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Methods to summarize change among land categories across time intervals

Robert Gilmore Pontius Jr[a], Roopa Krithivasan[a]*, Laura Sauls[a], Yan Yan[b], Yujia Zhang[c]

[a] *Graduate School of Geography, Clark University, Worcester MA, USA*

[b] *Palmetto Posting Inc., Spartanburg SC, USA*

[c] *School of Geographical Sciences and Urban Planning, Arizona State University, Tempe AZ, USA*

**Corresponding Author. 950 Main Street, Clark University, Worcester, MA 01610 USA. Email: RKrithivasan@clarku.edu*

ORCiD: Pontius 0000-0001-7287-5875, Krithivasan 0000-0003-4980-2699, Sauls 0000-0001-8868-7465, Yan 0000-0002-7530-4581, Zhang 0000-0001-7910-6286.

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Methods to summarize change among land categories across time intervals

Abstract

Time-series maps have become more detailed in terms of numbers of categories and time points. Our paper proposes methods for raster datasets where detailed analysis of all categorical transitions would be initially overwhelming. We create two measurements: Incidents and States. The former is the number of times a pixel's category changes across time intervals; the latter is the number of categories that a pixel represents across time points. The combinations of Incidents and States summarize change trajectories. We also describe categorical transitions in terms of annual flow matrices, which quantify the additional information generated by intermediate time points within the temporal extent. Our approach summarizes change at the pixel and landscape levels in ways that communicate where and how categories transition over time. These methods are useful to detect hotspots of change and to consider whether the apparent changes are real or due to map error.

Keywords: category, GIS, land change, flow matrix, time, transition

1 Introduction

Efforts to characterize land change frequently depend on the comparison of maps of land cover or use categories at two or more time points. Researchers can now access continental scale maps that show transitions among several categories across numerous time intervals. For example, the United States' National Land Cover Database (NLCD) contains at least 16 categories at four time points (U. S. Geological Survey 2016) and Europe's Coordination of Information on the Environment (CORINE) data contains 44 land cover categories at four time points (Feranec et al. 2016). Furthermore, simulation models can produce maps for multiple categories for any user-specified number of time points (National Research Council 2014). A large number of categories and/or time points introduces various challenges for representing change. First, researchers can become overwhelmed by the details. If a raster map has T time points and J categories, then the number of possible temporal trajectories for each pixel is J^T, which can be so numerous that researchers must reduce the data. Second, maps at many time points might appear nearly identical because persistence frequently dominates a landscape, while investigators are interested primarily in temporal change. Third, pairwise comparison of time points sometimes ignores whether change occurs at the same places across multiple time intervals. Fourth, researchers need to know whether and how the inclusion of intermediate time points offers more information than shown by the temporal extent's first and last time points. This article presents methods to address these challenges for summarizing the locations and sizes of categorical transitions across multiple time intervals.

Researchers can begin to understand and to communicate change in spatial phenomena by employing visual characterizations (Monmonier, 1990; Rhyne, Dykes, & MacEachren, 2006). Some common approaches for presenting spatio-temporal data exist, but they may be limited in their capacity to communicate trajectories of change across multiple time intervals. Since the 1990s, much of the literature on the characterization of spatial data has concerned three-dimensional (3D) representations, interactive data models, web-mapping, and other geovisualization tools (c.f., Carvalho, Augusto de Sousa, & Ribeiro, 2008; Elwood, 2008; Kwan & Lee, 2004). Land Change Science has been particularly energetic concerning geovisualization for multi-temporal spatial change patterns, with urban geography also contributing to conversations (Liu & Cai, 2012; Yuan, Sawaya, Loeffelholz, & Bauer, 2005). These discussions have often focused on interactive and/or 3D methods for data display (Andrienko et al. 2010;

Dykes et al. 2005; Rhyne et al. 2006; Thakur et al. 2013). However, Griffin, MacEachren, Hardisty, Steiner, and Li (2006) found little evidence that these methods communicate effectively the space-time interactions across all phenomena, though a few notable exceptions exist. For example, Tayyebi et al. (2015) developed a method to show land legacy pathways across multiple time points by specifying a sequence of single-digit category identifiers across multiple time points, which can produce an enormous number of possible pathways. The authors then presented their results in terms of summaries of groups of pathways.

A primary vehicle to communicate change is side-by-side maps of the same study area at multiple time points, which Monmonier (1990) calls the multiple-static-maps strategy (e.g. Tucci, Giordano, & Ronza 2010). This approach can show temporal evolution, but some have argued that this representation is not easy to interpret (Carvalho et al., 2008). The multiple-static-maps strategy might be well-suited to some studies of land change, but if change occurs on only a small percentage of the spatial extent, then the maps from the various time points can appear nearly identical (Aldwaik & Pontius, 2013). Furthermore, the multiple-static-maps strategy does not necessarily consider the durations between pairs of consecutive time points (Thakur et al., 2013; Wondrade, Dick, & Tveite, 2013).

A variety of analyses consider differences between pairs of time points where durations between time points may vary (de Beurs & Henebry, 2005; Huang, Pontius, Li, & Zhang, 2012; Kinkeldey, 2014; Liu & Cai, 2012). Pijanowski and Robinson (2011) developed a framework to consider transition pathways across multiple spatial scales ranging from global to regional, zonal, landscape, and patch. The authors' approach can produce an overwhelming number of metrics as the spatial resolution becomes finer.

Researchers frequently compute the change rate between two time points, but do not employ a single standard equation for that computation. A few visual methods exist to compare change rates for datasets that have more than one time interval (Aris, Shneiderman, Plaisant, Shmueli, & Jank, 2005; Lehmann, Prior, Williams, & Bowman, 2008). Some methods to compute change rates assume non-linear temporal change for each category, even when only two time points are available. Those methods assume that each category changes during each time interval as a proportion of the category's size at the interval's initial time point, as Markov chains do; however, Takada, Miyamoto, and Hasegawa (2010) showed that comparing Markov matrices that are based on different durations is not straightforward. Runfola and Pontius (2013) developed a flow matrix to express the area of each transition from one category to a different category during each time interval. They used the flow matrix to average the overall changes across time intervals that have various durations, but they did not measure the additional information generated by intermediate time points that are strictly between the pair of time points that bound the temporal extent.

Consideration of an entire sequence of time points can give deeper information than consideration of only the difference between the temporal extent's initial and final time points. The number and types of changes that a given pixel experiences across a sequence of time intervals provides potentially important information about change trajectories (Liu & Cai, 2012). For example, land change may be permanent as in typical urban development or may be temporary (Turner, 1989; van Breugel et al., 2013). Temporary changes may alternate between categories as in cyclical cultivation, or could be part of a progressive sequence of several categories (Mertens & Lambin, 2000). Efforts to model changes as trajectories have provided important insights into the likelihood of change during a time interval (Braimoh & Vlek, 2005; Mena, 2008). However, trajectories can be so complex that it is easy for scientists to get lost in the details, unless scientists first summarize the data in an easily interpretable manner. Therefore, scientists have called for methods to filter out the noise and to focus on the processes as opposed to the outcomes (Harrower, 2001).

Our paper offers methods to summarize, visualize, and analyze change among categories across multiple time intervals. Our methods apply to many fields, and are particularly relevant to Land Change Science.

2 Methods

2.1 Data

We illustrate the concepts using data from the Long Term Ecological Research (LTER) network. The Georgia Coastal Ecosystems (GCE) LTER site encompasses upland, intertidal, and submerged habitats on the central coast of Georgia, USA. Raster maps of GCE are available for five time points: 1974, 1985, 1991, 2001, and 2005. The spatial extent contains 248,344 pixels, each with a spatial resolution of 100 m by 100 m. Each pixel is categorized as one of 13 categories in the original data.

Our first step is to reduce the number of categories via category aggregation, because the number of possible trajectories for each pixel through five time points for 13 categories is 13^5 = 371,293. We are most interested in change, therefore we aggregate categories that persist or are involved in relatively small changes, but we maintain as disaggregated the categories that are involved in large changes, so that the aggregation maintains the largest changes between time points (Aldwaik, Onsted, & Pontius, 2015). We reclassified the original 13 categories into four categories and gave them single word names: Evergreen, Wet, Cut, and Other. Evergreen is called 'evergreen forest' in the original GCE data, while Wet is called 'forested wetland' and Cut is called 'Clearcut/Sparse', which is a type of managed forest. Other is an aggregation of 10 categories, which consist mostly of open water, non-forested wetland and urban. Evergreen, Wet and Cut are ordered from largest to smallest and together account for between 71 and 77 percent of the spatial extent across the five time points.

2.2 Visual presentation

We take two approaches to visual presentation, the first of which uses maps. Maps at the various time points convey the size of each category and show the outcomes of land change, but do not necessarily show clearly the transitions between the pairs of time points. Therefore, we also create a sequence of maps to show the loss of each category and the gain of each category during each time interval. The second approach uses stacked bar figures to visualize the sizes of annual loss and annual gain of each category during each time interval. The height of each bar is the size of land change per year, and the width of each bar is the number of years during the time interval. Therefore, the area of each stacked bar is proportional to the amount of change during the time interval. This approach is more space-efficient than a uniform-width bar chart that has white space around each bar and that uses length to show one dimension of the data (Kong, Heer, & Agrawala, 2010). Our maps and bar figures use a color palette that is accessible to the 4% of the population that have some form of visual color deficiency, especially related to an inability to distinguish red from green (Light & Bartlein, 2004; Olson & Brewer, 1997). The AWARE Center's Color Laboratory and ColorBrewer 2.0 offered guidance to select color palettes (Brewer, Hatchard, & Harrower, 2003; Wickline, 2002).

2.3 Incidents and States

Our fifth author wrote a computer program in the language Visual Basic for Applications embedded in Microsoft Excel that interfaces with the GIS software TerrSet (Eastman, 2014). Readers can obtain the code for free at www.clarku.edu/~rpontius. The program computes two fundamental concepts: Incidents and States. A pixel's number of Incidents is the number of times the pixel experiences a change across time intervals. Incidents can range from 0, indicating complete persistence, to the number of time points minus 1, indicating change across all time intervals. A pixel's number of States is the number of different categories that the pixel represents at all time points. States can range from 1, indicating complete persistence, to the smaller of the number of time points and the number of categories. In the case of GCE, the number of Incidents ranges from 0 to 4 and the number of States ranges from 1 to 4.

There are four combinations of Incidents and States that are noteworthy, and particularly helpful when summarizing change trajectories. Incidents = 0 implies States = 1 and means a pixel persists as a single category across all time intervals; we call this *Persistence*. Incidents = 1 implies States = 2 and means a pixel experiences exactly one change; we call this *One Incident*. Incidents > 1 and States = 2 means a pixel toggles back and forth between two categories, as can occur in cycles of growth and harvest; we call this *Toggle*. States > 2 implies Incidents > 1 and means a pixel experiences more than two categories; we call this *Multiple States*. We use maps to visualize Incidents, States, and their combinations for the spatial extent.

Incidents and States are metrics that summarize change. They intentionally ignore the durations of the various time intervals and ignore the sequence in which individual categories transition with each other.

2.4 Flow matrices

We created a method to quantify the additional information generated by inclusion of intermediate time points as opposed to only the first and last time points of the temporal extent. Our new method expands on the concept of the flow matrix, which expresses each transition from one category to a different category between two time points (Runfola & Pontius, 2013).

Table 1 gives the mathematical notation that our equations use. The first time interval begins at Y_1 and the last time interval ends at Y_T. Table 1 defines **E** as the annual flow matrix for the temporal extent, which begins at Y_1 and ends at Y_T. **E** ignores intermediate time points between Y_1 and Y_T. Equation 1 defines the entry e_{ij} in row i column j of **E** as the size of the area of transition from category i at Y_1 to category j at time Y_T divided by the duration of the temporal extent. The diagonal entries of **E** are blank, because diagonal entries imply persistence, and it does not make sense to divide the area of persistence by the number of years of the time interval. Moreover, when each transition between different categories experiences a constant area per year during a time interval, then each category will not necessarily experience a constant persistence per year during that time interval.

[Insert table 1 here.]

$$e_{ij} = \frac{A_{ij}}{Y_T - Y_1} \text{ for } i \neq j \qquad \textit{Equation 1}$$

Equation 2 defines the entry f_{ij} in row i column j of **F**, which is the annual flow matrix for all T-1 time intervals. **F** considers time points Y_1, Y_T, and all points in between. Equation 2 computes a weighted sum of the annual transition from category i to a different category j for each time interval. The weight for each time interval is the duration of the time interval divided by the duration of the temporal extent. The annual transition for each time interval is the size of the area of the transition divided by the duration of the time interval. The durations of the individual time intervals cancel mathematically. Thus the derived numerator in the far right of equation 2 is the size of the area that transitions from category i to a different category j during time interval $[Y_t, Y_{t+1}]$ summed over all time intervals. The derived denominator in the far right of equation 2 is the duration of the temporal extent, which is the sum of the durations of all time intervals. Equation 2 does not compute f_{ij} for i=j because the purpose of a flow matrix is to express change. Equation 3 sums each row of **F** to compute the annual gross loss from category i. Equation 4 sums each column of **F** to compute the annual gross gain to category j. Equation 5 defines U as the sum of all entries of **F**, which is equal to the sum of all gross losses, which is also equal to the sum of all gross gains. If change across all time intervals were spread uniformly across the temporal extent, then the annual change would be U, which is the uniform annual change used by Intensity Analysis (Aldwaik and Pontius 2012; 2013).

$$f_{ij} = \sum_{t=1}^{T-1}\left[\left(\frac{Y_t - Y_{t+1}}{Y_T - Y_1}\right)\left(\frac{B_{tij}}{Y_t - Y_{t+1}}\right)\right] = \frac{\sum_{t=1}^{T-1} B_{tij}}{Y_T - Y_1} \text{ for } i \neq j \qquad \textit{Equation 2}$$

$$L_i = \sum_{j=1}^{J} f_{ij} \qquad \text{Equation 3}$$

$$G_j = \sum_{i=1}^{J} f_{ij} \qquad \text{Equation 4}$$

$$U = \sum_{i=1}^{J} \sum_{j=1}^{J} f_{ij} = \sum_{i=1}^{J} L_i = \sum_{j=1}^{J} G_j \qquad \text{Equation 5}$$

E = **F** if and only if the number of Incidents in all pixels is less than 2. If the number of Incidents is greater than 1 for at least one pixel, then $e_{ij} < f_{ij}$ for at least one transition from category i to category j. It is also possible simultaneously that $e_{mn} > f_{mn}$ for some other transition from category m to category n. For example, if a pixel passes through a sequence from Evergreen to Cut to Other, then **E** tallies the pixel as a transition from Evergreen to Other, while **F** tallies two transitions, neither of which are from Evergreen to Other. If we were to ignore all intermediate time points, then the annual area of overall change that we would miss would be U minus the sum of the entries in **E**.

3 Results

Figure 1(a) shows the maps at the five time points, which illustrates how maps at various time points can appear similar even when the amount of change is substantial. The percentages of the spatial extent that change during each of the four sequential time intervals are: 20, 35, 29 and 19. Figures 1(b) and 1(c) show the maps of loss and gain respectively during each time interval. Figure 2 shows more explicitly the sizes of the loss and gain for each category for each time interval. The horizontal line is the uniform annual change U. The annual changes during the first and third time intervals are slow relative to the uniform annual change, while the annual changes during the other time intervals are relatively fast. Each category experiences both loss and gain during each time interval.

[Insert figure 1 here.]

[Insert figure 2 here.]

Figure 3(a) shows the location of Incidents for each pixel and Figure 3(b) shows the location of States for each pixel. Figure 3(c) maps the combination of Incidents and States. Figure 4 summarizes the percentage of the spatial extent occupied by each combination of Incidents and

States. Figure 4 shows that 45% of the spatial extent persists as a single category across all four time intervals, 18% experiences exactly one Incident, and 22% toggles back and forth between two categories.

[Insert figure 3 here.]

[Insert figure 4 here.]

Table 2 compares **E** with **F** and gives the results from equations 1-4. When we consider all five time points, the largest transitions are from Evergreen to Cut and from Cut to Evergreen, accounting for 19 and 21 square kilometers per year respectively. The transitions between Evergreen and Cut across time intervals tend to occur in the same pixels, therefore when we consider only 1974 and 2005, we see smaller transitions from Evergreen to Cut and from Cut to Evergreen, accounting for 3 and 4 square kilometers per year respectively. Table 2 intentionally uses a slash to separate each entry of **E** from the corresponding entry of **F**, because the ratio of e_{ij} to f_{ij} can be helpful to consider. For example, the transition from Cut to Evergreen has a small ratio of 4/21, because the size of the transition from Cut at the first time point and Evergreen at the last time point is a small proportion of the size of transitions from Cut to Evergreen during all time intervals. This implies that the pixels that were Cut at the first time point and eventually transitioned to Evergreen, then subsequently transitioned again from Evergreen to some other category. On the other hand, the transition from Wet to Evergreen has a large ratio of 6/8, because the size of the transition from Wet at the first time point to Evergreen at the last time point is a large proportion the size of transitions from Cut to Evergreen during all time intervals. This implies that the pixels that were Wet at the first time point and transitioned to Evergreen, then subsequently remained Evergreen through to the final time point. The entry in the lower right of Table 2 shows that if we were to consider only the two time points at 1974 and 2005, then the apparent annual change would be 28 square kilometers per year, while the amount of change across all time intervals is 83 square kilometers per year. Thus if we had ignored the intermediate time points, then we would have detected only about one-third of the amount of change revealed by all the time points.

[Insert table 2 here.]

4 Discussion

Figures 1 and 3 show raster maps of land change; however, the visual methods for characterization can have other applications. These cartographical representations of change could be particularly relevant for demographic research that examines categorical variables such as race, political party, etc. Furthermore, our methods could compliment more interactive geovisualization methods. For example, one could show the categories at each time point through a scroll-bar or animation (Monmonier, 1990).

Figures 3 and 4 show combinations of Incidents and States, which can reveal landscape dynamics or might expose errors in the maps. Evergreen and Cut are the categories most involved in change and those two categories toggle back and forth in the same pixels. The toggle relationship may indicate a cyclical pattern of land use, such as with managed timber extraction. Alternately, a toggle relationship between categories with similar spectral signatures could indicate classification errors in the same pixels at various time points. Pontius and Lippitt (2006) give a method to test whether classification errors can explain the temporal differences between maps. Enaruvbe and Pontius (2015) give methods to quantify whether classification errors could lead to overestimation or underestimation of change. Those two methods rely on estimates of the errors in the map, but such estimates are unavailable for some maps. Other ways to distinguish whether temporal difference is error or change is to consider the nature of the categories and additional qualitative information concerning the nature of the land change processes. For example, Washington-Ottombre et al. (2010) illustrate methods to measure the association between various land change processes and land cover patterns; thus if known processes do not match the data's patterns, then further examination of data quality is warranted. Müller et al. (2012) take this approach a step further by using known land use processes to refine their maps. In GCE, it is likely that transitions between Evergreen and Cut are real changes, because the region has cycles of timber harvest (Schmidt et al. (2013). However, if a toggle relationship were between categories such as Built and Forest, then it would be more plausible that error accounts for the apparent toggling relationship, because conversion from Built to Forest is usually not plausible. Pattern metrics can also help to distinguish whether error or real change causes map differences. If an individual pixel toggles between two categories while its neighbors persist and the size of the pixel is smaller than the suspected size of patches of change on the ground, then error is likely the source of the toggling. For example, built areas usually do not appear on the ground in isolated patches of 1 square meter.

Researchers must be cognizant also of how the duration between time points can influence the signal to noise ratio during the map production process (Christman et al. 2015). If the duration between two time points is shorter than the duration of land change, then differences between time points might be due more to error than to land change. For example, temporal differences due to seasonality might appear larger than the land change across years. However, longer time intervals can lead to other types of errors for various reasons such as inconsistent map production procedures between the time points, absence of field data for the past, and temporal variation in weather patterns (Christman et al. 2016).

The dates of the time points can also influence the ability to detect various processes. Schmidt et al. (2013) report that the GCE region had been experiencing residential development before the economic collapse of 2008. Therefore, if one wanted to see the effect of an event at a particular time point, then one would need maps before, at, and after the time point (Cunningham et al. 2015). If a process is cyclical, then it is necessary to consider how the duration of the cycle compares to the duration between the maps' time points. For example, if the duration of a timber harvest cycle is identical to the duration between the maps' time points, then the maps might show only the Cut category or only the Forest category at both time points; thus the maps would fail to show toggling of the change between the time points.

Table 2 compares **E** with **F** to show the additional change revealed by intermediate time points between the beginning and ending points of the temporal extent. The time points available are not necessarily related to when change occurs on the ground, but the time points can influence how researchers observe change. The inclusion of additional intermediate time points can allow entries of **F** to change, but with a limit. If the dataset has time intervals that are sufficiently short so as to contain each change event in each pixel, then inclusion of additional time points will not cause entries of **F** to change as long as the additional time points do not contain errors.

5 Conclusions

The methods described above produce outputs that communicate change among multiple categories across multiple time intervals, especially for situations where the data are so detailed that it is overwhelming to analyze immediately all categorical trajectories. The methods reduce the data so that researchers can summarize patterns before digging deeper into details. Two metrics, called Incidents and States, identify pixels that experience change in terms of number of transitions across time intervals and number of categories across time points. Certain combinations of Incidents and States suggest patterns over multiple time intervals that indicate potentially important trajectories for land change. Maps of the combinations can help investigators to identify hotspots of change and to begin to consider whether the apparent changes are real or due to map error. We also derived annual flow matrices to show the sizes of the categorical transitions. Pixels that transition more than once account for the difference between the annual flow matrix that uses all time points versus the annual flow matrix that uses only the two time points that bound the temporal extent. These flow matrices quantify whether change patterns between categories are more complex than a single time interval would suggest. We designed these methods for land-use planners, natural resource managers, remote sensing professionals, and land change scientists. We encourage our colleagues to use these methods to summarize, visualize, and analyze information concerning multi-category phenomena across time intervals, in order to understand detailed data that would otherwise be overwhelming.

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Tables

Table 1. Mathematical notation where italics indicate variables and bold indicates a matrix.

Symbol	Meaning
J	Number of categories
i	Index for a category at the start of a time interval
j	Index for a category at the end of a time interval
T	Number of time points
t	Index for a time point
Y_t	Year at time point t
A_{ij}	Size of area that transitions from category i at time Y_1 to category j at time Y_T
B_{tij}	Size of area that transitions from category i at time Y_t to category j at time Y_{t+1}
e_{ij}	Annual transition from category i to category j during time interval $[Y_1,Y_T]$
$\mathbf{E}$	Annual flow matrix using only the two time points that bound the temporal extent. $\mathbf{E}$ has J rows and J columns where the entries are e_{ij}. Diagonal entries are blank.
f_{ij}	Annual transition from category i to category j across all T-1 time intervals
$\mathbf{F}$	Annual flow matrix using all T time points. $\mathbf{F}$ has J rows and J columns where the entries are f_{ij}. Diagonal entries are blank.
G_j	Annual gain to category j across all T-1 time intervals
L_i	Annual loss from category i across all T-1 time intervals
U	Uniform annual change across all T-1 time intervals

Table 2. Flow matrix showing transitions from the row category to the column category in square kilometers per year. Diagonal entries are blank because diagonal entries represent persistence. Numbers before the slash are annual flows between the two time points that bound the temporal extent [1974, 2005], which derive from **E**. Numbers after the slash are annual flows across all four time intervals, which derive from **F**.

		To				Loss
		Evergreen	Wet	Cut	Other	
From	Evergreen		2/5	3/19	3/6	9/31
	Wet	6/8		1/5	2/3	10/16
	Cut	4/21	0/3		1/3	6/27
	Other	2/5	1/2	1/1		3/9
Gain		12/34	4/11	5/26	7/12	28/83

Figures

Figure 1. Maps of Georgia Coastal Ecosystems Long Term Ecological Research site: (a) land categories at five time points, (b) losing categories during four time intervals, (c) gaining categories during four time intervals, (d) spatial extent in black within the State of Georgia, USA.

Figure 2. Annual (a) Loss and (b) Gain by category during four time intervals.

Figure 3. Maps that summarize all four time intervals: (a) Incidents, (b) States, and (c) Combinations.

Figure 4. Percent of area occupied by each combination of Incidents and States.

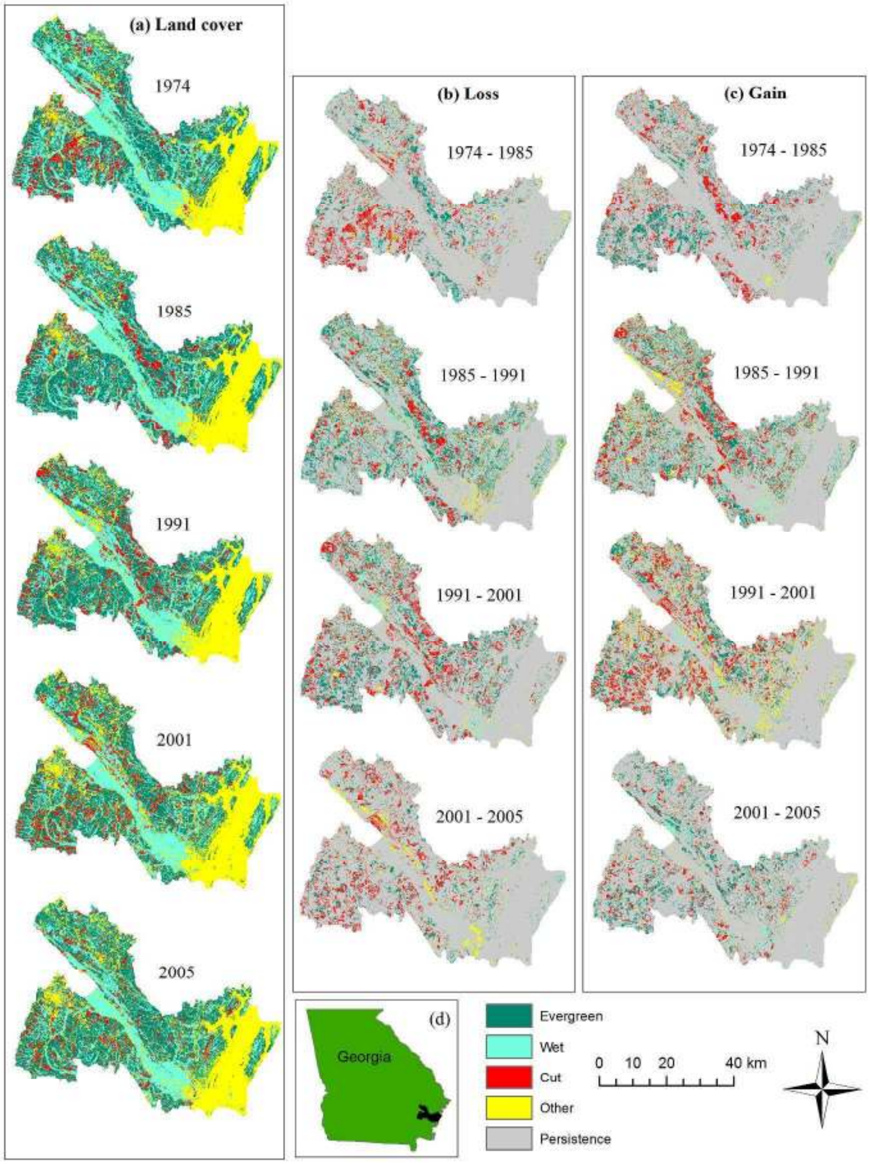

Figure 1. Maps of Georgia Coastal Ecosystems: (a) land categories at five time points, (b) losing categories during four time intervals, (c) gaining categories during four time intervals, (d) spatial extent in black within the State of Georgia, USA.

215x279mm (300 x 300 DPI)

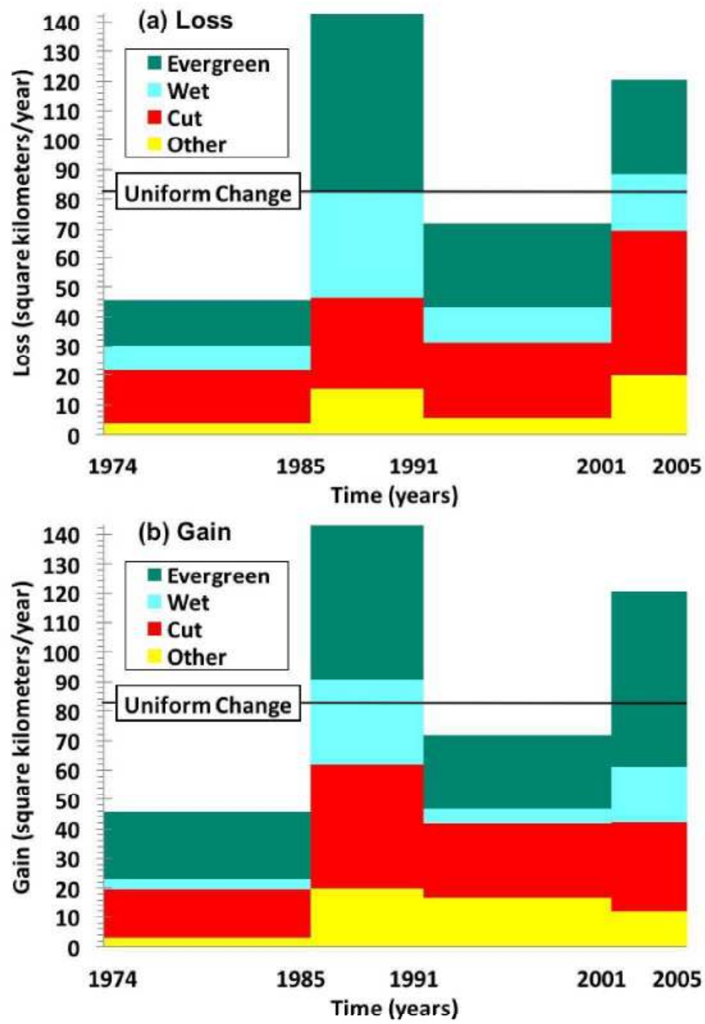

Figure 2. Annual (a) Loss and (b) Gain by category during four time intervals.

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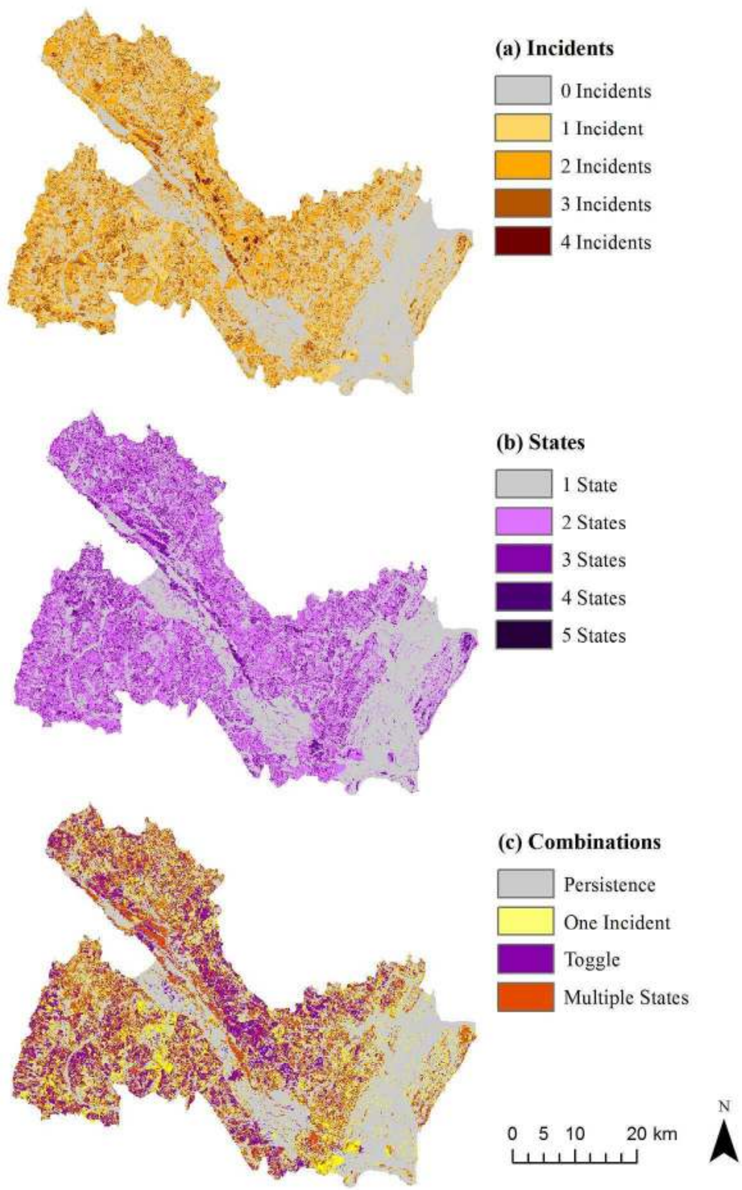

Figure 3. Maps that summarize all four time intervals: (a) Incidents, (b) States, and (c) Combinations.

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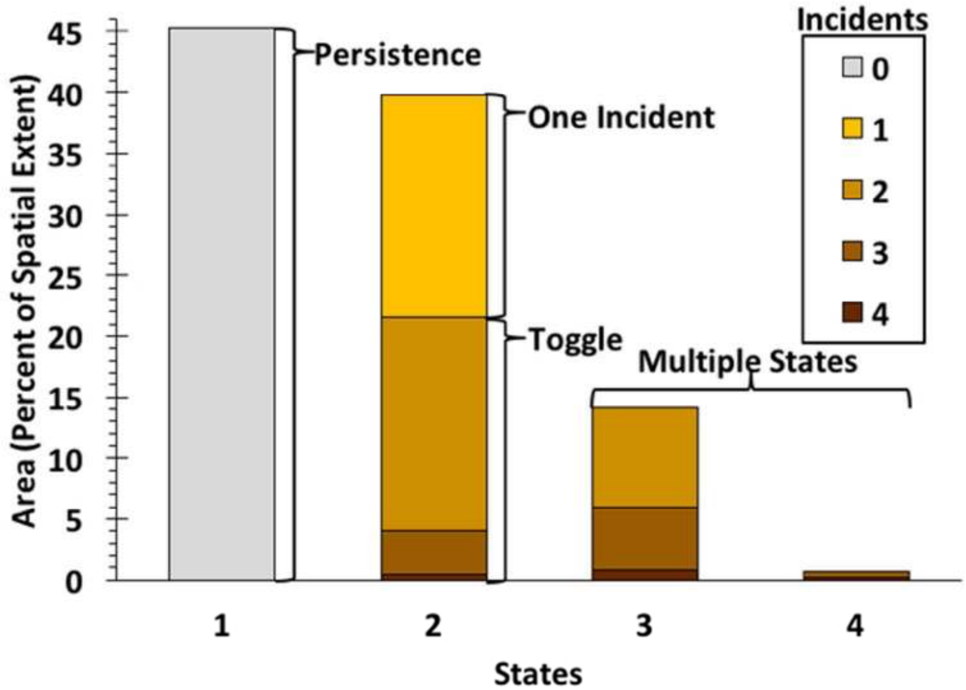

Figure 4. Percent of area occupied by each combination of Incidents and States.

227x165mm (72 x 72 DPI)