Uncertainty in the difference between maps of future land change scenarios

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Abstract

It is essential to measure whether maps of various scenarios of future land change are meaningfully different, because the differences among such maps serve to inform land management. This paper compares the output maps of different scenarios of future land change in a manner that contrasts two different approaches to account for the uncertainty of the simulated projections. The simpler approach interprets the scenario storyline concerning the quantity of each land change transition as assumption, and then considers the range of possibilities concerning the value added by a simulation model that specifies the spatial allocation of land change. The more complex approach estimates the uncertainty of future land maps based on a validation measurement of with historic data. The technique is illustrated by a case study that compares two scenarios of future land change in the Plum Island Ecosystems of northeastern Massachusetts, USA. Results show that if the model simulates only the spatial allocation of the land changes given the assumed quantity of each transition, then there is a clearly bounded range for the difference between the raw scenario maps, but if the uncertainties are estimated by validation, then the uncertainties can be so great that the output maps do not show meaningful differences. We discuss the implications of these results for a future research agenda of land change modeling. We conclude that a productive approach is to use the simpler method to distinguish clearly between variations in the scenario maps that are due to scenario assumptions versus variations due to the simulation model.

1 Introduction

1.1 Research objective

Scientists use scenario modeling in conjunction with land change simulation to envision the implications of choices that are likely to influence the quantity and spatial allocation of future land types (Kok et al. 2007). The solid lines and boxes of figure 1 illustrate a common approach to land change scenario analysis. The exercise begins with the creation of storylines, since a land change scenario is a story told in words, numbers, and maps concerning how the future could unfold. Typically, investigators construct a business as usual storyline that assumes continuation of past trends, and then create alternative scenario storylines that assume changes from past trends (Meadows et al. 2004). Each qualitative storyline then inspires inputs for a land change simulation model, since these models are designed to portray various future landscapes, based on the assumptions that they are given. The land change model ultimately produces maps of categories of future land transitions. Investigators presume that they can learn something by comparing the differences among the maps that the model produces for the various scenarios. This comparison can be helpful if the model portrays accurately the landscape that would occur if decision makers were to act in accordance with the assumptions of the qualitative storyline. This comparison can be misleading if the maps contain substantial uncertainty that is not communicated clearly. The purpose of this paper is to compare two approaches to address the uncertainty in the maps that land change scenario models can produce and to examine the implications of the uncertainty for the interpretation of the differences between scenarios.

[Insert figure 1 here.]

The dashed lines and boxes of figure 1 show the additional steps in methodology that this paper proposes. This paper presents two approaches to perform this part of scenario analysis. The proposed methods consider potential adjustments to each raw scenario map in order to generate an additional adjusted map that reveals the map's possible uncertainty. Then we measure the differences between the adjusted maps from the two different scenarios. Through this process, the methods of this paper allow one to address the question, "Are there meaningful differences between the raw scenario maps, given the model's uncertainty?" In other fields of research, scientists use statistical methods to determine whether observed differences are meaningful, given the level of certainty of the evidence. This paper proposes similar types of methods to address this question for scenario maps. We illustrate the methods for a study area in the Plum Island Ecosystems of northeastern Massachusetts, USA, which is a Long Term Ecological Research site of the United States' National Science Foundation (Figure 2).

[Insert figure 2 here.]

1.2 Literature review

This paper is the next in a sequence that examines the accuracy of models and the implications of those accuracies for projections of future land change. This research path started several years ago when Pontius (2000) showed how to separate quantity error from allocation error in the context of land change model validation. Pontius et al. (2004) built on those concepts to measure the accuracy of a land change model with respect to a null model at multiple resolutions using historic data, but that work did not examine the implications of the validation measurement for future projections. Pontius and Spencer (2005) showed how to extrapolate the overall accuracy of a model into the future at multiple resolutions, but their method neither produced a map to allow visualization nor quantified the various accuracies among multiple transitions. Pontius et al. (2006) addressed those two aspects, but they analyzed the uncertainty of only one business as usual projection into the future. This paper takes the next logical step in this path of inquiry to compare scenarios that are remarkably different on the raw surface, in order to see whether there are meaningful differences between the scenario maps when the uncertainties are considered. This topic is important since Pontius et al. (2008a) applied a validation procedure to thirteen applications of peer reviewed models and found that in only one case the model produced a larger amount of correctly simulated change than error at the resolution of the raw data. Validation measurements show that model outputs contain substantial uncertainties when they simulate past land change, so it is crucial that we have tools to understand the uncertainties as these models simulate future land change.

The world of land change modeling is large and growing. There are numerous approaches, and several different models can be found that illustrate each type of approach, so it can be difficult to know the most enlightening way to proceed. Popular approaches include neural nets, which are machine learning algorithms that mimic the human brain (Pijanowski et al. 2005). In addition, there are other models that possess various characteristics of intensive calibration algorithms (Goldstein 2004; Silva and Clarke 2002). Some of these are combined with cellular automata (Almeida et al. 2003; Clarke and Gaydos 1998; Engelen et al. 2003). Statistical models are yet another category that relies heavily on calibration using historic data (Hilferink and Rietveld 1999; McConnell et al. 2004). For example, the statistically based CLUE model is used frequently in conjunction with scenario modeling (Verburg et al. 2002). Agent based models are a class that simulates the decision-making of human actors who influence land change, thus can contain a very large number of control parameters (Brown et al. 2005; Castella and Verburg 2007; Manson and Evans 2007). Yet other models use an integration of many techniques (Pontius et al. 2007).

These models contain parameters that need to be set for each model run. There can be substantial uncertainty concerning which parameters should be modified and how they should be set to portray a particular scenario. Some models allow the user to set the parameters that determine the quantity of each transition separately from the parameters that determine the spatial allocation of the transitions. This feature is helpful when the scenario storylines dictate the quantity of each transition and then model's job is to simulate the spatial allocation of the land transitions. This paper's methods rely heavily on this important conceptual distinction between: (1) the quantity of the land transitions, and (2) the spatial allocation of the land transitions. We hope that we have designed the methods of this paper so that they are relevant to a variety of research programs that use various modeling approaches.

1.3 Sources of uncertainty

There are numerous potential sources of uncertainty for simulation models (Berk et al. 2002; Fang et al. 2006; Messina et al. 2008; Santer et al. 2003). We group these sources under three headings: the data, the model, and future land change processes. First, data are likely to contain many types of uncertainty, so the model is likely to read some erroneous information. For this paper, we use the best available digital maps and assume the data are correct, as is frequently done, in spite of the fact that we suspect that all data have errors. Secondly, models contain various types of uncertainty associated with how accurately their algorithms express important processes and use those relationships to simulate land transitions. This paper considers one way to quantify this type of uncertainty by performing a validation exercise, but we do not examine the qualitative internal workings of the components of the computer algorithms as would be necessary for a more comprehensive analysis. Thirdly, future land change processes can be uncertain because decision making involves human free will, which can be non-stationary at a variety of levels. This paper assumes that the scenario's qualitative storyline expresses the non-stationary aspects of future decision making, while the simulation model attempts to extrapolate stationary processes. Our approach concerning these three types of uncertainties is likely to make our results underestimate the total amount of uncertainty.

2 Materials and methods

2.1 Data

We illustrate the approach using maps of two land cover categories, i.e. forest versus non-forest, for 1971, 1985, and 1999, which we call reference maps. These data were originally produced using aerial photography, and then translated into vector maps that are freely available from the State of Massachusetts (www.mass.gov/mgis). The State has never assessed the accuracy of these maps. The Human-Environment Regional Observatory (www.clarku.edu/departments/hero) converted the maps to raster format with a pixel resolution of 30 m. The independent variables derive from the same source and are used to drive the simulation of the spatial allocation of forest change. These variables are slope, surficial geology, and 21 categories of land use in 1971.

2.2 Raw maps for two scenarios

The two future scenarios are different starting with their storylines concerning the quantity of each land transition. The scenarios are purposely designed to be substantially different in this respect in order to illustrate this paper’s concepts.

The business as usual scenario assumes a continuation of historic trends. The recent past shows a gross forest loss on 4% of the landscape and a gross forest gain on 1% of the landscape between 1985 and 1999. The business as usual scenario assumes these constant rates of annual increment in area until all the forest of 1999 has been lost, which occurs at approximately 2130. The business as usual scenario also assumes a constant annual area of gross forest gain over the next two hundred years as figure 3 portrays.

[Insert figure 3 here.]

[Insert figure 4 here.]

Figure 4 shows analogous information for an alternative scenario that assumes substantial changes from the historic processes of land transformation. It assumes an extreme case that has no gross forest loss, while forest experiences a gross gain until 2130, at which point the study area is 75 percent forest. Beyond 2130, the alternative scenario portrays a steady state landscape.

For each of the two scenarios, the land change model Geomod takes the quantities of projected land transitions and allocates them in space to produce maps of the future (Pontius et al. 2001). Geomod calibrates a relationship between the land cover of 1999 and the three independent variables mentioned in this paper's data section in order to generate suitability maps that it uses to allocate future transitions spatially. For this application of Geomod, land change is not stratified by sub-region and is not constrained to occur on the border between forest and non-forest.

2.4 Range for difference between maps, given storylines

Our first approach to uncertainty analysis computes the range for possible differences in the scenario maps, given the quantities of the transitions that the scenario storylines assume at each point in time. These quantities constrain the difference between the business as usual scenario map and the alternative scenario map. The raw scenario maps are guaranteed to agree concerning persistence of both forest and non-forest during the first several decades of the simulation regardless of the simulated spatial allocation because both scenario storylines call for persistence on much of the landscape. The scenario maps will never agree concerning forest loss because the alternative scenario never simulates forest loss. The least possible difference between the scenario maps would occur if the simulation model were to allocate forest gain as similarly as possible in the two scenarios; the greatest possible difference between the scenario maps would occur if the simulation model were to allocate forest gain at entirely different places for each scenario. We use the following notation to compute the least possible difference and the greatest possible difference between the scenario maps due to the spatial allocation algorithm, given the quantities dictated by the storylines.

$t \equiv$ index for future year.

$i, j \equiv$ indices for land categories.

$J \equiv$ number of categories.

$Atij \equiv$ quantity of land transition from category i at the beginning time of the simulation to category j at a future time t in percent of the study area for the alternative scenario.

$Btij \equiv$ quantity of land transition from category i at the beginning time of the simulation to category j at a future time t in percent of the study area for the business as usual scenario.

$Lt \mid Atij, Btij \equiv$ least possible difference between the scenario maps attributable to variation in simulated spatial allocation of the transitions at future time t in percent of the study area, given $Atij$ and $Btij$.

$Gt \mid Atij, Btij \equiv$ greatest possible difference between the scenario maps attributable to variation in simulated spatial allocation of the transitions at future time t in percent of the study area, given $Atij$ and $Btij$.

Equation 1 computes the least possible difference between scenarios, given the quantities of transitions in the alternative and business as usual scenarios. The least possible difference is 100 percent minus the greatest possible agreement. The double summation of the minimum function gives the greatest possible agreement based on the logic of Pontius and Connors (in press).

$$Lt \mid Atij, Btij = 100\% - \sum_{i=1}^{J}\sum_{j=1}^{J} \mathrm{MIN}\left[Atij,\ Btij\right] \qquad \text{equation 1}$$

Equation 2 expresses the greatest difference between the scenario maps as 100 percent minus the least possible agreement. The double summation of the maximum function in equation 2 gives the least possible agreement (Pontius and Connors in press). The single summation in round parentheses in equation 2 gives the quantity of category i at the beginning time, which is 1999 for our case study.

$$Gt \mid Atij, Btij = 100\% - \sum_{i=1}^{J}\sum_{j=1}^{J} \mathrm{MAX}\left[0,\ Atij + Btij - \left(\sum_{j=1}^{J} Btij\right)\right] \qquad \text{equation 2}$$

2.5 Estimated difference between maps based on validation

Pontius et al. (2006) inspires a more complex second method to analyze the uncertainties. This second uncertainty assessment consists of three steps: (1) to measure the uncertainty of the model using a validation procedure with historic information, (2) to use the results from step (1) to extrapolate the uncertainty of the model as it projects into the future, (3) to use the results from step (2) to create adjusted scenario maps so we can measure the difference between them.

Step (1) consists of an exercise where the quantities of the transitions are based on linear interpolation through the 1971 – 1985 calibration interval and then extrapolation through the 1985 – 1999 validation interval. Geomod allocates the transitions spatially based on calibration using the 1985 forest map. This generates a simulation map for 1999, which we compare to the reference maps for 1985 and 1999. Table 1 presents the quantitative foundation of the validation exercise for step (1). It summarizes the three-map comparison as a three-dimensional crosstabulation matrix, where the round parentheses show the bottom layer that gives the forest category in the simulation map of 1999 and the square brackets denote the upper layer that gives the non-forest category in the simulation map of 1999. Each number in table 1 gives a percent of the landscape. The bold numbers indicate simulated change and the non-bold numbers show simulated persistence. Italics denote correct simulations. Table 1 indicates that the simulation contains errors due to both imperfectly simulated quantities and allocations of transitions.

[Insert table 1 here.]

[Insert table 2 here.]

We convert the information of table 1 into measures of accuracy, given in table 2. Each conditional probability in table 2 is obtained by dividing each entry in table 1 by its row total found in the right-most column of table 1, therefore each row of conditional probabilities in table 2 sums to one. Again, the bold numbers denote the model's simulated change and the italics indicate a correct simulation. To create the adjusted maps, we focus on the four numbers in the forest column of table 2. Specifically, 0.90 is the probability that a pixel is forest in the reference map of 1999 when the model simulates it as a transition from forest in 1985 to forest in 1999, 0.89 is the probability of forest when the model simulates from forest to non-forest, 0.04 is the probability of forest when the model simulates from non-forest to forest, and 0.02 is the probability of forest when the model simulates from non-forest to non-forest.

Step (2) contains assumptions for how the simulation accuracies in table 2 decay towards randomness concerning both the quantity and spatial allocation of the simulation as it projects from 1999 farther into the future. Figure 5 portrays these assumptions where the vertical axis is the conditional probability that a pixel is truly forest in the future, given the simulated transition for that pixel. Each of the four curves relates to one of the model's four simulated transitions. The conditional probabilities in 2013 in figure 5 match the numbers in the forest column in table 2, since the method assumes that the model will have the same level of accuracy in year 2013 as it had when it simulated the land transitions during the validation interval, since the duration of the validation interval is 14 years. When the model projects scenarios beyond year 2013, the method assumes that the model's accuracy decays to an accuracy that is equivalent to randomness. For our case study, this expected random accuracy is ½ because there are two categories. In general, the expected random accuracy is one divided by the number of categories (Foody 1992, Pontius 2000). All four curves approach ½ asymptotically and are interpolated through the points at years 1999 and 2013 using an exponential decay curve. We choose an exponential decay curve because it is the simplest curve that expresses our assumptions about convergence to randomness and can be fit uniquely given the validation data. Pontius et al. (2006) give the equations for the curves for multiple categories. Pontius and Spencer (2005) found that these types of exponential decay curves approximated the decay in overall accuracy to within one percentage point for a 14-year interval for which data were available in Central Massachusetts. These estimated accuracies are a function of the validation measurement, and are independent of the assumptions in any future scenario. They imply that the future simulation will have errors in terms of both the spatial allocation of the transitions and the quantity of the transitions, since the validation exercise revealed both types of errors.

[Insert figure 5 here.]

Step (3) uses the values for each curve of figure 5 to convert pixels in each raw scenario map into pixels that show the conditional probability of forest at any future time. The resulting maps of conditional probabilities are the adjusted scenario maps mentioned in figure 1. We then compare the adjusted maps for the two scenarios by comparing the absolute differences in the conditional probabilities. Equation 3 expresses the overall difference Dt between the adjusted maps at time t as 100 percent minus the agreement between the adjusted maps, where the triple summation gives the agreement based on the logic of Pontius et al. (2008b).

$$Dt = 100\% - \sum_{i=1}^{J}\sum_{a=1}^{J}\sum_{b=1}^{J}\left\{ Qtiab \times \sum_{k=1}^{J} \mathrm{MIN}\left[Etiak, \quad Etibk \right] \right\} \qquad \text{equation 3}$$

where

t ≡ index for future year.

i, j, k, a, b ≡ indices for land categories.

J ≡ number of categories.

Qtiab ≡ percent of the study area that shows land transition from category *i* at the beginning time of the simulation to both category *a* at the future time *t* for the alternative scenario and category *b* at a future time *t* for the business as usual scenario.

Etijk ≡ extrapolated user's conditional probability of a pixel being category *k* at time *t*, given a scenario simulates it as transitioning from category *i* at the beginning of the simulation to category *j* in the raw scenario map of time *t*.

Dt ≡ adjusted difference between scenarios at time *t* in terms of percent of the landscape.

Pontius et al (2006) give the equations to compute *Etijk*. These conditional probabilities can be viewed as soft classifications, since each *Etijk* is bounded between zero and one and conforms to equation 4.

$$\sum_{k=1}^{J} Etijk = 1 \qquad \text{equation 4}$$

3 Results

Figure 6 shows the relevant maps for the two scenarios, with the 1999 landscape at the left and the future landscapes to the right. The upper two rows in figure 6 give the raw scenario maps, while the bottom two rows show the adjusted scenario maps based on our method to account for the uncertainties using validation. The raw business as usual scenario is dominated by forest loss and the alternative scenario is dominated by forest gain. At the initial time, all of the conditional probabilities of forest are either 0 or 1 because we assume the data are correct, thus each forest pixel is black and each non-forest pixel is white in the initial adjusted maps. Over the next century, the adjusted maps become grayer due to uncertainty; however they still show some contrast. In the second century, the adjusted maps become very similar in spite of large differences in the raw scenario maps.

[Insert figure 6 here.]

Figure 7 shows the difference between the business as usual scenario map and the alternative scenario map in terms of percent of the landscape. The solid line with filled circles shows the difference between the raw scenario maps as a percent of the pixels that are different. This raw difference peaks at 65 percent of the landscape in 2130. Based on the first simpler method to account for the uncertainties, the least line and the greatest line show the range for the difference that the spatial allocation algorithm could possibly produce, given the quantity of each transition dictated by the scenario storylines. The raw line and the least line are identical, because Geomod's spatial allocation maximizes the overlap between the forest gain in the business as usual scenario and the forest gain in the alternative scenario. The dotted line near the horizontal axis shows that three percent is the maximum difference between the adjusted scenario maps when using the second more complex method to estimate the uncertainties based on the validation measurement. The dotted line is not within the range of the least and greatest lines because the second method assumes that the simulation has errors concerning both the spatial allocations and the quantities of the transitions, as the validation step revealed. This demonstrates how the second method to compute the adjusted maps fails to maintain the transition quantities in the storylines.

[Insert figure 7 here.]

The results in figure 7 for the differences that are estimated by validation are not particularly sensitive to our assumption in step (2) that the conditional probabilities decay to randomness. If we were to assume that the conditional probabilities in table 2 are constant through time, then the difference over the next two centuries between the adjusted maps would be less than two percent. The reason is that most of the difference between the raw scenario maps derives from locations where the business as usual map portrays forest loss and the alternative map portrays forest persistence, but the conditional probability of forest for these two transitions is 0.89 and 0.90 respectively according to the validation exercise. This reflects the model's weak ability to distinguish between land change and land persistence during the validation interval, which is typical for land change models (Pontius et al. 2008a).

4 Discussion

4.1 Uncertainty in scenarios and predictions

There is a philosophical debate concerning the role of uncertainty in scenario analysis. One view holds that uncertainty is irrelevant to scenario analysis because storylines are not predictive; scenarios can be tested for internal consistency and plausibility but not for accuracy. A counter view holds that uncertainty has an important role in scenario analysis in order to examine the link between the qualitative storyline and its quantitative expression in numbers and maps. We think that the role of uncertainty in scenario analysis depends on the level of prediction that is incorporated into the modeling. Some types of scenarios consist entirely of clearly articulated storylines that have no elements of prediction, hence do not have uncertainty. Other types of scenarios have vague storylines that rely almost entirely on predictive models to translate the storylines into numbers and maps. Many models that produce maps of the future incorporate elements of both qualitative storylines and predictions. We define a model as predictive when it attempts to simulate what will happen based on a calibration algorithm, thus it is usually possible for a predictive model to have a validation step, in which case one can apply both our methods to account for uncertainties. The following three paragraphs present three examples to illustrate the range of possibilities for the integration of scenario storylines and predictions.

If the storyline completely dictates the numbers and maps, then uncertainty is not relevant. For example, the State of Massachusetts created maximum buildout scenarios for all of its towns. The scenario storyline stated that future land development will occur on all parcels that are not yet developed and that are not protected. This scenario is stated clearly, simply, and comprehensively by its storyline. The entire scenario can be mapped by overlaying a map of present non-developed land on a map of non-protected areas. The procedure lacks calibration, validation, and prediction. There is no estimation of the future time for the portrayed landscape and no attempt to state the likelihood of this outcome. Indeed many investigators think the outcome is not likely. Nevertheless, these buildout maps have been helpful to structure conversations within towns concerning land management. In fact, the stakeholders' responses to the maps might inspire them to take actions in order to assure that maximum buildout is not realized. One advantage of this type of scenario is that the general public can interpret the maps easily because the storyline is straight forward. If there is any uncertainty in this buildout scenario, it is associated with possible errors in the input maps. For these types of scenarios, this paper's methods of uncertainty analysis are not relevant.

Other types of scenarios contain storylines that only partially dictate the future maps, so they rely on predictive models to specify the remaining information to construct the maps. In some cases, the storyline is specified at one scale and the modeling is performed at another scale (Solecki and Oliveri 2004). For example, the dyna-CLUE model has been used to create fine resolution maps of land change scenarios for the European Union (Verburg et al. 2006, Verburg et al. 2008). The storylines are described at the global and regional levels in terms of assumptions about economic growth, trade and policy. A series of models is used to quantify the effects of these storylines on land use patterns by linking general equilibrium models at the global scale to a spatially explicit land use model at the pixel scale that shows the resulting changes in landscape pattern for each region. Therefore, variation at the coarse scale is dictated by the storyline, and variations at finer scales are dictated by calibrated, predictive models. Consequently, one could use the methods of this paper to analyze the spatial allocation of the land categories at these finer scales. Pontius et al. (2007) present additional methods that can separate the components of correctness and error at the global level, the regional level, and the pixel level. Those methods could help to assess the uncertainty of multiple-scale scenarios for which the storyline dictates the quantity of each land type by region, and the predictive model dictates the spatial allocation of each land type by pixel.

Yet other types of scenarios have storylines that are so vague that they rely heavily on calibration procedures and predictive models to translate the storylines into numbers and maps. For example, the business as usual qualitative storyline is typically stated as “a continuation of past practices, i.e. no new policy initiatives”. Therefore, a calibrated model usually translates the storyline into numbers and maps based on extrapolation from past trends. This storyline might be helpful in some cases but can be nonsensical in other cases because it assumes that business has been usual during the calibration and validation intervals. The business as usual storyline makes little sense in many regions where recent business has not been usual, such as in Vietnam and the Czech Republic, where there have been substantial changes in political, economical and agricultural systems (Castella et al. 2005; Václavík 2008). While these are two extreme cases, humans can and do modify management strategies constantly at several scales, so it makes sense first to examine the data for stationary processes before using the data to calibrate a model for a business as usual strategy. It is not reasonable to construct a business as usual scenario for sites where processes have been non-stationary, nevertheless it would be technically possible to extrapolate patterns in historic data using a statistically calibrated model. Such a model could be called a prediction, and the validation exercise would expose substantial errors in terms of both the quantity and spatial allocation of the land changes. Our second method to estimate the uncertainties based on validation would be well suited to assess these types of heavily calibrated models in which the quantity and spatial allocation of the land change process can be viewed as a prediction. The methods of this paper would show that a business as usual scenario has high uncertainty for study areas where historic trends have been turbulent, but has lower uncertainty for areas where historic trends have been stable at the scale of the data during the calibration and validation intervals.

4.2 Challenges of calibration, validation and extrapolation

The paper exposes some severe practical and theoretical challenges to the conventional approach to modeling that calls for calibration with historic data, validation with contemporary data, and extrapolation into the future. That conventional paradigm might be productive if it were to produce maps of different scenarios that are meaningfully different, given the levels of uncertainty as estimated by the validation exercise. However, this is not the situation for our case study, and we suspect that other research programs are likely to witness similar results (Pontius et al. 2008a). There are three main reasons why levels of uncertainty as estimated by validation are likely to continue to be enormous and/or misleading, even if we were to adopt a more complex model. These reasons relate to the three sources of uncertainty mentioned in this paper's introduction concerning: the data, the model, and future land change processes.

Even if all data were perfectly accurate, there are usually substantial limitations concerning data availability. Calibration and validation usually require land cover maps from three points in time. Data availability usually dictates the duration of these time intervals. Rigorous separation of calibration and validation information through time insists that independent variables must show conditions that pre-date the validation interval. This puts severe restrictions on the selection of independent variables, since available data usually portray contemporary conditions, such as roads and protected areas, as opposed to historic conditions. In cases where historic data are scarce, calibration and validation time intervals can be much smaller than the duration over which the investigator would like the scenario to project into the future. This is important since Pontius et al. (2008a) showed that models have difficulty predicting change accurately over time intervals for which the amount of change is small. This is certainly the case with this paper's example, where the calibration and validation intervals are both 14 years and each contain about five percent change on the landscape. We project the scenarios over a much longer duration to illustrate our methods and their implications. It may go against some readers' intuition that the validation measurement could offer much insight concerning accuracy when the model projects over centuries, especially in light of the much shorter calibration and validation intervals. The purpose of this paper is to illustrate this point by assessing uncertainty explicitly, rather than by intuition. However, even if we were to witness high validation measurements based on accurate data of land cover and independent variables for several points in history, then the approach to estimate uncertainty based on validation would still have conceptual problems for the second reason, which we describe next.

The validation step does not necessarily reveal information about the model's ability to simulate accurately a variety of different types of processes through time. If the validation step reveals high accuracy, then it simply means that the processes of land change observed during the calibration interval were stationary through the validation interval, for the variables and mechanisms that the model considers. If the validation step reveals low accuracy, then it means that the processes of land change observed during the calibration interval were not stationary through the validation interval. So the validation measurement tells us mainly about the stationarity of the process with respect to the information that the model considers. But, if we wanted to know the level of stationarity of the processes, then we could more simply study the historic information directly without the use of a predictive model. The validation measurement offers us little guidance to estimate the accuracy of the model for cases where we ask the model to produce a variety of maps that portray various alternative processes through time, which is usually the purpose of scenario analysis. Even if we were to witness high validation measurements through intervals when there have been non-stationary processes, then the approach to estimate uncertainty based on validation would still have conceptual problems for projections into the future, due to a third reason described next.

We want to use scenario analysis to gain insight into future decisions for which there might be no historical precedence, but the data used for calibration and validation portray only one path of a possibly infinite range of land changes that could have occurred in the past, because land changes are a function of human free will. An important purpose of scenario analysis is to portray the implications of decisions that have never been taken before, in which case calibration and validation with historic data does not reveal appropriate estimates of uncertainty, and probably underestimates the levels of uncertainty.

Consequently, there are a variety of practical and theoretical reasons why we favor the first simpler method to compute and to communicate uncertainty. Some study sites have land cover maps from only one or two points in time, in which case it would be impossible to implement the approach to estimate uncertainty based on validation. If a map from only one initial time were available, then it would still be possible to implement the first simpler approach to compute the range of uncertainty due to spatial allocation, given the assumed quantity of each future transition. Furthermore, the first approach has fewer assumptions concerning the uncertainty of the model as it projects into the future, and its assumptions are easier to understand and less controversial than the second approach. Lastly, the simpler method to compute bounds for future land change is not constrained by the observed historical processes in terms of their data, stationarity, and range.

4.3 Agenda for land change modeling

What are the implications of our results for the future agenda of land change modeling? Each modeler will need to answer this question in the context of a particular project. These results have profound implications for the approach to land change modeling in our Plum Island Ecosystems study area, where one of our purposes is to assess land change scenarios of suburban sprawl for vulnerability to drought (Hill and Polsky 2007). We have decided to alter our modeling approach substantially, because this paper reveals that there is so much uncertainty associated with the approach that we have taken since 2000 concerning calibration, validation, and extrapolation. We have decided to take a step away from intensive calibration routines. More simply, we are planning to examine the data directly for evidence of stationarity or non-stationarity of historic land change processes and to explain those qualitatively with respect to the decisions humans have made to manage the land at a variety of scales: household, town, state, national, and global. Then we will construct clearly articulated policy relevant storylines, similar to Conway and Lathrop (2005), regardless of whether the proposed land change processes have historical precedence. For example, Massachusetts is considering various forms of legislation concerning smart growth and affordable housing. It makes sense to design scenarios according to the proposed legislation, while it would make little sense for these scenarios to be based on calibration of historical processes, because the proposed laws did not exist in the past. The explicit purpose of the proposed legislation is to blaze a new direction away from historic trends. We suspect that this type of modeling will help the members of our diverse research team to communicate better with stakeholders and with each other, as recommended by Nicolson et al. (2002). Most importantly, we will strive to distinguish clearly the variations in scenario maps that are due to the storylines versus the variations that are due to the simulation model. The raw, least, and greatest lines of figure 7 give one way to illustrate this, since the storyline dictates the bounds on the range and the simulation model dictates the placement of the raw scenario within the range.

5 Conclusions

This paper has examined the role of land change models and uncertainty in scenario analysis. For the case study, the two methods to compute uncertainties give remarkably different results concerning whether there are meaningful differences between the scenario maps. Using the first method, we see substantial differences between the scenario maps when the uncertainty is expressed as a range for the model's possible spatial allocations, as constrained by the storyline's assumed quantity for each land transition. This paper gives equations that determine this range. There are miniscule differences between the adjusted scenario maps when uncertainty is estimated by validation with historical data as computed by the second more complex method. The calibration and validation paradigm is hampered by: 1) quality and availability of data, 2) limited variety and possible non-stationarity of historic processes, and 3) lack of historical precedence for possible future decisions. We conclude that a productive path forward is to use this paper's first set of simpler methods to distinguish between the variations in scenario maps that are due to assumptions of the storylines versus the variations that are due to uncertainties in the simulation model.

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Tables

Table 1. Three-dimensional matrix to quantify the validation of the simulated change from *T1*=1985 to *T2*=1999. Round parentheses give the forest layer for the simulated map of 1999 and square brackets give the non-forest layer for the simulated map of 1999. Bold indicates simulated change as opposed to persistence. Italics show correctly simulated transitions. All numbers are in percent of the landscape.

		reference 1999		
		Forest	non-forest	total
reference 1985	Forest	*(34.94)* **[3.89]**	(3.87) ***[0.47]***	(38.81) **[4.36]**
	non-forest	***(0.00)*** [1.11]	**(0.01)** *[55.69]*	**(0.01)** [56.80]
	Total	(34.94) [5.00]	(3.88) [56.16]	(38.82) [61.16]

Table 2. Three-dimensional matrix of observed user's conditional probabilities, given a simulated transition. Each row is a different simulated transition. Round parentheses give the forest layer for the simulated map of 1999 and square brackets give the non-forest layer for the simulated map of 1999. Bold indicates simulated change. Italics indicate the conditional probabilities of the simulation being correct, given the simulated transition.

		reference 1999		
		forest	non-forest	Total
reference 1985	Forest	*(0.90)* **[0.89]**	(0.10) ***[0.11]***	(1.00) **[1.00]**
	non-forest	***(0.04)*** [0.02]	**(0.96)** *[0.98]*	**(1.00)** [1.00]

Figures

page

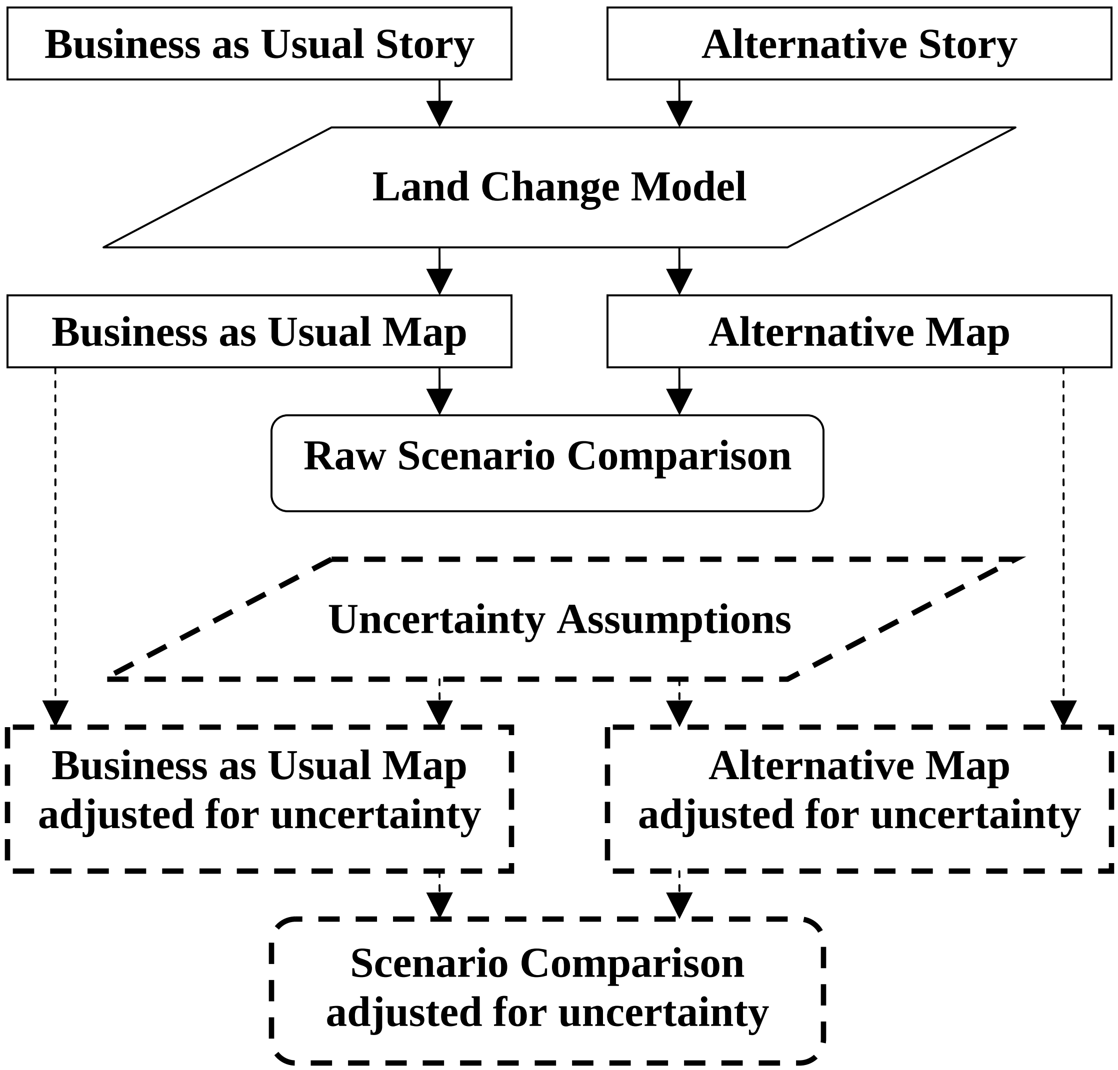

Figure 1. General approach to scenario modeling shown in solid lines, and this paper's additional methodological contribution to account for uncertainty shown in dashed lines.

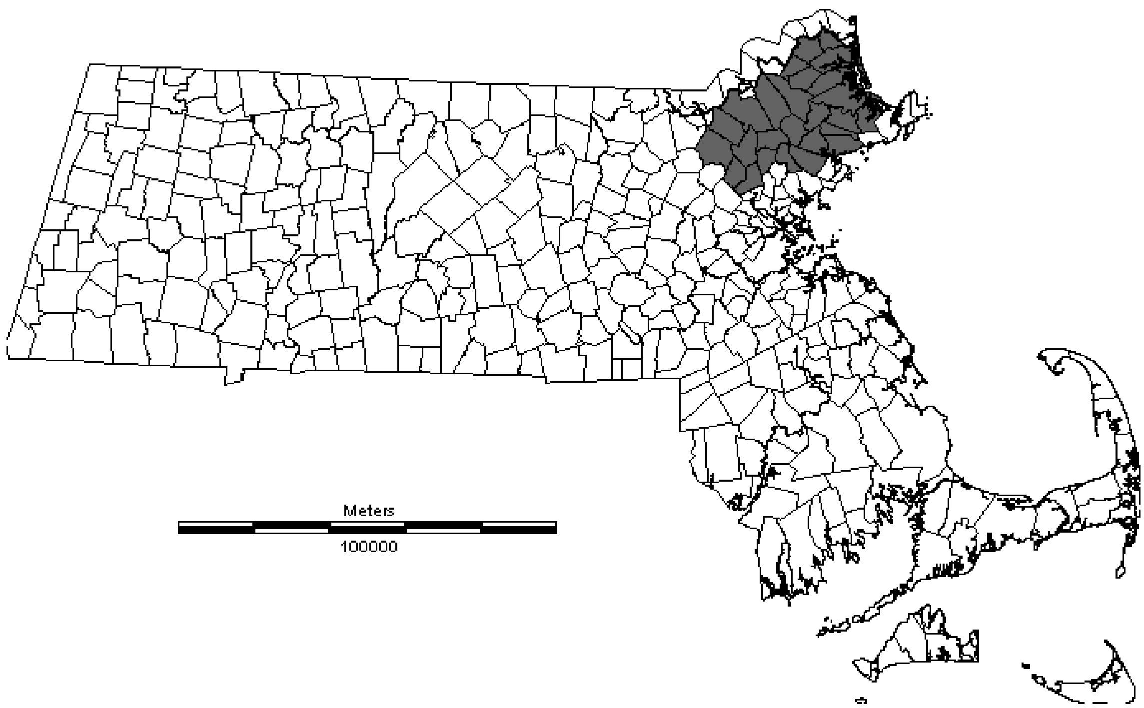

Figure 2. Twenty six towns of the Plum Island Ecosystems in northeastern Massachusetts, USA.

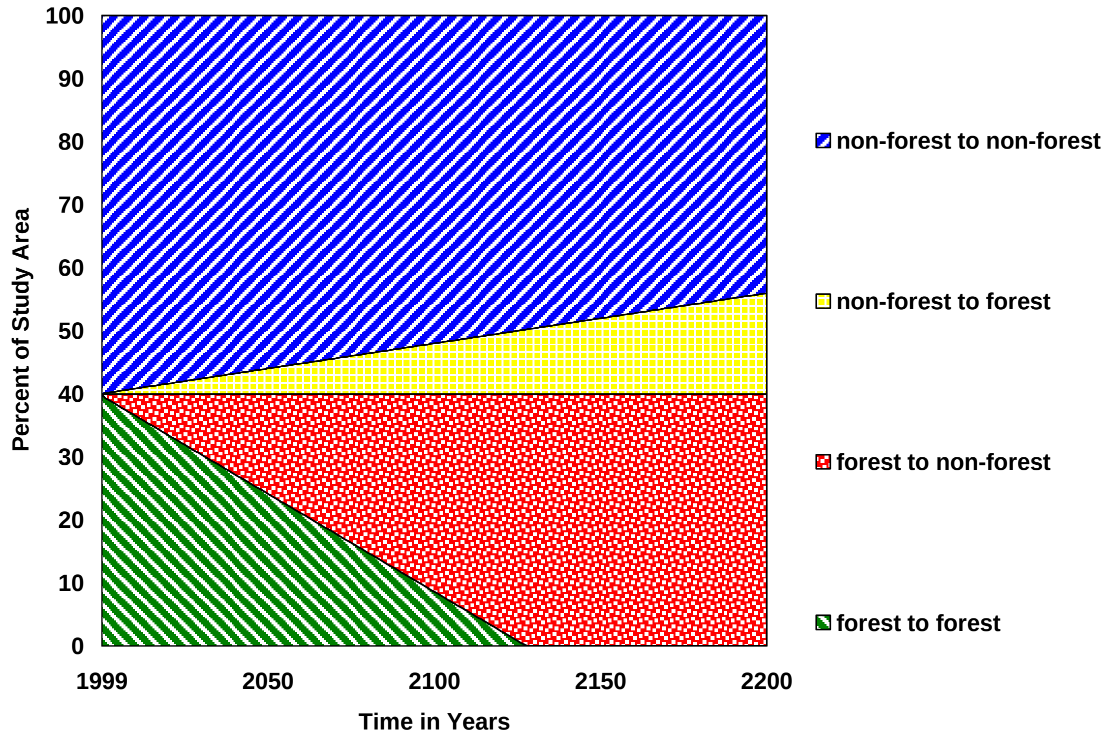

Figure 3. Quantity of each land transition over time for the business as usual scenario.

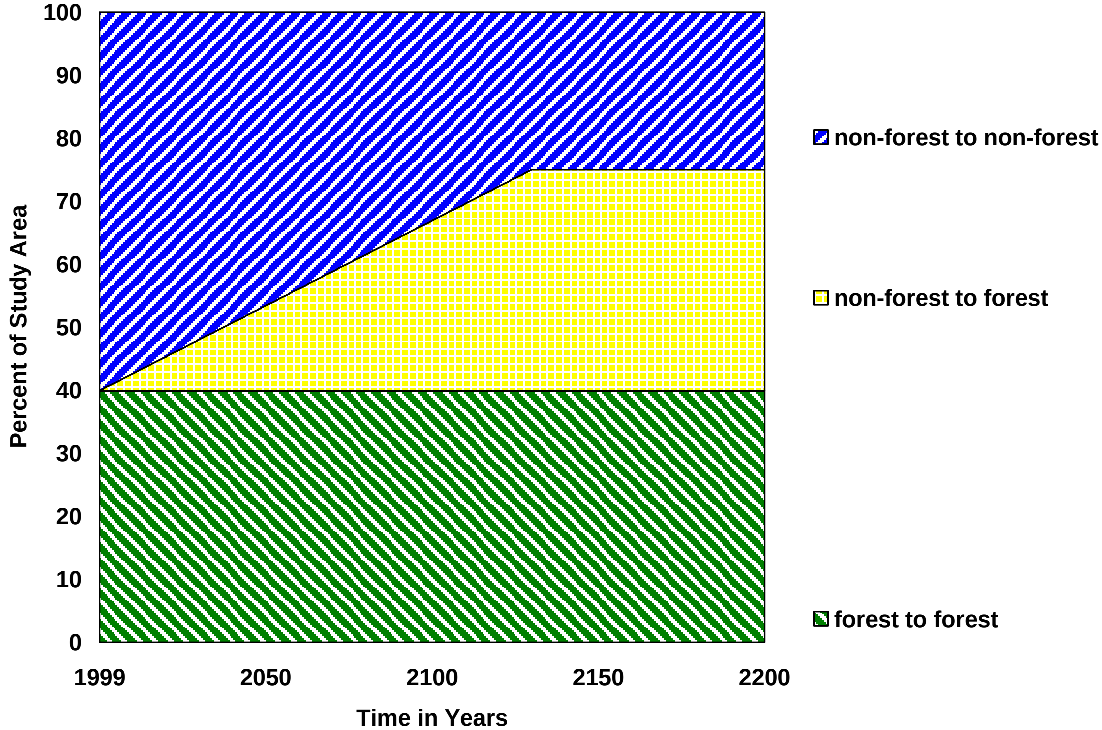

Figure 4. Quantity of each land transition over time for the alternative scenario.

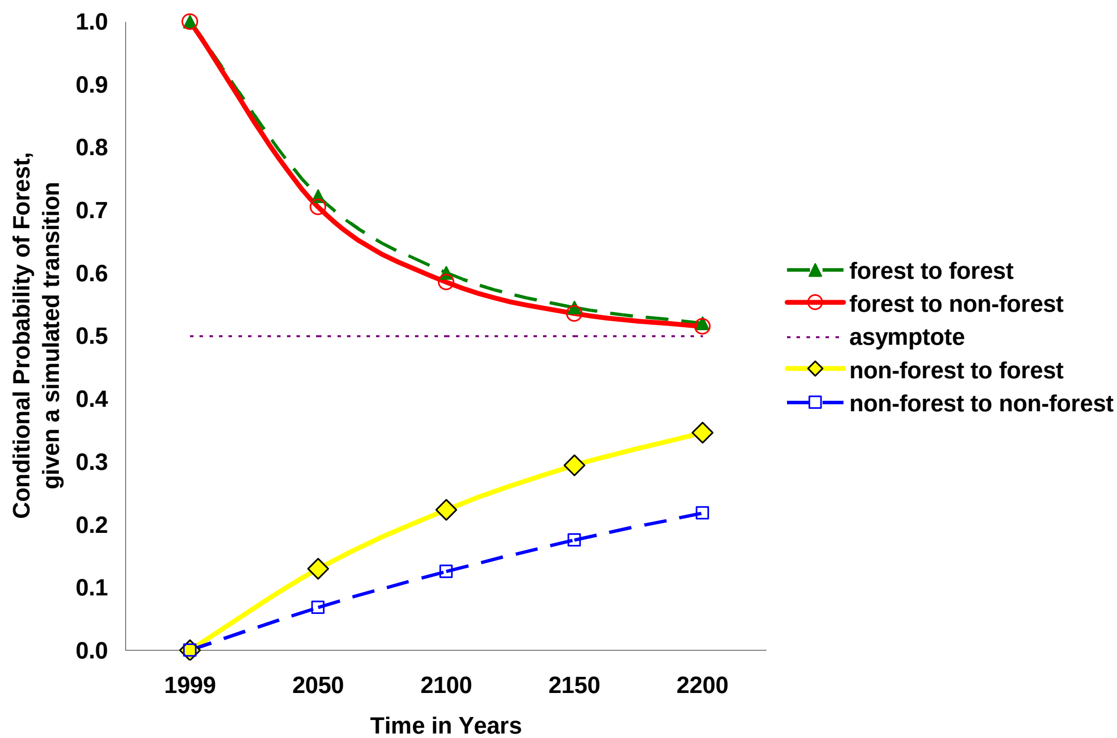

Figure 5. Conditional probability of a pixel being forest, given each of the four simulated transitions over time.

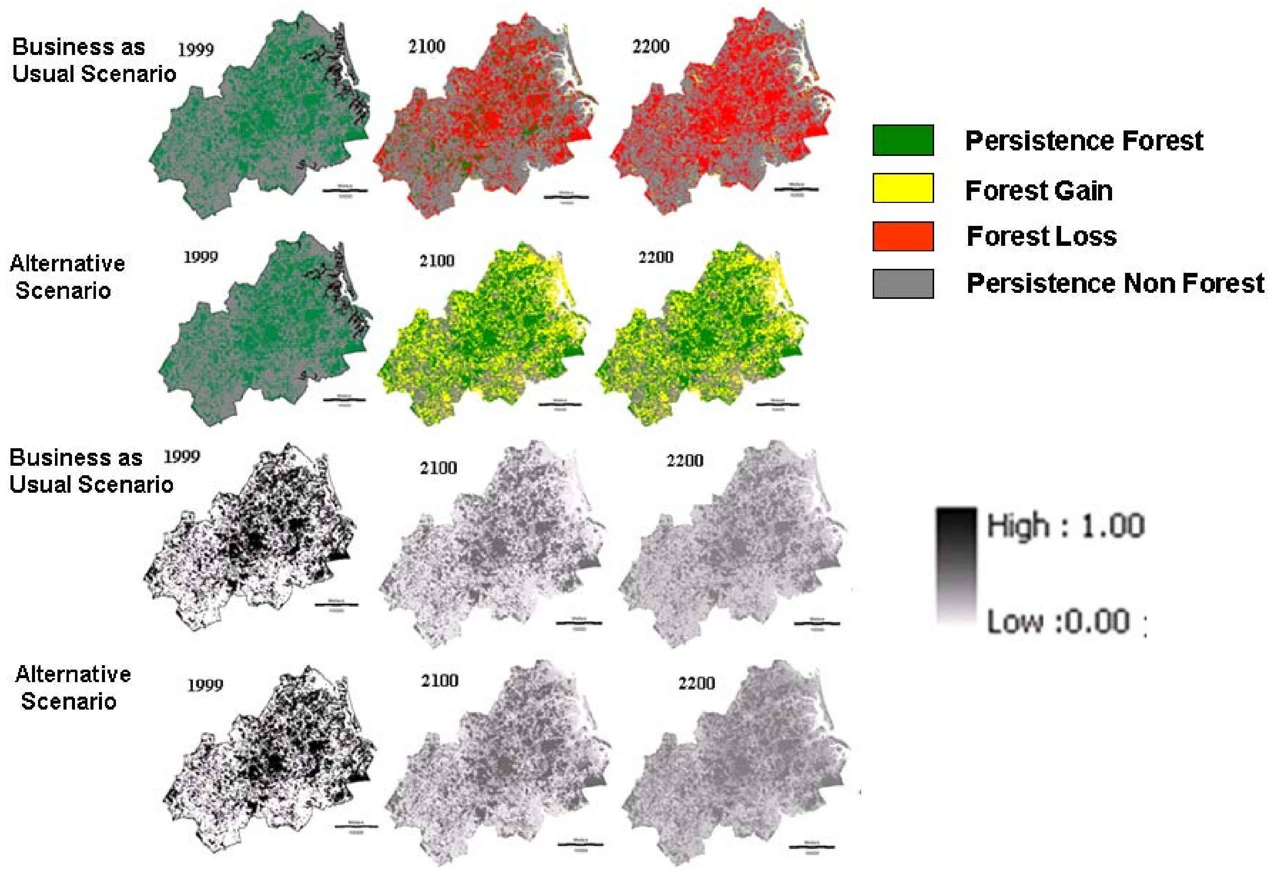

Figure 6. Scenario maps where the three columns represent years 1999, 2100 and 2200. The uppper two rows are the raw scenario maps of categorical transitions, while the lower two rows are the corresponding adjusted scenario maps that show the conditional probability of forest, given the simulated transitions.

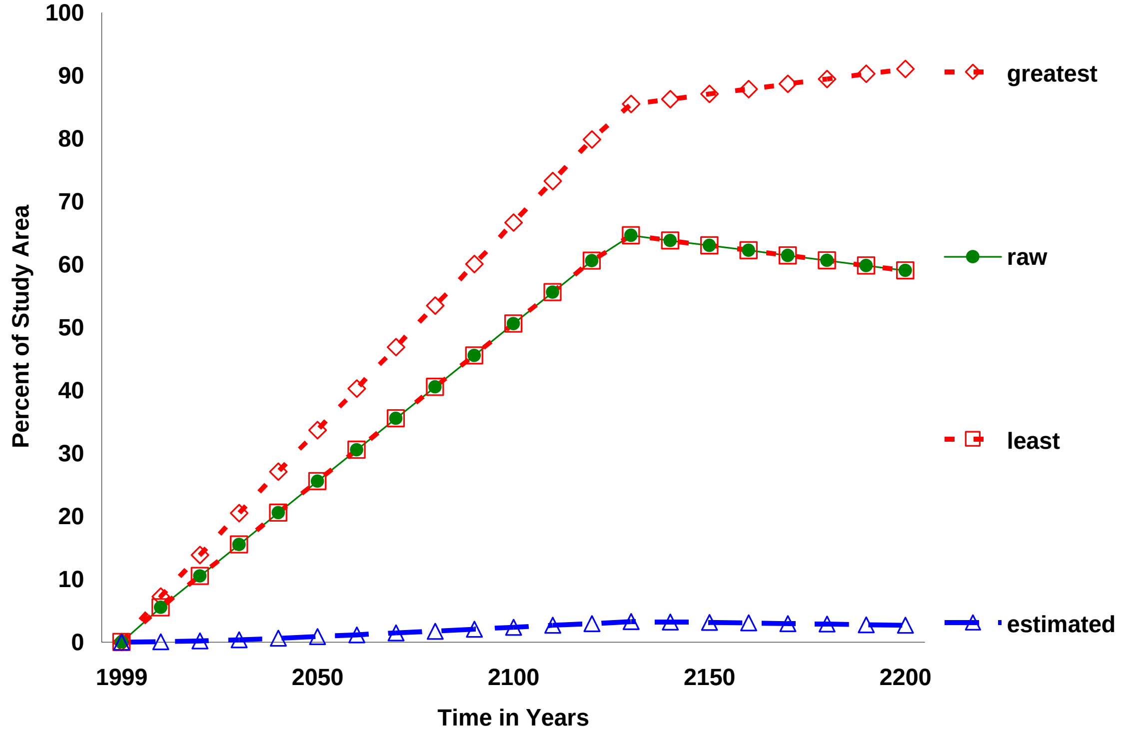

Figure 7. Difference between the business as usual scenario map and the alternative scenario map, for four cases: raw difference, least difference given storyline's quantities, greatest difference given storyline's quantities, difference given uncertainty estimated by validation.