Discriminant models for uncertainty characterization in remotely sensed land cover

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***Abstract*—Discriminant space defining area classes is an important conceptual model for uncertainty characterization in area-class maps. It needs to be adapted for use with real data sets, as area classes intended are rarely completely and unambiguously defined by empirical data classes. This paper explores its applications in land cover mapping and land cover change analyses. Through experiments using real data sets, it was found that there are significant differences between the results obtained by referring to data classes and those by information classes, and uncertainty characterization is well supported by discriminant models and geostatistics, which accommodate spatio-temporal interdependence in error occurrences and enable quantification of effects due to partially random measurement errors and systematic categorical discrepancy, respectively.**

Keywords: uncertainty, area classes, discriminant space, geostatistics, land cover change

I. INTRODUCTION

Land cover mapping and change detection have been extended from local, regional, national, to global scale, it is required that error in remotely sensed land cover information and its propagation in derivative products be quantified and handled correctly (Stehman, 2009; Pontius and Petrova, 2010). For error modeling in geo-processing, however, simple applications of the law of variance and covariance propagation without accounting for spatial dependence will lead to biased quantification of standard errors in derived data and analysis results (Burnicki, Brown, and Goovaerts, 2007). Thus, the method of discrimiant space was proposed, which reinforce consistency in area-class mapping and replicability in error modeling (Goodchild *et al.*, 2007).

The discriminant space is also called **Z** space because it is often described as a vector field $\mathbf{Z}(x)$ of dimension b with b being a positive integer, where x denotes a location within the problem domain A. The discriminant model provides a function η linking the **Z** values at a point x to the class at that point: $c(x)= \eta(\mathbf{Z}(x))$, so that any point in geographic space maps to a point in the **Z** space. For uncertainty characterization in bi-temporal imagery based land cover change categorization, the discriminant models should be generalized so that the linear models remain applicable for bi-temporal measurements.

Discriminant models assume that there exists a true value $m_z(x)$ hence a true class label $C(x)$ at every location, and measurement $\mathbf{Z}(x)$ containing error $\delta\mathbf{Z}$ leads to error-prone area-class $C^*(x)$. It is important to recognize that empirical discrminant models do not always support a one to one correspondence between $m_z(x)$ and $C(x)$. Thus, data classes should be discerned from de-noised measurement, which can be used to bridge the gap between measurement and information classes (Richards and Kelly, 1984).

This paper explores discriminant models and geostatistics for uncertainty characterization in land cover information. This is pursued by devising methods for mapping area classes in the space of discriminant covariates and projecting errors from discriminant space to area classes in the geographic space. Spatially explicit quantification of spatial uncertainty in land cover classes and their change is facilitated by transforming and summarizing stochastically simulated class-defining covariates. Uncertainty due to data and information class semantics will be discussed separately from that due to measurement errors. Experiments with real data sets will be carried out to demonstrate the effectiveness of discriminant models in uncertainty characterization and how to deal with data and information class semantic discrepancy.

II. METHODS

A. Mapping from Discriminant Realizations to Area Classes

To implement discriminant models, class models are required, which map measurement to classes and, for error simulation, equal-probable realizations **Z** to realizations of area-class map *C*. A classifer can be seen as the mapping from measurement to class labels and expressed as:

$$\hat{C}(x) = \eta(\mathbf{Z}(x)) = \arg\max_{k=1,\ldots,K} f_k(\mathbf{Z}(x)) \tag{1}$$

where f_k calculates measures of proximity to indicate categorical similarity to class k, with the predicted prevailing class $\hat{C}(x)$ taking the maximum utility. To map probabilistic distributions of classes in **Z** space, kernel density estimation may be used as a nonparametric way of estimating the probability density function of a random variable.

The research is supported by "973 Program" grants. *(project No. 2007CB714402-5 and project No. 2006CB701302)*

Multivariate joint distributions may also be estimated through b-dimensional kernels.

While data classes k are associated with $\mathrm{m}_z(x)$ by a data-specific membership function $f_k(\mathrm{m}_z)$, correspondence between data classes $\hat{C}(x)$ and information classes $C(x)$ should also be described. We may assert that information class i is related to data class k by means of a transition probability vector $p_{i|k}(x)$, which measures the strength of association of data class k with the information class i and may be usefully interpreted as the probability that data class k mapped at location x is actually true class i. In a changing environment, the class labels i and k refer to categorized changes so that transition probability $p_{i|k}(x)$ is still cognate but needs to be interpreted properly, i.e., class labels i and k being "from-to" classes themselves.

B. Bayesian Classification Algorithm

Consider change categorization based on bi-temporal measurement. Post-classification comparison can be modified to accommodate temporal dependence. Let $\mathbf{z}^1(x)$ and $\mathbf{z}^2(x)$ stand for the observations at times 1 and 2, respectively. Suppose $\{\nu_i, i=1, \ldots, K_1\}$ and $\{\omega_j, j=1, \ldots, K_2\}$ are the sets of possible classes at times 1 and 2, respectively. According to Bayes theorem, this process of compound classification is written as:

$$\hat{C}_1(x) = \nu_k \text{ and } \hat{C}_2(x) = \omega_l \text{ if and only if} \quad (2)$$
$$p(\nu_k, \omega_l \mid \mathbf{z}^1(x), \mathbf{z}^2(x)) = \max_{i,j} p(\nu_i, \omega_j \mid \mathbf{z}^1(x), \mathbf{z}^2(x))$$

where $\hat{c}_1(x)$ and $\hat{c}_2(x)$ are the predicted class label for location x at time 1 and 2, respectively.

To derive classification rule in terms of class-conditional density function and prior probabilities as in Bayesian classification, class-conditional independence is assumed as a reasonable approximation, and the joint class-conditional density can be then expressed as:

$$p(\nu_i, \omega_j \mid \mathbf{z}^1(x), \mathbf{z}^2(x)) \approx p(\mathbf{z}^1(x) \mid \nu_i) p(\mathbf{z}^2(x) \mid \omega_j) p(\nu_i, \omega_j) \quad (3)$$
$$= \frac{p(\nu_i \mid \mathbf{z}^1(x)) p(\omega_j \mid \mathbf{z}^2(x)) p(\nu_i, \omega_j)}{p(\nu_i) p(\omega_j)}$$

Knowledge of prior probabilities and estimation of single-date class probabilities is required for the Bayesian classification algorithm described in (3). The former can be obtained from expert knowledge, historical data, or observations from regions having comparable conditions or undergoing similar change.

*C. **Z** Based Stochastic Simulation*

Z based stochastic simulation was done to generate equal-probable area-class maps based on realized **Z**, which can be used to compute summary statistics, such as means and standard deviation of individual class proportions over specific areas or different land cover transitions for land cover change. For a random field $\mathbf{Z}(x)$, conditional sequential simulation refers to the technique whereby some data, denoted as (n), are available. The sequential simulation algorithms for simulating a single realization are outlined as follows: 1) Assign any conditioning data (n) to the grid; 2) Define a random path visiting all nodes $\{x_i\}$ in the grid; 3) Construct a conditional distribution; 4) Draw a simulated value $z(x_i)$ from the conditional distribution; 5) Add simulated value to data-set $(n+i-1)$, and 6) Continue to the next node along the random path until all nodes are exhausted.

III. EXPERIMENTS

A. Study Area and Data Sets

An area of central Montana, USA, located at $46°25' \sim 48°30' N$ and $108°04' \sim 111°10' W$, was chosen as the study area, as we had collaborative research on land cover mapping in this region with scientists at University of Montana, Missoula. Different land cover types exist in this area, forming a very complex landscape. The NLCD 1992–2001 Land Cover Change Retrofit product developed by scientists at MRLC was used to derive more accurate and useful land cover change data than would be possible by direct comparison of NLCD 1992 and NLCD 2001. This product (downloaded from http://www.mrlc.gov) contains unchanged pixels from the NLCD 2001 land cover dataset (6 class labels), and changed pixels labeled with a "from-to" class code (12 change classes). The 6 land cover labels are 1-open water, 2-barren/sand, 3-forest, 4-grassland/shrub, 5-agriculture, and 6-wetlands. Analysis of the results for the conterminous United States indicated that about 3 percent of the land cover dataset changed between 1992 and 2001 (Fry *et al.*, 2009). Also downloaded were Landsat 5 Thematic Mapper (TM) images (P38/R27) flown on July 17th, 1992 (time 1) and August 11th, 2001 (time 2), with bands 1-5 and 7 at 30 meters resolution. A subset covering 500 by 500 Landsat TM image pixels was used as the data set for the studies. This study was chosen for its terrain undulation and typicality in land cover and change types.

B. Data Processing

Tasseled cap transformation was performed with the bi-temporal Landsat TM images, and bands of brightness and greenness were selected and transformed via Choleski factorization so that Euclidean distance can be computed in lieu of Mahalanobis distance. This resulted in the discriminant covariates at times 1 and 2, respectively. The trend surfaces were discerned for Z_1 and Z_2 fields at time 1 and time 2, then the corresponding residual surfaces for the bi-temporal vectors were obtained, denoted as $\{R_1^{(1)}, R_2^{(1)}\}$ and $\{R_1^{(2)}, R_2^{(2)}\}$. As will be described later, stochastic simulation in the **Z** space was performed on these de-trended data sets. A training set of 2500 pixels was sampled selectively to represent land cover changes observed, with 1252 changed pixels and 1248 unchanged pixels. Based on the land cover change map describing the "from-to" change types, land cover types for single-date maps at times 1 and 2 were labeled the "from" and the "to" types, respectively.

Plot all pixels (smoothed trend surfaces) in the **Z** space discretized into a grid of 256 by 256 cells and summarize land cover class labels of pixels falling in individual grid cells. The majority class labels in these grid cells were taken as the labels of data classes so that all pixels were separable in the **Z** space. This gave rise to maps showing data classes of land cover in 1992 and 2001, respectively, which correspond but do not equal to NLCD land cover classes (considered to be information classes). Further, it was possible to identify pure pixels based on purity of class labels in discretized **Z** space, from which pure pixels were singled out for accuracy testing.

Data classes for the 2,500 training pixels were recorded based on the data class maps derived above. Thus, we had two sets of training data for 1992 and 2001 land cover mapping, one for data classes and the other for NLCD classes. The training samples were used for kernel-based density estimation in the **Z** space, which resulted in two sets of probability vector maps. In addition to land cover change maps derived from post-classification comparison, it was also possible to derive land cover change from these single-date land cover probability maps based on the Bayesian classification rule specified in (3).

By the discriminant method of error modeling, stochastic simulation of **Z** surfaces was carried out by using **sgsim** in GSLIB on the basis of conditional data sets $\{r_1^{(1)}, r_2^{(1)}\}$ and $\{r_1^{(2)}, r_2^{(2)}\}$, respectively. The realized residual surfaces $\{R_1^{(1)}, R_2^{(1)}\}$ or $\{R_1^{(2)}, R_2^{(2)}\}$ were added to the corresponding trend surfaces, to simulate equal-probable and error-contaminated Z data. The discriminant variables were simulated with 100 realizations. These simulated Z data were input to an interpolator on the time-specific probability surfaces to produce class probabilities and hence land cover realizations. For each time point, 100 realized area-class maps were generated and summarized with respect to class statistics.

Also output was a discrete classification output from a pool of 100 realized area-class maps. Such procedures were undertaken for the data sets for time 1 and time 2, respectively. Results based on both data classes and NLCD classes of land cover were obtained.

TABLE I. MEANS AND STANDARD DEVIATION (IN BRACKETS) OF LAND COVER TRANSITIONS DERIVED FROM POST-CLASSIFICATION COMPARISON AND BAYESIAN CLASSIFICATION (REFERRING TO DATA CLASSES; UNITS: %)

	Reference							*post-classification comparison*							*Bayesian classification*						
								2001													
1992	1	2	3	4	5	6	Total	1	2	3	4	5	6	Total	1	2	3	4	5	6	Total
(a) pure pixels (44,994)																					
1-open water	0.19	0.002	0.09	0	0.004	0	0.29	0.01 (0.01)	0.15 (0.04)	0.06 (0.02)	0	0.01 (0.01)	0.06 (0.02)	0.29 (0.05)	0.15 (0.04)	0.08 (0.01)	0.06 (0.02)	0	0.03 (0.02)	0.25 (0.03)	0.58 (0.08)
2-forest	0.04	53.68	3.49	0	0.001	0.01	57.23	1.64 (0.61)	38.72 (9.73)	7.85 (3.99)	0	0.53 (0.30)	22.49 (7.63)	71.23 (4.62)	11.11 (2.35)	11.24 (1.99)	2.79 (1.01)	0	0.61 (0.32)	25.08 (4.02)	50.83 (7.66)
3-grassland shrub	0.14	8.01	30.41	0.004	1.31	0.07	39.95	0.35 (0.16)	2.23 (1.16)	13.03 (1.77)	0	1.83 (1.68)	2.49 (1.15)	19.93 (3.16)	4.43 (0.83)	0.57 (0.22)	2.63 (0.37)	0	1.24 (0.56)	2.48 (1.14)	11.35 (2.43)
4-barren sand	0	0	0	0	0	0	0	0.01 (0)	0.15 (0.04)	0.04 (0.02)	0	0.01 (0)	0.06 (0.03)	0.26 (0.04)	0	0	0	0	0	0	0
5-agriculture	0.03	0.01	1.85	0	0.50	0.04	2.42	0.15 (0.06)	1.51 (1.04)	1.49 (0.33)	0	0.64 (0.25)	1.57 (0.69)	5.35 (1.82)	3.44 (0.64)	0.98 (0.40)	1.56 (0.28)	0	1.38 (0.36)	3.64 (1.10)	10.99 (2.12)
6-wetlands	0	0.02	0.07	0	0.01	0.02	0.11	0.06 (0.03)	0.50 (0.76)	0.92 (0.61)	0	0.43 (0.21)	1.05 (0.78)	2.95 (1.99)	5.40 (1.37)	3.50 (1.35)	3.00 (0.59)	0	1.67 (0.47)	12.68 (3.32)	26.25 (6.10)
Total	0.41	61.71	35.90	0.004	1.83	0.14	100	2.21 (0.75)	43.25 (10.97)	23.39 (3.70)	0	3.44 (2.22)	27.71 (8.30)	100	24.53 (3.02)	16.36 (1.46)	10.04 (1.19)	0	4.93 (1.58)	44.13 (3.82)	100
(b) all pixels (250,000)																					
1-open water	0.04	0.001	0.02	0	0.001	0	0.06	0.01 (0.01)	0.10 (0.04)	0.22 (0.05)	0	0.01 (0.01)	0.05 (0.02)	0.40 (0.05)	0.23 (0.03)	0.06 (0.01)	0.13 (0.02)	0	0.04 (0.02)	0.22 (0.03)	0.69 (0.05)
2-forest	0.01	12.80	2.95	0	0.004	0.01	15.77	1.30 (0.63)	20.73 (7.33)	23.05 (7.63)	0	1.05 (0.62)	12.72 (4.57)	58.85 (10.25)	9.61 (2.32)	5.22 (1.31)	3.69 (1.32)	0	1.01 (0.48)	12.70 (2.94)	32.23 (7.24)
3-grassland shrub	0.04	3.06	73.88	0.002	2.18	0.27	79.42	0.51 (0.28)	3.74 (2.62)	18.41 (6.43)	0	1.69 (1.45)	4.23 (2.18)	28.59 (9.87)	3.80 (0.98)	0.62 (0.24)	2.54 (0.76)	0	0.80 (0.41)	2.27 (0.97)	10.03 (2.94)
4-barren sand	0.0008	0	0.002	0	0	0	0.002	0.01 (0)	0.08 (0.03)	0.17 (0.03)	0	0.01 (0.01)	0.05 (0.02)	0.32 (0.04)	0	0	0	0	0	0	0
5-agriculture	0.008	0.002	3.23	0	1.04	0.12	4.39	0.14 (0.06)	1.10 (0.55)	3.24 (1.04)	0	0.61 (0.34)	1.67 (0.68)	6.77 (1.98)	4.45 (0.94)	0.92 (0.29)	2.08 (0.51)	0	1.43 (0.42)	4.30 (1.00)	13.18 (2.42)
6-wetlands	0	0.01	0.29	0	0.02	0.03	0.35	0.09 (0.06)	0.57 (0.71)	2.35 (2.26)	0	0.54 (0.29)	1.52 (1.00)	5.07 (4.03)	12.27 (2.07)	3.99 (1.15)	8.81 (1.36)	0	3.21 (1.01)	15.59 (2.81)	43.88 (5.92)
Total	0.09	15.86	80.37	0.002	3.24	0.42	100	2.06 (0.88)	26.33 (9.43)	47.45 (7.80)	0	3.92 (2.24)	20.24 (5.76)	100	30.37 (2.83)	10.81 (1.84)	17.24 (1.88)	0	6.50 (2.07)	35.08 (4.08)	100

TABLE II. MEANS AND STANDARD DEVIATION (IN BRACKETS) OF LAND COVER TRANSITIONS DERIVED FROM POST-CLASSIFICATION COMPARISON AND BAYESIAN CLASSIFICATION (REFERRING TO NLCD CLASSES; UNITS: %)

	Reference							*post-classification comparison*							*Bayesian classification*						
								2001													
1992	1	2	3	4	5	6	Total	1	2	3	4	5	6	Total	1	2	3	4	5	6	Total
(a) pure pixels (44,994)																					
1-open water	0.52	0	0.01	0	0	0	0.53	0.25 (0.08)	0.56 (0.30)	0.33 (0.10)	0.14 (0.05)	0.17 (0.08)	0.13 (0.05)	1.58 (0.51)	10.67 (1.59)	4.37 (0.96)	2.08 (0.39)	2.68 (0.41)	3.20 (0.81)	6.38 (1.68)	29.38 (2.77)
2-forest	0.06	74.54	0.28	0	0.01	0	74.89	4.88 (3.60)	41.17 (5.84)	7.92 (2.16)	0.37 (0.36)	0.95 (0.70)	7.28 (4.91)	62.57 (6.38)	0.82 (0.35)	0.13 (0.08)	0.03 (0.03)	0.008 (0.01)	0.05 (0.04)	0.26 (0.21)	1.30 (0.59)
3-grassland /shrub	0	0	24.40	0	0	0	24.40	0.69 (0.30)	0.96 (0.54)	5.34 (2.38)	2.76 (1.20)	2.31 (1.95)	1.38 (1.02)	13.44 (2.85)	0.0004 (0.001)	0 (0)	0.0001 (0.0005)	0.0002 (0.001)	0.0005 (0.001)	0.0002 (0.001)	0.001 (0.002)
4-barren/sand	0	0	0	0	0	0	0	0.03 (0.02)	0.18 (0.04)	0.08 (0.03)	0.03 (0.03)	0.03 (0.04)	0.04 (0.02)	0.39 (0.08)	0	0	0	0	0	0	0
5-agriculture	0.02	0	0.11	0	0.04	0	0.17	0.26 (0.24)	2.42 (2.25)	0.92 (0.45)	0.19 (0.10)	1.07 (0.29)	0.84 (0.52)	5.70 (3.34)	7.00 (0.86)	1.19 (0.49)	0.75 (0.12)	1.86 (0.23)	2.78 (0.49)	4.66 (0.85)	18.24 (1.38)
6-wetlands	0	0	0	0	0	0.01	0.01	0.88 (0.62)	5.22 (3.01)	3.11 (1.38)	0.60 (0.51)	3.49 (1.01)	3.02 (1.05)	16.32 (5.52)	16.57 (2.06)	5.28 (1.06)	3.36 (0.53)	6.19 (0.66)	8.41 (0.83)	11.26 (2.03)	51.08 (2.15)
Total	0.60	74.54	24.80	0	0.05	0.01	100	6.99 (4.30)	50.51 (5.73)	17.70 (4.09)	4.10 (1.89)	8.01 (3.52)	12.69 (5.54)	100	35.07 (3.87)	10.97 (2.30)	6.23 (0.87)	10.74 (1.17)	14.43 (1.97)	22.57 (4.42)	100
(b) all pixels (250,000)																					
1-open water	0.09	0	0.01	0	0	0	0.10	0.16 (0.06)	0.22 (0.10)	0.41 (0.12)	0.09 (0.07)	0.17 (0.06)	0.22 (0.06)	1.27 (0.29)	7.17 (0.91)	1.99 (0.54)	1.22 (0.17)	3.85 (0.73)	4.38 (0.83)	7.54 (0.78)	26.15 (2.30)
2-forest	0.02	16.60	0.24	0	0.10	0.02	16.98	4.28 (1.92)	15.66 (2.96)	13.42 (4.45)	1.21 (1.78)	2.13 (1.36)	9.06 (2.69)	45.76 (8.85)	0.20 (0.12)	0.03 (0.02)	0.008 (0.01)	0.006 (0.008)	0.02 (0.02)	0.08 (0.09)	0.33 (0.25)
3-grassland /shrub	0	0.002	73.10	0	0.08	0.002	73.18	1.42 (0.98)	1.17 (1.06)	7.38 (3.66)	1.96 (1.90)	1.93 (1.62)	3.14 (2.20)	16.97 (7.98)	0.0002 (0.0003)	0 (0)	0.00004 (0.0001)	0.0001 (0.0002)	0.002 (0.003)	0.002 (0.0003)	0.0008 (0.0007)
4-barren/sand	0.001	0	0	0.01	0	0	0.01	0.03 (0.01)	0.08 (0.02)	0.12 (0.03)	0.02 (0.03)	0.03 (0.02)	0.07 (0.02)	0.35 (0.08)	0	0	0	0	0	0	0
5-agriculture	0.01	0	0.41	0	7.23	0.12	7.77	0.35 (0.25)	0.90 (0.69)	1.42 (0.68)	0.22 (0.22)	1.11 (0.35)	1.31 (0.60)	5.31 (2.15)	5.62 (0.51)	0.44 (0.18)	0.49 (0.18)	3.09 (0.10)	3.75 (0.54)	6.13 (0.29)	19.52 (0.59)
6-wetlands	0	0	0	0	0	1.97	1.97	2.22 (1.14)	3.11 (1.45)	9.47 (3.82)	1.46 (1.83)	6.26 (2.05)	7.82 (2.40)	30.34 (7.89)	12.66 (1.21)	2.73 (0.76)	2.69 (0.76)	10.04 (0.29)	9.68 (0.82)	16.20 (0.94)	54.00 (2.01)
Total	0.12	16.60	73.75	0.01	7.41	2.11	100	8.45 (3.31)	21.13 (4.10)	32.21 (6.12)	4.97 (5.09)	11.63 (4.56)	21.60 (4.61)	100	25.64 (2.24)	5.19 (1.42)	4.40 (0.39)	16.99 (2.23)	17.83 (2.05)	29.95 (1.14)	100

IV. DISCUSSIONS

Results of means in different land cover classes and transitions referring to data classes are reported in Table I, while those concerning class statistics in reference to NLCD classes are listed in Table II. In Table I, results under the heading "reference" are those obtained by tallying land cover maps of data classes, and for transitions in between with respect to pure and all pixels, respectively. The results based on NLCD maps are shown under the heading "reference" in Table II.

Means in both Tables I and II reveal individual class proportions and transition magnitudes so that their relative abundance or dominance may be interpreted. The rows display the proportions of the six classes in 1992, whereas the columns display the proportions in 2001. Thus, the off-diagonal elements represent the proportion of the landscape that experienced a transition from class i to class j between 1992 and 2001 ($i \neq j$), and the main diagonal elements indicate the proportion of land classes that showed persistence.

Consider the comparison between reference data and post-classification comparison. Dominant land cover classes or transitions identified based on pure pixels are persistent with respect to both reference data and post-classification comparison. This can be said for both data and NLCD classes of land cover. However, results with respect to all pixels are not quite the same. Table I (b) shows results based on data classes over all pixels: grassland/shrubland remains unchanged and is the dominant type according to reference data, but forest to grassland/shrubland transition is dominant according to post-classification comparison. A similar pattern of results can be discerned in Table II (b), which shows results based on NLCD classes over all pixels.

The dominant change types identified through Bayesian classification are not the same as reference data indicate for pure pixels. As shown in Table I, Bayesian classification with respect to data classes indicates that "forest to wetlands" becomes the dominant transition type according to statistics based on pure pixels, while wetlands remains the unchanged dominant class when examining all pixels. Results from Bayesian classification with respect to NLCD classes are shown in Table II, which indicate that "wetlands to open water" becomes the dominant transition type according to summary based on pure pixels, while wetlands remains the unchanged dominant class when examining all pixels. This is because the results of Bayesian classification are sensitive to prior class probabilities and their joint probabilities, whose specification was based on pure pixels and might not be representative of the whole study area.

The relationships among standard deviation in different groupings are not straightforward. Standard deviation for classes and transition computed over pure pixels tends to smaller than that over all pixels where mixed pixels dominate the study area. Standard deviation computed based on data classes over pure pixels is generally smaller than that based on NLCD classes, especially when judged relative to the means. This is not evident of the results summarized over all pixels.

V. CONCLUSIONS

This paper has shown that geostatistics equipped with discriminant models is capable of quantifying spatial uncertainty in spatio-temporal land cover information. In particular, error statistics reported in this paper show great discrepancies between those obtained by referring to data classes vs. those to NLCD classes, and between those summarized over pure vs. all pixels. Interpretation in terms of data classes and over pure pixels seems to be more consistent than otherwise. Discriminant-based stochastic simulation has demonstrated its utility for propagating uncertainty in area classes to change information through reproducing auto- and cross-covariance in the process variables underlying the landscape dynamics and by honoring conditional data. The proposed methods are applicable for a range of scales and facilitate error propagation in land use and land cover change.

Discriminant models lead to greater interoperability in geo-processing with both continuous and discrete fields. For continuous variables, biases between estimated and true means can be used to measure their accuracy, while variance can be used to indicate their precision. Biases and variance should be used in combination so that error behaviors may be better elucidated. This paper has shown that a similar typology can be usefully implemented for analysis of uncertainty in land cover information, which originates from different sources, such as discriminant variables' deficiency, sampling errors, measurement errors, and various others. Further research should also be directed towards spatial and statistical analysis of the different error statistics, such as those obtained in the studies, so that we may conduct a well-informed and practically meaningful uncertainty management.

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