

# LAND-COVER CLASSIFICATION OF REMOTELY SENSED DATA USING KALMAN FILTERING

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This paper deals with application of a new model established by the Kalman filtering theory to the land-cover classification of Landsat TM data. The results compared to existing three classification techniques showed that classification accuracy could be improved in average by using the Kalman filtering model. Furthermore, this model has a considerable advantage in real world application, being not limited by the spatial resolution of remotely sensed data and making it possible to carry out classification when there are many land-cover categories contained in a small area unit having the size of the order of 200m × 200m.

*Key Words: Kalman filtering, land-cover classification, reflectance of spectral band, remotely sensed data*

## 1. INTRODUCTION

Remotely sensed data have been used extensively to generate land-cover information for a variety of purposes using a wide range of classification approaches<sup>1),2)</sup>. For land-cover classification of remotely sensed data, accuracy is usually one of the principal problems. In this paper we will discuss a new model established by the Kalman filtering theory for classifying land-cover. More precisely, our aim is to develop a new model for identifying the reflectance of Landsat spectral bands for each land-cover category (henceforth referred to as just "category" for brevity) and also another new model of the land-cover classification of remotely sensed data.

Traditionally, conventional techniques of land-cover classification of multispectral remotely sensed data, such as maximum likelihood and linear discriminant function model, are well suited to deal with pure pixels giving one category per pixel in those areas which are in the relatively simple

land-cover<sup>3),4)</sup>. The common features of those methods are that a pixel is necessarily classified into one category even if it is actually composed of different categories (i.e., a mixed pixel) and the reflectance of spectral bands for each category is estimated by selection of training sets that represent typical examples of each land-cover class<sup>5),6),7)</sup>. Inamura(1987) explained the relation between the reflectance of a mixed pixel and misclassification of remotely sensed data, which existed in the conventional techniques<sup>8)</sup>. Since a mixture of the reflectance of different categories can cause different reflectance features, in the conventional methods a mixed pixel may not only possibly be classified into one of several categories which compose this mixed pixel, but also may be classified into other categories that actually do not exist in the mixed pixel. That is one of the factors of restricting accuracy of the conventional classification models.

Since the conventional classification models can not be used satisfactorily in

processing mixed pixels, it is very necessary for some new comprehensive techniques to be developed and to improve classification accuracy to strive for further progress.

In this research, we considered two processing models: one to identify the reflectance of spectral bands for each category, not requiring a special selection of sample pixels (training sets), and the other to decompose mixed pixels which contain multiple information from the different categories, getting proportion of categories in a given area. Each of the two models plays an important part of the classification for improving the overall classification accuracy.

To develop an efficient technique which can be applied to extract more information and get higher accuracy for the classification, a new model was set up in our research by means of the Kalman filtering theory, for both the process of the reflectance identification and the process of category decomposition. It is noted that concerning Kalman filtering application numerous papers have been written ranging from spacecraft orbit determination to demographics of cattle production<sup>9), 10), 11), 12)</sup>. To allow comprehensive evaluation of the Kalman filtering model, it was compared to several different existing models.

## 2. THE STUDY AREA AND DATA USED

Study area was selected in order to show the efficiency of the new model under the condition of multiple land-cover information in Odawara city and its vicinity area in Kanagawa Prefecture (Fig. 1). The study area was divided into two parts, a training site (2km×8km) and a test site (2km×8km). The training site was used to extract the reflectance of the spectral bands for each category and the test site to verify the efficiency of the developed land-cover classification model.

Remotely sensed data were collected from a Landsat-5 Thematic Mapper scene (107-36, 28/10/1993) and six of TM spectral bands (TM1~5 and TM7 band) were used. The base categories individuated for classification analysis were: water, farmland and paddy field, orchard, forest and residential district. To validate the land-cover classification the actual proportion of

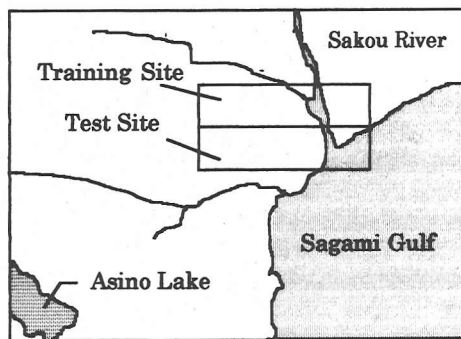


Fig. 1 The study area

each category was determined from the land use map available for the area at the scale of 1:25,000 and color aerial photograph acquired in the same period at the scale of 1:10,000 was used for reference.

The study area was divided into many small area units of the size 200m×200m (the size of 7×7 pixels), to conform with the request of analysis. The study was carried out with the proportion of the categories and the average values of the reflectance of spectral bands corresponding to those small area units.

## 3. METHODOLOGY

### (1) Identification model for categorical reflectance of spectral bands

Since it can be assumed that the response of each pixel, in any spectral band  $j$ , includes the influence induced by  $m$  categories, its resulting reflectance value  $y_j$  can be seen as a linear combination of the responses of each component supposed to be in the mixed target. Relating to each small area  $k$  in the study area, the basic mixture model can be formulated as follows:

$$y_j(k) = r_1(k) \cdot x_{j1}(k) + r_2(k) \cdot x_{j2}(k) + \dots \\ + r_m(k) \cdot x_{jm}(k) + e_j(k)$$

where

$y_j(k)$ : reflectance of the  $j$ -th spectral band in area  $k$

$r_i(k)$ : proportion of the mixture component for the  $i$ -th category in area  $k$

$x_{ji}(k)$ : reflectance of the  $j$ -th spectral band for the  $i$ -th category in area  $k$

$e_j(k)$ : noise term for the  $j$ -th spectral band in area  $k$

The above formulation can be seen as an observation equation with  $x_i(k)$  denoting vector  $(x_{1i}(k), x_{2i}(k), \dots, x_{6i}(k))$  as state variable and  $y_j(k)$  as observation measurement. It can be simplified with the coefficient matrix  $\Lambda(k)$  of the category's proportion and the vector  $x(k) = (x_1(k), x_2(k), \dots, x_m(k))^T$  of the reflectance of spectral bands for each category, which is unknown number to be identified through the following system of equations.

$$y(k) = \Lambda(k) \cdot x(k) + e(k)$$

where  $y(k)$  is the vector made up of  $y_j(k)$  as its  $j$ -th element.

The basic assumptions are that those targets are arranged continuously in space with small change of the reflectance from one target to the next of its neighbors. Thus a state equation can be derived from the following general structure.

$$x(k+1) = x(k) + v(k)$$

The vector  $e(k)$  and  $v(k)$  were assumed as the output noise and input noise and were white noise sequences described as follows:

$$E[e(k)] = 0; \quad E[v(k)] = 0$$

$$E[v(k) \cdot v(k)^T] = R_1$$

$$E[e(k) \cdot e(k)^T] = R_2$$

Where  $E[\cdot]$  denotes the expectation, and  $R_1$  the variance and covariance of  $v(t)$  and  $R_2$  the variance and covariance of  $e(t)$ .

With these assumptions and knowledge of the system variables, the Kalman filtering theory can be applied<sup>9)</sup>. An algorithm form of the model is then given as

$$\begin{aligned} \hat{x}(k|k) &= \hat{x}(k-1|k-1) \\ &+ K(k) \cdot [y(k) - \Lambda(k) \cdot \hat{x}(k-1|k-1)] \end{aligned}$$

where

$$K(k) = S(k) \cdot \Lambda^T(k) \cdot [\Lambda(k) \cdot S(k) \cdot \Lambda^T(k) + R_2]^{-1}$$

$$S(k) = P(k-1) + R_1$$

$$P(k) = S(k) - K(k) \cdot \Lambda(k) \cdot S(k).$$

$K(k)$  denotes the gain matrix of the Kalman filtering algorithm,  $S(k)$  and  $P(k)$  the variance and covariance matrix of the estimation error of  $x(k)$  before and after the observation measurement  $y(k)$  is given,

respectively.

$\hat{x}(k|k)$  is referred to as the filtered estimate of  $x(k)$  using  $y(k)$ . The reflectance of spectral bands for each category can be identified from the estimated values of  $\hat{x}(k|k)$  averaged over the convergent range to be illustrated in the following chapter.

## (2) The estimation model for categories

Let the reflectance of spectral bands for each category given by the average value of the estimates  $\hat{x}(k|k)$ 's be denoted by  $h = (h^T_1, h^T_2, \dots, h^T_m)^T$  with  $h_{ji}$  as the  $j$ -th element of  $h_i$ . Also, let  $z(k) = (z_1(k), z_2(k), \dots, z_m(k))^T$  be proportion of the categories that will be estimated here in the test site. First, we considered the observation equation for the proportion estimation with TM data of six bands as follows:

$$\begin{aligned} \begin{pmatrix} y(k) \\ 1 \end{pmatrix} &= \begin{pmatrix} h_1 \\ 1 \end{pmatrix} \cdot z_1(k) + \begin{pmatrix} h_2 \\ 1 \end{pmatrix} \cdot z_2(k) + \dots \\ &+ \begin{pmatrix} h_m \\ 1 \end{pmatrix} \cdot z_m(k) + \begin{pmatrix} e(k) \\ 0 \end{pmatrix} \end{aligned}$$

In the above observation equation the number 1 on the lefthand side, which is considered as the sum of the proportion of all categories in each small area  $k$ , is used as a limit parameter for the calculation. It should be useful for improving accuracy of the previous Kalman filtering model<sup>13)</sup>.

The equation can be rewritten in the matrix form with the coefficient matrix designated as  $H$ .

$$y(k) = H \cdot z(k) + \theta(k)$$

where  $y(k) = (y(k)^T, 1)^T$  and  $\theta(k) = (e(k)^T, 0)^T$ .

Assuming that there is only a slight change of land-cover between one target (a small area unit in our research) and the next of its neighbors, the state equation can be described as:

$$z(k+1) = z(k) + w(k)$$

where  $w(k)$  denotes the noise. Kalman filtering can be applied with the similar formulae as in the previous section. The algorithm form of the model are given as shown below:

$$\begin{aligned} \hat{z}(k|k) &= \hat{z}(k-1|k-1) \\ &+ \bar{K}(k) \cdot [y(k) - H \cdot \hat{z}(k-1|k-1)] \end{aligned}$$

and

$$\bar{K}(k) = \bar{S}(k) \cdot H^T \cdot [H \cdot \bar{S}(k) \cdot H^T + \bar{R}_2]^{-1}$$

$$\bar{S}(k) = \bar{P}(k-1) + \bar{R}_1$$

$$\bar{P}(k) = \bar{S}(k) - \bar{K}(k) \cdot H \cdot \bar{S}(k)$$

where

$\hat{z}(k|k)$ : estimated proportion of the categories in area  $k$  with observation measurements  $y(q)$  ( $q=1, 2, \dots, k$ ) given

$\bar{K}(k)$ : the Kalman gain matrix

$\bar{S}(k)$ : variance and covariance matrix of estimation error of  $z(k)$  before  $y(k)$  is observed

$\bar{P}(k)$ : variance and covariance matrix of estimation error of  $z(k)$  after  $y(k)$  is observed

$\bar{R}_1$ : variance and covariance of  $w(k)$

$\bar{R}_2$ : variance and covariance of  $\theta(k)$

#### 4. APPLICATION AND ANALYSIS OF RESULT

Application of the new model by means of Kalman filtering was accomplished using TM data of six spectral bands (TM1~5, TM7). To assess the accuracy and generalization capability of the model, the results were compared to three representative classification techniques of existing models: maximum likelihood, linear discriminant function and quadratic programming model.

##### (1) Identification of the reflectance of spectral bands for each category

TM data of six bands were used as observation measurement and proportion of the categories in each small area unit in the training site as state measurement. The reflectance of spectral bands for each category was determined by the aforementioned identification model.

In this section, two kinds of small area units (i.e., size of  $200\text{m} \times 200\text{m}$  and size of  $800\text{m} \times 800\text{m}$ ) were tested to see the capability and stability of the reflectance of spectral bands (the converged values) calculated by the model. As the calculation step proceeds from  $k-1$  to  $k$ , small area units are shifted by only one pixel's distance so that they may overlap each other and only small change in land-cover may occur from

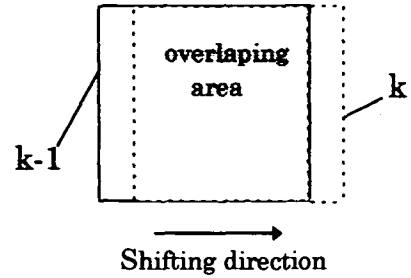
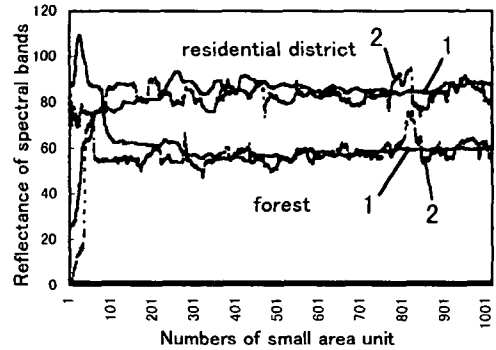


Fig.2 Shifting system of small area units



1. small area size of  $800\text{m} \times 800\text{m}$
2. small area size of  $200\text{m} \times 200\text{m}$

Fig.3 The stability feature of reflectance for forest and residential district identified for two kinds of small area size

one unit to the next as illustrated in Fig.2. Some of calculated results are shown in Fig.3 which depicts the change of reflectance calculated by the identification model for forest and residential district. The results show that the reflectance of spectral band are more stably converged in larger area units than in smaller area units. One reason is that errors of area proportion for each category which was used in the identification model are likely to be reduced as the area unit is enlarged. It is stated that the categorical reflectance calculated from larger area unit was utilized in the estimation model in our research.

The change of the reflectance of TM2 and TM7 bands for five categories calculated in size of  $800\text{m} \times 800\text{m}$  area units are exhibited in Fig.4. and Fig.5 by way of showing the convergent features. The results show the reflectance of spectral bands is stably converged in the latter parts of calculation

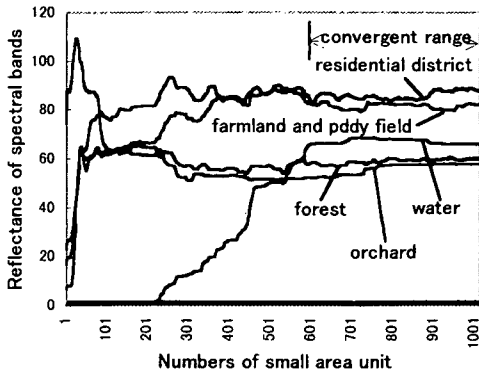


Fig.4 Change of the identified categorical reflectance of TM2 band with the number of shifting small area unit

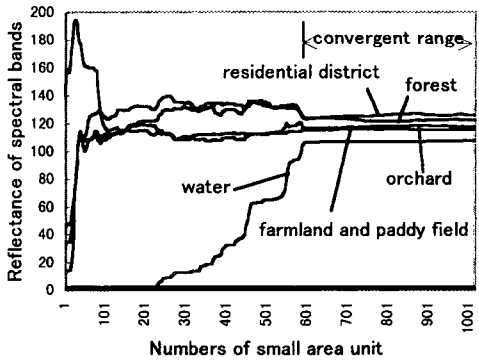


Fig.5 Change of the identified categorical reflectance of TM7 band with the number of shifting small area unit

steps (called convergent range here) from which the reflectance of TM bands for each category could be drawn out. In our research, the averages over the convergent range were used as the reflectance of spectral bands for each category.

The results mentioned above show that the reflectance of spectral bands for each category could be better identified by using larger area units of the size of 800m×800m in which information of many pixels is mixed.

## (2) Estimation of area proportion for each category

The area proportion of each category in each small area unit in the test site was estimated by the estimation model using the

Table 1 Model comparison based on different estimation error indices

	Kalman filtering	Quadratic programming	Linear discriminant	Maximum likelihood
RME	0.8833	0.9459	0.9985	0.9857
WRE	0.8977	1.3504	1.1301	1.3522
MAE	0.1751	0.2830	0.2359	0.3043
RMSE	0.1666	0.1964	0.2133	0.2449
$\eta$	0.7380	0.7086	0.6924	0.6546
$\rho$	0.7738	0.7450	0.7340	0.6775

Table 2 Categorical comparison of the models based on RMSE

Class	Kalman filtering	Quadratic programming	Linear discriminant	Maximum likelihood
1	0.1438	0.1910	0.0487	0.0499
2	0.1401	0.1607	0.1652	0.1341
3	0.1570	0.2012	0.3163	0.3647
4	0.2152	0.2542	0.2588	0.3257
5	0.1731	0.1597	0.1754	0.2005
Average	0.1666	0.1964	0.2133	0.2449

(Description of class) 1:water 2:farmland and paddy field 3:orchard 4:forest 5:residential district

reflectance of spectral bands for each category determined by the identification model. Being compared with actual area proportion of each category, the results obtained from the estimation model are presented in Table 1 along with the results of three other classification techniques. It is revealed from the Table that all classification error indices employed here (to be defined in the appendix) are consistently and substantially improved by using the Kalman filtering model compared to maximum likelihood, linear discriminant function or quadratic programming model.

Root mean square errors(RMSE) for five categories are individually shown in Table 2. It is pointed out that overall error magnitude of the Kalman filtering model is lower than that of other models compared. However, in the estimation of the specific class of land-cover, water for instance, maximum likelihood or linear discriminant model outperforms the proposed model. The reason for it is probably that a simple category as water has a quite evident spectral reflectance which dose not need to be decomposed and thus it is much fitter to the estimation mechanism of the two statistical models mentioned above. A little bit more

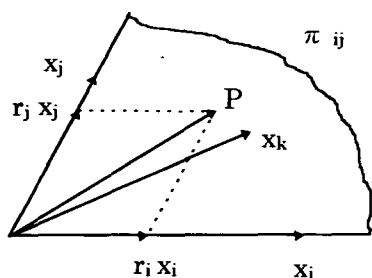


Fig.6 Relation between position of spectral vectors and misclassification of radiance data reflected by ground area that is consisted of several ground objects.

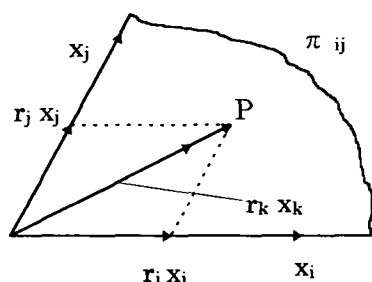


Fig.7 Relation between decomposed spectral vector and misclassification of radiance data reflected by ground area that is mainly consisted of category k.

elaborating, the category decomposition methods can lessen misclassification for mixed pixels as explained by Inamura<sup>9)</sup>, another misclassification happens in the process of category decomposition for the pixels. We termed this misclassification "decomposition misclassification", contrary to the misclassification occurred in classifying the mixed pixels by the conventional models (that is termed as "composition misclassification"). For explanation, Fig.6<sup>9)</sup> and Fig.7 show the relationship of two kinds of the misclassification.

Because the generalized distance of data P combined by  $x_i$  and  $x_j$  is shorter to  $x_k$  than to  $x_i$  and  $x_j$  in the expanded plane  $\pi_{ij}$  as can be seen from Fig.6, the data is probably misclassified into category  $k$ <sup>9)</sup>. The misclassification in Fig.7 is reverse to that in Fig.6, happening as a result of a contrary action to composition misclassification in Fig.6. Thus the data P that is mainly in

category  $k$  is probably misclassified into category  $i$  and  $j$  by category decomposition. The existence of this kind of decomposition misclassification seems one of the reasons for relatively higher error in water in our research. The means of how to improve the method of analysis to lessen the decomposition misclassification is still groped about in Kalman filtering model as well as other category decomposition model.

As a conclusion, it is stated that the land-cover classification accuracy can be improved in average by using the Kalman filtering model. Also, efficiency of the proposed model is remarkable in that by means of identification process it is possible to extract reflectance mode of spectral bands for categories from a comparatively large area unit of the size around 1km<sup>2</sup> which can be of a mixture of land-cover information. That means the use of the proposed model would not be restricted by spatial resolution of remotely sensed data which is a primary factor to affect accuracy of the classification in the previous classification methods<sup>14), 15)</sup>. Hence with some other remote sensing data of lower spatial resolution, such as MSS, a similar classification information or accuracy could be obtained by the proposed model.

### (3) Extension of the classification

Taking advantage of the identification process of reflectance of spectral bands for each category in the Kalman filtering model, it will be possible to classify data into much more classes of land-cover information than investigated above. In this research a further classification was accomplished with thirteen classes of land-cover (they were: 1: water, 2: paddy field, 3: farmland, 4: grassland, 5: bare-land, 6: orchard, 7: forest, 8: sandy land, 9: road and parking lot, 10: railway, 11: concrete building, 12: tile-roofed house, 13: workshop etc. which is not concrete).

Due to limitation of spatial resolution of remotely sensed data, it was difficult to extract reflectance of spectral bands for some categories in thirteen categories by means of selection of training sets. Therefore, the reflectance of spectral bands for thirteen categories obtained by the proposed identification model was also used in the three existing classification models employed here for evaluating efficiency of the Kalman filtering model. The variance and covariance

of the reflectance for each category required for use in the maximum likelihood model as well as linear discriminant function model were extracted from variance and covariance matrix of estimation error  $P(k)$  formed in the process of identification. More precisely, as the estimate  $\hat{x}(k|k)$  in the convergent range makes a good approximate value for the expectation of the categorical reflectance of spectral bands, diagonal  $6 \times 6$  minor matrix  $P_i (i=1 \sim m)$  of  $P$  (as shown in eq.(1)) which is defined as the average of  $P(k)$ 's in the convergent range was utilized as an approximate variance and covariance matrix of the  $i$ -th categorical reflectance of spectral bands.

$$P = \begin{bmatrix} \overbrace{P_1}^{6 \times 6} & \overbrace{P_2}^{6 \times 6} & \dots & \overbrace{P_m}^{6 \times 6} \\ \vdots & & & \end{bmatrix} \quad (1)$$

In these senses, all of the employed comparison models could be called hybrid model.

The results of these different models evaluated by the indices of overall estimation errors for thirteen categories are shown in Table 3. Also, RMSE for each of thirteen categories is shown in Table 4 individually.

It is seen from the results that a relatively higher accuracy of classification is achieved by the Kalman filtering model in spite of the fact that much more mixed pixels should be formed in the small area units than before because of thirteen land-cover categories to cope with in classification. Among the existing models compared, the highest overall accuracy is attained by quadratic programming model, which is a typical category decomposition model based on least square estimation. The results explain again that the category decomposition model helps lessen misclassification which is caused by some mixed pixels.

It is likely that the minute division of land-cover makes less change of the reflectance in each category and helps improve extraction of reflectance of spectral bands for each category, and thereby brings about a higher accuracy of classification. This is very significant to improve accuracy of classification for required number of categories in the real life survey and to achieve much more information of land-cover

Table 3 Model comparison using overall error for thirteen categories

	Kalman filtering	Quadratic programming	Linear discriminant	Maximum likelihood
RME	0.6806	0.4302	0.7071	0.7072
WRE	0.9801	1.0219	1.4631	1.2703
MAE	0.1119	0.2712	0.2558	0.3324
RMSE	0.1047	0.1514	0.1759	0.1727
$\eta$	0.6042	0.5258	0.4343	0.4597
$\rho$	0.5390	0.4461	0.1685	0.2674

Table 4 Categorical comparison using RMSE for thirteen categories

Class	Kalman filtering	Quadratic programming	Linear discriminant	Maximum likelihood
1	0.1520	0.2695	0.2565	0.0599
2	0.0827	0.0850	0.1251	0.1061
3	0.1071	0.1313	0.2681	0.1293
4	0.1065	0.1703	0.1691	0.1356
5	0.1267	0.2417	0.2359	0.1931
6	0.1110	0.1077	0.2324	0.0841
7	0.0679	0.0608	0.0667	0.1655
8	0.0802	0.0608	0.0662	0.0644
9	0.1193	0.1475	0.1772	0.1876
10	0.0634	0.0591	0.0595	0.0555
11	0.1492	0.1652	0.1499	0.1629
12	0.0811	0.1926	0.2085	0.2794
13	0.0564	0.0617	0.0330	0.3449
Average	0.1047	0.1514	0.1759	0.1727

(Description of class) 1:water 2:paddy field 3:farmland 4:grassland 5:bare-land 6:orchard 7:forest 8:sandy land 9:road and parking lot 10:railway 11:concrete building 12:tile-roofed house 13:workshop etc. which is not concrete

from remotely sensed data. Finally, it should be reminded that by using the conventional models only, it is hardly possible to get any information for thirteen classes of categories for lack of the categorical reflectance characteristics.

### 5. CONCLUSION

The present research has succeeded in exhibiting the efficiency of the new model established by the Kalman filtering theory for land-cover classification of remotely sensed data. The validity test results showed that the model was suitable to land-cover classification for the site of complex land-cover, in which multiple information from different categories is contained in a small

area, while the classification accuracy of the conventional statistical models was fairly affected by the complexity of the land-cover which usually results in formation of a plethora of mixed pixels in a subject area.

The model of Kalman filtering has made it possible to overcome the problem of extracting reflectance of spectral bands for some specific categories, such as road and concrete building and so on, of which sampling site is very difficult to be selected, a problem that dominates accuracy of the classification. Furthermore, the model has a considerable advantage in application, being not limited by spatial resolution of remote sensing data, and making much more classes of categories to be classified possibly.

Outcomes mentioned above show that the proposed model can be certainly regarded as a new practical method for land-cover classification of remotely sensed data.

The higher accuracy of classification and much more information to be extracted from remotely sensed data are still expected. Also, the decomposition misclassification is inherent in category decomposition methods, including the Kalman filtering model in our research. Consequently further refinement of the method of analysis will be of necessity in future research work.

## APPENDIX

Table A1 Definition of error indices

RME (relative mean error):

$$(1/N) \sum_j |\hat{z}(j) - z(j)| / z(j)$$

WRE (weighted relative mean error):

$$\sqrt{\left[ \frac{1}{\sum_j z(j)} \right] \sum_j \left[ \frac{\{\hat{z}(j) - z(j)\}^2}{z(j)} \right] z(j)}$$

MAE (mean absolute error):

$$(1/N) \sum_j |\hat{z}(j) - z(j)|$$

RMSE (root mean square error):

$$\sqrt{(1/N) \sum_j [\hat{z}(j) - z(j)]^2}$$

$\eta$  (coefficient of concordance):

$$1 - RMSE / \left[ \sqrt{\sum_j \hat{z}(j) / N} + \sqrt{\sum_j z(j) / N} \right]$$

$\rho$  (correlation coefficient):

$$\frac{\sum [z(j) - \bar{z}][\hat{z}(j) - \bar{\hat{z}}]}{\sqrt{\sum [z(j) - \bar{z}]^2 \sum [\hat{z}(j) - \bar{\hat{z}}]^2}}$$

N: number of data

$z(j)$ : actual value

$\hat{z}(j)$ : estimated value

$\bar{z}$ : average of actual value

$\bar{\hat{z}}$ : average of estimated value

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## カルマンフィルタによる土地被覆分類の方法

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本論文では、リモートセンシングデータを用いたカテゴリ分解原理に基づく土地被覆分類手法としてカルマンフィルタ理論を応用した新しいモデルを提案した。複数カテゴリ混在地域に対する適用結果の分析から、本提案モデルは、既存の最尤法、判別分析法及び二次計画法を用いた代表的な3手法との比較において、総合的にみた土地被覆分類精度の向上を図り得ることがわかった。本研究で提案したモデルは各土地被覆カテゴリの分光特性抽出と土地被覆分類がリモートセンシングデータの分解能に敏感に影響される問題を克服して得ており、したがって、200m×200m程度の小区域に多数のカテゴリが混在しているような場合においても土地被覆分類を行い得る構造になっている。