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Estimating the uncertainty of land-cover extrapolations while constructing a raster map from tabular data

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Abstract. This paper presents novel techniques to estimate the uncertainty in extrapolations of spatially-explicit land-change simulation models. We illustrate the concept by mapping a historic landscape based on: 1) tabular data concerning the quantity in each land cover category at a distant point in time at the stratum level, 2) empirical maps from more recent points in time at the grid cell level, and 3) a simulation model that extrapolates land-cover change at the grid cell level. This paper focuses on the method to show uncertainty explicitly in the map of the simulated landscape at the distant point in time.

The method requires that validation of the land-cover change model be quantified at the grid-cell level by Kappa for location (Klocation). The validation statistic is used to estimate the certainty in the extrapolation to a point in time where an empirical map does not exist. As an example, we reconstruct the 1951 landscape of the Ipswich River Watershed in Massachusetts, USA. The technique creates a map of 1951 simulated forest with an overall estimated accuracy of 0.91, with an estimated user's accuracy ranging from 0.95 to 0.84.

We anticipate that this method will become popular, because tabular information concerning land cover at coarse stratum-level scales is abundant, while digital maps of the specific location of land cover are needed at a finer spatial resolution. The method is a key to link non-spatial models with spatially-explicit models.

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Key words: Land-use change, Geomod, model, Kappa, uncertainty

JEL classifications: C0, O0, Q0, Z0

1 Introduction

1.1 Uncertainty analysis in predictive models

Land-use and land-cover change modeling has become an extremely common tool to understand and to extrapolate land-use change. Land-change modelers commonly assess the goodness-of-fit of calibration (Wu and Webster 1998, Lo and Yang 2002, Silva and Clarke 2002). Fewer modelers assess the goodness-of-fit of validation (Lowell 1994, Kok et al. 2001, Pontius and Schneider 2001). In this paper, we use a measurement of the goodness-of-fit of model validation to assess the level of certainty we should expect in the extrapolation by a land change model to a point in time where reference information for validation does not exist. To do this, we draw on fuzzy set theory, which has been used extensively in the remote sensing community (Foody 1996, Zhang and Foody 1998, Lewis and Brown 2001, Foody 2002). Specifically, we apply the concept of partial membership to a category in our analysis of uncertainty in extrapolations by simulation models.

Models commonly predict future landscapes (Veldkamp and Lambin 2001). However, it is also important to generate maps of past land cover for scientific applications where processes occur over decades, centuries, millennia, or longer (Harrison et al. 1998, Hall et al. 1995). Examples are climate change and soil nutrient dynamics. For these processes, the condition of the landscape in the past can have a large influence on the condition of the landscape in the present and future. Therefore, it is essential to develop models that can take maximum advantage of the sparse data that exist for past land cover. It would be helpful if modelers could use coarse-level tabular data to make maps that have a spatial resolution similar to other contemporary information at a finer grid cell-level resolution. For example, data exist for historic land cover by global region over the last century (Richards and Flint 1994), but modelers want to use that information expressed on a one degree by one degree grid in order to make it compatible with climate change models (Hall et al. 1995). It is even more common for tabular data to exist at the resolution of the political unit, such as the town, county, or state. Much of these data remain unconnected to GIS-based models because the information is not in the form of digital maps.

Therefore, there exists a need to create methods that can allocate coarse stratum-level tabular information concerning land cover to a finer resolution grid. This is clearly a job for a spatial allocation simulation model. However, simulation models are not perfect, so it is essential to develop tools to measure the level of certainty that exists in the maps generated by spatial allocation models. Unfortunately, the sophistication and complexity of many models is much greater than our ability to validate them. It is frequently impossible to know the level of confidence we should have in the output of simulation models because we have poor tools to quantify the level of certainty in the model. In recent research into methods of validation, a central theme has been the need to analyze the validation at multiple resolutions (Kok et al. 2001). Another theme has been the need to separate components of agreement due to specification of quantity of each land cover category from the agreement due to specification of location of each land cover category (Veldkamp and Lambin 2001).

This paper connects the ideas of the two previous paragraphs. This paper shows a method by which a modeler can use a simulation model to allocate coarse stratum-level tabular information of land cover to a finer resolution map of grid cells. Most importantly, this paper shows the level of certainty we can have in such simulated maps. We compute the certainty based on the concepts of the latest tools for model validation. The validation technique is somewhat independent of the particular model, hence the methods described in this paper apply to models that predict crisp classified cells, such as: Markovian, agent based, cellular automata, etc. This technique to assess uncertainty is an essential tool to create a link between non-spatial models that function on stratum-level information and spatial models that function on finer grid cell-level information. We illustrate the procedure with an example from a watershed in Massachusetts, USA.

1.2 Study area

The Ipswich River Watershed is located in northeastern Massachusetts, thirty miles north of Boston (Fig. 1). The watershed covers 404 square kilometers and includes all or parts of 22 towns. A national environmental organization, American Rivers, designated the Ipswich River as one of the 20 most threatened rivers in the United States. It cited water withdrawals, development, and pollution as reasons for the designation, stating that, “so

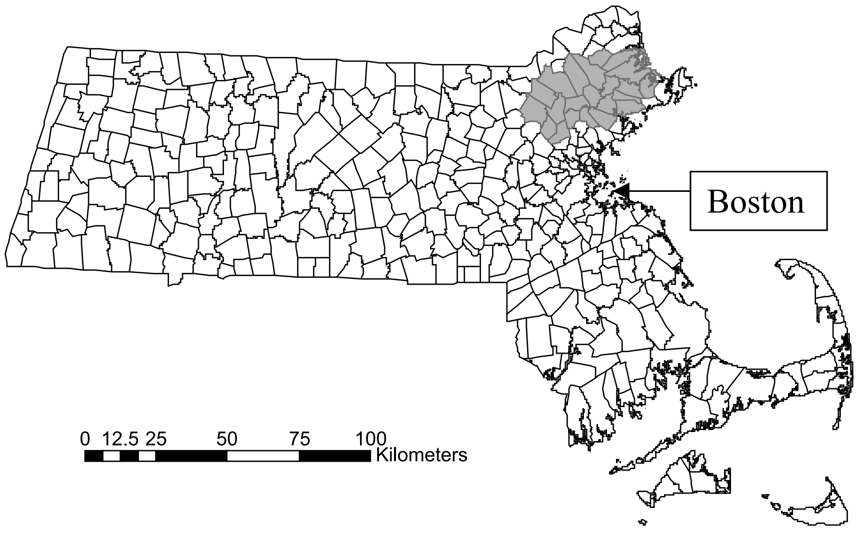

Fig. 1. The shaded polygons are the 22 towns of the Ipswich River Watershed within the State of Massachusetts

much water is removed from the Ipswich River Watershed for municipal water supply, industry, and irrigation that the river can literally run dry" (Zarriello and Ries 2000).

When it does flow, the Ipswich River empties into Plum Island Sound, which is one of the Long Term Ecological Research sites of the United States' National Science Foundation. It is important to understand the land-use and land-cover change patterns of the Ipswich River Watershed because of the watershed's influence upon the ecology of Plum Island Sound. The most common form of land-use change is deforestation for new residential land.

Ecologists believe that historical land-cover legacy conditions help determine the pattern of nutrient loading into the sound currently taking place. Pontius et al. (2000) give some evidence that the density of forest influences present nutrient export from the watershed. We do not know the extent to which the spatial arrangement of past forest influences nutrient export; therefore we would like to test the hypothesis that it does. To do this, we need a map that shows the spatial distribution of historic forest cover. A map of the historical landscape would provide an indication of the land-cover legacy conditions, hence would enable scientists to test hypotheses concerning the influence of past land use on present nutrient loading. Unfortunately, maps at the grid cell-level are not available in digital form; however tabular statistics of forest cover at the town level are available.

At the town level, it is possible to create a map that accurately portrays the quantity of past forest cover because we have tabular data on historic forest cover at the town level. We can use a simulation model to create a map of historic forest cover at a finer grid cell-level resolution that is compatible with our other maps. We want to know the certainty of the grid cell-level information in the simulated map of historic land cover, specifically with regard to the simulated location of the land use category. This paper supplies a method to create a simulated map of historical land cover with a known level of certainty at a fine grid cell-level resolution.

2 Methods

2.1 Data

Massachusetts Executive Office of Environmental Affairs supplied vector maps used in this analysis free of charge through their internet site (MassGIS 2002). As is typical of free data, the maps lack sufficient metadata, so it is not possible to know precisely the data's quality concerning: georegistration precision, RMS error, classification accuracy, etc. All maps were converted to a uniform 30 m × 30 m grid because the land use change model requires raster data. The conversion procedure assigns to each pixel the category found at the centroid of the pixel. We select a 30 m × 30 m grid for both scientific and practical reasons. Based on our communication with the map maker (David Goodwin, personal communication), the vector data is likely to be precise to approximately 30 m, but certainly not more precise than 30 m. More than 99% of the vector polygons contain an area larger than one 30 m × 30 m pixel. Conversion to a coarser resolution would substantially distort the information in the vector data. Equally importantly, 30 m resolution is the finest resolution that produces digital files that are acceptable in size for computation; finer resolutions would produce files that are too large. Finally, we would like for our database to be generally consistent with satellite imagery; and much satellite imagery is at the 30 m resolution.

Three of the maps are land cover for 1971, 1991 and 1999. Figure 2 shows the 1991 forest cover map. All cells are hard classified into a crisp set, which means that each cell is completely in either the forest category or the non-forest category. In this example, we analyze two land types because it is easiest for the reader to grasp, however the method can apply to any number of land types, as the equations demonstrate. In Fig. 2, the 22 towns that occupy the watershed are outlined in gray. The entire analysis is stratified by the 22 towns.

Data for land cover in 1951 are available in tabular form by town, i.e. by stratum (MacConnell and Cobb 1974; MacConnell et al. 1974). From 1951 to 1999 the change in forest area shows a smooth decrease from 56% to 40% of the study area.

An additional map gives the age of the housing stock at the census tract level. Information on housing is important to consider when predicting forest change because much of the recent deforestation is attributable to the increase in residential area.

2.2 Approach overview

Table 1 shows the approach in terms of its two necessary model runs. The first model run begins with the landscape of 1991 then simulates the

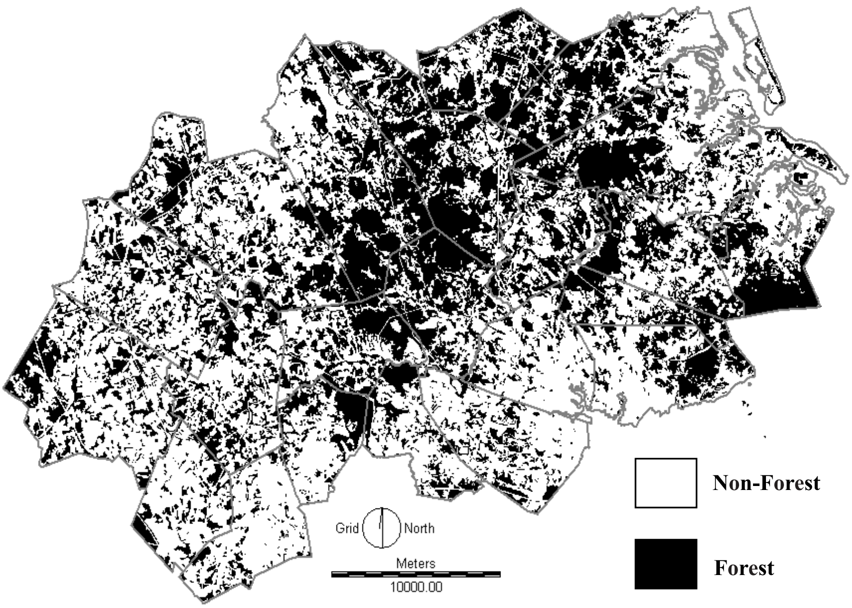

Fig. 2. Reference 1991 land cover map with 22 towns outlined in gray

Table 1. Description of model runs

Information	First run for validation	Second run for extrapolation
Simulation duration	from 1991 to 1971	from 1971 to 1951
Models inputs	town-level % of forest in 1971 and grid cell-level maps of: a] land cover in 1991 (Fig. 2) b] land cover in 1999 c] house age in 2000	town-level % of forest in 1951 and grid cell-level maps of: a] land cover in 1971 (Fig. 4) b] land cover in 1999 c] house age in 2000
Model output of crisp categories	grid cell-level maps of simulated forest versus non-forest in 1971 (Fig. 3)	grid cell-level maps of simulated forest versus non-forest in 1951 (Fig. 8)
Uncertainty analysis results	Kappa for location = 0.80 (Fig. 5)	grid cell-level map of probability of forest in 1951 (Fig. 9)

landscape of 1971. The purpose of the first model run is to validate the model and to quantify its goodness-of-fit. The first run's input information consists of both tabular information at the town level and mapped information at the grid cell level. The town-level information is the percent of forest and non-forest in 1971. The grid cell-level information consists of maps of the age of houses and land cover for 1991 and 1999. The output for the first model run is a map of grid cells that are crisp classified as either forest or non-forest simulated for 1971. For the uncertainty assessment of the first model run, we validate the output by comparing the simulated map of 1971 to the reference map of 1971. The validation is measured by the statistic Kappa for location, denoted Klocation (Pontius 2000, 2002). Klocation describes the extent to which the model is able to generate an accurate 1971 simulated map at the grid cell level. The purpose of the first model run from 1991 to 1971 is to obtain the value of Klocation, which indicates the confidence we have in the model's ability to specify the location of the grid cells within the towns. Klocation is an important measure of the goodness-of-fit of the validation that we compute and store for use in the second model run.

The third column of Table 1 describes the second model run, which begins with the landscape of 1971 then simulates the landscape of 1951. We call this the extrapolation run because we have no reference map for 1951 at the grid cell level. The town-level input information is the percent of forest and non-forest for 1951, whereas the grid cell-level input information is maps of house age and land cover for 1971 and 1999. The output for the second model run is a map of grid cells crisp classified as either forest or non-forest simulated for 1951. For the uncertainty assessment of the second run, we adjust the output of the model to convert it from crisp categories to fuzzy categories, so the cells express the certainty of membership in the forest category. The adjustment is based on the value of Klocation that the first model run generated. The remainder of this methods section describes the simulation model, the Klocation statistic, the uncertainty adjustment, and the 1951 map accuracy assessment.

2.3 The simulation model

The focus of this paper is the adjustment to the output from a simulation model, which is the final step at the bottom of the third column in Table 1. The specific simulation model used is not particularly important. In fact, the adjustment method is applicable to a variety of Markovian, cellular automata and agent based models. Nonetheless, it is helpful for the reader to understand the specific model used in this application. Therefore, this section gives a brief description of the model Geomod. For a comprehensive explanation of Geomod, see Pontius et al. (2001).

Geomod is a GIS-based land-cover change model, which quantifies factors associated with land-cover and can simulate the spatial pattern of land-cover change forward or backward in time. In this paper's application, Geomod selects locations for forest cover according to three decision rules: (1) allocation by town of the accurate quantity of forest and non-forest according to tabular data, (2) selection of grid cells for forest cover change according to a suitability map, and (3) prediction of persistence for the category that grows during the simulation. The first decision rule allows Geomod to assign the correct quantity of forest area and non-forest area to each town. The second decision rule allows Geomod to replace forest on the landscape at those non-forest cells that are likely to have been sites of recent deforestation according to a suitability map. The suitability map is based on the house age and an analysis of the pattern of land change between 1991 and 1999. The suitability map shows relatively high likelihood for recent deforestation at locations that have relatively new houses. The suitability map shows relatively low likelihood for recent deforestation at locations that are either non-residential or have relatively old houses. The third decision rule is particularly important because land cover persistence dominates most landscapes.

The data indicate that there is more forest as we go further back in time. Therefore, the effect of the third decision rule is that Geomod does not change the cells that are already forest as Geomod simulates backwards in time. If a cell is forest in 1991, then Geomod will predict that it will be forest in 1971. If a cell is non-forest in 1991, then Geomod might predict that it was forest in 1971, depending on its suitability. As Geomod simulates land cover change backwards in time, it searches among only the non-forest cells to determine which cells would most likely have been forest at a previous point in time, depending on the suitability map. Geomod is doomed to fail at all locations that experience afforestation between 1971 and 1991, which constitute only 0.35% of the study area.

The 1991 reference map of land cover (Fig. 2) is used as the starting point of the simulation to 1971. A simulated landscape is produced for 1971 (Fig. 3). The 1971 reference map of land cover (Fig. 4) is used for validation against the 1971 simulated landscape. The output from Geomod is a map of crisp classified cells, meaning that each cell is entirely within the forest category or the non-forest category. Geomod does not compute the probability of a cell being in a category. At the town level, the quantity of forest and non-forest in the simulated map matches the 1971 reference information. However the locations of some of the individual grid cells are incorrect. Next, we use the Klocation statistic to measure the accuracy of the simulation at the grid cell level.

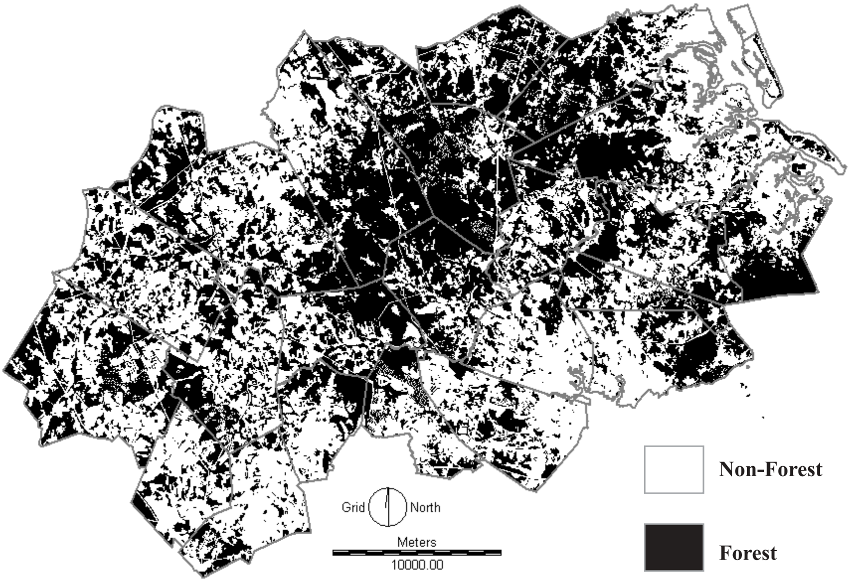

Fig. 3. Simulated 1971 land cover map resulting from the 1991 to 1971 Geomod prediction for 22 towns outlined in gray

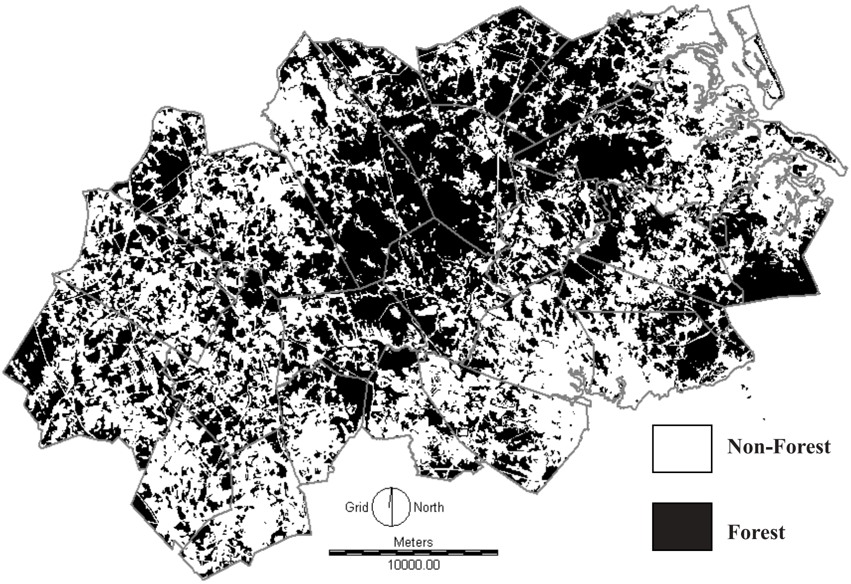

Fig. 4. Reference 1971 land cover map for 22 towns outlined in gray

2.4 Klocation statistic

Figure 5 shows that the agreement between the 1971 simulated map (Fig. 3) and the 1971 reference map (Fig. 4) is 91%. Furthermore, Fig 5 separates the overall percent correct into two components of agreement, called quantity and location. Pontius (2000, 2002) give the details of the technique to generate the individual components in Fig. 5. The first component is attributable to the fact that the model allocates the correct quantity of forest and non-forest to each town. If the simulation model were to allocate the 1971 quantity of forest and non-forest to grid cells selected randomly within the towns, then the expected agreement between the 1971 simulated map and the 1971 reference map would be the region shown as the bottom speckled area on Fig. 5. In this case, the agreement attributable to the town-level quantities is 53%. Equation 1 calculates this agreement.

Cell level agreement due to quantity $\equiv$

$$Y = \frac{\sum_{t=1}^{T}\sum_{n=1}^{Nt}\left(Wtn \times \left[\sum_{j=1}^{J} MIN(Rtnj,\ Rt \cdot j)\right]\right)}{\sum_{t=1}^{T}\sum_{n=1}^{Nt} Wtn} \qquad (1)$$

where

Rtnj = proportion of category j in cell n of town t, which is 0 or 1;
Rt·j = proportion of category j in town t, which is between 0 and 1;
Nt = number of cells in town t;
Wtn = weight of cell n of town t, which is 1 for the cells in the study, and 0 else;
T = number of strata, which is 22 towns in our example;
J = number of categories, which is 2: forest and non-forest.

The middle cross-hatched segment of Fig. 5 shows the second component of agreement, which is due to the model's ability to specify the grid cell-level

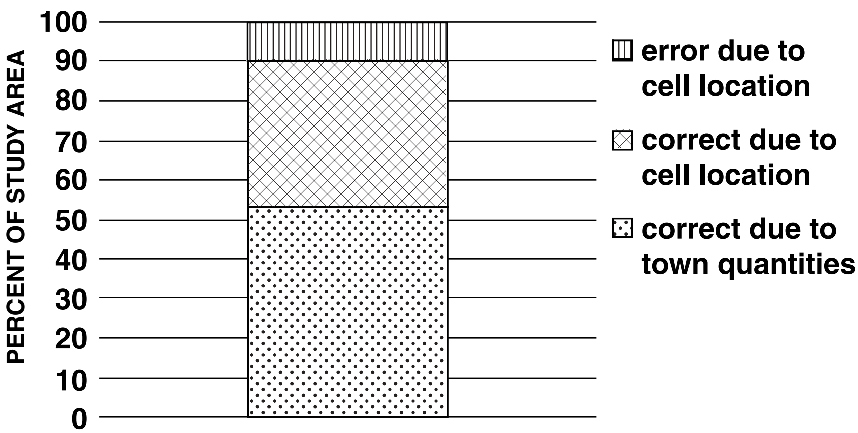

Fig. 5. Components of agreement and disagreement between simulated 1971 map and reference 1971 map

locations correctly within towns. The top, pinstriped segment of Fig. 5 is the error associated with the model's inability to allocate the grid cell-level locations perfectly within towns.

If the simulation model were to allocate the forest and non-forest at random grid cell locations within the towns, then the expected agreement between the simulated map and the reference map for 1971 would be 53%. If the simulation model were to allocate perfectly all the forest and non-forest at the correct grid cell locations, then the agreement between the simulated map and the reference map for 1971 would be 100%. Geomod's simulation attained 91% correct, which is 0.80 of the way between 53% and 100%, therefore Kappa for location, denoted Klocation, is 0.80. Equation 2 gives the formula for Klocation.

$$\text{Klocation} = (\text{M} - \text{Y})/(\text{Z} - \text{Y}) \tag{2}$$

where

M = proportion agreement between reference map and model output;
Y = proportion agreement due to quantity, given in equation 1;
Z = maximum possible agreement between the reference map and a perfect model output, given the specification of quantity of each category.

Figure 5 shows an example where M = 91%, Y = 53% and Z = 100%. Z is 100% when the specification of quantity of each category is perfectly correct, as in our example. But Z would be less than 100% if there were an error in specification of quantity of at least one of the categories. Pontius (2000, 2002) defines and describes in depth the Kappa for location statistic, denoted Klocation. Klocation is a variation on the more common Kappa index of agreement (Cohen 1960). In the case where Z = 100%, Klocation is equivalent to the standard Kappa Index of agreement, but this paper gives the more generalized Klocation, so this paper's methods can be used to assess the uncertainty of a wider variety of applications. Klocation is designed specifically to measure the agreement between two maps in terms of the grid cell-level location of categories, given a specification of the quantity of each category. Klocation measures this cell-level location-specific agreement separately from the agreement attributable to the fact that each town has the correct quantity of each land cover category. Equation 2 gives a version of Klocation that is designed for the case where the analysis is stratified by town, hence Y is given by Eq. 1.

Klocation measures how well the simulation model specifies the location of forest and non-forest at the grid cell level within the towns. If the simulation model were to allocate the land cover categories at random grid cell locations within the towns, then the expected value of Klocation would be zero. If the simulation model were to allocate perfectly the land cover categories at the correct grid cell locations within the towns, then the value of Klocation would be 1. Figure 5 shows a result for which Klocation is 0.80.

2.5 Uncertainty adjustment

Our final procedure is to run Geomod from 1971 to 1951, where the model categorizes each cell as a crisp category, either forest or non-forest, then we use Klocation of 0.80 to adjust the crisp classification of the 1951 simulated landscape. We select Klocation of 0.80 as our best guess at an appropriate Klocation because 0.80 was the value attained in the validation of the 1991-1971 Geomod run. The Geomod output for the 1951 simulated map shows each grid cell as either pure forest or pure non-forest. The proportion of forest and non-forest in each town is accurate because Geomod allocates the 1951 tabular data. However, it is likely that some of the individual cells are in the wrong location and some are in the correct location, but there is no way to tell for certain which are correct and which are incorrect because grid cell-level information for 1951 does not exist. Nonetheless, if we assume a Klocation of 0.80 for the simulation from 1971 to 1951, then we can adjust each simulated cell of 1951 to express the estimated level of certainty for the 1951 simulated landscape. The logic of the adjustment is as follows.

If Klocation is 1, then no adjustment to the crisp Geomod output is necessary, because Klocation = 1 implies that the Geomod simulation is perfect. In other words, if Klocation is 1, then the probability that a 1951 cell is forest, given that Geomod says it is forest, is 1; and the probability that a 1951 cell is non-forest, given that Geomod says it is non-forest, is 1.

Alternatively, if Klocation is 0, then Geomod's ability to specify the grid cell-level location is equivalent to random. When Klocation is 0, the probability that a 1951 grid cell is forest is the proportion of the town that is forest; and the probability that a grid cell is non-forest is the proportion of the town that is non-forest. In other words, if Klocation is zero, then the simulation model gives no additional information concerning the grid cell-level location of forest or non-forest. When Klocation is zero, the only information concerning the probability of a cell being forest or non-forest derives from the town-level tabular data.

However, the model has a Klocation between 0 and 1. Therefore, the probability of a cell being in a specific category, given that the model says it is that category, is given by Eq. 3.

$$\begin{aligned} \mathrm{Pt(j|Mk)} &= \mathrm{Qt \cdot j} + [\mathrm{Klocation} \times (1 - \mathrm{Qt \cdot j})] \quad \text{if } \mathrm{j = k} \\ &= \mathrm{Qt \cdot j} \times (1 - \mathrm{Klocation}) \quad \text{if } \mathrm{j \neq k} \end{aligned} \tag{3}$$

where

Pt(j|Mk) = the probability that a cell in town t is category j given that the model says it is category k,

Qt·j = proportion of town t that is category j,

Klocation = the best guess at the model run's grid cell-level certainty, which ranges from 0 to 1.

2.6 Accuracy assessment with an unknown landscape

One of the most powerful aspects of this uncertainty adjustment method is that we can calculate the expected agreement between the simulated output and the real landscape of 1951, even though we do not have a map of the real landscape of 1951. This technique depends on the assumptions that our estimate of Klocation is appropriate, that the stratum-level quantities of land cover are accurate, and that the grid cells of the unknown 1951 reference map are hard classified into crisp categories.

Note that if Klocation = 0, then Eq. 3 implies that the adjusted simulation output predicts that the probability of a 1951 grid cell being forest is the proportion of the town that is forest, and that the probability of a grid cell being non-forest is the proportion of the town that is non-forest. In this case when Klocation = 0, Eq. 4 gives the agreement between the 1951 simulated map and the unknown 1951 reference map, where the variable definitions are the same as in Eq. 1.

Agreement due to town level quantities ≡

$$A = \frac{\sum_{t=1}^{T}\left(\left[\sum_{n=1}^{Nt} \mathrm{Wtn}\right] \times \left[\sum_{j=1}^{J} (\mathrm{Rt} \cdot \mathrm{j})^2\right]\right)}{\sum_{t=1}^{T}\sum_{n=1}^{Nt} \mathrm{Wtn}} \tag{4}$$

Equation 4 is a simplified version of Eq. 1. Equation 4 is true because in each town, the proportion of cells hard classified as category j in the unknown 1951 reference map is Rt·j. Also, in town t, for every cell of the adjusted simulated map, the probability of being in category j is Rt·j when Klocation = 0

We are interested in the case where Klocation is between 0 and 1. Equation 5 gives the estimated overall agreement between the 1951 simulated map and the unknown 1951 reference map. Equation 5 is also the estimated overall agreement between the 1951 adjusted map and the unknown 1951 reference map. In Eq. 5, Z and Klocation are as defined in Eq. 2 and A is the agreement given by Eq. 4.

$$\text{Estimated overall agreement} \equiv B = A + \text{Klocation} \times (Z - A) \tag{5}$$

In our example's application of Eq. 5, Z is 1 because Geomod allocates the quantities that are specified by the 1951 tabular data, which we assume are accurate. If Klocation = 1, then Geomod's unadjusted simulated map is perfect, and equation 5 shows that the agreement with the unknown 1951 reference map is 100%. If Klocation = 0, then the expected agreement between Geomod's unadjusted simulated map and the unknown 1951 reference map is A, given by Eq. 4. In practice, Klocation is usually between 0 and 1.

Equation 5 gives the estimated agreement between the 1951 simulated map and the unknown 1951 reference map. However, if the estimate of Klocation is not accurate, then the actual agreement will vary from the estimated agreement. Nevertheless, there is a limit to how much the actual agreement can vary from the estimated agreement. The maximum agreement between the unadjusted simulated map and the unknown 1951 reference map is 100%, which would be the case if Geomod happened to specify the grid cell locations perfectly. The minimum agreement is constrained by the quantities of land cover types in each town. If any one category accounts for greater than half of the land cover in a town, then the minimum agreement is greater than zero. Equation 6 gives the minimum agreement between the unadjusted simulated map and the unknown 1951 reference map. Equation 6 is true because the cells of both maps are hard classified into crisp sets.

Minimum agreement due to town level quantities $\equiv$

$$C = \frac{\sum_{t=1}^{T}\left(\left[\sum_{n=1}^{Nt} Wtn\right] \times \left[\sum_{j=1}^{J} MAX(0, [2 \times Rt \cdot j] - 1)\right]\right)}{\sum_{t=1}^{T}\sum_{n=1}^{Nt} Wtn} \tag{6}$$

The procedure to adjust for uncertainty converts the unadjusted simulated map from a hard classification into a fuzzy classification, where each adjusted grid cell has some proportion of membership in each land cover category. This adjustment constrains the maximum percent correct to be less than 100%. It also constrains the minimum percent correct to be greater than agreement given in Eq. 6. Equation 7 gives the maximum agreement between the unknown 1951 reference map and the adjusted simulated map. Equation 8 gives the minimum agreement between the unknown 1951 reference map and the adjusted simulated map.

$$\text{Maximum adjusted agreement} = B + \text{Klocation} \times (Z - B) \tag{7}$$

$$\text{Minimum adjusted agreement} = B - \text{Klocation} \times (B - C) \tag{8}$$

3 Results

Figure 6 shows the agreement between the unknown 1951 reference map and the 1951 simulated map, including the levels and ranges of certainty. Figures 7–9 show the mapped results. The next several paragraphs relate Fig. 6 to Figs. 7–9.

If the only information available were the fact that 56% of the entire study area was forest in 1951, then one would make a map in which every pixel in the landscape shows a fuzzy membership in the forest category of 0.56. Such

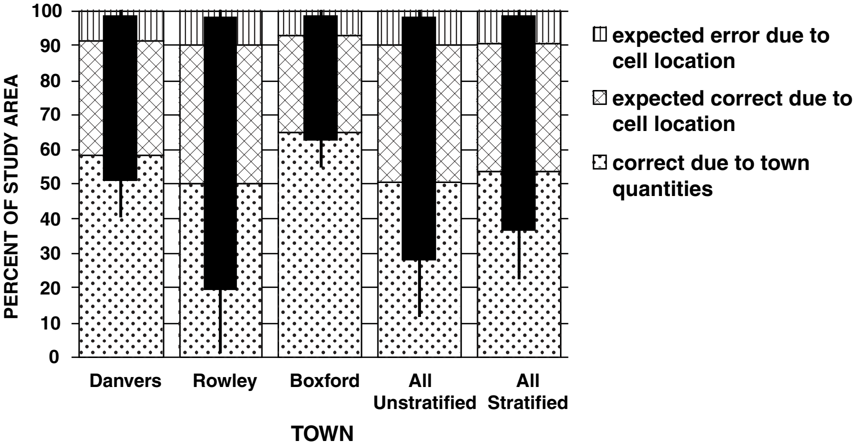

Fig. 6. Components of agreement and disagreement between 1951 simulated map and unknown 1951 reference map, including certainty bounds

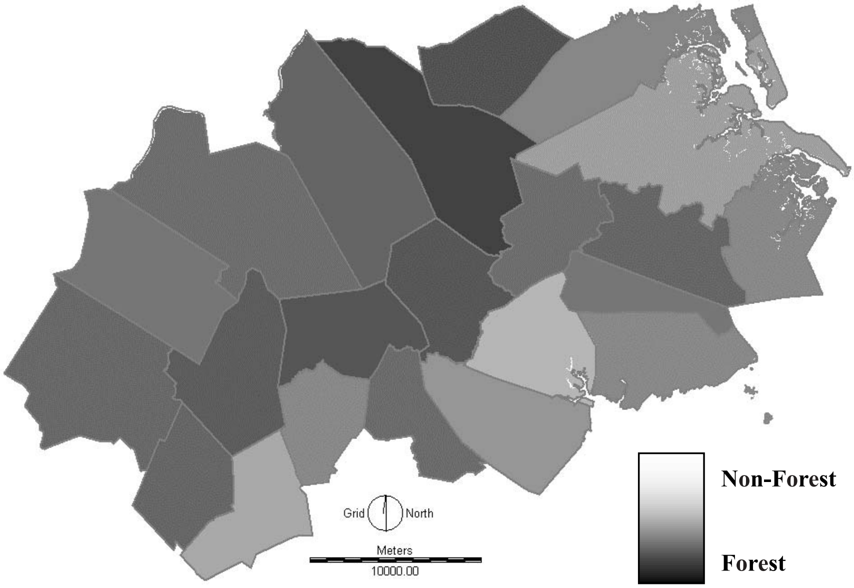

Fig. 7. A 1951 land cover map where the membership in the forest category of every grid cell is the proportion of forest within the cell's town, for each of the 22 towns outlined in gray

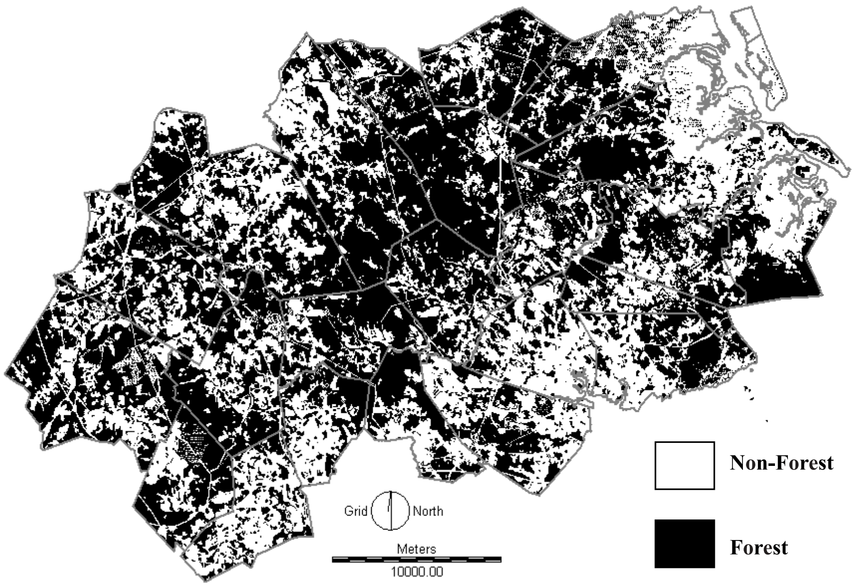

Fig. 8. A 1951 land cover map simulated by Geomod where the membership of each grid cell is hard classified into a crisp set of either forest or non-forest for 22 towns outlined in gray

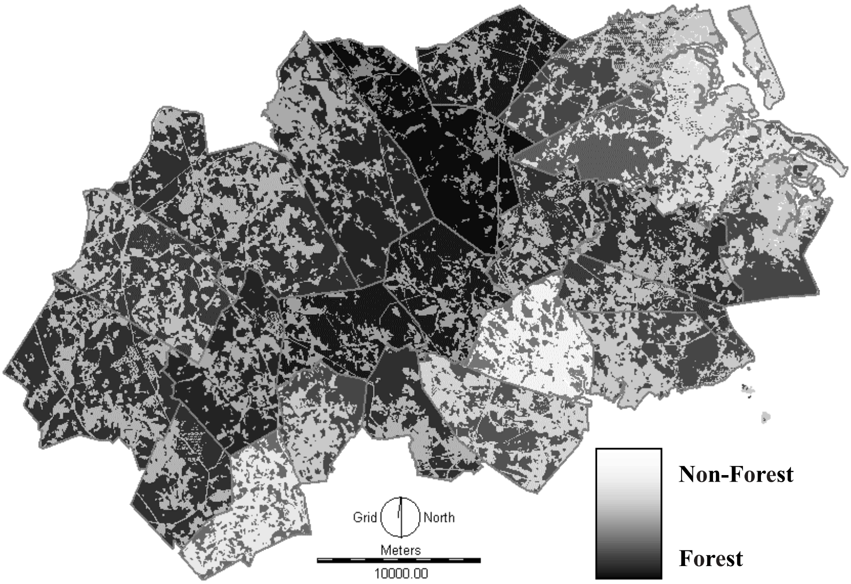

Fig. 9. A 1951 land cover map simulated by Geomod and adjusted for uncertainty such that the membership of each grid cell has a fuzzy membership in the forest category for 22 towns outlined in gray

a map fails to provide any information on the spatial distribution of forest and non-forest within the study area. Since the said map shows no town-level stratification, Eq. 4 with $T = 1$ computes the agreement between the said map and the unknown 1951 reference map as 51%. Figure 6 shows this 51% agreement as the speckled lower portion of the bar for the "All Unstratified" study area.

Figure 7 shows the 1951 landscape that one could portray if the only information one had were the proportion of forest by town. In Fig. 7, every grid cell in each town shows the proportion of forest within that town, which ranges from 30% to 77% based on the 1951 tabular data. Every cell within a specific town is homogenous and shows a fuzzy membership in the forest category. In other words, Fig. 7 shows the results one would obtain if one had a simulation model with Klocation of 0. Equation 4 computes the agreement between Fig. 7 and the real unknown map of 1951 as 54%. Figure 6 shows this 54% agreement as the speckled lower portion of the bar for the "All Stratified" study area.

Figure 8 shows Geomod's best guess at the 1951 landscape. Each cell is hard classified as a crisp category of either forest or non-forest. The proportion of forest and non-forest matches the 1951 tabular data. However, the simulation result of Fig. 8 overstates the certainty in the grid cell-level category membership, because Fig. 8 shows each cell classified as complete membership in exactly one category. We suspect that some of the cells of Fig. 8 are misclassified, however we do not know which ones are in the wrong location and which ones are in the correct location because we do not have a reference map of 1951 at the grid cell resolution. Figure 8 fails to show the level of certainty we should have in the simulated classification.

Equation 5 computes the estimated agreement between Fig. 8 and the unknown map of the real 1951 landscape as 91%, assuming Klocation = 0.80. Figure 6 shows this 91% agreement as the sum of the dotted portion and cross-hatched portion of the bar for the "All Stratified" study area. The top pinstripe portion of Fig. 6 shows the expected 9% error in the Geomod specification of grid cell-level location.

Figure 9 succeeds in showing the level of certainty we should have in the simulated classification at the grid cell-level. Figure 9 derives from Fig. 8 and a Klocation of 0.80. Figure 9 shows each cell containing a proportion of membership in the forest category, based on both Eq. 3 and the town-level tabular data of 1951. Therefore, Fig. 9 shows our most appropriate representation of the 1951 landscape, because it portrays an appropriate level of certainty. An important aspect of Fig. 9 is that it shows the correct proportion of forest in each town according to the tabular data for 1951, even though no cell is entirely forest or non-forest. According to Eq. 3, if a cell is classified as forest in Fig. 8, then it has a probability between 0.86 and 0.95 of being forest, as shown in Fig. 9, depending on the town proportion of forest. If a cell is classified as non-forest in Fig. 8, then it has a probability between 0.84 and 0.94 of being non-forest, as shown in Fig. 9, depending on the town proportion of non-forest. These conditional probabilities are known popularly as user's accuracies.

The expected agreement between the unknown 1951 reference map and Fig. 8 is the same as the expected agreement between the unknown 1951 reference map and Fig. 9. Figure 6 shows this 91% agreement as the sum of the dotted portion and cross-hatched portion of the bar for the "All Stratified" study area. However, the possible variation in agreement is larger for Fig. 8 than for Fig. 9. For Fig. 8, the maximum agreement is 100%, and the minimum is 23% according to Eq. 6. Figure 6 shows this variation by the thin vertical line of the box & whisker plot on the "All Stratified" bar. For Fig. 9, the maximum agreement is 98% according to Eq. 7, and the minimum is 37% according to Eq. 8. Figure 6 shows this variation by the wide vertical line of the box & whisker plot on the "All Stratified" bar.

The first three bars of Fig. 6 show the levels of certainty of the simulation for three towns. In the 1951 tabular data, the percent of forest in the towns of Danvers, Rowley, and Boxford are respectively 30%, 49%, and 77%. The level of certainty is low and the range in the certainty is large for Rowley, where the proportions in the land cover categories are spread evenly. The level of certainty is higher and the range in the certainty is smaller for Danvers and Boxford, where one land cover category dominates.

4 Discussion

4.1 Value of information at various resolutions

The sequence of Figs. 7–9 shows the usefulness of the methodology. Figure 7 shows the map one can create with the information concerning only the proportion of forest and non-forest at the spatial resolution of the town. Figure 8 shows the map that a simulation model can create with perfect information concerning the proportion of forest at the spatial resolution of the town, but with imperfect information concerning the proportion of forest and non-forest at the spatial resolution of the grid cell. Figure 8 fails to express uncertainty. Figure 9 shows the map that one can create with a simulation model output of Fig. 8 and a measure of uncertainty at the grid cell resolution, so Fig. 9 expresses the 1951 landscape with an appropriate level of certainty.

The value of the information at these various resolutions is a function of the landscape of 1951. For example, in 1951, the study area is 56% forest. Therefore, with information at neither the town level nor the grid cell level, the most we can say is that each cell has a 0.56 probability of being forest and 0.44 probability of being non-forest.

The value of the information in Fig. 7 is a function of the distribution of the proportion of each category in each town. At one extreme, if the proportion of forest in each town were exactly the same, i.e. 56% in each town, then the town-level information would not be any more useful than the study area-level information. At the other extreme, if each town were either 100% forest or 0% forest, then the town-level information would be extremely useful because it would allow us to specify the category of each grid cell within each town perfectly. Figure 7 shows a situation that is between these two extremes. Equation 4 shows that the agreement between Fig. 7 and the unknown real landscape of 1951 is 54%.

If the Geomod simulation shown in Fig. 8 is better than random at specifying the locations of forest within the towns, then the agreement between figure 8 and the unknown real landscape of 1951 is between 54% and 100%. If the simulation from 1971 to 1951 shown in Fig. 8 is worse than random at specifying the locations of forest within the towns, then the agreement between Fig. 8 and the unknown real landscape of 1951 is between 23% and 54%. We think that the model simulation between 1971 and 1951 is 0.80 of the way between random and perfect. Therefore the estimated agreement between Fig. 8 and the unknown real landscape is 91%.

4.2 Is the model good?

Klocation of 0.80 is high, relative to most researchers' experience with land-use change modeling (Schneider and Pontius 2001, Hall et al. 1995). Monserud and Leemans (1992) categorize a Kappa in the range from 0.70 to 0.85 as "very good". The reason for this high Klocation is landscape persistence. That is, a good predictor of where forest will be at one point in time is the location of the forest at some other point in time. In fact, if the model would have predicted net change from 1991 to 1971 at random locations, then the Klocation would have been 0.74 due to the fact that the model generally predicts persistence. Hence, most of the apparent success of the model is attributable to landscape persistence. The influence of Geomod's suitability map boosts the Klocation from 0.74 to 0.80.

If there had been no change between 1999 and 1971, then the Geomod prediction of 1971 would have been perfect because when there is no change in the quantity of any category, Geomod predicts no change in the grid cell location. In this case, Klocation would have been 1. Obviously, if a landscape never changes, then a perfect predictor of the state at a particular point in time is the state of the landscape at some other point in time.

In this sense, Geomod correctly predicts landscape persistence in terms of location. Not all models have that characteristic. For example Markov models can predict swapping of location among categories, even when there is no net change in the quantity of categories. When the quantity of forest does not change over time, then Geomod predicts neither deforestation nor regrowth, even though deforestation on the real landscape at one location can be countered by forest regrowth at some other location. In the Ipswich River Watershed, there is very little of this type of swapping of location of forest due to deforestation at one place and regrowth at another place, therefore Geomod is relatively successful at predicting both land cover persistence and one way change in quantity of forest. Geomod would likely perform poorly on landscapes that are dominated by swapping.

4.3 Extrapolation beyond validation interval

We claim that the Klocation from the 1991–1971 simulation validation is our best guess of model performance between 1971 and 1951. The Klocation from 1991 to 1971 is a good selection if the process of land use change between 1991 and 1971 is similar to the process between 1971 and 1951. If the process during the two intervals is substantially different from one another, then Eq. 3 should not use the Klocation from the 1991–1971 validation.

For example, the process of 1971–1991 land change was predominately one of steady deforestation for new residential land. If this was also the case between 1951 and 1971, the Klocation adjustment should be appropriate. However, if the process of 1951–1971 land change involved a substantial amount of forest regrowth at some locations combined with massive deforestation at other locations of 1951 forests, then the Klocation from 1991 to 1971 would over estimate the certainty of the model performance between 1971 and 1951. Based on what we know of the history of land-use change in the region, we think there was a steady mechanism of land-use change between 1951 and 1991, therefore our adjustment methods should work well.

On the other hand, it can be possible for the adjustment method to understate the level of certainty. For example, the range of time should have a great influence on the selection of an appropriate Klocation, because forest persistence has a large influence on Klocation. If we were to simulate from 1971 to 1970, then we would expect that the simulated map of hard classified categories should be very accurate because landscape persistence should be extremely high during one year. Therefore the appropriate Klocation to use for the uncertainty adjustment should be close to 1 when simulating over short time intervals. In our application, the time interval for validation is 20 years, and the time interval for extrapolation is 20 years. The proportion of change during the validation interval is similar to the proportion of change during the extrapolation interval.

We would not recommend the method for extrapolations farther back in time beyond 1951 because we know that the process of land change in Massachusetts was fundamentally different in the first half of the 1900s than in the second half. Specifically, the predominant land conversion was from non-forest to forest in the first half of the 1900s, as agricultural land was abandoned. The second half of the 1900s experienced conversion from forest to non-forest due to growth in residential areas. This method is recommended for extrapolations where the process of land conversion is smooth and fairly consistent. The mathematics of the method will give a result regardless of the true process of change, but one should take into consideration qualitative knowledge of the process of land change when interpreting the result.

4.4 Certainty concerning the quantity of land types

The next major development in this methodology should be to incorporate certainty in the estimated quantity of the land cover types. In this paper's example, we assume that the town-level quantities of land cover types are accurate. However, any estimate of quantity has some level of uncertainty. If we were to combine the uncertainty of the town-level quantities with uncertainty in the grid cell-level locations, then we would have a comprehensive analysis of uncertainty.

It would be especially important to incorporate the uncertainty in the town-level quantities in order to be able to link non-spatially explicit models with spatially explicit models. For example, many non-spatially explicit scenario models predict the quantity of land cover types by strata, such as global regions (Gallopin et al. 1997). The predictions of these stratified non-spatially explicit models can be fed into a spatially explicit model, such as Geomod, which could allocate the coarse stratum-level quantities to finer grid cells. Then the methods of this paper could be used to make statements about the gird cell-level certainty of the predicted future landscape. However, when a non-spatial model makes predictions of the future quantity of each land cover type by stratification unit, there is obviously substantial uncertainty because the future is usually difficult to predict. In order to have a comprehensive analysis of certainty, we must combine the certainty of the quantities of the land cover types with the certainty of the locations of the land cover types. This will be the next step in the development of this paper's method of uncertainty analysis.

5 Conclusion

We have provided a method to allocate coarse stratum-level information concerning land cover to a finer resolution map of grid cells. Most importantly, we have shown a method to assess the accuracy of an extrapolated fine resolution map, even when a fine resolution reference map does not exist. The method estimates the level of certainty and defines the bounds of certainty in the resulting fine resolution map. This technique will be useful for a variety of GIS applications where the researcher wants to take advantage of stratum-level tabular information. The method also provides a crucial tool to link non-spatial models with spatially explicit models, such as Markov models, cellular automata models and agent based models.

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