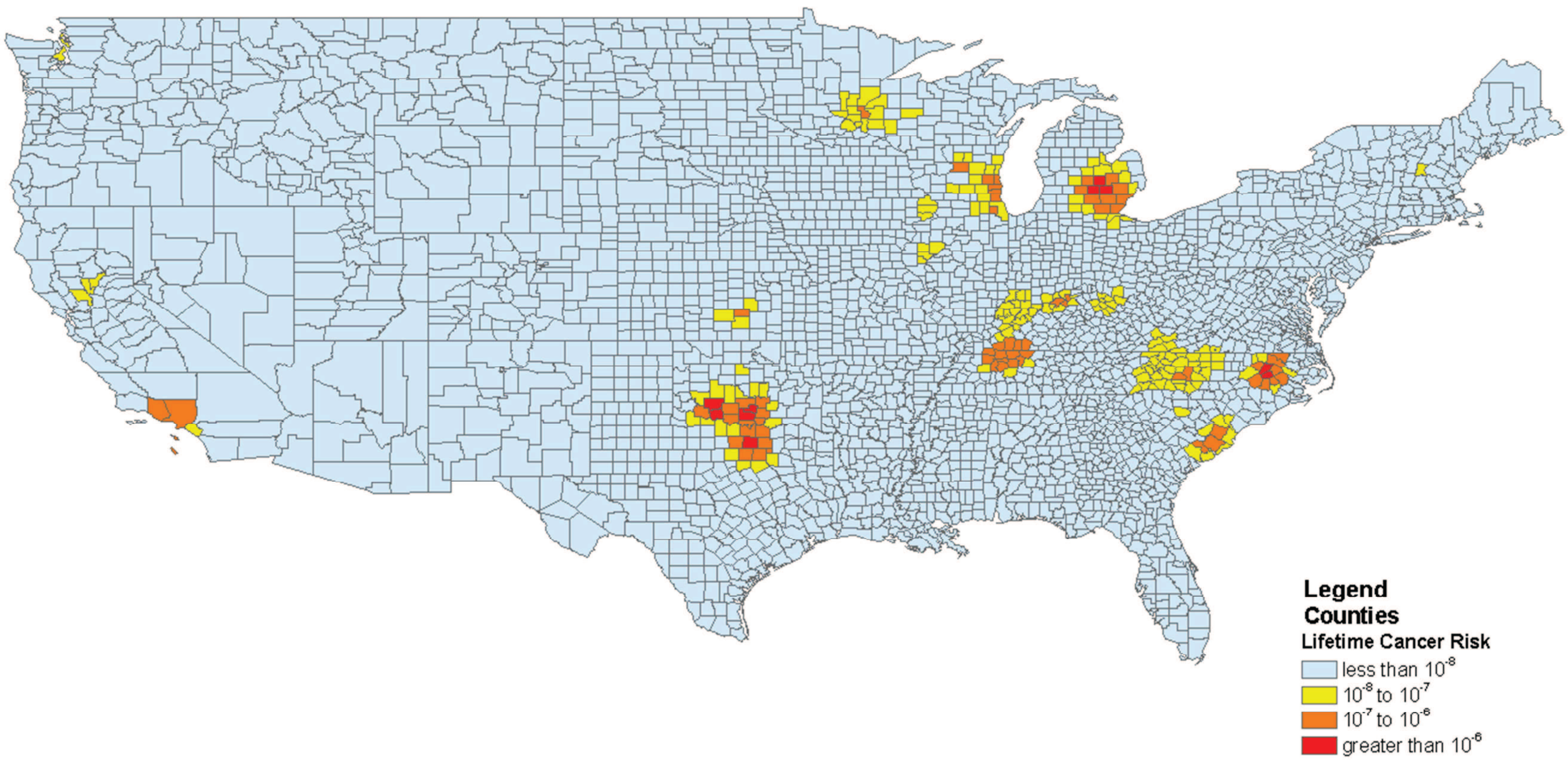
NAICS 2211: Electric Power Generation, Distribution and Transmission



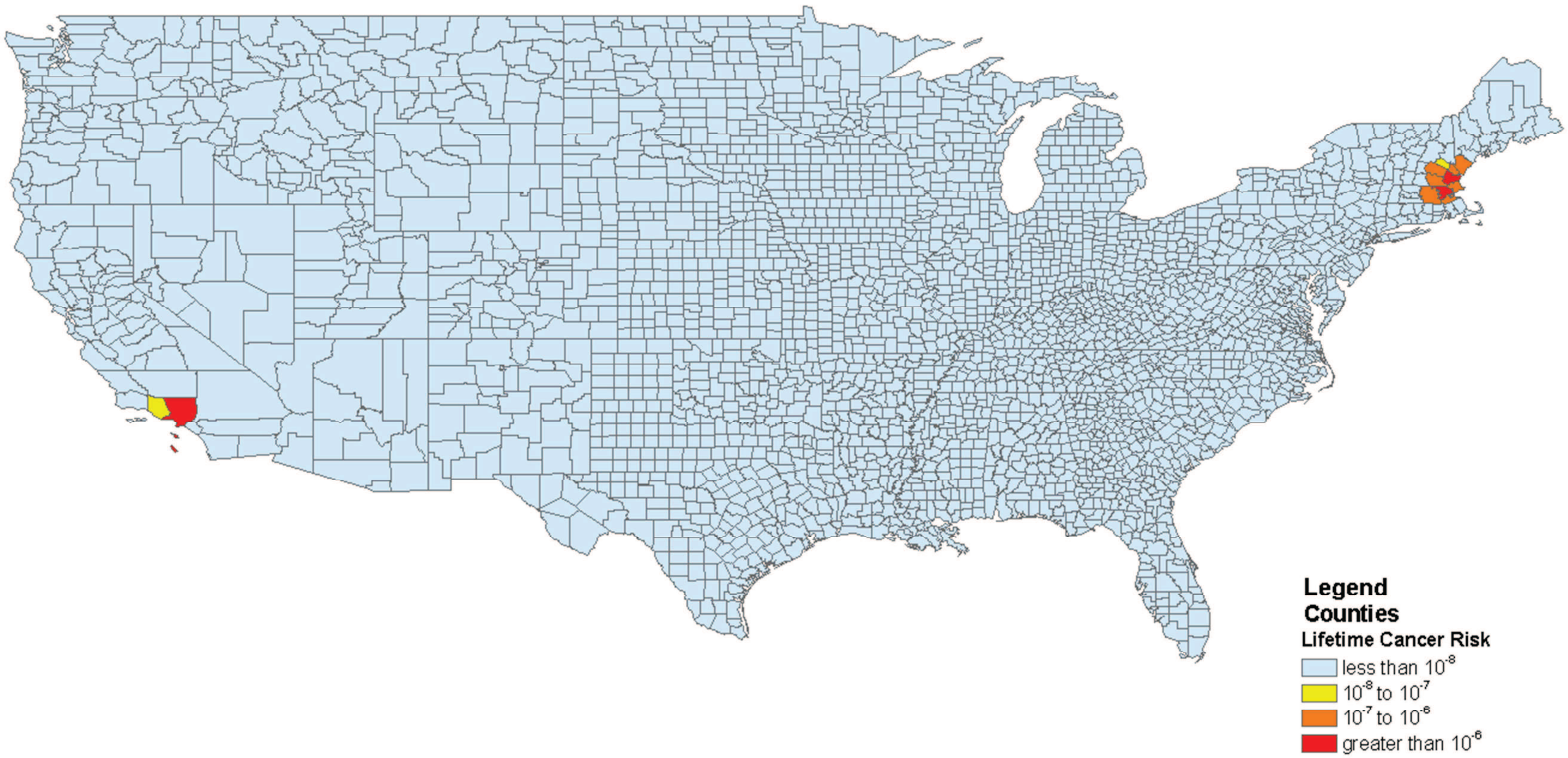
NAICS 32: Manufacturing of Paper, Petroleum and Coal Products,
Chemicals, Plastics and Rubber Products, and Nonmetallic Minerals, and Printing



NAICS 33: Combined Metal Manufacturing Sectors



NAICS 54: Professional, Scientific and Technical Services



C. Supply Chain Emissions

For the four major Cr(VI)-emitting sectors about 6 out of 44 tonnes of airborne Cr(VI) emissions were associated with their supply chain production for other sectors (including their own). For the power generation, wood and chemicals manufacturing, and metal manufacturing sectors, purchases by facilities from other facilities also in these sectors were responsible for the bulk of emissions. A small portion of facility emissions in these sectors was for supply chain purchases as inputs to each of the other sectors. However, in the scientific services sector, more than half of its emissions were associated with its production in the supply chains of the other sectors. (Figure S3). Reducing emissions throughout the entire supply chains of products presents an additional way for companies to reduce their impacts.

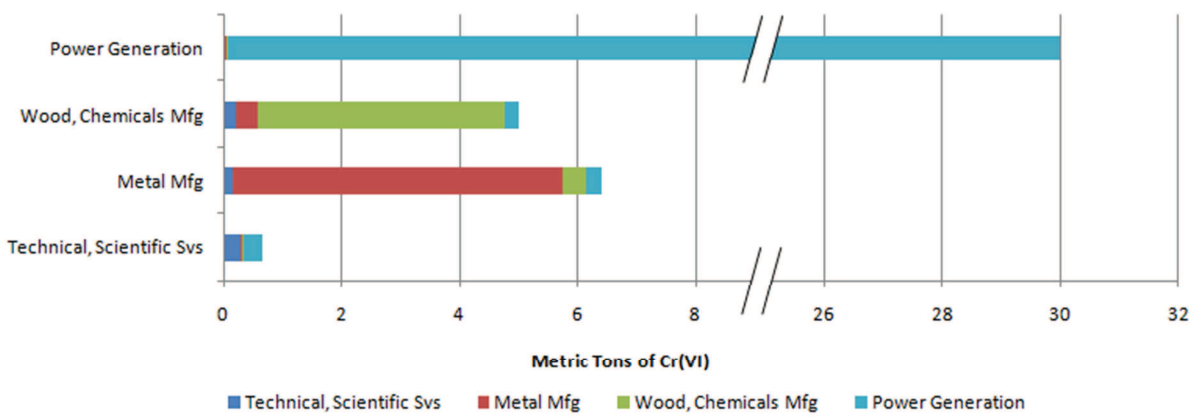


Figure S3. Emissions of Cr(VI) produced by Sectors Due to Facility and Supply Chain Economic Activity as Inputs to Other Sectors

D. Dispersion Model

Our economic-spatial risk model uses EPA's AERMOD program to model plumes due to point source emissions. AERMOD was developed by the American Meteorological Society and the EPA Regulatory Model Improvement Committee and improves upon prior dispersion models and has been EPA's preferred air dispersion model for regulating air toxics since December of 2005 (U.S. Environmental Protection Agency 2006). AERMOD is intended to be used for modeling the fate and transport of a single pollutant from an industrial facility or cluster of facilities in the same area. AERMOD is a Gaussian plume model and uses pollutant parameters from specific stacks at facility locations, including emissions, stack height, stack width, exit velocity, exit temperature, and gas flow rate; weather station data, including 30 dispersion parameters; and pollutant specifications, such as half-life and particle deposition size, to estimate annual average ambient air concentrations of pollutants. AERMOD assumes a linear relationship between emissions and ambient air concentration, so if we double the emissions from a point source the resulting ambient air concentration also doubles.

The model uses emissions data and stack parameters at facility locations from the EPA National Emissions Inventory (NEI). EPA compiles NEI data with input from numerous State and local air agencies, tribes, and industry. This is the same data that the EPA uses to make regulations on air toxics. The model uses atmospheric data from the National Weather Service for 120 weather stations for each hour for the year 1991 (Figure S4). This data is processed using EPA's AERMET. AERMET takes standard meteorological observations and specified default values for surface characteristics at weather stations and to compute planetary boundary layer parameters, including Monin-Obukhov length. Surface characteristics and specified default values include surface roughness (amount of vegetation and building coverage), which is assumed to be 0.25 meters for many trees, bushes and few buildings, Bowen ratio (ratio of energy fluxes from one medium to another by sensible and latent heating, respectively), which is assumed to be 1.0 for equal partition of fluxes, and albedo (ratio of reflected to incident light), which is assumed to be 1.0 during the day and between 0.25-0.5 at night (U.S. Environmental Protection Agency 2007).

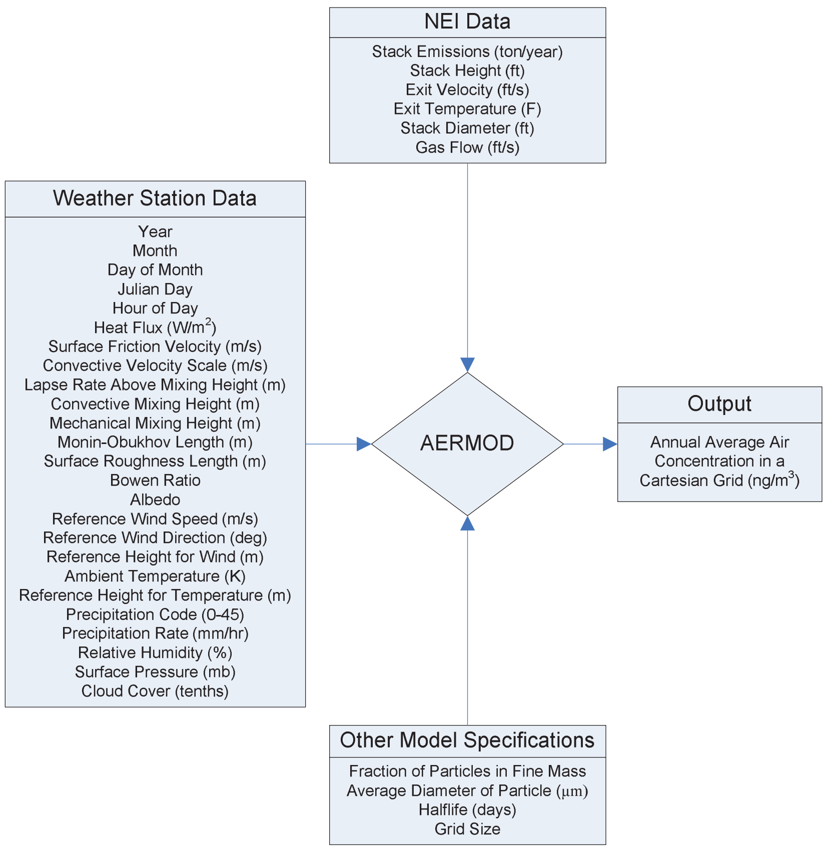


Figure S4. AERMOD's inputs and outputs.

We assign each NAICS facility to its closest weather station and input into AERMOD the distances in the zonal direction, x (west to east), and the meridional direction, y (south to north), from each facility to the nearest weather station using the expressions:

$$x = \cos\left(0.5\left(latitude_{centroid} + latitude_{facility}\right)\right) \times \frac{40{,}075}{360} \times \left(longitude_{centroid} - longitude_{facility}\right) \quad \text{(S1)}$$

$$y = \frac{40{,}075}{360} \times \left(latitude_{centroid} - latitude_{facility}\right) \quad \text{(S2)}$$

Where 40,075 is the circumference of earth in kilometers. The distance between each degree of latitude is 40,075 km/360, and the distance between each degree of longitude is 40,075 km/360 times the cosine of the point halfway between the latitude of the facility and the latitude of the centroid.

AERMOD's input file only handles one weather station at a time so to model the resulting air concentration from emissions across the country it has to be run separately for each of the 120 weather stations. AERMOD is also run separately for each of the economic NAICS codes included in the NEI data set.

Sample results retrieved from AERMOD's output file are presented in terms of annual average air concentration for a plume on a Cartesian grid. Grid size around weather stations is specified as -150 km by +300 km in the x direction and -250 km by 300 km in the y direction with 50 km intervals, because we are fairly certain that this size grid contains every plume. Interpolation from the Cartesian grid of sample points is used to find the ambient air concentration at county centroids. The equation of the plane defined by the three vertices of a triangle is as follows:

$$z = f(x, y) = -\frac{A}{C}x - \frac{B}{C}x - \frac{D}{C} \quad \text{(S3)}$$

Where A, B, C, and D are computed from the coordinates of the three vertices ($x1$, $y1$, $z1$), ($x2$, $y2$, $z2$), and ($x3$, $y3$, $z3$):

$$
\begin{aligned}
A &= y_1(z_2 - z_3) + y_2(z_2 - z_3) + y_3(z_1 - z_3) \\
A &= z_1(x_2 - x_3) + z_2(x_3 - x_1) + z_3(x_1 - x_2) \\
A &= x_1(y_2 - y_3) + x_2(y_3 - y_1) + x_3(y_1 - y_2) \\
A &= -Ax_1 - By_1 - Dz_1
\end{aligned}
\qquad \text{(S4)}
$$

E. Exposure and Risk Model

For each county our economic-spatial risk model estimates human lifetime individual cancer risk (*LIR*) due to the air pathway via the resulting ambient concentration C_E (μg/m^3) at the county centroid and an EPA unit risk factor *URF* (μg/m^3), which is based on default exposure factors and a chemical-specific cancer slope factor (U.S. Environmental Protection Agency 2007) (U.S. Environmental Protection Agency 2007):

$$LIR = URF \times C_E \qquad \text{(S5)}$$

Additional exposure pathways, such as ingestion or dermal absorption, can be added for pollutants with other cancer or non-cancer endpoints. The number of cancer cases per year, *I*, is modeled as:

$$I = \frac{LIR \times P}{T} \qquad \text{(S6)}$$

Where *P* is the population of each county based on county population data from the US Census Bureau and *T* is a lifetime of 70 years.

F. Discussion of Uncertainties

There are several important uncertainties and limitations in model data and methods that impact our confidence in the results that we discuss here (Holmes, Graham et al. 2009). Among these are uncertainties in the NEI Cr(VI) emissions, the linear model assumption, AERMOD, the meteorological data, pollutant specifications, interpolation to the county centroid, exposure assumptions, including the unit risk factor, and Census Bureau economic output data and EIO-LCA modeling. We also evaluate the model for its ability to predict Cr(VI) air concentrations and risk using external datasets.

Uncertainties introduced by the NEI Cr(VI) emissions data are difficult to quantify. Because data are reported from a variety of sources, there is uncertainty in their level of detail, quality and geographic coverage. Emissions inventories are likely to underestimate total emissions due to omitted sources (Harris and Davidson 2005); however, emission estimates for included sources can be either high or low. Where individual metal compounds cannot be reported and the mass of chromium is reported instead, there is uncertainty due to the use of simplifying assumptions regarding speciation of Cr(VI) based on default profiles for different processes. Despite these uncertainties, the NEI may be the best emissions inventory available at this time (U.S. Environmental Protection Agency 2006). We are not able to find an independent emissions inventory with which to compare these data. The assumption that emissions respond directly to economic sector output most likely overestimates the elasticity of emissions, due to capacity and regulatory constraints on source facilities.

The South Coast local air district in California reports the emissions for the scientific services sector in Los Angeles County that are included in the NEI and is the best source of information available. Emissions are reported to meet requirements, such as the Hot Spots Program (AB 2588) and statewide rules in place that are enforced by the district for chrome plating. NEI point source emissions estimates of Cr(VI) from chrome plating operations are typically measured directly by facilities through stack tests, according to the local pollution control agency, California Air Resources Board (CARB) (U.S. Environmental Protection Agency 2006; Takemoto 2009).

There are uncertainties in economic output data, and the EIOLCA in general, such as aggregation of unlike goods in some sectors (Lenzen 2001; U.S. Census Bureau 2006). There is additional uncertainty due to our method of estimating supply chain emissions, in which we aggregated supply chain economic activity by three-digit NAICS (i.e. 321, 332, etc.) before multiplying by associated emissions factors. Neither of these factors presents a significant problem at this time since we do not estimate impacts from supply chain emissions, but when we do, it will be more important.

The AERMOD atmospheric dispersion model is applied with a number of simplifications, though overall errors are likely to be only moderate given the annual averaging period employed. There is uncertainty due to the simplifying assumptions of Gaussian plume modeling. There is further uncertainty in inputs into AERMOD, such as the meteorological data, which is based on a prior year's meteorology in this analysis, and which has simplified values for surface characteristics at weather stations. These simplifications do not produce fine resolution in specific localities, but they are sufficient for the resolution of the data in this study. Additionally, some uncertainty is introduced into the model due to using meteorological data from the closest weather station. For example, the atmospheric conditions for facilities located far from weather stations may be different due to topography. Topography was not taken into account in this analysis because the resolution of the data did not warrant that kind of detail, but it could be added in future analyses. Finally, there is uncertainty due to using upper bound assumptions for pollutant specifications input into the AERMOD, such as half-life and particle size. Neither of these significantly changes the Cr(VI) ambient air concentration based on varying half-life and particle deposition size over the specified ranges for Cr(VI), from 16 hours to 5 days (Kimbrough, Cohen et al. 1999), and from 0 to 2.5 microns (Goyal, Small et al. 2005), respectively, for a sample of facilities (power utilities nearest to the Pittsburgh weather station) (Figure S5). This is perhaps due to Cr(VI) particles having a relatively short transport range.

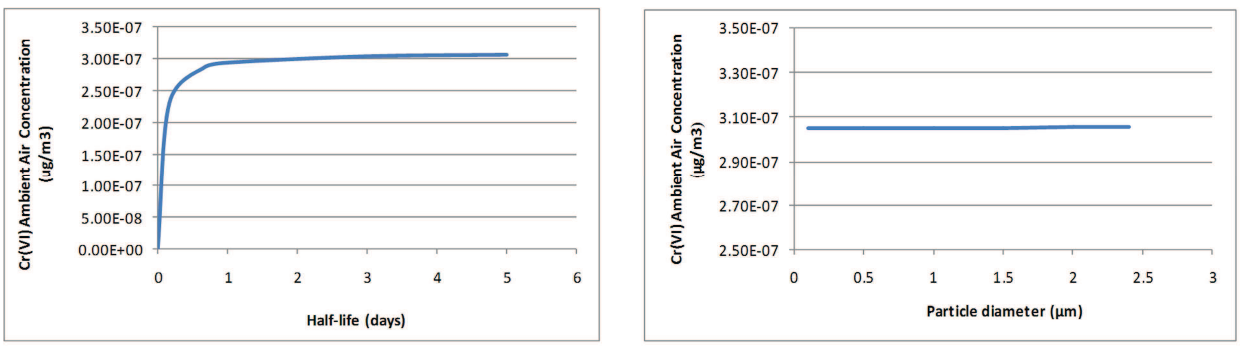


Figure S5. Simulated annual average air concentration of Cr(VI) ($\mu g/m^3$) for power utilities nearest to the Pittsburgh weather station by half-life (holding particle deposition size at 2 μm) (left) and by particle deposition size (holding half-life at 5 days) (right). Neither variable significantly changes the Cr(VI) ambient air concentration over the specified ranges for Cr(VI).

Uncertainty introduced due to using the county centroid as opposed to the average of the census tract centroids to estimate ambient concentration and risk in a county accounts for nearly a factor of 10 underestimation using the coarser versus the finer spatial resolution in the case of Los Angeles. The County was chosen because it is one of the largest counties with major population centers and industries along its western edge (as opposed to in the center); though it is not likely to be representative of other counties. However, because Angeles County turned out to be the major driver of risk and cancer cases in the country, this becomes a significant uncertainty, and considering this would add to predicted risk and cancer cases there.

There are several uncertainties introduced by methods to estimate exposure based on the predicted ambient concentration at the county centroid. There is uncertainty introduced by assuming exposure for 24 hours a day for a lifetime. Thus, this study does not take into account uncertainty in the exposed population based on the fact that people move from city to city. Proper consideration of this would lessen the variance of the national population distribution of exposure and risk. Nor does this study take into account the uncertainty introduced by people moving from one location to another throughout the day (population time-activity budgets). Marshall et al. (2006) carried out this type of mobility analysis for Cr(VI) exposure in Los Angeles and showed that it can increase exposure, resulting in an inhalation-relevant concentration that is 30% higher than the ambient concentration (Marshall, Granvold et al. 2006). Other assumptions may cause error in the exposure estimate as well, such as assuming a constant adult body weight and breathing rate over a lifetime. There is uncertainty in the unit risk factor for Cr(VI) from inhalation, which is based on assumptions that may overestimate risk by few orders of magnitude in an attempt to protect the most sensitive populations (an uncertainty factor of 300 is applied to account for factors such as variation in the human population), such as that there is no level of exposure or threshold for carcinogens for which the possibility to cause harm is zero (U.S. Environmental Protection Agency 2007). These uncertainties in exposure calculations (an underestimation due to not considering population time-activity budgets and an overestimation due to using the unit risk factor) could result in an overestimation of predicted risk levels in Los Angeles County of at least an order of magnitude. As such, some of the errors resulting from simplifications in our analysis are more likely to cause overestimates, while others are more likely to yield underestimates.

An attempt was made to characterize the relationship between overall emissions and measured ambient concentrations at EPA monitors using the EPA AirData dataset (U.S. Environmental Protection Agency 2007). AirData is an annual summary of ambient concentrations of criteria and hazardous air pollutants at monitoring sites in cities and towns (U.S. Environmental Protection Agency 2007). However, the model did not correspond well with the monitor locations, which tend to be found relative to highways, and we did not have location data for mobile sources to see if those accounted for the discrepancy. As another means of evaluating the model, we compared simulated annual average ambient air concentrations based on running the model again using NEI chromium compounds emissions for 2002 (see Table S2 above in the Supporting Information for a breakdown of chromium compound data by sector) (U.S. Environmental Protection Agency 2006) with 2002 NATA model results. NATA results for Cr(VI) were not available on the website (U.S. Environmental Protection Agency 2009). The total chromium comparison is a good indicator of the model's ability to predict Cr(VI) concentrations because Cr(VI) is a component of total chromium and has a generally consistent ratio in the environment. The ratio was found to be about 10 to 20 percent based on comparing observed EPA AirData concentrations for Cr(VI) and chromium compounds at EPA monitoring sites (n=4). In a study by CARB, this value was found to be just slightly lower at 3 to 8 percent (California Air Resources Board 1985). A difference between our model and the NATA is that the NATA's predicted ambient concentrations in a county are estimated by taking the average of the values at the centroids of census tracts as opposed to values predicted at the county centroids.

Despite differences in the models both predicted similar ambient concentrations with the same mean value for counties of 2 x 10^{-4} μg/m^3 (Figure S6).

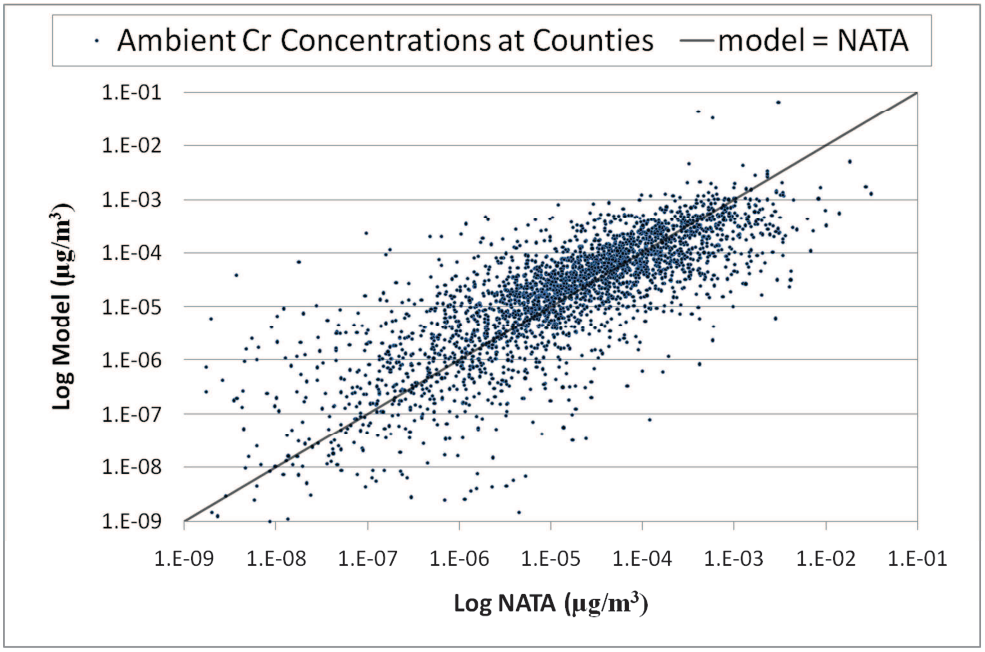


Figure S6. Ratio of simulated annual average ambient concentrations for chromium compounds at counties to NATA reported values.

Although the 2002 NATA is a credible source it tends to underestimate concentrations of chromium compounds in the environment typically by a factor of 2-3 and up to a factor of almost 100 (Logue 2009). Factors such as a facility's proximity to mobile sources and highways or soil resuspension may be responsible for the discrepancy. When background sources such as soil resuspension are considered, industrial sectors are recognized to contribute emissions indirectly due to past stack emissions that have led to the buildup of toxics concentrations in soil and air. Thus, in many areas ambient concentrations of Cr(VI) will likely be dominated by soil and dust resuspension from naturally occurring sources, or from historic chromium emissions deposited to the land surface, roadways, and buildings (total exposure and risk are thus underestimated, recognizing that our estimates are limited to the exposures and risks associated with current emissions to the air) (Harris and Davidson 2005).

Modeled annual cancer incidence due to Cr(VI) point sources in 2002 of about one case is consistent with EPA's modeled cancer cases due to Cr(VI) point sources in 1999 of about 0.7 (assuming an average lifetime risk of 42 in a million from all air toxics, a 4% contribution by Cr(VI), a 10% contribution by point sources, a population of 288 million, and a lifetime of 70 years) (Palma 2007).

In conclusion we believe that errors in model methods and data could result in a net shift in the absolute risk associated with current ambient emissions of Cr(VI) either upward or downward; however, we are not aware of any estimate at this time that is more accurate or precise.

APPENDIX B. SUPPORTING INFORMATION FOR "A DECISION SUPPORT FRAMEWORK FOR SCIENCE-BASED MULTI-STAKEHOLDER DELIBERATION: A CORAL REEF EXAMPLE"

Florida Keys Coral Reefs Workshop - June 2009

Pre-Workshop Stakeholder Assessment of Preferences and Beliefs for Resource Management

Name: ______________________________ Affiliation: ____

Note: Participants names or affiliations will not be identified in any presentation of results without your approval.

1. Beliefs Regarding Relationships Between Environmental Pressures and Outcomes. Here we would like your estimate of the effects of different environmental conditions on the following ecological and economic outcomes in the Florida Keys area: **a) coral reef health and quality**; **b) fisheries health and vitality**; and **c) tourism and economic growth**. For each of the combinations of environmental conditions (a row in each table), assign a percentage (between 0% and 100%) to reflect your belief in the likelihood of a good outcome. Good outcomes correspond to: a) healthy, high quality coral reefs; b) good fisheries health and vitality; or c) high levels of tourism and economic growth, for the respective tables.

a) Effect of Environmental Conditions on the Health and Quality of Coral Reefs

Environmental Conditions			Percent Chance that Coral Reef Health and Quality will be Good (assign value between 0% and 100%)
Water Quality (sediments, nutrients, algae, etc.)	Overfishing Occurs	Climate Change (increased ocean temperature and acidification)	
Poor	Yes	High	
Poor	Yes	Low	
Poor	No	High	
Poor	No	Low	
Good	Yes	High	
Good	Yes	Low	
Good	No	High	
Good	No	Low	

b) Effect of Coral Reefs and Climate Change on Fisheries Health and Vitality

Environmental Conditions		Percent Chance that Fisheries Health and Vitality will be Good (assign value between 0% and 100%)
Coral Reef Health	Climate Change (increased ocean temperature and acidification)	
Good	Low	
Good	High	
Poor	Low	
Poor	High	

c) Effect of Environmental & Economic Conditions on Tourism and Economic Growth

Environmental or Economic Condition			Percent Chance that Tourism and Economic Growth will be Good (assign value between 0% and 100%)
Land Use and Wastewater Restrictions	Fisheries Health and Vitality	Coral Reef Health	
No	Good	Good	
No	Good	Poor	
No	Poor	Good	
No	Poor	Poor	
Yes	Good	Good	
Yes	Good	Poor	
Yes	Poor	Good	
Yes	Poor	Poor	

2. Additional research studies involving data collection, experiments and modeling have the potential to provide improved characterizations of the relationships between the environmental and economic pressures and the environmental outcomes described above. Based on your understanding of current science and what information is needed to make management decisions, please respond to the following:
   a. I believe the following scientific uncertainties to be most important to resolve in the Florida Keys:
   ____
   ____
   b. I suggest the following study be conducted (what, how, by whom)? ________________
   ____
   ____

3. Preferences for Outcomes. Here we would like to understand the relative importance you place on coral reef health, water quality in coastal waters, tourism & economic growth, and fisheries health and vitality. Please assign value points to each outcome, so that the points sum to 100. For example, if you value each outcome equally, you will assign value weights of 25 to each. If you only value one of the outcomes, but not the other three, you will assign 100 points to the valued outcome and 0 points to the other three outcomes, etc.

	Outcome				
	Good Coral Reef Health & Quality	Good Coastal Water Quality	High Levels of Tourism & Economic Growth	Good Fisheries Health & Vitality	–> Σ Sum
Assigned Value Weight →					100

APPENDIX C. SUPPORTING INFORMATION FOR "THE ROLE OF SCIENTIFIC STUDIES IN BUILDING CONSENSUS AMONG STAKEHOLDERS IN ENVIRONMENTAL DECISION MAKING: A CORAL REEF EXAMPLE"

BLANK ELICITATION FORM

Participant Assessment of Objectives, Values, and Beliefs
Coral Reef Decision Support Workshop: Guánica Bay Watershed, Puerto Rico

Name: ______________________________ Affiliation: ____

Note: Participants names or affiliations will not be identified in any presentation of results without their approval.

1. Environmental Resources and Outcomes
   A. Please rate the resources and outcomes that should be considered in decision making for **environmental quality and coral reef management** in the Guánica Bay Watershed in terms of their importance and value to you. Add others that you believe should be included.

Resources and Outcomes (check one box for each outcome)	***Importance and Value to you***				
	Unimportant	Low	Medium	High	Very High
Guánica Bay Water Quality					
Coral Reef Health					
Fisheries					
Drinking Water Quality					
Agriculture					
Tourism					
New Construction and Development					
Other					
Other					
Other					

B. (Optional) Please identify your specific objectives for the economic and environmental future of the Guánica Bay Watershed. You may include items from part A above and, if you wish, specific goals and measures, such as target water quality standards, percent coral reef recovery, etc.

2. <u>Environmental Threats (Cause-Effect Relationships among Drivers, Pressures, States, and Impacts)</u>

The purpose of this section is to identify the principal cause-effect relationships that impact the resources and outcomes in the Guánica Bay Watershed. Several common relationships are presented as examples. Please evaluate these and others you identify as important. In each case, provide your best estimate and associated confidence regarding the strength of the relationship. *(Two examples are given with illustrative values.)*

Environmental Threat (Driver/Pressure):	Affected Resource/Outcome (States/Impacts):	Strength of Relationship is (assign % chance with an X):	I am ___ confident in my estimate (check one box):		
			Slightly	Somewhat	Very
Example: Smoking	*Lung Cancer*	0 ———— X —— 100 (You might give this answer if you are quite certain there is a strong relationship.)			*X*
Example: Global Warming	*More Frequent and Severe Hurricanes*	0 —X———— 100 (You might give this answer if you are quite uncertain about the relationship.)	*X*		
1. Sewage and wastewater treatment plant loadings	Reservoir and drinking water quality	0 ———— 100			
2. Sewage and wastewater treatment plant loadings	Bay water quality	0 ———— 100			
3. Agrochemical discharges	Reservoir and drinking	0 ———— 100			
4. Agrochemical discharges	Bay water quality	0 ———— 100			
5. Sediment loadings	Reservoir and drinking water quality	0 ———— 100			
6. Sediment loadings due to clear-cutting	Bay water quality	0 ———— 100			
7. Sediment loadings due to building construction	Bay water quality	0 ———— 100			
8. Bay water quality (<u>nutrient level</u>)	Coral reef health	0 ———— 100			
9. Bay water quality (<u>sediment level</u>)	Coral reef health	0 ———— 100			
10. Bay water quality (<u>toxics and pathogens</u>)	Coral reef health	0 ———— 100			
11. Ocean acidification	Coral reef health	0 ———— 100			
12. Ocean temperature rise	Coral reef health	0 ———— 100			
13. Coral reef health	Fisheries	0 ———— 100			
14. Coral reef health	Tourism	0 ———— 100			

3. <u>Alternative Management and Policy Options</u>

A. The purpose of this section is to identify the management actions that would be viable and effective for reducing environmental threats or ensuring the important resource outcomes in the **Guánica Bay Watershed**. Several common relationships are presented as examples. Please evaluate these and others you identify as important. For each indicate your best estimate of the amount of improvement that would result from taking the management action and associated confidence. *An example with an illustrative value is provided.*

I believe that this Management Option: *would improve:*	**This Outcome:**	**By this amount (check one box):** A Little	Moderately	A Lot	**I am ___confident in my estimate (check one box):** Slightly	Somewhat	Very
Example: Anti-smoking advertising	*Respiratory Health*		X			X	
1. Restrictions on agrochemicals	Reservoir and Drinking Water Quality						
2. Wastewater treatment wetlands	Bay Water Quality						
3. Advanced wastewater treatment	Bay Water Quality						
4. Rio Loco streambank riparian plantings	Bay Water Quality						
5. Hydroseeding of areas with bare soil in high elevation erodible soil areas	Bay Water Quality						
6. Cover crop outreach and cost share to high elevation coffee farms	Bay Water Quality						
7. Restoration of Guánica Lagoon	Bay Water Quality						
8. Reef education for youth and their parents	Bay Water Quality						
9. Subsidy for shade grown coffee	Bay Water Quality						
10. Marine protection areas	Coral Reef Health						
11. Other							
12. Other							
Identify a <u>portfolio</u> of options that you believe would be best, and predict its overall effect on → 1. 2. 3. 4.	Bay Water Quality						
	Coral Reef Health						
	Other?						

4. <u>Key Uncertainties and Scientific Studies to Address Management and Policy Options</u>

Please identify key data gaps or scientific uncertainties that you believe limit our ability to understand and manage the coral reefs and related ecosystems in the Guánica Bay Watershed. For each, suggest additional monitoring or scientific studies that would likely reduce these uncertainties. *An illustrative example is provided.*

Key scientific uncertainties and data gaps:	This uncertainty could be reduced by the following study or studies	I believe this study will reduce the uncertainty by this amount (check one box):			I am ___confident in my estimate (check one box):		
		A Little	Moderately	A Lot	Slightly	Somewhat	Very
Example: Nitrogen loss rates in the Rio Loco	*a. Calibration and use of a watershed nutrient model, such as SPARROW*	X				X	
	b. Intensive monitoring program for sediment & nitrogen transport in Rio Loco		X				X
			(These answers indicate a belief that the monitoring study is more likely to be effective than model development.)				
1.	1a.						
	1b.						
	1c.						
2.	2a.						
	2b.						
	2c.						
3.	3a						
	3b.						

Glossary

Drivers – Socioeconomic sectors that drive human activities (Waste disposal, agriculture, construction, fisheries, tourism).

Ecosystem Services – The products of ecological functions or processes that directly or indirectly contribute to human well-being (clean air and water, food and fiber, erosion and flood control, habitat and biodiversity, climate stability, and aesthetic enjoyment).

Hydroseeding – A planting process which utilizes a slurry of seed and mulch, which is transported in a tank, either truck- or trailer-mounted and sprayed over prepared ground in a uniform layer.

Impacts – Effects of environmental degradation on ecosystem functioning, affecting the quality and value of ecosystem services.

Management and policy options – a number of alternatives that are under the control of decision makers and from which one or a combination of several of them (to be implemented as a strategy) can be chosen.

Pathogen – Microorganisms (e.g., bacteria, viruses, or parasites) that can cause disease in humans, animals and plants.

Pressures – Human activities that stress the environment (Discharge, boating activities, climate change, land use/land cover change, coastal erosion).

Riparian – Of or relating to or located on the banks of a river or stream.

States – Reflect condition of the natural and living phenomena (such as air, water and soil parameters and growth, survival and reproductive parameters).

Strength or magnitude of the relationship (between variables) – The degree to which one variable is associated with or can cause a change in a second variable (i.e., between decisions and outcomes).

Toxics – Poisonous chemicals

Uncertainty – Inability to predict outcomes due to random variability (for example, streamflow is sometimes high and sometimes low) or incomplete scientific knowledge regarding causal relationships (for example, how does a given concentration of sediments in the harbor affect coral reef growth rates).

References

SPARROW: http://water.usgs.gov/nawqa/sparrow/

QUESTIONS IN THE FACE-TO-FACE ELICITATION

1. How would you rate the following outcomes in relation to one another? (e.g., a 1 for tourism and a 2 for fish indicates that fish health is twice as important as tourism health).

tourism -
fish -
coral -

2. What percentages of the total loadings (nutrient and sediment) to the Guanica inland water system comes from development, agriculture, and sewage, respectively? (percentages should sum to 100%)

development -
agriculture -
sewage -

3. How sure are you that the lagoon will work (i.e., be effective in reducing loadings that enter the Bay)?

I am _% sure that the lagoon will work

4. What are the probabilities that the following sets of environmental stressors would produce: a) good/bad coral reef health; and b) good/bad fisheries health, respectively? (percentages should sum to 100%)

stressors for coral reef health:
water quality (WQ),
ocean warming/acidification (OW)
marine protection areas (MPA)

Stressors for fisheries health:
coral reef health (CR)
ocean warming/acidification (OW)
marine protection areas (MPA)

Example 1 - If water quality is considered to be most responsible, followed by ocean acidification/warming, and then marine protection areas (considered useless in this example), and no synergism is assumed, the following probabilities could apply:

25% WQ/OW/MPA
20% WQ/MPA
25% WQ/OW
5% MPA/OW
20% WQ
0% MPA
5% OW

Example 2 - If water quality combined with ocean warming/acidification and MPAs is thought to be the most important set of stressors contributing to coral health, followed by water quality and ocean warming/acidification, and then followed by water quality and MPAs, and assuming synergism among the various factors, the following probabilities could apply:

50% WQ/OW/MPA
30% WQ/OW
10% WQ/MPA
4% MPA/OW
5% WQ
1% MPA
2% OW

a. Probabilities that these sets of stressors lead to good/bad coral
reef health:

% that it's all 3 (WQ/OW/MPA) -
% that it's these 2 (WQ/MPA) -
% that it's these 2 (WQ/OW) -
% that it's these 2 (MPA/OW) -
% that it's only 1 factor (WQ) -
% that it's only 1 factor (MPA) -
% that it's only 1 factor (OW) -

b. Probabilities that these sets of stressors lead to good/bad fisheries health:

% that it's all 3 (CR/OW/MPA) -
% that it's these 2 (CR/MPA) -
% that it's these 2 (CR/OW) -
% that it's these 2 (MPA/OW) -
% that it's only 1 factor (CR) -
% that it's only 1 factor (MPA) -
% that it's only 1 factor (OW) –

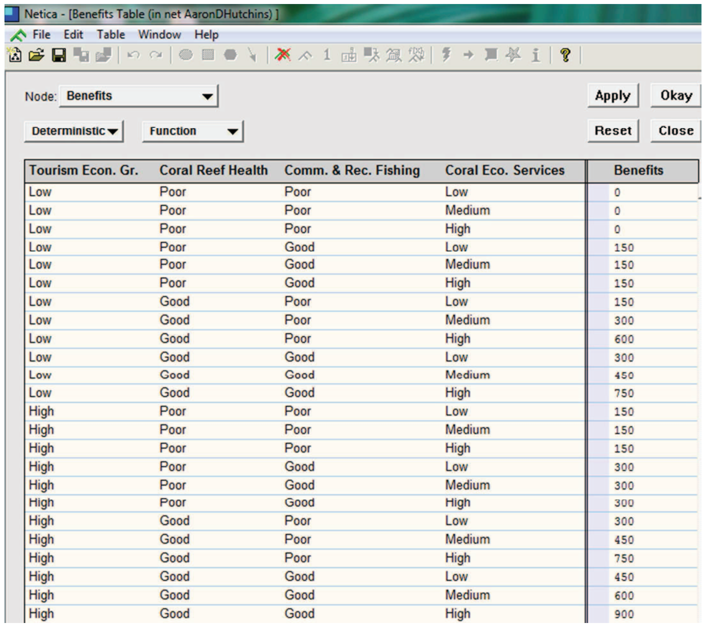
EXPLANATION OF BBN

Our BBN was designed to represent the current situation of coral reefs stressors and management in the Guánica Bay Watershed, Puerto Rico from the viewpoint of stakeholders. Based on elicitations and discussions at the workshop in Puerto Rico, we developed a model in Netica based on the DPSIR/DL framework that summarizes the essential components involved in coral reefs management. We included management options, environmental processes, and ecosystem services outcomes. Each node in Figure 2 represents a particular variable that is part of coral reefs management. Each arrow in Figure 2 represents a causative link between two nodes. In this explanation of the model we use the BBN and inputs for Participant A.

At the lower right of the diagram is the endpoint of the BBN: *Benefits*. *Benefits* is continuous variable distributed over ten intervals, and a function of *Tourism*, *Fisheries*, *Coral Reef Health* and *Coral Eco Services* (ecosystem services), the four inputs or outcomes of interest to stakeholders that influence the level of benefits. Generally, the greater the inputs, the greater the resulting benefits. However, the total benefits are weighted according to the elicited values stakeholders place on each outcome in relation to each other. For example, Participant A believes that coral health is twice as important as tourism and fisheries and has the following equation for benefits (the particular values applied to the weightings are set to correspond to values used throughout the model and will be discussed later in this document):

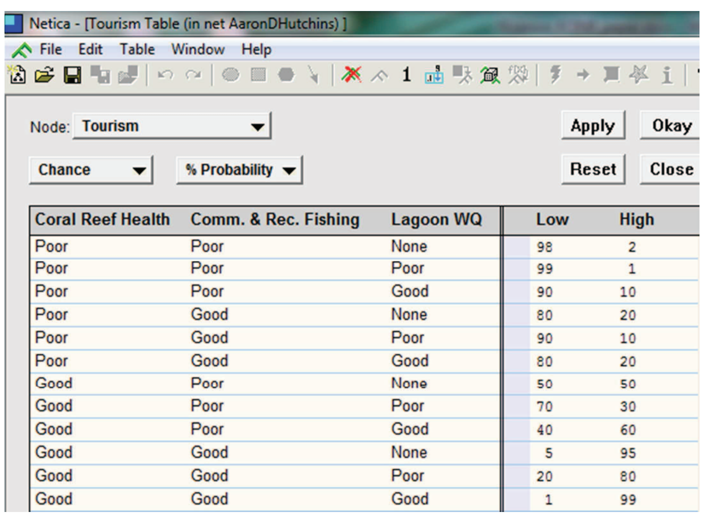
Benefits = 150**Tourism* + 150**Comm. & Rec Fishing* + 300* *Coral Reef Health***Coral Eco Services*

The following is the data table in Netica for *Benefits* for Participant A:



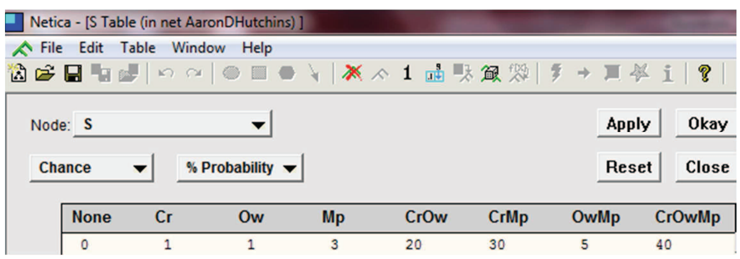
Tourism Econ. Gr.	Coral Reef Health	Comm. & Rec. Fishing	Coral Eco. Services	Benefits
Low	Poor	Poor	Low	0
Low	Poor	Poor	Medium	0
Low	Poor	Poor	High	0
Low	Poor	Good	Low	150
Low	Poor	Good	Medium	150
Low	Poor	Good	High	150
Low	Good	Poor	Low	150
Low	Good	Poor	Medium	300
Low	Good	Poor	High	600
Low	Good	Good	Low	300
Low	Good	Good	Medium	450
Low	Good	Good	High	750
High	Poor	Poor	Low	150
High	Poor	Poor	Medium	150
High	Poor	Poor	High	150
High	Poor	Good	Low	300
High	Poor	Good	Medium	300
High	Poor	Good	High	300
High	Good	Poor	Low	300
High	Good	Poor	Medium	450
High	Good	Poor	High	750
High	Good	Good	Low	450
High	Good	Good	Medium	600
High	Good	Good	High	900

The first input into *Benefits*, *Tourism,* is a discrete variable and can be either low or high. *Lagoon WQ*, *Comm. & Rec Fishing*, and *Coral Reef Health* are three inputs that influence the level of tourism. With improvements in these inputs come improvements in tourism. The following is the data table in Netica for *Tourism* for Participant A:



Coral Reef Health	Comm. & Rec. Fishing	Lagoon WQ	Low	High
Poor	Poor	None	98	2
Poor	Poor	Poor	99	1
Poor	Poor	Good	90	10
Poor	Good	None	80	20
Poor	Good	Poor	90	10
Poor	Good	Good	80	20
Good	Poor	None	50	50
Good	Poor	Poor	70	30
Good	Poor	Good	40	60
Good	Good	None	5	95
Good	Good	Poor	20	80
Good	Good	Good	1	99

The second input into *Benefits*, *Comm. & Rec Fishing*, is a discrete variable and can be either poor or good. *Coral Reef Health, Marine Protect (MPAs)*, *FishLinks*, and *Ocean Warm/Acid* are four inputs that influence the level of *Comm. & Rec Fishing*. As coral reef health improves and if MPAs are applied, the probability that fishing will be good tends to increase. As ocean warming/acidification increases, the probability that fishing will be good tends to decrease. *FishLinks* is a discrete variable that contains elicited probabilities (that sum to 100%) that varying sets of environmental stressors (coral reef health, MPAs, and ocean warming/acidification) will produce poor or good fisheries. *FishLinks* can be influenced by a node *Fisheries Research*, a discrete variable that allows for the possibility of testing the effects of different research outcomes for *FishLinks*, and updating prior probabilities based on new evidence. The probability that fishing will be good is adjusted by the elicited inputs into *Fish Links*, which can take into account the belief that there is synergism among variables. For example, Participant A's inputs into *FishLinks* are shown in the table below:



None	Cr	Ow	Mp	CrOw	CrMp	OwMp	CrOwMp
0	1	1	3	20	30	5	40

The higher the probability placed on a set of stressors that contains coral reef health and MPAs, the higher the probability that fishing will be good. The higher the probability placed on a set of stressors that contains ocean warming/acidification, the lower the probability that fishing will be good tends. The following is the data table in Netica for *Comm. & Rec Fishing* for Participant A:

Netica - [Fisheries Table (in net AaronDHutchins)]

File Edit Table Window Help

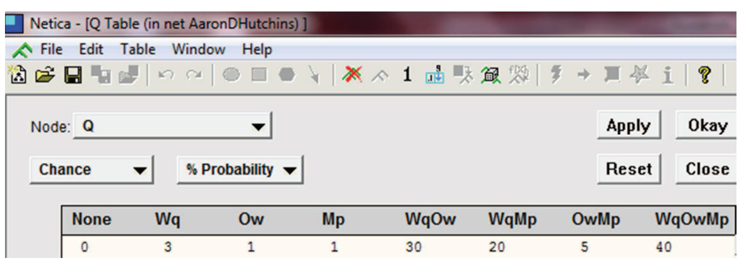
Node: Fisheries

Chance | % Probability

Apply | Okay | Reset | Close

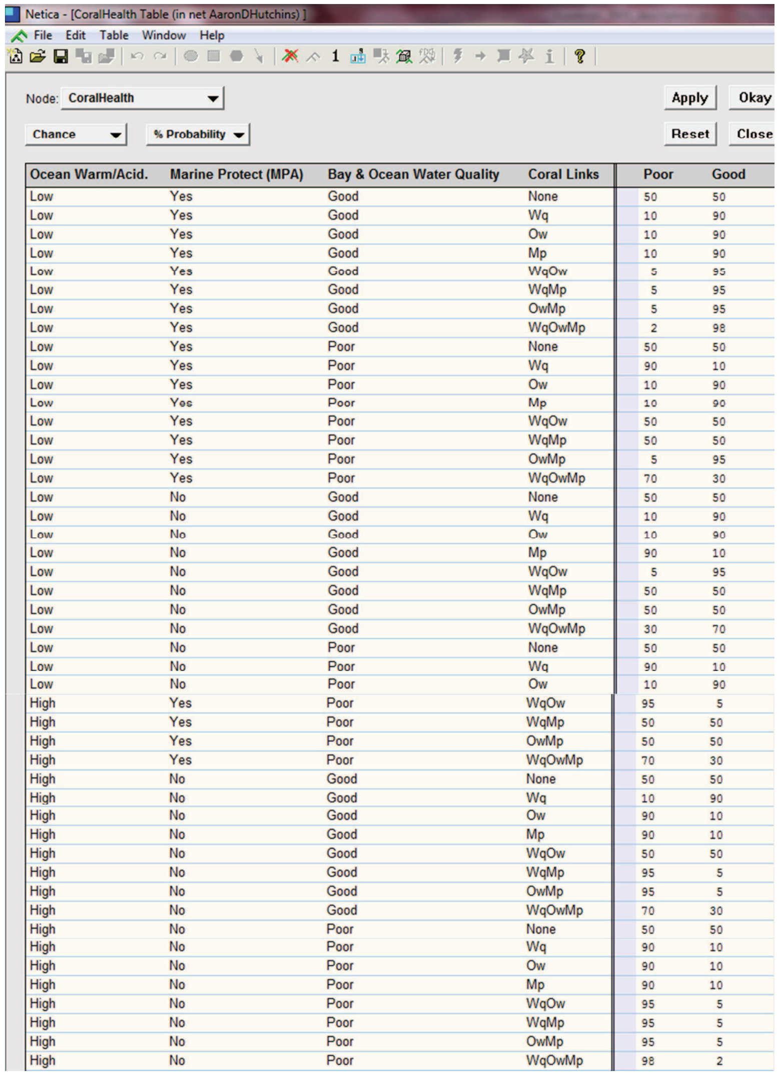
Coral Reef Health	Ocean Warm/Acid.	Fish Links	Marine Protect (MPA)	Poor	Good
Poor	Low	None	Yes	50	50
Poor	Low	None	No	50	50
Poor	Low	Cr	Yes	80	20
Poor	Low	Cr	No	80	20
Poor	Low	Ow	Yes	20	80
Poor	Low	Ow	No	20	80
Poor	Low	Mp	Yes	20	80
Poor	Low	Mp	No	80	20
Poor	Low	CrOw	Yes	50	50
Poor	Low	CrOw	No	50	50
Poor	Low	CrMp	Yes	50	50
Poor	Low	CrMp	No	90	10
Poor	Low	OwMp	Yes	10	90
Poor	Low	OwMp	No	50	50
Poor	Low	CrOwMp	Yes	30	70
Poor	Low	CrOwMp	No	70	30
Poor	High	None	Yes	50	50
Poor	High	None	No	50	50
Poor	High	Cr	Yes	80	20
Poor	High	Cr	No	80	20
Poor	High	Ow	Yes	80	20
Poor	High	Ow	No	80	20
Poor	High	Mp	Yes	20	80
Poor	High	Mp	No	80	20
Poor	High	CrOw	Yes	90	10
Poor	High	CrOw	No	90	10
Poor	High	CrMp	Yes	50	50
Poor	High	CrMp	No	90	10
Poor	High	OwMp	Yes	90	10
Poor	High	OwMp	No	90	10
Poor	High	CrOwMp	Yes	70	30
Poor	High	CrOwMp	No	95	5
Good	Low	None	Yes	50	50
Good	Low	None	No	50	50
Good	Low	Cr	Yes	20	80
Good	Low	Cr	No	20	80
Good	Low	Ow	Yes	20	80
Good	Low	Ow	No	20	80
Good	Low	Mp	Yes	20	80
Good	Low	Mp	No	80	20
Good	Low	CrOw	Yes	10	90
Good	Low	CrOw	No	10	90
Good	Low	CrMp	Yes	10	90
Good	Low	CrMp	No	50	50
Good	Low	OwMp	Yes	10	90
Good	Low	OwMp	No	50	50
Good	Low	CrOwMp	Yes	5	95
Good	Low	CrOwMp	No	30	70
Good	High	None	Yes	50	50
Good	High	None	No	50	50
Good	High	Cr	Yes	20	80
Good	High	Cr	No	20	80
Good	High	Ow	Yes	80	20
Good	High	Ow	No	80	20
Good	High	Mp	Yes	20	80
Good	High	Mp	No	80	20
Good	High	CrOw	Yes	50	50
Good	High	CrOw	No	50	50
Good	High	CrMp	Yes	10	90
Good	High	CrMp	No	50	50
Good	High	OwMp	Yes	90	10
Good	High	OwMp	No	90	10
Good	High	CrOwMp	Yes	30	70
Good	High	CrOwMp	No	70	30

The third input into *Benefits*, *Coral Reef Health*, is a discrete variable and can be either poor or good. *Bay & Water Quality*, *Marine Protect (MPAs)*, *Coral Links*, and *Ocean Warm/Acid* are the four inputs that influence the level of coral health. As bay water quality improves and if MPAs are applied, coral reef health increases. As ocean warming/acidification increases, the probability that coral reef health will be good decreases. *Coral Links* is a discrete variable that contains elicited probabilities (that sum to 100%) that varying sets of environmental stressors (MPAs, ocean water quality, and ocean warming/acidification) will produce poor or good coral health. *Coral Links* can be influenced by a node *Coral Effects Research*, a discrete variable that allows for the possibility of testing the effects of different research outcomes for *CoralLinks*, and updating prior probabilities based on new evidence. The probability that coral reef health will be good is adjusted by the elicited inputs into *Coral Links*, which can take into account the belief that there is synergism among variables. For example, Participant A's inputs into *CoralLinks* are shown in the table below:



None	Wq	Ow	Mp	WqOw	WqMp	OwMp	WqOwMp
0	3	1	1	30	20	5	40

The higher the probability placed on a set of stressors that contains ocean water quality and MPAs, the higher the probability that coral reef health will be good. The higher the probability placed on a set of stressors that contains ocean warming/acidification, the lower the probability that fishing will be good tends. The following is the data table in Netica for *Coral Reef Health* for Participant A:



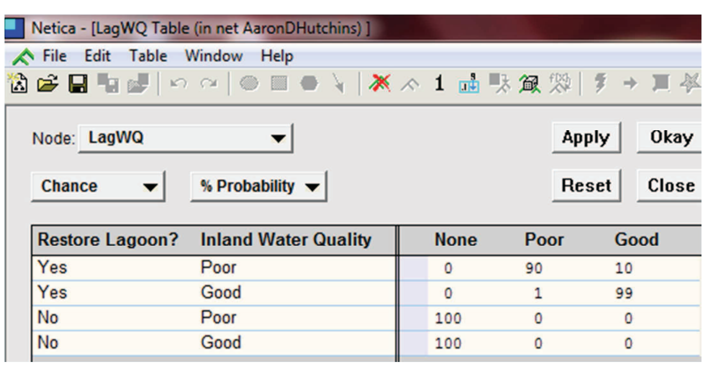
Ocean Warm/Acid.	Marine Protect (MPA)	Bay & Ocean Water Quality	Coral Links	Poor	Good
Low	Yes	Good	None	50	50
Low	Yes	Good	Wq	10	90
Low	Yes	Good	Ow	10	90
Low	Yes	Good	Mp	10	90
Low	Yes	Good	WqOw	5	95
Low	Yes	Good	WqMp	5	95
Low	Yes	Good	OwMp	5	95
Low	Yes	Good	WqOwMp	2	98
Low	Yes	Poor	None	50	50
Low	Yes	Poor	Wq	90	10
Low	Yes	Poor	Ow	10	90
Low	Yes	Poor	Mp	10	90
Low	Yes	Poor	WqOw	50	50
Low	Yes	Poor	WqMp	50	50
Low	Yes	Poor	OwMp	5	95
Low	Yes	Poor	WqOwMp	70	30
Low	No	Good	None	50	50
Low	No	Good	Wq	10	90
Low	No	Good	Ow	10	90
Low	No	Good	Mp	90	10
Low	No	Good	WqOw	5	95
Low	No	Good	WqMp	50	50
Low	No	Good	OwMp	50	50
Low	No	Good	WqOwMp	30	70
Low	No	Poor	None	50	50
Low	No	Poor	Wq	90	10
Low	No	Poor	Ow	10	90
High	Yes	Poor	WqOw	95	5
High	Yes	Poor	WqMp	50	50
High	Yes	Poor	OwMp	50	50
High	Yes	Poor	WqOwMp	70	30
High	No	Good	None	50	50
High	No	Good	Wq	10	90
High	No	Good	Ow	90	10
High	No	Good	Mp	90	10
High	No	Good	WqOw	50	50
High	No	Good	WqMp	95	5
High	No	Good	OwMp	95	5
High	No	Good	WqOwMp	70	30
High	No	Poor	None	50	50
High	No	Poor	Wq	90	10
High	No	Poor	Ow	90	10
High	No	Poor	Mp	90	10
High	No	Poor	WqOw	95	5
High	No	Poor	WqMp	95	5
High	No	Poor	OwMp	95	5
High	No	Poor	WqOwMp	98	2

Coral Reef Health is multiplied by *Coral Eco. Services*, a discrete variable with probabilities set at 25% that they are low, 50% that they are medium, and 25% that they are high. *Coral Eco. Services* can be influenced by a node *Coral Eco. Services Research*, a discrete variable that allows for the possibility of testing the effects of different research outcomes for *Coral Eco. Services*, and updating prior probabilities based on new evidence.

Marine Protect (MPAs), an input into both *Comm. & Rec Fishing* and *Coral Reef Health*, is one of the five management options included in the model. *Marine Protect (MPAs)* is a discrete variable and can be either applied (Yes = 100%) or not (No = 100%). Implementation of MPAs is believed to increase the probabilities that coral reef health and fishing are good.

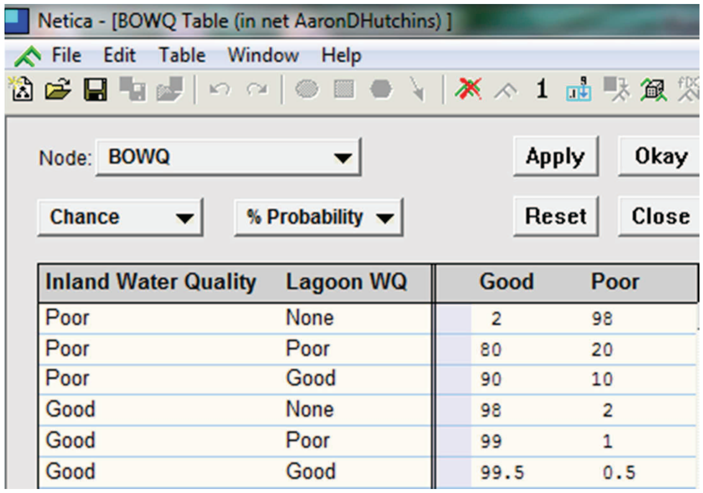
Ocean Warm/Acid, an input into both *Comm. & Rec Fishing* and *Coral Reef Health*, is a discrete variable and can be either high or low. Left to chance these probabilities are set at 50% that it is low and 50% that it is high.

Bay & Ocean Water Quality, an input into *Coral Reef Health,* is a discrete variable and can be either poor or good. *Inland Water Quality* and *Lagoon WQ* (water quality) are the inputs that influence the level of bay water quality. As the probability that inland and lagoon water quality are good increase, the probability that bay water quality will be good also increases. *Lagoon WQ* is a discrete variable and can be either None (if the node is not activated), poor, or good. This node is only activated when the management option, *Restore Lagoon*, is implemented. *Restore Lagoon*, is a discrete variable and can be either applied (Yes = 100%) or not (No = 100%). Restoring the lagoon is believed to increase the probability that bay and ocean water quality will be good if inland water quality is not too poor. The following is the data table in Netica for *Lagoon WQ* for Participant A:



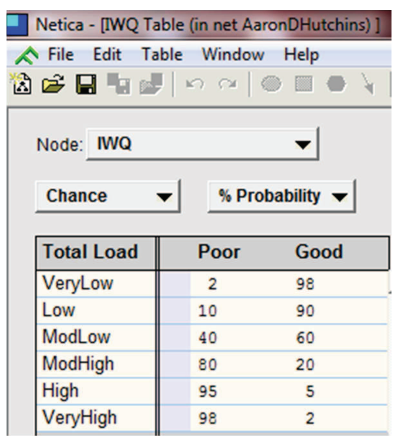
Restore Lagoon?	Inland Water Quality	None	Poor	Good
Yes	Poor	0	90	10
Yes	Good	0	1	99
No	Poor	100	0	0
No	Good	100	0	0

The following is the data table in Netica for *Bay & Ocean Water Quality* for Participant A:



Inland Water Quality	Lagoon WQ	Good	Poor
Poor	None	2	98
Poor	Poor	80	20
Poor	Good	90	10
Good	None	98	2
Good	Poor	99	1
Good	Good	99.5	0.5

Inland Water Quality, an input into *Lagoon WQ* and *Bay & Ocean Water Quality*, is a discrete variable and can be either poor or good. *Total Load* is the main input into *Inland Water Quality*. The following is the data table in Netica for *Inland Water Quality* for Participant A:



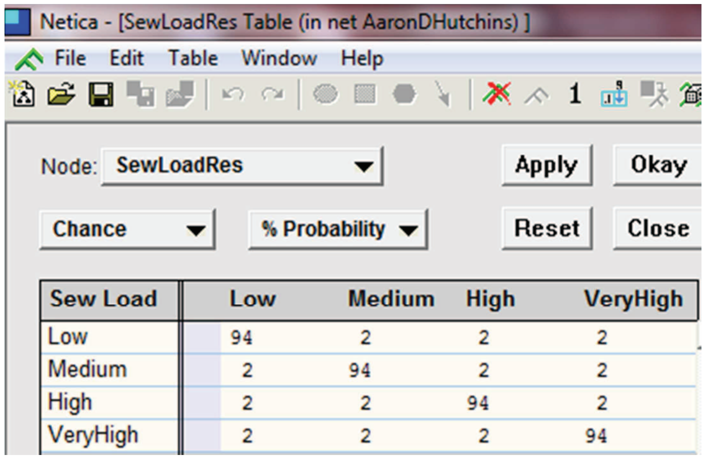
Total Load	Poor	Good
VeryLow	2	98
Low	10	90
ModLow	40	60
ModHigh	80	20
High	95	5
VeryHigh	98	2

Total Load, the total pollution load, is a continuous variable distributed over six intervals (very low, low, moderately low, moderately high, high and very high) and a function of individual loading sources (*SewLoad*, *AgLoad*, and *DevLoad*) and their associated hypothetical reductions (*SewRed*, *AgRed*, and *DevRed*) (management options), as shown in the following equation:

$$Total\ Load = SewLoad \times \left(1 - \frac{SewRed}{100}\right) + AgLoad \times \left(1 - \frac{AgRed}{100}\right) + DevLoad \times \left(1 - \frac{DevRed}{100}\right)$$

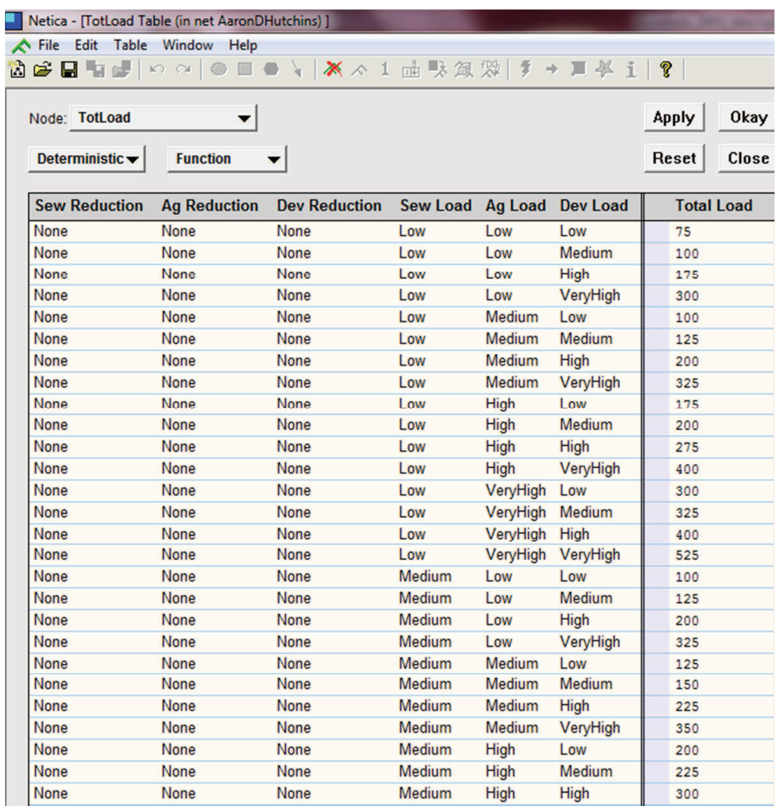
SewLoad, AgLoad, and DevLoad are discrete variables and can be low, medium, high, or very high. Loadings distributions for the individual sources were computed over the low, medium, high, and very high in a manner that minimized variance based on stakeholders' prior beliefs. As the distributions tend toward the very high, the total load tends toward the very high. Loadings values included in the model are relative (and therefore unitless) though roughly scale to mg/L concentrations of suspended solids in unpolluted source waters (very low = 0-25; low = 25-50), moderately polluted source waters (moderately low = 50-125; moderately high = 125-250) and highly polluted source waters (high = 250-500; very high = 500-750). The range of values used for *TotalLoad* of 0 to 750 was thought to allow for a more realistic distribution (with six intervals from low to very high) than would a smaller range. Since the analysis is of a comparison of benefits, the actual units used are not important.

SewLoad, *AgLoad*, and *DevLoad* can be influenced by the nodes *Sew Load Research*, *Ag Load Research*, and *Dev Load Research*, which are discrete variables with four possible outcomes each, and which allow for the possibility of testing the effects of different research outcomes, and updating prior probabilities based on new evidence. The following table in Netica for *SewLoad* shows the likelihood functions (false+/false- rates) for Participant A (they indicate that the research is nearly perfect, with the probability that the correct inference is made equal to 94%):



Sew Load	Low	Medium	High	VeryHigh
Low	94	2	2	2
Medium	2	94	2	2
High	2	2	94	2
VeryHigh	2	2	2	94

The management options, *SewRed*, *AgRed*, and *DevRed*, are discrete variables and can be set to a 0% (None), 40%, 70% or 90% reduction. The following is the first and last parts of the lengthy data table in Netica for *TotalLoad* for Participant A:



Sew Reduction	Ag Reduction	Dev Reduction	Sew Load	Ag Load	Dev Load	Total Load
None	None	None	Low	Low	Low	75
None	None	None	Low	Low	Medium	100
None	None	None	Low	Low	High	175
None	None	None	Low	Low	VeryHigh	300
None	None	None	Low	Medium	Low	100
None	None	None	Low	Medium	Medium	125
None	None	None	Low	Medium	High	200
None	None	None	Low	Medium	VeryHigh	325
None	None	None	Low	High	Low	175
None	None	None	Low	High	Medium	200
None	None	None	Low	High	High	275
None	None	None	Low	High	VeryHigh	400
None	None	None	Low	VeryHigh	Low	300
None	None	None	Low	VeryHigh	Medium	325
None	None	None	Low	VeryHigh	High	400
None	None	None	Low	VeryHigh	VeryHigh	525
None	None	None	Medium	Low	Low	100
None	None	None	Medium	Low	Medium	125
None	None	None	Medium	Low	High	200
None	None	None	Medium	Low	VeryHigh	325
None	None	None	Medium	Medium	Low	125
None	None	None	Medium	Medium	Medium	150
None	None	None	Medium	Medium	High	225
None	None	None	Medium	Medium	VeryHigh	350
None	None	None	Medium	High	Low	200
None	None	None	Medium	High	Medium	225
None	None	None	Medium	High	High	300

…

Ninety	Ninety	Ninety	High	Medium	Medium	22.5
Ninety	Ninety	Ninety	High	Medium	High	30
Ninety	Ninety	Ninety	High	Medium	VeryHigh	42.5
Ninety	Ninety	Ninety	High	High	Low	27.5
Ninety	Ninety	Ninety	High	High	Medium	30
Ninety	Ninety	Ninety	High	High	High	37.5
Ninety	Ninety	Ninety	High	High	VeryHigh	50
Ninety	Ninety	Ninety	High	VeryHigh	Low	40
Ninety	Ninety	Ninety	High	VeryHigh	Medium	42.5
Ninety	Ninety	Ninety	High	VeryHigh	High	50
Ninety	Ninety	Ninety	High	VeryHigh	VeryHigh	62.5
Ninety	Ninety	Ninety	VeryHigh	Low	Low	30
Ninety	Ninety	Ninety	VeryHigh	Low	Medium	32.5
Ninety	Ninety	Ninety	VeryHigh	Low	High	40
Ninety	Ninety	Ninety	VeryHigh	Low	VeryHigh	52.5
Ninety	Ninety	Ninety	VeryHigh	Medium	Low	32.5
Ninety	Ninety	Ninety	VeryHigh	Medium	Medium	35
Ninety	Ninety	Ninety	VeryHigh	Medium	High	42.5
Ninety	Ninety	Ninety	VeryHigh	Medium	VeryHigh	55
Ninety	Ninety	Ninety	VeryHigh	High	Low	40
Ninety	Ninety	Ninety	VeryHigh	High	Medium	42.5
Ninety	Ninety	Ninety	VeryHigh	High	High	50
Ninety	Ninety	Ninety	VeryHigh	High	VeryHigh	62.5
Ninety	Ninety	Ninety	VeryHigh	VeryHigh	Low	52.5
Ninety	Ninety	Ninety	VeryHigh	VeryHigh	Medium	55
Ninety	Ninety	Ninety	VeryHigh	VeryHigh	High	62.5
Ninety	Ninety	Ninety	VeryHigh	VeryHigh	VeryHigh	75