Uncertainty in the Tracking and Analysis Framework Integrated Assessment: The Value of Knowing How Little You Know

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Integrated assessment models have the potential to provide a wealth of information on linked environmental and economic systems. By incorporating the latest models of energy markets and regulatory frameworks, environmental processes and effects, and economic costing and valuation, an integrated assessment allows the modeler to thoroughly investigate all dimensions of an issue in a sophisticated and powerful manner. As a model grows in size and complexity, issues of model robustness and proper interpretation of results become increasingly important. While models of environmental-economic systems are, by definition, inexact, few modelers attempt to bound their model results with confidence intervals or other estimates of model precision. Such estimates are invaluable in providing modeler and model interpreter alike with information on model result robustness and applicability.

The Tracking and Analysis Framework (TAF) team has created a model to estimate the economic and ecological effects of the 1990 Clean Air Act Amendment, Title IV. TAF has been coded in the Analytica modeling environment. Analytica allows model variables to be represented as ranges of values, defined as probability distributions. Using Monte Carlo techniques to propagate uncertain values through the model, model results can reflect the uncertainty in model inputs and construction. Rank correlations and elasticities can be computed to gauge model input parameter importance and model sensitivities.

These tools allow modelers to view model results in the proper context: Are model results invariant with respect to model component uncertainty and variability? They also help pinpoint the uncertain model components which most affect model results, and may therefore merit additional research to reduce overall model uncertainty.

In this paper, we describe the methods used to characterize uncertainty and variability in the TAF model. We also describe the related processes of uncertainty and sensitivity analysis in the TAF model, and relate the results of these processes back to the progressive refinement of the model itself. We use actual results from the Soils-Aquatics, Visibility, and Human Health modules to demonstrate the techniques described.

1. Introduction

Integrated Assessments have been used in a number of environmental modeling domains (Parson 1996, Rotmans 1996). The Tracking and Analysis Framework applies integrated assessment methods to the acid precipitation problem in North America. In this paper, we describe the methods used in the analysis of our integrated assessment model. We discuss options for the treatment of uncertainty in integrated assessment models, characterization of uncertainties, uncertainty analysis, and sensitivity analysis. The TAF project is documented extensively in a series of reports available on the TAF Web site: http://www.lumina.com/taflist. In these proceedings there are two other papers on the TAF project as a whole: 1) an introduction to the TAF project and its objectives, and 2) a description of the collaborative tools and process used to build TAF. Other papers in these proceedings summarize results from specific TAF modules.

2. Summary of TAF

The Tracking and Analysis Framework (TAF) is an integrated assessment of acid precipitation damages and the effects of Title IV of the 1990 Clean Air Act Amendment in reducing acid precipitation effects. TAF integrates component models of utility emissions and control costs, pollutant transport and deposition, effects on visibility, soils and aquatics ecosystems, and human health, and valuation of the costs and benefits of these effects. To ensure that each component represented the state of the science in its respective modeling domain., each of the models was constructed and refined by a group expert in that field. Thus, TAF is the work of a team of over 30 analysts and scientists from ten institutions around the US. Lumina Decision Systems was responsible for the overall design of the TAF architecture and the integration of the components. Extensive use of the internet, including the World Wide Web, facilitated communication and information exchange across the team. (cite other JAWMA paper).

Despite our ability to harness the latest modeling techniques in each domain, representing the current scientific understanding, we knew that there were multiple model domains where considerable uncertainty in parameter and model form still existed. Thus we selected a modeling environment (Analytica) capable of propagating model uncertainties, and a process designed to identify and characterize those uncertainties.

We chose an integrated assessment framework, as opposed to a suite of related but unlinked models, because of the ability of an integrated assessment to meet the needs of the TAF project:

- To provide comparable results across a variety of effects (visibility, aquatics, human health), for a common region (continental US), and over a single time horizon (1995-2030).
- To provide insight about model assumptions and components which contribute significantly to overall results.
- To suggest productive areas for future research and additional modeling based on an assessment of the current models critical uncertainties and omissions.

Rather than focus on the quantitative results of TAF in this paper, we've chosen to highlight our use of analytical techniques in the assessment to uncover important insights about the character of the model results. We hope TAF will serve as an example of the analysis possible when integrated assessment methodologies are used.

3. Approach to representation and analysis of uncertainty

The TAF model has approximately 1000 variables, many of which are multidimensional arrays of values. Each variable may contain data (as a scalar or table) or a formula based on other variables' values. TAF's integrated design and large size underscore the need for detailed analysis of the model results and their dependency on model characteristics and assumptions. We used Monte Carlo techniques to propagate uncertainty and variability through the model. Median Latin Hypercube sampling was used, with a sample size of 25.

3.1 Types of Uncertainty

To say that a model 'incorporates uncertainty' will mean different things to different people. We incorporate probabilistic variables in TAF to represent **uncertain values** or relationships: quantities that we cannot measure accurately, quantities that vary across some unaccounted for domain, and to adjust model forms which do not precisely reflect empirical measurements.

Variable quantities are uncertain because their value varies, seemingly stochastically, over some dimension, usually time. For example rainfall in Toledo varies from year to year, based on climatological and meteorological drivers. We can empirically measure the historical value of this quantity, and use its historical variability to characterize our uncertainty about its value in future periods. Some of the quantities considered variable in TAF are day to day (meteorological) fluctuations in relative humidity, and year to year (climatological) fluctuations in transport of pollutants. A key aspect of variability is that it diminishes as use increase the length of the period over which you are averaging.

Uncertainty in model parameters can be based on expert judgment or on empirical estimates of a parameter's value. Such values are uncertain because of measurement error due to an incomplete sample, imperfect measurement equipment, or other difficulties in measurement. Parameters in concentration-response functions in the health module typify this type of uncertainty.

Uncertainty in model functional forms can be based on subjective, expert judgment or on validations of the model against empirical data. In either case the imprecision in model results can be represented with an error term that modifies the model result to produce a range of plausible values. For example, the aquatics module includes terms representing uncertainties in the relationship between acid neutralizing capacity and alkalinity, based on the standard errors of regression coefficients used to define the relationship.

Uncertainty in reduced model forms are based on comparisons of full-form with reduced-form model results. Some of the models in TAF are simplified versions of more complicated models (known as reduced-form models). Reduced-form model use is appropriate when the uncertainty in the full-form model is significantly greater than the uncertainty added through the use of the reduced-form model in its place. For example, the aquatics module contains terms representing the error in the fit of the reduced-form lake calcium model to the MAGIC calcium model.

Both types of uncertainty exist in TAF. We explicitly include probabilistic terms in each of the TAF modules to represent these uncertainties. For example, a population estimate for California in 2010 of 38 million is replaced by a normal distribution with a mean of 38 million and a standard deviation of 1.5 million. When the model is evaluated, random draws from this distribution are used in the model in place of the mean estimate.

Including uncertainty is not a means of de facto validation; the TAF team still performed calibration and validation of their models. By adding terms representing known uncertainties, we hope to bound what

8. Re-evaluate the model inputs and their uncertainties based on results. Identify outputs that could benefit from reductions in uncertainty in specific inputs and model forms that could substantially benefit from reductions in uncertainty.

Note that this process can be applied to each module individually to assess the effects and importance of the uncertainties arising in each module, as well as to the integrated model as a whole to assess the effects and importance of uncertainties from each module on aggregate model results. When concentrating on a single module it is desirable to have estimates of the values and uncertainty of the key inputs from preceding modules - for example, the ambient atmospheric concentrations of pollutants for the visibility effects module and the human health effects modules, and the web and dry deposition of pollutants for the aquatic ecosystem effects module.

Because the model is coded in the Analytica modeling environment, we were able to use Monte Carlo modeling to propagate uncertainty and variability of both model inputs and model forms in TAF. Analytica allows probabilistic quantities to be expressed analytically, or using sample data to construct a custom distribution function. Figure 1 illustrates use of Analytica's function finder to construct a beta probability distribution.

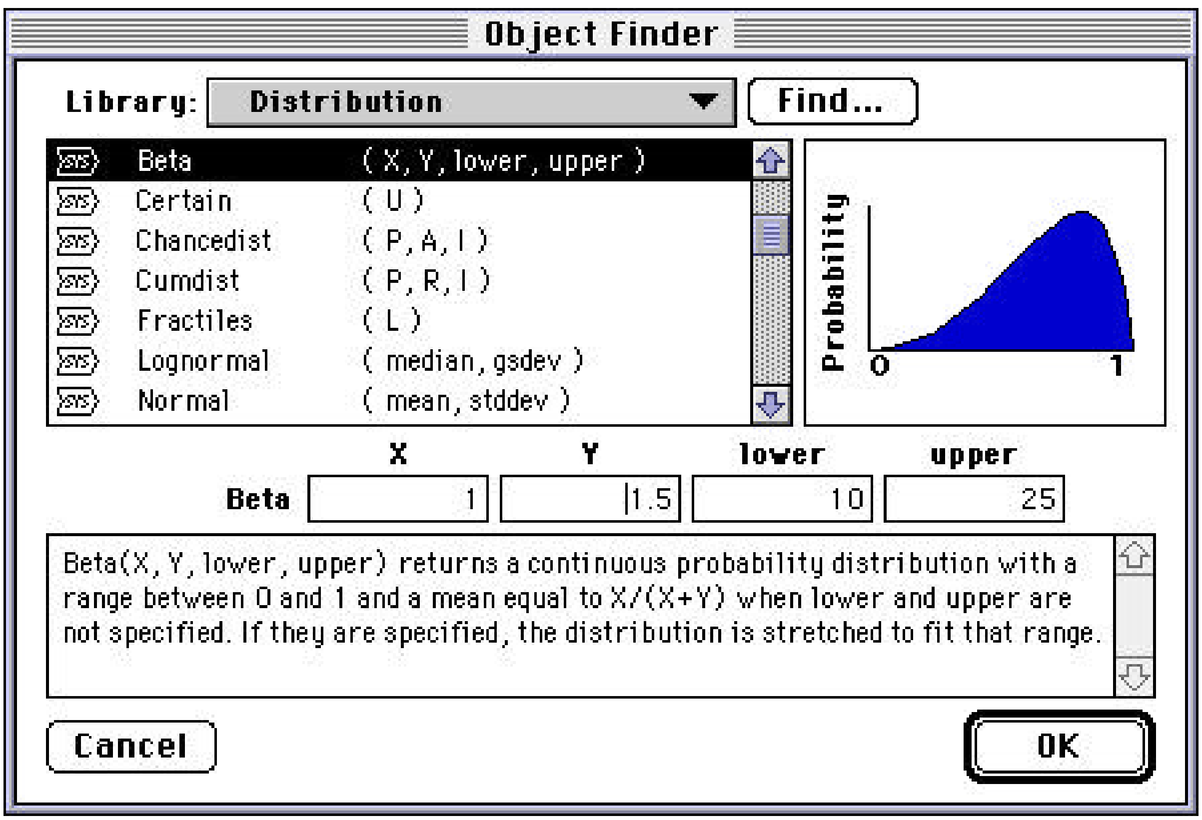


Figure 1. Analytica's object finder allows analytical specification of probability distributions.

3.3 Analytical Tools for Uncertainty in Integrated Assessments

Using the Analytica modeling environment, uncertain variables were defined as probability distributions. The Analytica software allows automated propagation of these distributions using Monte Carlo techniques. For the runs described in this paper we used Median Latin Hypercube Sampling, with a sample size of 25. (Morgan and Henrion 1992)

3.3.1 Analyze distributions of outputs

Because many of the inputs are defined as probability distributions, the associated model outputs are probability distributions. Analytica allows reporting of probabilistic model results using several different methods. Modelers can view a result's mean, standard deviation, median, minimum, and maximum values, a cumulative distribution or probability density function, as well as confidence intervals around the mean. To save space, we review results here with mean and standard deviation, or with 90% and 50% confidence intervals around the median, even though the other characterizations are available within the model.

With estimates of output uncertainty, we can review the model results in a new light: Does the uncertainty in any result change its robustness or associated policy implications?

3.3.2 Calculate sensitivity of outputs to inputs

For a particular output, it is useful to determine which inputs wield the greatest influence on its value. After calculating the outputs themselves, we perturb the inputs and observe the change in the outputs. We show the results of these calculations for some inputs in the following section on visibility effects.

3.3.3 Calculate importance of input variability to output variability

After incorporating uncertainty into model forms and inputs, a key question is: "Where did the uncertainty come from?" Importance analyses allow us to examine the correlation between uncertainty in inputs and the resulting uncertainty in outputs. To avoid distortions in importance analyses due to nonmonotonic relationships (often caused by nonnormal input distributions) we rank the input and output results by sample and calculate the correlation of the ranks across inputs and outputs. (Iman and Conover 1980) These rank correlation analyses provide values from 0 to 1, with higher numbers indicating greater input variable uncertainty effect on output variable uncertainty. Given the sample sizes used in TAF for rank correlation calculations, we can be confident that values above 0.2 indicate a significant (at the 95% confidence level) correlation between inputs and outputs.

4. The Model Framework

The effects modules are driven by the pollutant ambient concentration and deposition data calculated by the pathways module, which in turn receives state-level emissions data from the emissions module. We describe those modules here only briefly. The interested reader is directed to the TAF documentation on the TAF World Wide Web site (http://www.lumina.com/taflist) for more detailed documentation, as well as a fully functional version of the model itself.

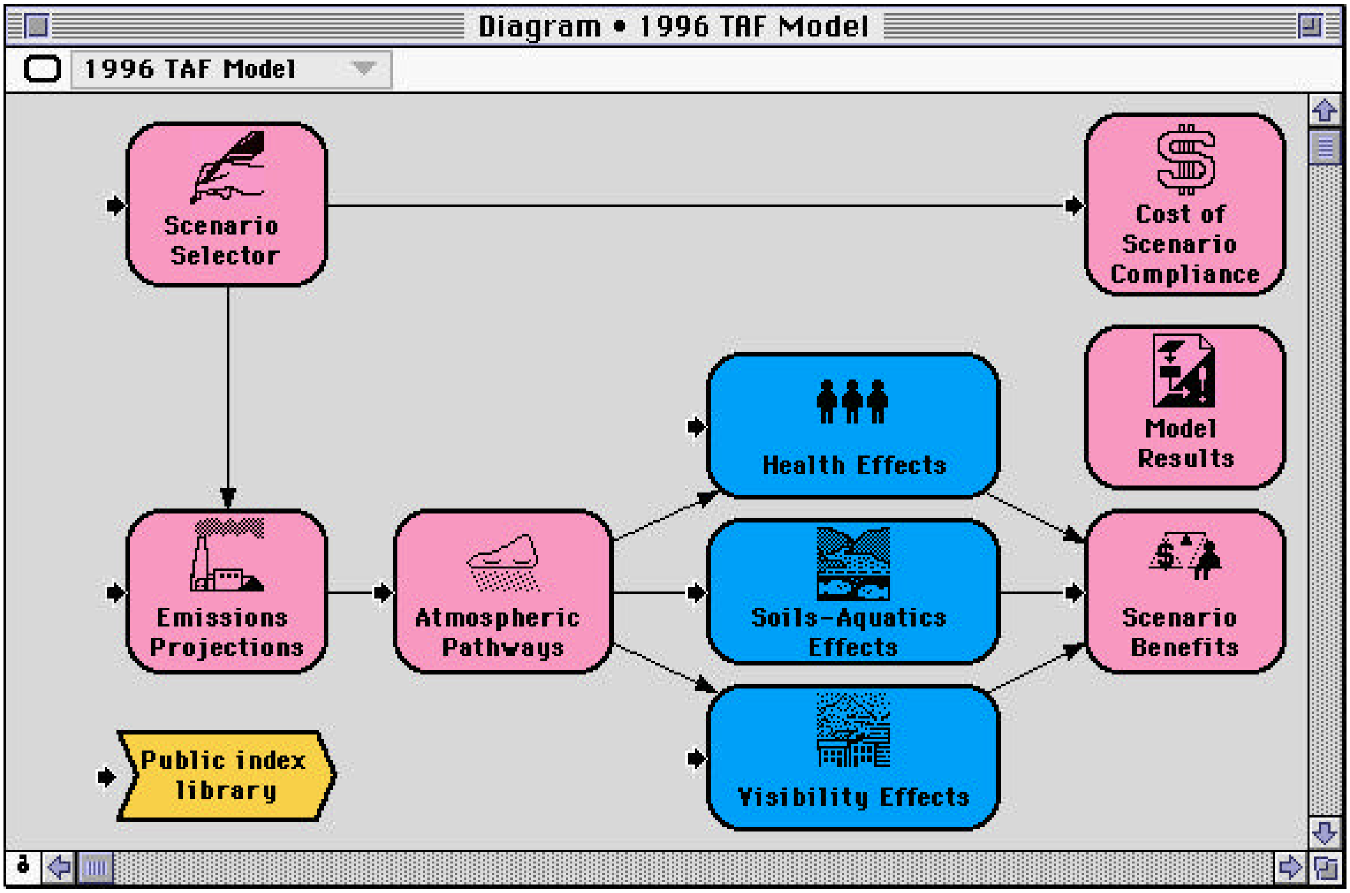


Figure 2. Screenshot from Analytica showing top-level of the TAF model.

5. Emissions Module

The emissions module, developed at Argonne National Laboratory, utilizes a least cost abatement selection algorithm, together with a unit-level abatement cost database, to estimate the abatement costs associated with the tenets of Title IV of the Clean Air Act Amendment. A limited number of abatement options are offered for each unit, including scrubbing, fuel switching, and blending low- and high- sulfur coals. Some NOx controls are also applied to boilers, although regulations for these controls follow Title IV. The NOx control algorithms cannot be modified by policy options current available in TAF.

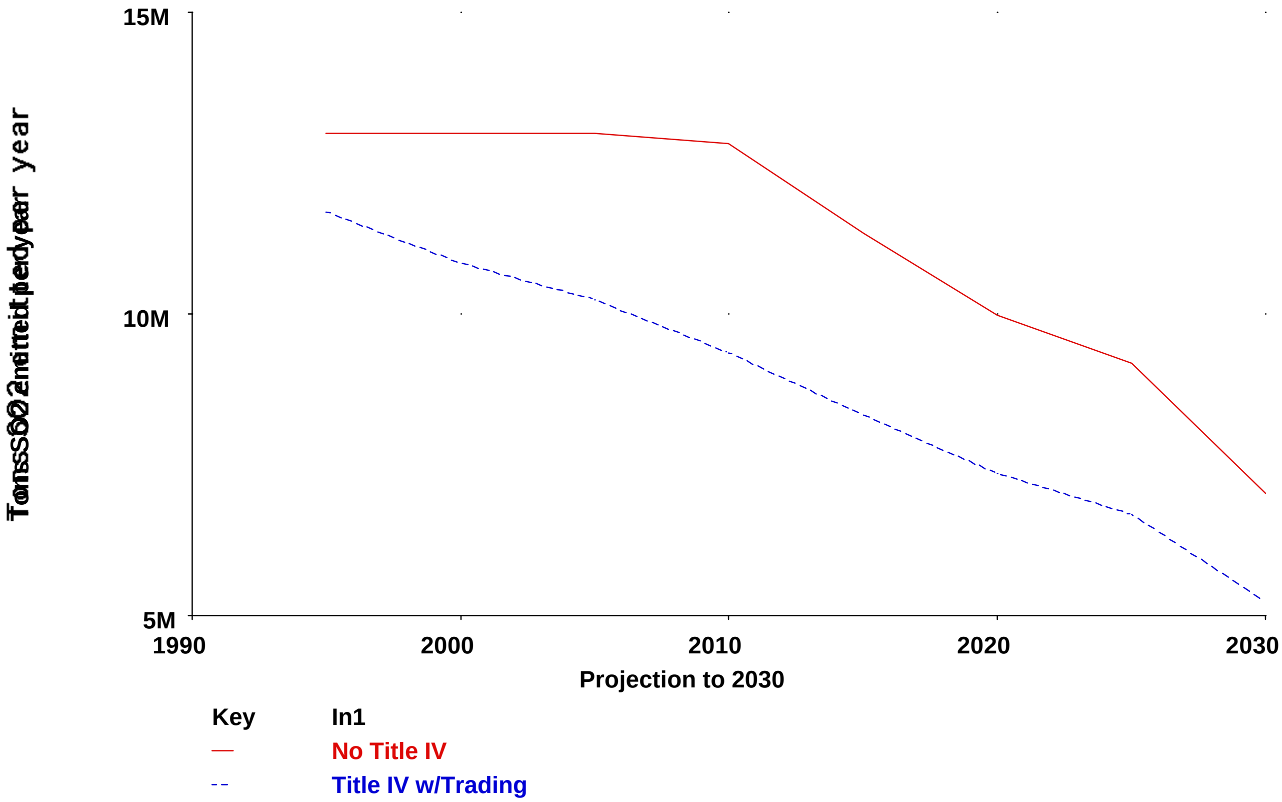


Figure 3. National Utility SO_2 Emissions. Title IV (comparison) emissions vs. emissions without Title IV (baseline). 1% annual load growth, 60 year average plant retirement age.

Figure 3 illustrates North American utility SO2 emissions under two scenarios: one assuming implementation of Title IV of the Clean Air Act, and one assuming pre-1990 regulation is upheld for existing sources.

The emissions model incorporated in this version of TAF utilizes parametric analysis to locate critical model sensitivities to selected inputs. Plant retirement age and demand growth are treated parametrically, using retirement ages of 50, 60 and 70 years, and national electricity demand growth of 1 and 3%. Initial analyses of the emissions model suggest that both parameters have little effect on emissions in the next 10 years. Younger retirement ages dramatically reduce emissions at the end of the study period by bringing more new, cleaner plants on-line, this reduces the effect, and importance of the Title IV regulations. By 2025, emissions reductions due to Title IV are nearly zero if a uniform 50 year rather than a uniform 60 year retirement age is assumed. Assuming a 60-year retirement age instead of a 70 year reitrement age decreases 2025 emissions reductions attributable to Title IV by 33%.

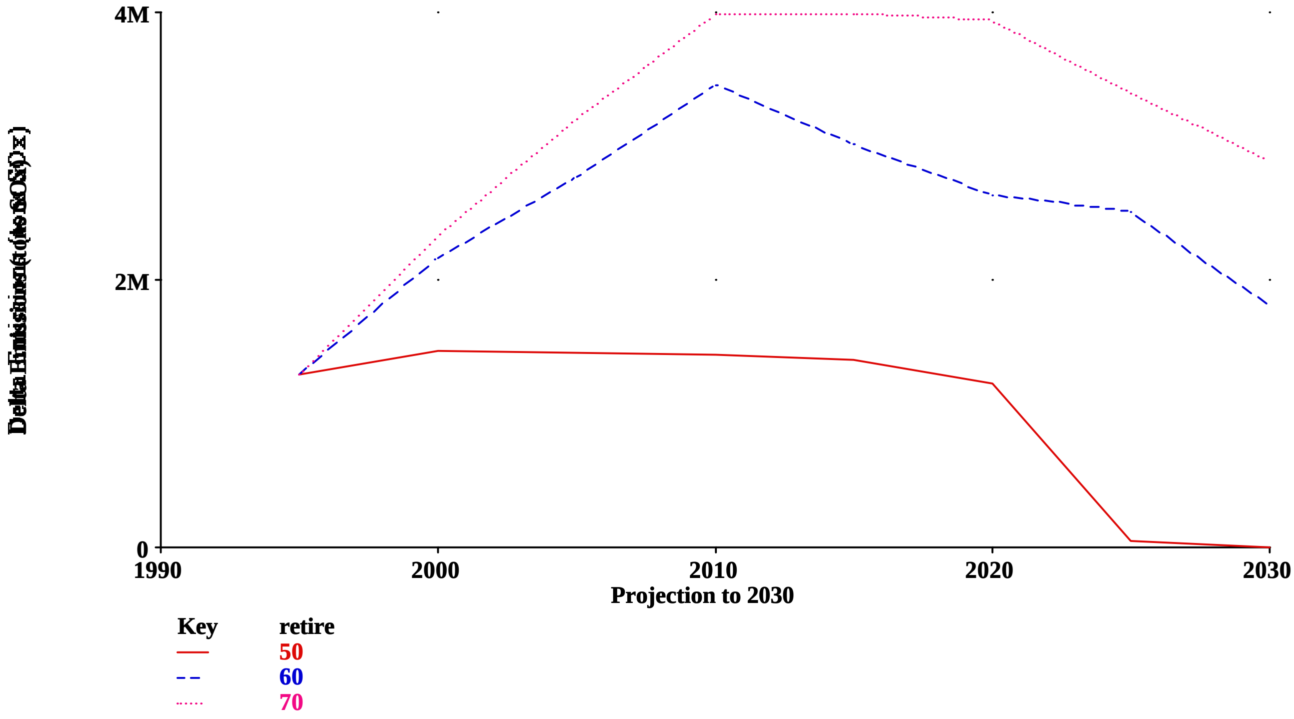


Figure 4. National SO_2 Utility Emissions reductions under CAAA Title IV given varying average plant retirement ages, 50-70 years.

Demand growth, on the other hand, has less of an effect on Title IV emissions reductions. Changes in emissions reductions are roughly proportional to growth rates.

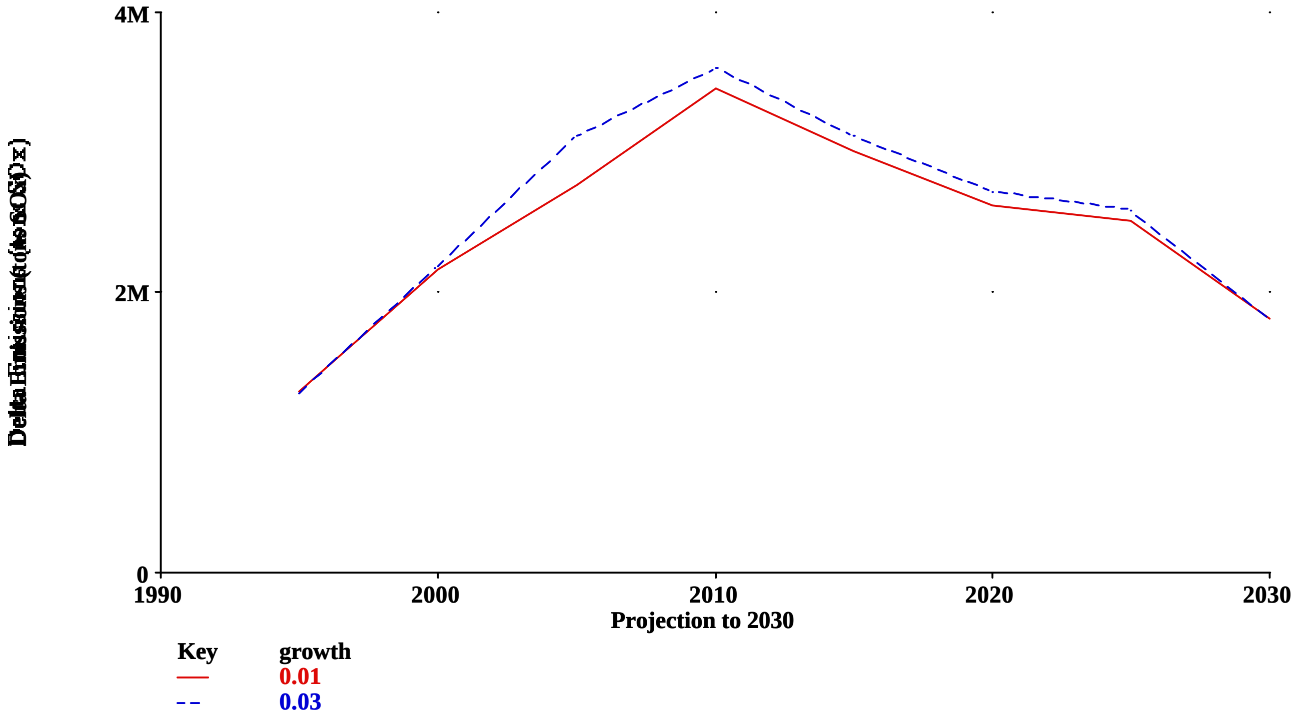


Figure 5. National SO_2 Utility Emissions reductions under the CAAA Title IV given varying demand growth rates, 1% and 3% per year.

Now that we have identified plant retirement age as a critical factor, it is important to consider what factors may affect that retirement rate. Exogenous factors, such as a transition to a competitive market for power, and new, inexpensive generation technologies will affect the retirement rate of plants currently on-line.

Because TAF is an integrated assessment, we can propagate these scenarios through the model and determine what effect if any, different retirement age assumptions have on reduced acid precipitation effects in the presence of Title IV regulations. We'll revisit this issue in a few sections to demonstrate the assessment integration.

The current emissions module is a very recent addition to the TAF model. In future analyses, additional parameterizations in the emissions module will be performed to discover additional critical model inputs and assumptions. Unless otherwise stated, all calculations described in this paper are driven by the Title IV vs. no Title IV scenarios, assuming 1% demand growth per year and an average plant retirement age of 60 years.

6. Pathways Module

The pathways module utilizes linear source receptor matrices to calculate seasonal ambient pollutant concentration and deposition estimates integrated over states and at a few selected point receptors, based on state-level emissions data from the emissions module. Because the TAF module is primarily concerned with annual averages of deposition and ambient pollutant concentration levels (a few exceptions are handled downstream in the assessment), a linear approximation of transport processes is appropriate.

The source-receptor matrices are from ASTRAP (Advanced Source Trajectory Regional Air Pollution model, TAF 1996). Using historical emissions data, the ASTRAP matrices have been validated against ambient concentration/deposition data. A set of 11 years of wind and precipitation data have been used in the model to estimate the variability of model results based on climatological variability. The resulting variability in ambient concentration and deposition estimates was then incorporated into the module to represent climatological variability. Normal distributions representing the annual variability of the source/receptor relationship are multiplied by the concentrations and depositions estimated at each receptor site.

This variability is significant when examining the baseline or Title IV pollutant concentrations alone, but when the Title IV concentrations are subtracted from the baseline concentrations to obtain an estimate of concentration reductions under Title IV, much of the year to year variability due to climatological differences is canceled out. Thus, we're left with estimates of ambient concentration reduction as shown in Figure 6. The climatological variability factored into the transport of pollutants has a measurable effect on reductions in pollutant concentrations, as demonstrated by the confidence interval surrounding the mean estimate of ambient pollutant concentration. In the following sections we'll compare this variability to other sources of variability and uncertainty that affect acid precipitation damage estimates.

Where possible, we extend these results to make general statements about the character of the modeling domain and productive areas of future acid precipitation research.

The TAF visibility module, developed by Argonne National Laboratory, is a variant of the Visibility Atmospheric Simulation Model (VASM) model developed by Ed

Table 1. Sources of uncertainty in visual range estimates

Variable	Coefficient of Variation (sd/mean)	Sensitivity of Result (dy/dx)	Uncertainty Importance (0-1.0)
Humidity	.15	27.9	0.32
Climatological Variability of S,N Species	.08	41.0	0.53
Climatological Variability of Other Species	.10	20.7	0.11
Meteorological Variability of all species	.80	80.0	0.89

The data compiled in Table 1 permits comparisons of the contributors to uncertainty in visual range improvements at Shenandoah National Park. The meteorological (day-to-day) variability is the most variable of the sources of uncertainty listed, as illustrated by its coefficient of variation. The results also suggest a strong influence of meteorological variability on the visual range result, as indicated by the (relatively) higher sensitivity of the visual range result to a small change in the meteorological variability value. Given these data, it follows that the meteorological variability is responsible for more of the variability in the visual range result than any other term, as indicated by the uncertainty importance estimate of 0.89.

8. Aquatics Effects: Ranking aquatics module uncertainties and valuation uncertainties

The aquatics module is a reduced form version of the MAGIC model. Using deposition data from the pathways module and Adirondack lake background data, the module calculates lake pH, acid neutralizing capacity, base saturation, fish species richness, and fish acid stress indexes for 33 Adirondack lakes. The module has been calibrated to data and results from the MAGIC model, and performs comparably, despite its much more modest computational requirements.

For this discussion we will limit our focus to the Acid Stress Index (ASI). The ASI (also known as the conditional mortality rate) is a common estimate of the loss of fish species in an acidified lake (Baker et al. 1990). The ASI is an estimate of the increased likelihood that a fish of a given life stage will die when exposed to the specified water quality conditions, over and above the mortality expected in a circumneutral reference water. Higher numbers indicate higher stress and increased likelihood of death. The benefits module in TAF uses the acid stress index computed at the Adirondack lake sites, for three fish species, to estimate the catch per unit of effort expended by recreational fishermen. Figure 8 contains the Rainbow Trout ASI results for a single Adirondack Lake in the presence and absence of Title IV regulation.

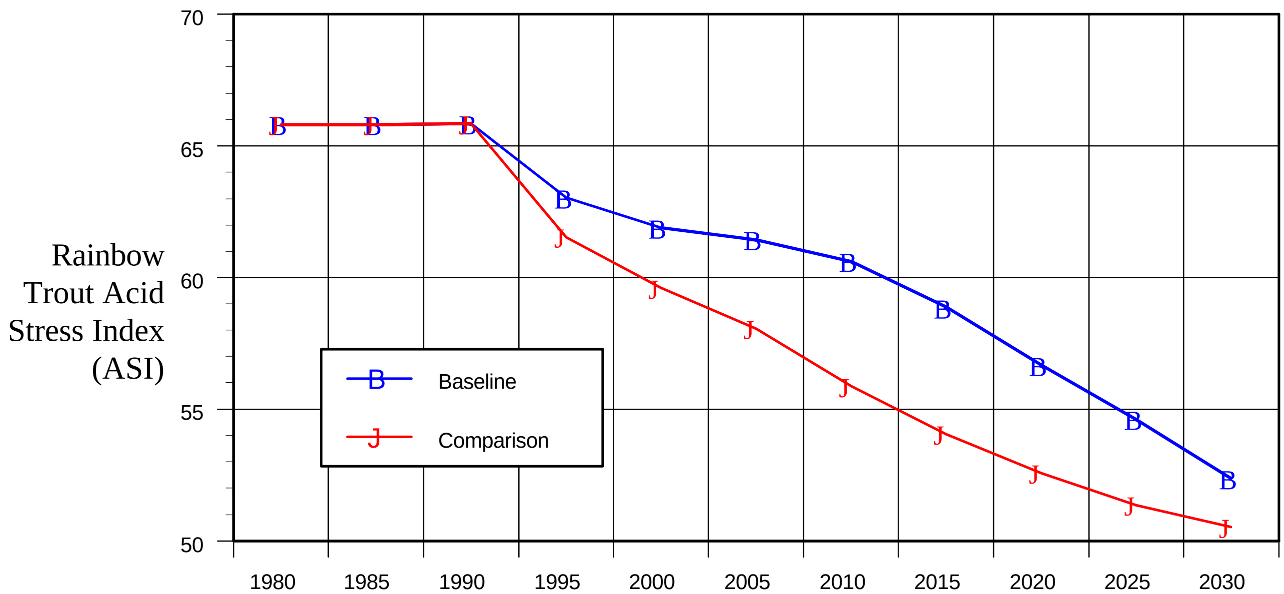


Figure 8. Rainbow Trout Acid Stress Index for an Adirondack Lake. Title IV (comparison) vs. No Title IV (baseline).

The estimates of ASI in Figure 8 are bounded by some uncertainty, as defined in the transport module and the aquatics module. Figure 9 shows median, 50% and 90% probability intervals for the difference in ASI reductions between the Title IV and no Title IV scenarios, as shown in Figure 8.

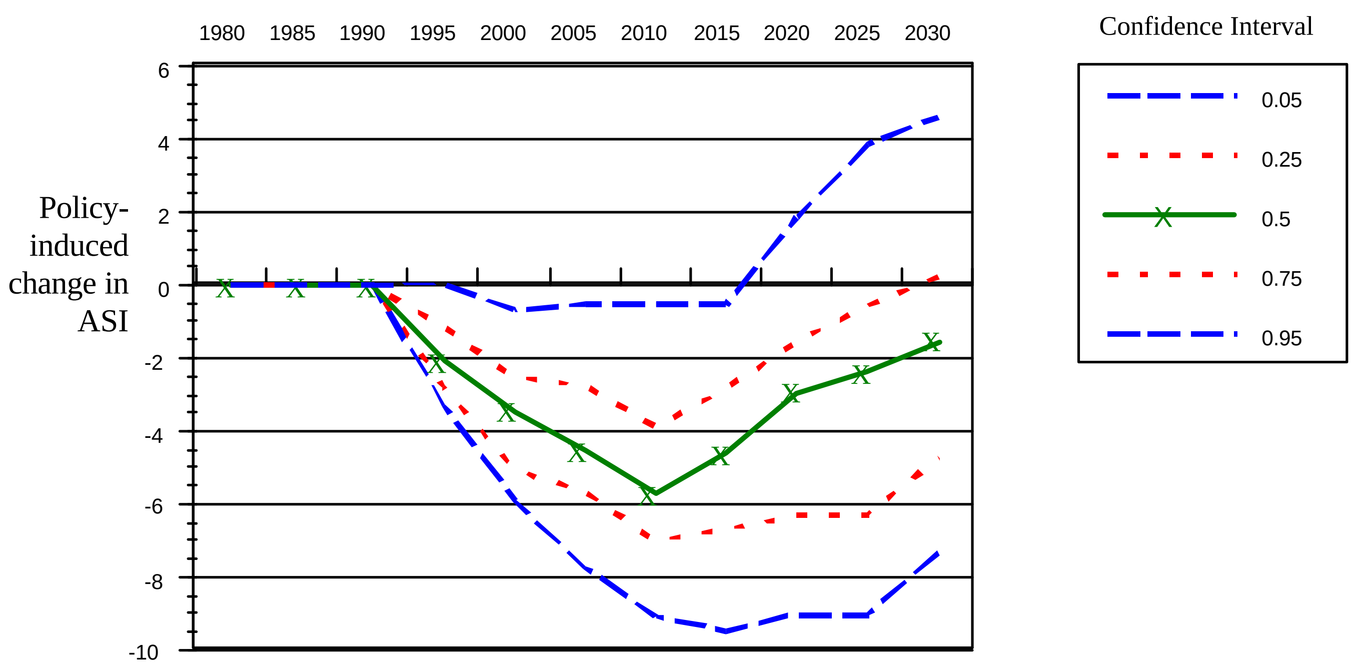


Figure 9. Title IV induced change in Acid Stress Index for Rainbow Trout.

The uncertainty around the ASI term includes a fraction above zero, indicating that, when the uncertainty in the aquatics modeling and natural climatological variability is taken into account, we cannot guarantee a reduction in the Acid Stress Index. That said, the chance of a non-zero, favorable change in ASI (i.e., a reduction) is quite large. Now we can use an importance analysis to compare the relative contributions of the uncertainties in the model to the ASI results. The uncertainties affecting the ASI include:

- Uncertainty in deposition from the pathways module. This is similar to the climatological variability in the visibility module, except it is expressed as cumulative acidic deposition instead of annual ambient concentration.
- Uncertainties in the fit between the MAGIC model and empirical data. There are four components to this uncertainty: uncertainty in the estimation of lake calcium concentrations, uncertainty in the estimation of acid neutralizing capacity, uncertainty in the estimation of lake pH from acid neutralizing capacity, and uncertainty in the estimation of ASI from lake pH (described with four parameters).
- Uncertainties in the fit between the reduced-form model (RFM) version in TAF and MAGIC itself. There are two components to this uncertainty: uncertainty in the estimation of lake calcium concentrations, and uncertainty in the estimation of lake acid neutralizing capacity.

The RFM and MAGIC uncertainties were quantified from the results of linear and nonlinear regressions. Climatic variability was quantified by measuring variability in ASTRAP deposition results using historical wind trajectory data from 11 separate years. These sources of uncertainty are ranked using an importance analysis. The results of the Analysis are shown in Figure 10.

deposition. Because the overarching uncertainties in MAGIC dominate the uncertainty in the result, we conclude that the reduced-form version of MAGIC within TAF performs comparably to MAGIC.

Note also that the climatological variability is not large compared to some of the other uncertainties. This is true in part because much of the climatological uncertainty is canceled out when one takes the difference of baseline and comparison scenario results. The climatological uncertainty is the same across the two scenarios, so it is reduced when the difference of the two scenarios is taken.

This analysis identifies the conversion of pH to ASI and of ANC to pH as critical sources of uncertainty in the aquatics module. The conversion of ANC to pH is accomplished using a four parameter non-linear equation based on work by Small and Sutton (1986), calibrated to data for the 33 Adirondack lakes considered in TAF. Whether this source of uncertainty should be refined and reduced in future versions of the aquatics module depends on the effect of this uncertainty in calculation of aquatics benefits.

The Benefits module converts ASI values for the 33 Adirondack lakes in the Aquatics module into monetary benefits estimates for recreational fishermen. The calculation of benefits is accomplished using data on the relationship between ASI and fish catches per unit effort. These improvements in catches per unit effort are valued using fishermen's stated value of their fishing catch. The results of these calculations, together with the uncertainty associated with the monetary benefits estimate, is given in Figure 11.

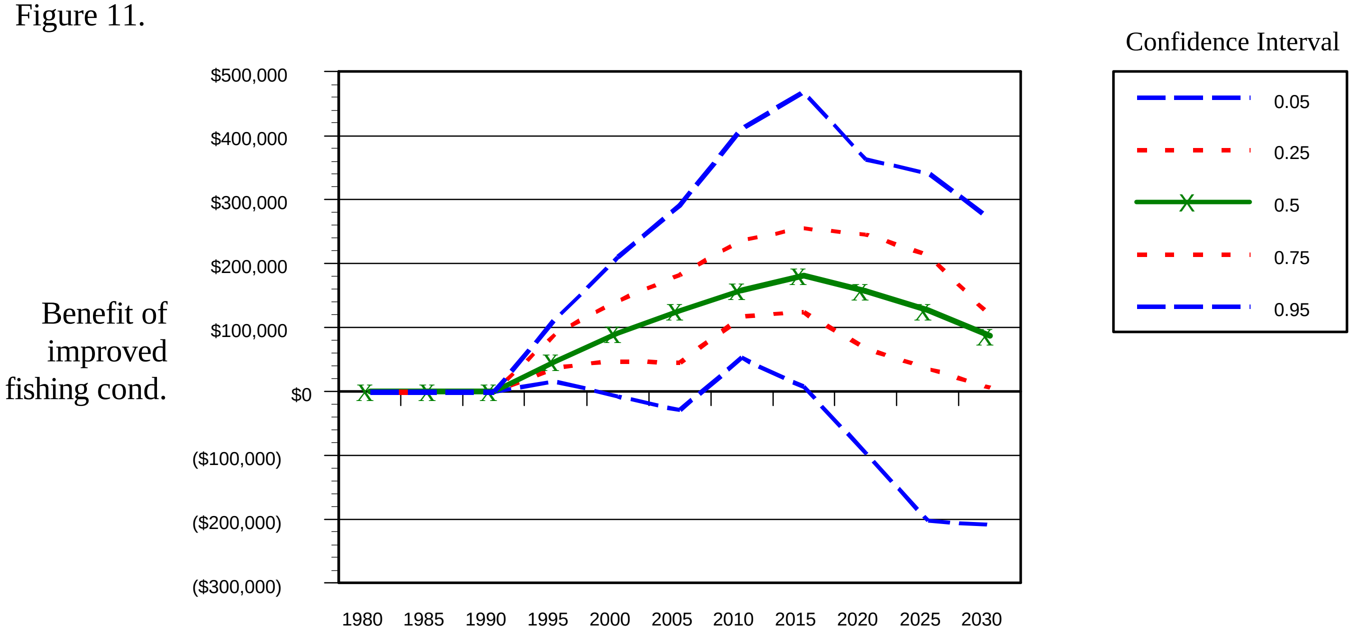


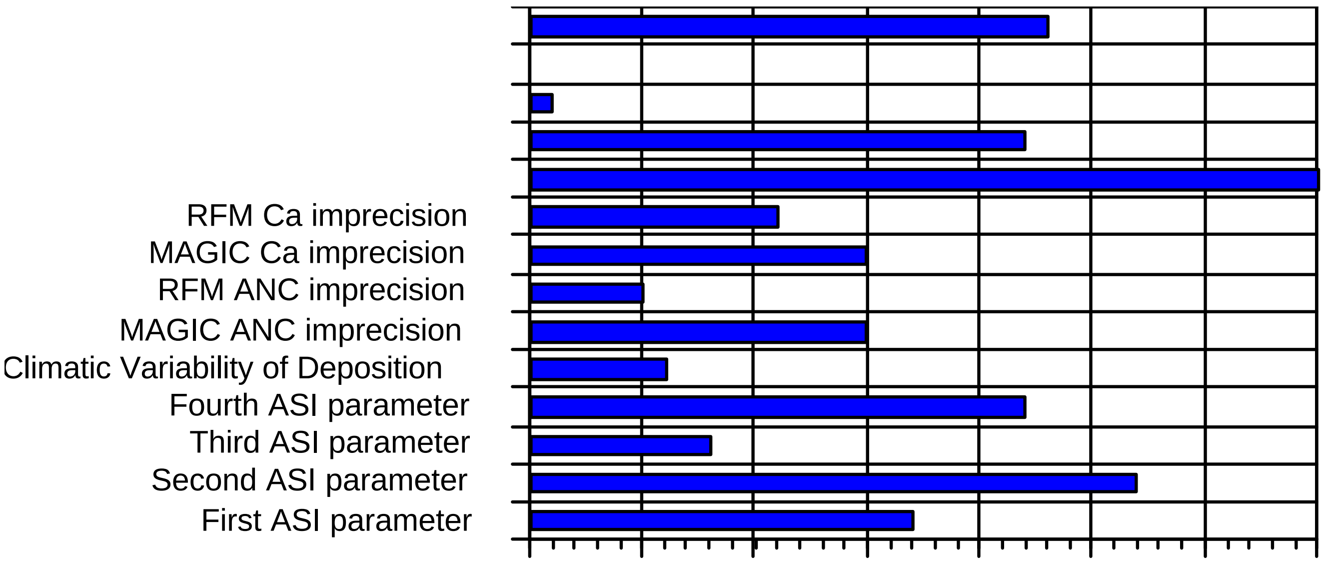
Figure 11. Benefits of increased fish catches in Adirondack lakes following Title IV implementation.

For local fishermen in the region surrounding the Adirondack lakes, model results suggest a sizable benefit for Title IV exists. However, this benefit is bounded by considerable uncertainty. These uncertainties include those already discussed in the Aquatics module, joined by a new set of uncertainties in the valuation of benefits calculations. The valuation uncertainties include:

- Uncertainty in the relation between the ASI and the catch per unit effort (CPUE).
- The fishermen's stated value of each unit of improvement in the catch per unit effort.

- The number of anglers in the Adirondack region and the number of angler-days annually.

The uncertainties in the ASI-CPUE relation and the value of increases in CPUE were derived from fits of each relation to the data used to derive that relation. Anglers and angler-day estimates were based on exponential extrapolations of 1988 angler data using census data. Historical interstate differences in population growth were used to estimate uncertainty in angler growth projections. The rank correlations of these uncertainties' influence on the aquatics benefit estimate are given in Figure 12.



- The projected estimate of the exposed population
- The variability in ambient pollutant concentrations due to climatological factors

Examining the outcome of a single mortality study encoded within TAF provides an illustration of these uncertainties. Figure 13 provides an estimate of reductions in mortality in New York state due to the implementation of Title IV.

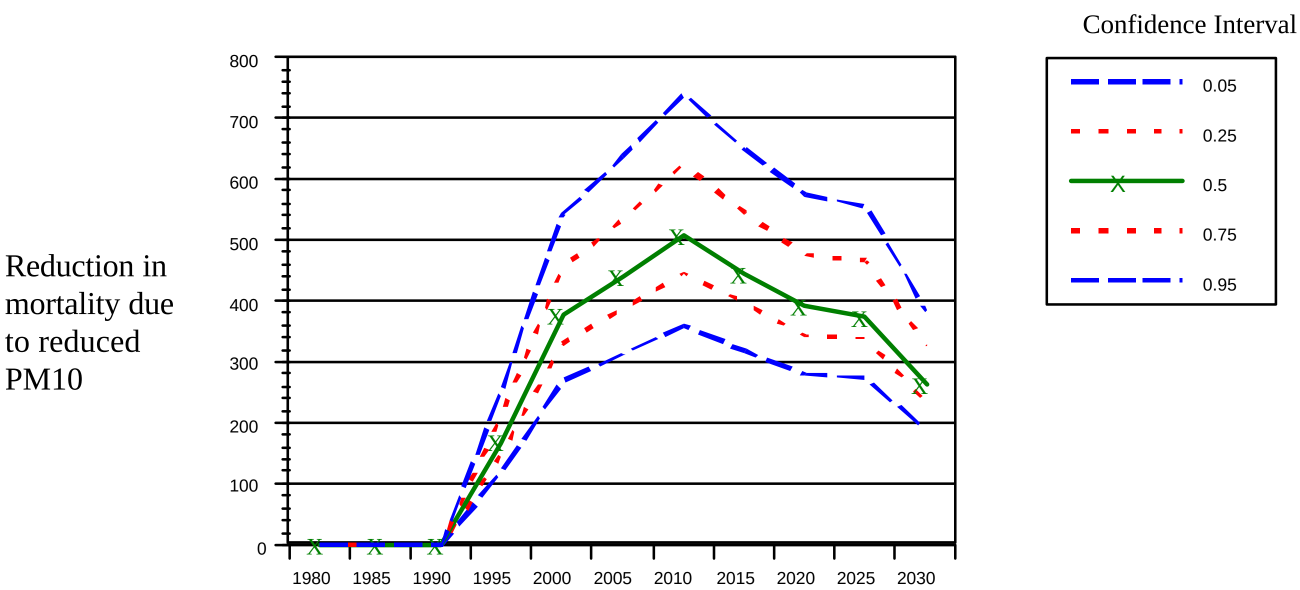


Figure 13. Annual reduction in mortality due to PM10 reductions from Title IV.

In the result illustrated in Figure 13, the concentration response relationship and associated uncertainty is from a study by Pope et al. (1995). How much of the uncertainty in the mortality reduction estimate stems from uncertainty in the concentration-response function? Conducting an importance analysis allows us to compare the contributions of the uncertain inputs, as shown in Figure 14.

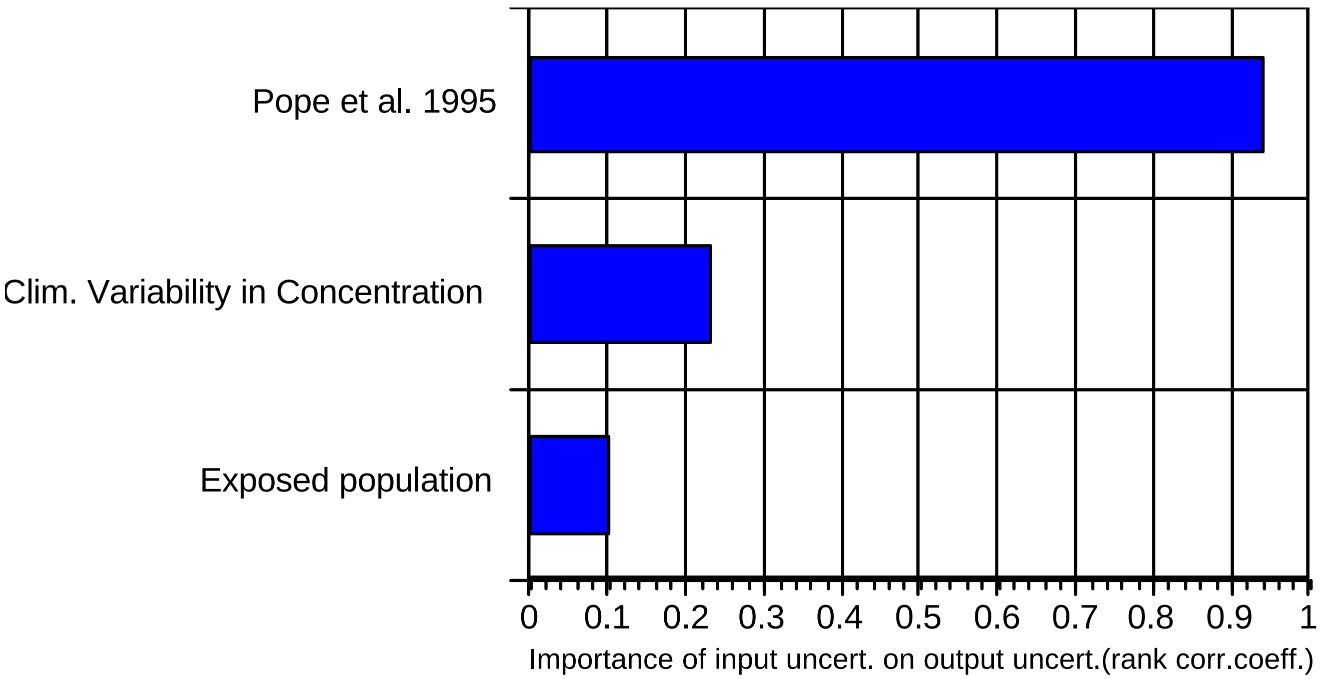


Figure 14. Importance of uncertain inputs on mortality incidence estimate.

The concentration response function contributes more uncertainty than climatological variability or uncertainty in population projections. When we follow the mortality result into the benefits module and investigate the uncertainty surrounding a monetary estimate of mortality benefits, uncertainty in the concentration response function is less critical than uncertainty in the value of a statistical life.

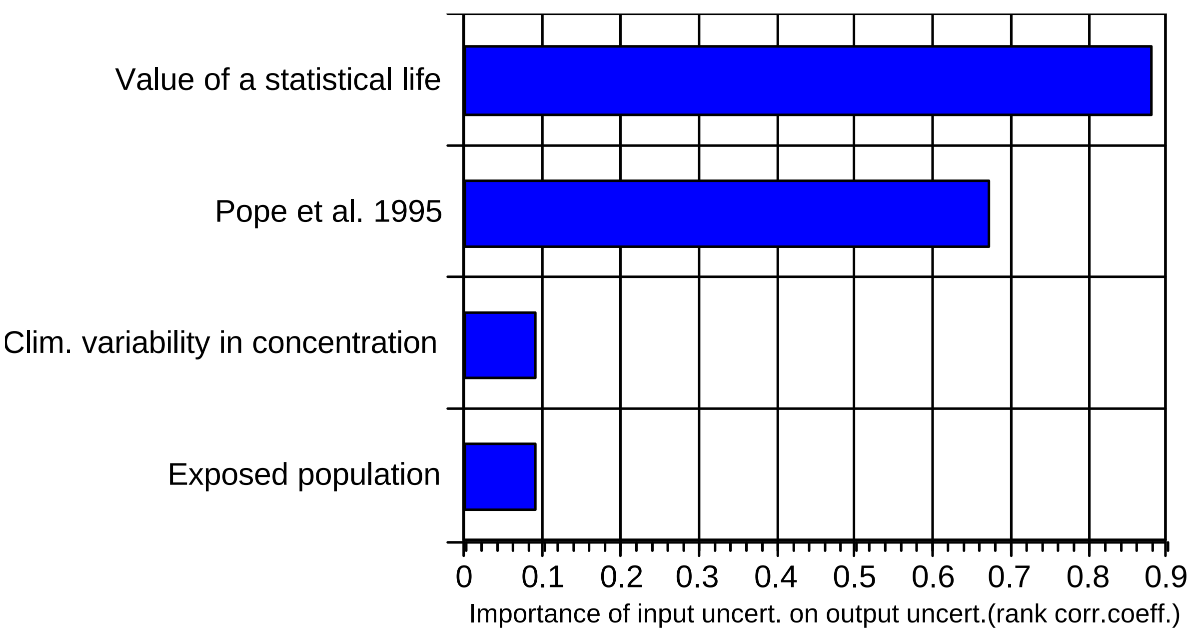


Figure 15. Importance of uncertain inputs on mortality benefits estimate.

Figure 15 suggests that, despite the uncertainty in the mortality estimate, it is the uncertainty surrounding the value of a statistical life that contributes most to an estimate of mortality benefits. While this may not seem surprising given the controversy and difficulty surrounding any method for valuing reductions in mortality (see Lee et al. 1994 for a thorough review of the literature of the valuation of mortality risk changes), this ranking of uncertainties may not always hold true. Figure 16 illustrates that some epidemiological studies may have levels of uncertainty of the same magnitude as the Value of a statistical life study used to value mortality benefits.

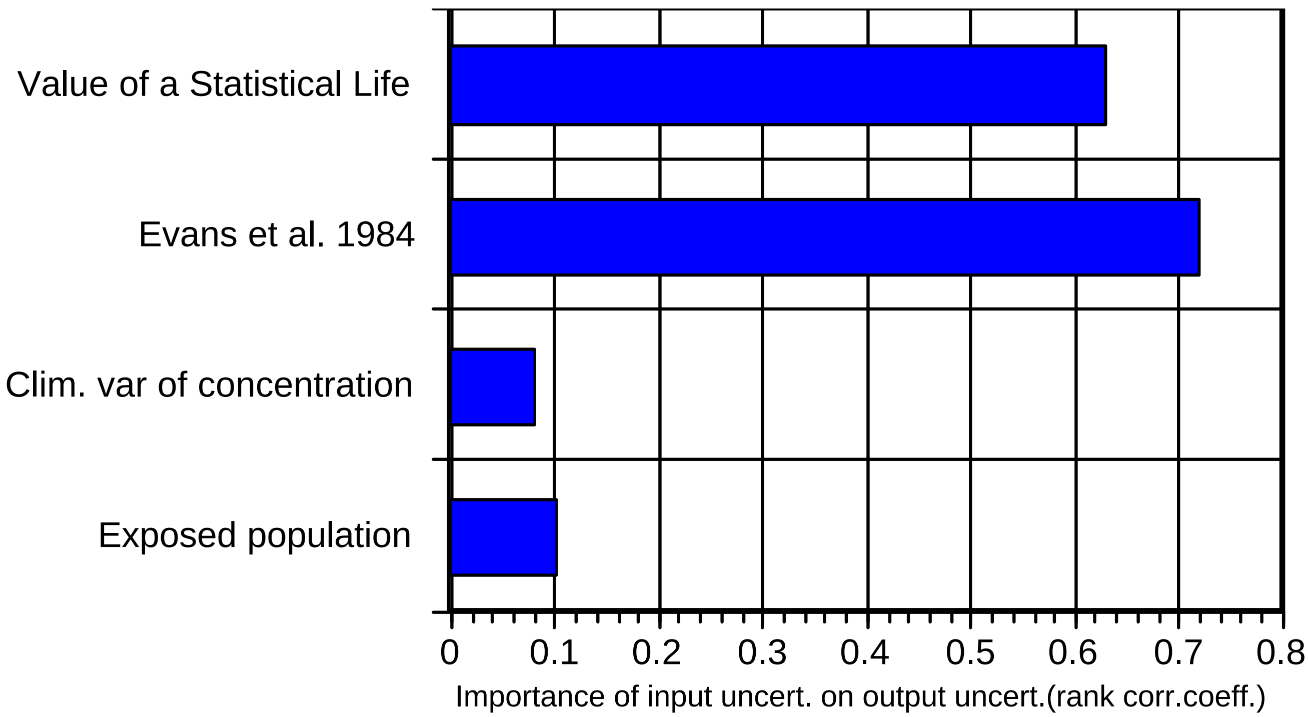


Figure 16. Importance of uncertain inputs on mortality benefits when Evans et al. concentration response function is used.

10. Revisiting Emissions Assumptions: Comparing parameterizations to model uncertainties

As a final example of the integrated assessment, we take the difference of the mortality reduction assuming a 1% demand growth rate (in the emissions module) from the mortality reduction in New York assuming a 3% demand growth rate. By calculating the uncertainty around this difference, we can determine if the two scenarios provide significantly different results, relative to the other uncertainties in the TAF model. The difference in mortality reductions across the two scenarios are given in Figure 17.

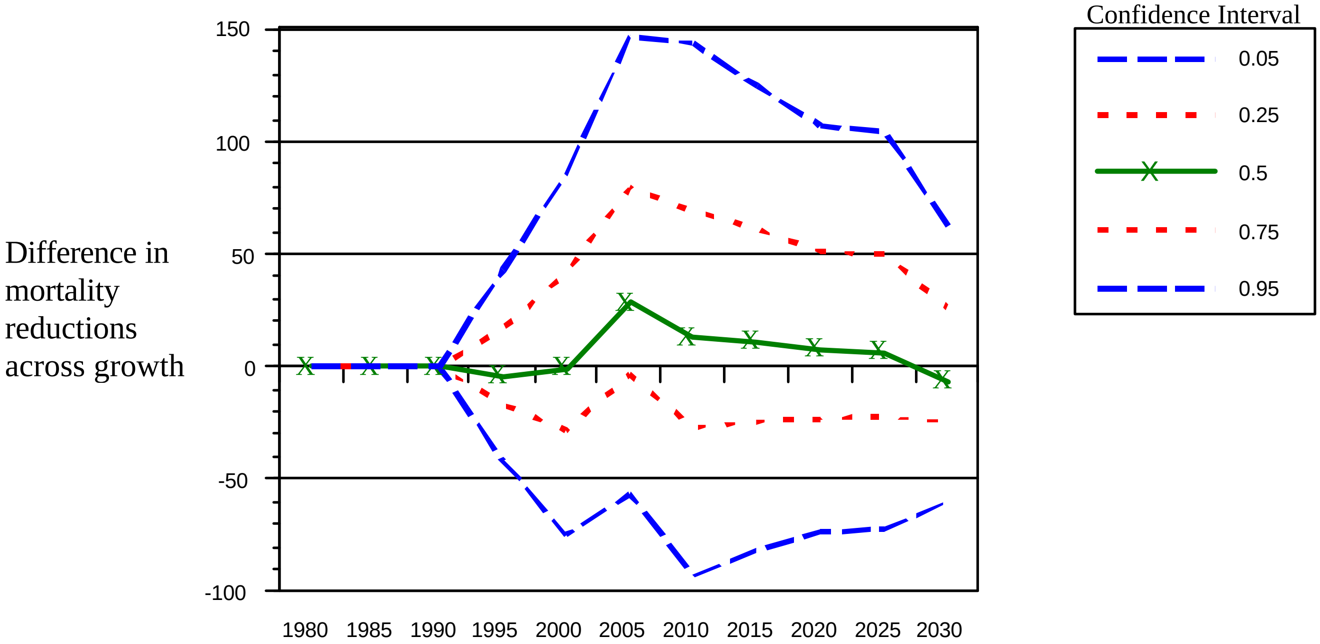


Figure 17. Confidence intervals around differences in mortality reductions in low and high electricity demand growth scenarios.

Even though the differences in emissions growth assumptions are parameterized, and not treated probabilistically, we are still able to compare the differences of the parameterizations against the other uncertainties in the model. The confidence bands in Figure 18 suggest an insignificant difference between the two scenarios; the difference is not significantly different from zero, and the confidence bands, generated by the other uncertainties in TAF, suggest that the difference in mortality reductions across the two growth rates are swamped by other uncertainties in the model. Thus we can conclude that the choice of emissions growth rate (between 1% and 3% per annum) is not a critical input assumption when estimating TAF mortality benefits.

We can perform a similar analysis comparing model results using different average plant retirement age assumptions. Figure 18 demonstrates that using a 60 or 70 year retirement age to calculate projected emissions has a significant effect on mortality reductions. Even the lower 95%ile confidence band exceeds zero, suggesting that, given the other uncertainties characterized in TAF, the choice between a 60 or 70 year retirement age assumption has a nonzero effect on mortality reduction estimates. Reductions under the 60 year retirement age estimate are reduced on average by 100-200 incidences, compared to the 70 year retirement age scenario. This is because the Title IV amendments have the greatest impact on existing plants. If these plants are kept online longer (retiring later) then they are affected by the Clean Air Act for a longer period of time, and we can expect greater pollutant reductions due to the Clean Air Act legislation.

As mentioned earlier, existing plant retirement ages are dependent on a variety of factors, including the effects of the transition to a retail electric power market. From our analysis here, we conclude that continued refinement of plausible utility industry responses to competitive and regulatory pressures is necessary to improve our understanding of acid precipitation effects reductions due to the Clean Air Act.

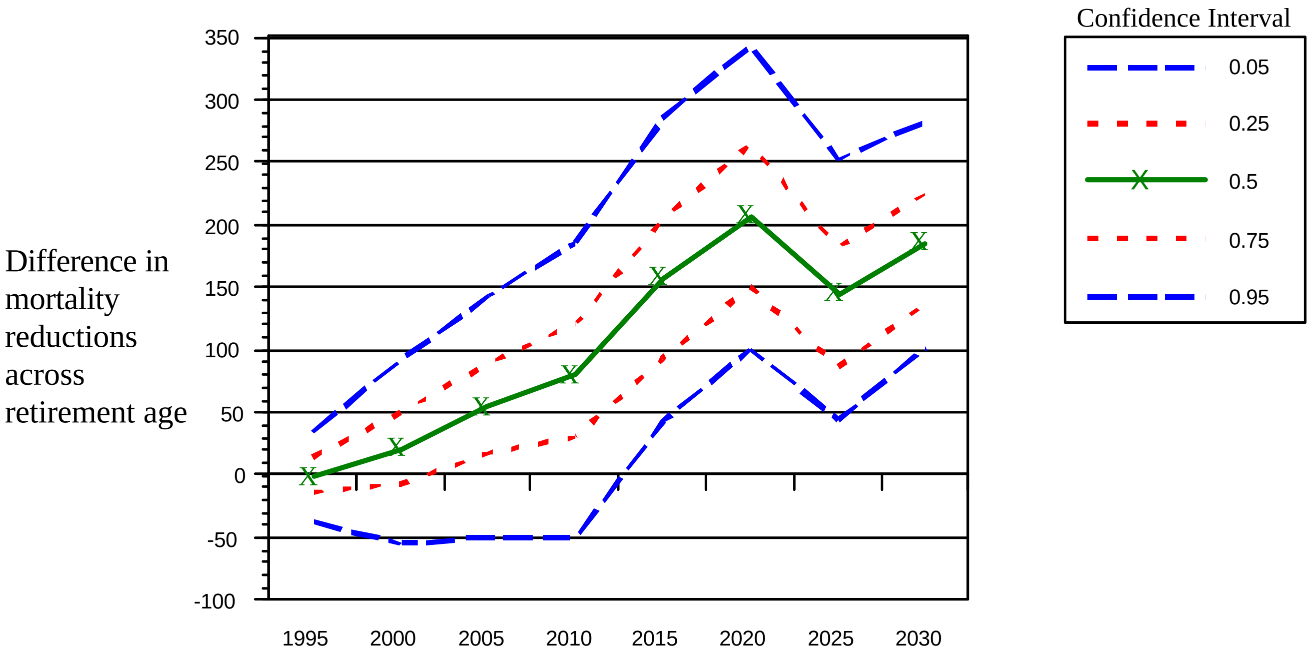


Figure 18. Confidence intervals around differences in mortality reductions in 60 year and 70 year plant retirement age scenarios.

11. Future Work

The analyses described here are just a small sample of the potential of integrated assessment. Future analyses in TAF will compare results not only across effect modules, but also across unmodelled effects using back-of-the envelope scoping analyses. These analyses will permit prioritization of additional modules to be added to the TAF framework.

As we integrate additional information on the costs of Title IV regulations on utilities, we'll compare utility costs to the benefits calculated in TAF to determine whether the subset of benefits we've calculated are sufficient to suggest that Title IV is cost effective. We'll also be able to compare the geographic distribution of costs with the distribution of benefits, because TAF calculates both costs and benefits on a state level.

By utilizing integrated assessment methods for TAF, we've accomplished a great deal in a relatively short amount of time. Our model is able to compare uncertainties which propagate through several modules, and compare uncertainties across different effects and benefits. We're able to comprehensively identify those inputs and model forms model sensitive to change and most influential in their effects on output uncertainty. These abilities allow TAF to provide important information on future research priorities and our confidence in current estimates of acid rain damages and Title IV benefits.

12. Acknowledgments

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