Characterizing Location and Classification Error Patterns in Time-Series Thematic Maps

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***Abstract*—The goals of this letter are to study the spatial patterns of location error and of classification error in spatio–temporal datasets, assess the role of environmental factors in determining error rate and pattern, and test for possible correlation within and between these error types in space and time. A multiple regression was used to determine the effects of local environmental factors (topography, vegetation cover) on each error type. Topographic structure and vegetation cover had significant effects on location error, where larger error was associated with north-facing aspects, steeper slopes and woody vegetation cover. Classification error was also affected by topography, and vegetation cover. Slope was the major factor that affected classification quality. Strong correlation was found between error in different time steps, for both error types. Correlation between these two error types in the same time step was much smaller and in most cases insignificant.**

***Index Terms*—Change detection, classification error, error analysis, error estimation, misregistration, spatio–temporal database.**

I. Introduction

As THE ANTHROPOGENIC processes of land transformation across the earth are accelerating, change detection becomes a critical means for accurate description of such processes in regional and local scales. A number of authors have raised the problem of accuracy in multitemporal datasets, where the main concerns are the impact of error in the coregistration of time-series maps or images on the estimates of change [1]–[3] and the impact of attribute error in each layer in the dataset on the accuracy of the dataset as a whole [4]. These concerns correspond to the two major types of error in spatio–temporal datasets, location error, and classification error, respectively.

Error in spatial datasets may be nonrandomly distributed in space. It may have complex spatial patterns, independent of patterns in the image it is derived from. Errors of different sources may interact and, thus, increase uncertainty further [5]. In fact, for a single time-step, nonrandom spatial patterns in georeferenced satellite images were found for location error [6] as well as for classification error [7].

An accurate assessment of uncertainty in spatio–temporal datasets depends on good error models; such models, in turn, need to account not only for the spatial patterns of each error source alone, but also for possible correlation between both error sources in space and time. The existence of such complex error patterns was suggested recently [1], [2], [6], but was not tested for in actual datasets.

Another important task of studies of uncertainty in spatial data is the identification and quantification of the factors affecting error [5]. Previous studies have stressed the role of internal factors (quality of ground control points (GCPs) for location error, the classification method used for classification error). In this letter, statistical methods are used in order to quantify effects of external, environmental factors (topography, vegetation) on data accuracy.

The goals of this letter are 1) to test for possible correlation within and between these error types in space and time, and 2) to assess the role of environmental factors in determining error rate and pattern.

II. Methods

A. Spatio–Temporal Dataset

A case study in which the dynamics of oak woodlands are studied over a period of 56 years [8] was used for the study of error patterns. Five aerial photos of the Hastings Natural History Reservation and surroundings (Monterey County, CA), taken in 1939, 1956, 1966, 1971, and 1995, were scanned. All photos were panchromatic with high spatial resolution, 1 : 20,000, except the 1995 photo which was color 1 :18 000. 14 ground control points were identified in all photos and measured in the field using a Magellan ProMARK-X-CM GPS receiver. Differential solutions for the GCPs were determined using base station data from The SIVA Center at Monterey Bay. Horizontal standard deviation for the 14 GCPs ranged from 0.32–1.92 m, with a median of 0.59 m. Orthophotos were produced using the ground control points, a high-resolution DEM (digital elevation model) of the area, and camera calibration reports. The spatial resolution (pixel size) of all orthophotos was 0.6 m.

The classification process followed the methods described by Carmel and Kadmon [9]. Basically, this is a hybrid of supervised/unsupervised classification, followed by a spatial filter. The classification scheme included three distinct vegetation classes: oak woodland, chaparral, and grassland.

B. Error Assessment

One goal of this letter is to test error patterns of different error sources and different time steps for possible correlation. Toward this end, a special effort was made to document both error sources across the study area using the same point locations in all time steps.

Location error was estimated for each photo in 40 locations across the scene that were identified in all photomaps. For a

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TABLE I
LIST OF POTENTIAL PREDICTORS FOR THE MIXED MODEL

Variable	Measurement
Year	Nominal variable, indicating the year the image was taken (1939, 1956, 1971 or 1995)
Trees	Proportion cover of trees within a 5 m radius around each point
Grass	Proportion cover of herbaceous vegetation within a 5 m radius around each point
Elevation	Elevation in m above sea level
Slope	Slope inclination
aspect-ns	A binary variable indicating north aspects vs. south aspects
aspect-ew	A binary variable indicating east aspects vs. west aspects
aspect-ns*slope	The interaction term between slope and the north-south component of aspect
aspect-ew*slope	The interaction term between slope and the east-west component of aspect

TABLE II
CORRELATION (SPEARMAN COEFFICIENT) IN ERROR BETWEEN DIFFERENT POINTS IN TIME AND BETWEEN ERROR SOURCES

(a) Correlation in location error between time steps.

	1939	1956	1971
1939	--	--	--
1956	0.43*	--	--
1971	0.49**	0.71**	--
1995	0.19^{NS}	0.71**	0.67**

(b) Correlation in classification error between time steps.

	1939	1956	1971
1939	--	--	--
1956	0.42*	--	--
1971	0.28^{NS}	0.43*	--
1995	0.14^{NS}	0.38*	0.45*

(c) Correlation between location error and classification error in the same year.

1939	1956	1971	1995
0.03^{NS}	0.17^{NS}	0.05^{NS}	0.01^{NS}

N = 40. * P<0.05, ** P<0.01

given point in a specific image, location error was defined as the Euclidean distance between point location on that specific image and location of the same point in a reference image. The 1966 orthophoto was set as a reference, to which all other images were compared, and was not used in further analysis. Error values in these 40 points were used to calculate correlation between time steps.

Classification error was previously assessed using a stereoscope-aided manual photo-interpretation of at least 350 points for each image. High classification accuracy was found in that assessment for all images (percentage classified correctly [PCC] ranged from 0.88 to 0.94; see [8, Table IV]). In the present letter, the reliability of the manual interpretation as a reference was assessed, comparing the 1995 manual interpretation with results of a ground survey that covered 89 locations. An agreement of 0.96 was found between the two methods, and the manual interpretation was, thus, considered reliable for all images. Next, the set of 40 point-locations, identified in all images that was used to assess location accuracy was used here to assess classification accuracy as well. For a point location, classification can be either "true" if it is in agreement with the reference) or "false" (otherwise). This binary value is not sufficient for estimating error pattern, neither for assessing possible correlation with location error, a continuous variable. The goal was thus to construct a local estimate of the error matrix and the PCC. Toward this end, the local classification accuracy was estimated for a circle of 5-m radius around each of the 40 point locations. The area of the image contained within each circle ($\sim$220 pixels) was classified manually for each image. The manual classification was compared with the computerized classification described above, to construct an error matrix and derive the PCC value for each circle. These data were used to calculate correlation in classification error between time steps, as well as correlation between classification and location error in the same time step.

C. Statistical Analysis

The goal of the statistical analyses was to determine the effects of local factors and of large-scale trends in the image on location error and on classification error. The dependent variables were point-specific location error and circle-specific classification error in the 40 point-locations described above, in each of the four years (1939, 1956, 1971, 1995). These observations were not independent. Thus, a mixed regression model was used, with the explanatory variables time (as a nominal variable) and environmental factors (indexes of topography and vegetation, all as interval-scaled variables). Mixed regression is a flexible tool, suitable for cases where various structures of correlation occur within the dependent variables. The model assumed unspecified correlation structure between time points and independence between locations after allowing for scale and time. Three major groups of predictors were included (Table I): 1) year; 2) topographic variables (elevation, slope, aspect and the interaction term between slope and aspect); and 3) vegetation cover (circle-specific percentage cover of trees, chaparral and grass (the sum of these three variables is a unity in all observations; thus, chaparral cover was omitted). Insignificant variables ($P > 0.1$) were omitted in a backward process, and the procedure was rerun. The $P > 0.1$ threshold level was selected because of the small sample size ($n = 40$).

III. RESULTS

RMSE location error in all four years was 2.6 $\pm$ 0.66 m, and average PCC was 0.88 $\pm$ 0.05 m. Correlation between location error in different time steps was moderate [Spearman coefficient ranged from 0.43 to 0.71, significant in all cases but one; see Table II(a)]. Correlation between classification error in different time steps was less prominent [Spearman coefficient ranged from 0.14 to 0.45, insignificant in two cases, Table II(b)]. Correlation between error types in the same time step was insignificant in all four time points [Table II(c)].

The mixed regression model revealed significant effects of environmental factors (both topography indexes and vegetation cover) on location error (Table III). Slope related positively to location error (steeper slopes had larger location error). Higher elevations had smaller error, and north-facing slopes had larger location error than south-facing slopes (Table III). The interaction term between slope and the north-south component of

TABLE III
RESULTS OF THE MIXED MODEL FOR LOCATION ERROR

Effect	Subtype	Estimate
Intercept		37.312***
year	1939	2.152^{NS}
year	1956	-2.643*
year	1971	-0.478^{NS}
year	1995	0
slope		0.646*
aspect-ns	North	-4.932*
aspect-ns	South	0
aspect-ns*slope	North	0.881*
aspect-ns*slope	South	0
grass		-6.112*
trees		-15.825***

N = 160. * p<0.1, ** p<0.05, *** p<0.01, ^{NS} Not Significant

TABLE IV
MIXED MODEL RESULTS FOR CLASSIFICATION ERROR

Effect	Subtype	Estimate
Intercept		0.8112***
year	1939	0.06372**
year	1956	0.09011***
year	1971	-0.01636^{NS}
year	1995	0
trees		0.1067*

N = 160. * p<0.1, ** p<0.05, *** p<0.01, ^{NS} Not Significant

aspect was also significant (the effect of slope on error was more prominent on south-facing slopes than on north-facing slopes). High cover of both trees and grasses was associated with smaller location error, meaning that chaparral is associated with increased location error. Expectedly, year was a highly significant predictor of location error as well.

The regression model for classification error ended up with only two significant predictors: year and cover of trees (increased cover of trees was associated with increased classification error); topographic indexes did not affect classification accuracy significantly (Table IV).

IV. Discussion

Recently, several studies addressed the issue of error in spatio–temporal data [1], [3], [10]. Yet, an error analysis for the case of time-series thematic maps has not been carried out before. The present letter analyzes the structure of the two major types of error in a spatio–temporal thematic dataset and detects correlations between them in space and time. Then, a mixed regression model is used to identify effects of local environmental factors on location error and on classification error. Taken together, results of this study reveal nonrandom error patterns, including local variability (as revealed by the mixed regression model), and correlation between time steps.

A moderate and significant correlation was found between error of the same type in different times, while correlation between the two error types in the same time step was weak and insignificant. The observed strong correlation between location error in different images in a time-series is not surprising, since all images were georectified based on the same set of ground-surveyed locations. The quality and geometric relationships of the ground control points is thought to be a major determinant of the spatial pattern in location error [6] (although my results suggest that topography also affects location error considerably). Some correlation is also expected for classification error in different time steps, since vegetation types and specific regions that are misclassified in one image have high probability of being misclassified in another image. The correlation values calculated for classification error in different time steps were lower than for location error and still fair.

The case for correlation between location error and classification error is less clear. Both location accuracy and classification accuracy are affected by land cover. To the extent that these factors affect both classification and georectification similarly, some correlation between location error and classification error, although weak and indirect, could be expected. Such relations were not detected in this study, where correlation between the two error types was small and insignificant. This finding is particularly important for error models that attempt to incorporate both error types into a single estimate [8], [11].

This study found that topography indexes as well as vegetation cover have a significant contribution to the magnitude of location error. Low elevations, steep slopes, and north-facing aspects were all associated with increased location error. All these may be attributable to a combination of larger stretch in the georectification process and poorer illumination [9].

The major findings of this letter, including correlation between time steps, lack of correlation between error sources, and the environmental factors that affect error are probably true for most studies of time-series raster images derived from airphotos. The extent to which these conclusions are relevant to satellite images is less clear. However, at least the correlation between errors in different time steps, pointed out in this letter, is likely to be present in any remotely sensed spatio–temporal data.

V. Conclusion

Inferences can be drawn from this letter, regarding both components of error management, namely error reduction and error assessment. Much effort has been directed into improving accuracy of spatial data and the present letter can add few hints. When ground control points are collected, it would be beneficial if more points are allocated preferentially to areas where accuracy is expected to drop, and more effort should be put into the measurement and identification of these points. This letter shows that such areas include steeper slopes, particularly north-facing slopes (perhaps due to more shade in the northern hemisphere), and forested land.

Perhaps more important, conclusions of this letter are relevant to modeling uncertainty in time-series thematic maps. Uncertainty in spatial data is inevitable [5]. However, information on the uncertainty in estimated parameters may be used for evaluating the risk that a specific outcome of further analysis of the information will be incorrect [12], or for incorporating the variability of the parameters of interest into ecological and environmental models, using stochastic simulations [13]. Error modeling has become a major means to provide such spatially explicit information on data uncertainty. Most spatially explicit error models were developed for a single data layer (typically for DEM and its derivatives, e.g., [12], but there exist also models of multilayer databases and time-series [3], [10]. To date, two different models were developed for the special case of multilayer thematic raster maps [8], [11], in which both location error and classification error have to be accounted for in each layer. Both of these models assume that error in each time step is independent of error in other time steps and that location error and classification error are independent of each other. The present letter reveals that while the former assumption may hold in actual datasets, the latter assumption may not. A version of the combined location–classification error model [8] that accounts for correlation between time steps is the subject of an on-going research in our laboratory.

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