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Estimation of Water Areas in the Amazon on Landsat-TM Images

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Abstract

This paper presents the result of estimating water areas in the Amazon from the optical remote sensing data by using a new fuzzy estimation method and edge data. Conventionally, multi-temporal image data with different water heights are used to estimate the flooded areas. Optical sensors such as Landsat-TM may be limited by their inability to penetrate cloudcover in the Amazon regions. However, they have been well stocked in comparison with SAR (Synthetic Aperture Radar) image data and are useful to classify landcovers. Thus, this paper proposes a method that uses only one optical image data to estimate the flooded area, called várzea. Distinction between a pure pixel and a mixel (mixed pixel) is computed, and the occupancy of landcover classes in the study area is estimated by a fuzzy estimation method. In addition, estimation maps of the water areas at high and low levels are drawn from the occupancy of landcover classes and the situation of water areas is estimated. It is observed that the estimation results using the occupancy can match the local situation in the study area. As a result of this work, the estimation ratio indicates that water areas around Parintins-city, Brazil, at high level is an increase of about 58 % compared with water areas at low levels. The proposed method is applied to this particular regions, but this approach can also be applied to larger water areas considering várzea areas. Therefore, it is confirmed that the proposed method is very useful to estimate water areas in the Amazon from the optical remote sensing images.

Key words : remote sensing, várzea, fuzzy estimation, edge data, water level changes, mixel, landcover class

I. Introduction

It is reported that the water level in the middle and lower Amazon reaches its highest from May to July and its lowest from October to November (Hida *et al.*, 1995). The change of the water level reaches about 10 meters at Manaus located in the riverside of Rio Negro, Brazil. Because of these changes, an area may come under water at high levels. Such an area, called várzea, has a lot of relation to human activities in the Amazon region, and particular attention has been paid toward separate the area to other landforms

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(IBGE, 1977 ; Sternberg, 1995).

A direct survey of a wide area such as the Amazon is neither practical nor economical. On the other hand, the remote sensing technique, nowadays, is very useful and efficient for offering a synoptic view over a wide area. Therefore, the analysis technique with the remote sensing data is effective to monitor inundation and estimate water areas in the Amazon (Leal *et al.*, 1995 ; Vörösmarty *et al.*, 1996).

Using the remote sensing data, it is considered that the use of the multi-temporal image data with different water heights is a common method for the estimation of inundation of the basin scale (Ahn *et al.*, 1993). A method based on the landcover classification using only one optical remote sensing data can be useful to understand the change in the water areas. In the tropical regions around the Amazon, optical sensors such as Landsat-TM (Thematic Mapper) may be limited by their inability to penetrate cloudcover (Hashimoto and Tsuchiya, 1995). It is therefore reported that the flood plain and vegetation are delineated using SAR (Synthetic Aperture Radar) image (Hess *et al.*, 1995). However, Landsat-TM data has been well stocked in comparison with SAR image data and are useful to classify landcovers. For these reasons, a new method using optical remote sensing data for estimating várzea areas is proposed in this paper. The method considering mixel (mixed pixel) is based on a fuzzy estimation method and edge data. This paper presents the estimation results for landcover classification and attempts to compare the estimation results with the local landforms obtained in the ground survey. A case study is conducted and this paper also tries to draw estimation maps of water areas for high and low levels.

II. Method

The primary objective of this work is to estimate várzea areas by using the optical remote sensing image. In the conventional remote sensing supervised classification such as the maximum likelihood method, classification results area represented in an one-pixel-one-class method (Wang, 1990), and the majority information in a pixel can not be extracted. Therefore, class mixture needs to be considered. The approach employed in this analysis is as follows : 1) distinction between mixels (mixed pixels) and pure pixels is calculated, 2) estimation of the occupancy of landcover classes, and 3) drawing the estimation maps of water areas at high and low levels.

1) Fuzzy estimation method

(*a*) *A linear function between mixel and pure pixel*

It has been reported that remote sensing data essentially includes several external disturbance components, namely, path radiance, sunglitter, scattering and absorption of atmosphere, surface wave of water, and noise of the sensing system (Yokoyama, 1983). There are also the problems in data handling. For example, training data for supervised classification is selected by an operator based on subjectivity. It has been also considered that the distribution of the CCT count value (luminous intensity) was including the fuzziness (Ishibuchi, 1992). Therefore, we assume that its distinction is a fuzzy number on a spectral space.

Information in a pixel of the remote sensing data is represented as one-pixel-some-class instead of one-pixel-one-class considering the sensor's resolution. They are called mixels (mixed pixels). It is also assumed that the spectral characteristics of the mixel can be seen as a linear function of reflection levels of the pure pixels corresponding to the component classes. The linear function is expressed by using the following equation.

$$\vec{P} = \sum_{c=1}^{N} \alpha_c \vec{M}_c \quad (1)$$

$$\sum_{c=1}^{N} \alpha_c = 1 \quad (2)$$

$$\alpha_c \geqq 0 \quad (3)$$

The meaning of the above equation is explained as follows:

$\vec{P} = (p_1, \cdots, p_k)^t$ is the spectral of the mixel.

$\vec{M}_c = (m_{11}, \cdots, m_{kc})^t$ is the spectral of the pure pixel.

$\vec{\alpha} = (\alpha_1, \cdots, \alpha_N)^t$ is the occupancy of the landcover classes.

$_{c=1\sim N}$: number of landcover classes.

$_k$: number of spectral bands of the image data.

The occupancy of the landcover classes α_c and $_{c=1\sim N}$ are calculated by equation (1), (2) and (3) are used as bound conditions.

(*b*) *The estimation model with the fuzzy simplification reasoning method*

A production rule for the estimation ratio of landcover classes on the pixel is defined according to a linear function between mixels and pure pixels, and then the occupancy of the landcover classes is calculated with the fuzzy simplification reasoning method (Nishida *et al.*, 1993).

A fuzzy knowledge base is composed of two elements: production rule and membership function. A production rule for the occupancy of the landcover classes in each pixel is given as follows:

$$\begin{array}{ll} \text{rule: } & R_{i1} \cdots \text{and } R_{ik} \rightarrow \vec{Z}_i \\ \text{input: } & X_1 \cdots \text{and } X_k \\ \hline \text{output: } & \vec{Z}_0 \end{array} \quad (4)$$

When the occupancy of the landcover classes is set optionally, the definition (4) means the estimation knowledge on a mixel in the fuzzy set.

where

R_{ij} is a fuzzy set of the mixel of the band j,

$\vec{Z}_i$ is a set value of the occupancy: $[\vec{Z}_i = (\alpha_{i1}, \cdots, \alpha_{iN})]$,

$\vec{Z}_0$ is the output number estimated of the occupancy: $[\vec{Z}_0 = (\alpha_1, \cdots, \alpha_N)]$,

X_j is the input value of the spectral band j,

$_N$ is the number of set classes,

and $_{j=1\sim k}$ is the number of spectral band of the image data, respectively.

The sum of the occupancy of landcover classes is assumed as one and the bound condition is given as follows;

$$\sum_{c=1}^{N} \alpha_c^i = 1, \ \alpha_c^i \geqq 0 \ (c=1, \cdots, N) \quad (5)$$

The agreement between input value (from X_1 to X_k) and each production rule is obtained with the min-operation as given by

$$h_i = \mu_{i1}(X_1) \wedge \cdots \wedge \mu_{ik}(X_k) \quad (6)$$

The output value $\vec{Z}_0$ is expressed as follows.

$$\vec{Z}_0 = \frac{\sum_{i=1}^{n} h_i \vec{Z}_i}{\sum_{i=1}^{n} h_i} \quad (7)$$

The component of the output vector $\vec{Z}_0$ and α_c can be expressed as

$$\alpha_c = \frac{\sum_{i=1}^{n} h_i \alpha_c^i}{\sum_{i=1}^{n} h_i} \quad (8)$$

The sum of each component of the output vector,

$\sum_{c=1}^{N} \alpha_c = 1$ can be expressed as

$$\sum_{c=1}^{N} \alpha_c = \frac{\sum_{c=1}^{N} \sum_{i=1}^{n} h_i \alpha_c^i}{\sum_{i=1}^{n} h_i} = 1 \quad (9)$$

In calculating estimation occupancy, the above definition is satisfied with equation (5).

(c) *Membership function*

The CCT count value of each spectral band is employed as a membership function on a basis of characteristics of set landcover classes. When $f_c(x_j)$ is a probability density function of each class, function $f_c(x_j)$ using the average, variance of the training data (m^*_{cj}, σ^{*2}_{cj}) can be expressed as follows ;

$$f_c(x_j)=\frac{1}{\sqrt{2\cdot\pi\cdot\sigma^{*2}_{cj}}}\exp\left\{-\frac{(x_j-m^*_{cj})^2}{2\cdot\sigma^{*2}_{cj}}\right\} \qquad (10)$$

where

$f_c(x_j)$ is probability density function of the class c,

m^*_{cj} is the average of the band j in the class c,

and σ^{*2}_{cj} is the variance of the band in the class c, respectively.

When the maximum value of the probability density function is assumed as max $f_p(x_j)$, membership function $\mu_p(x_j)$ is given by

$$\mu_p(x_j)=\frac{f_p(x_j)}{\max f_p(x_j)}=\exp\left\{-\frac{(x_j-m_{pj})^2}{2\cdot\sigma^2_{pj}}\right\} \qquad (11)$$

where,

$f_p(x_j)$ is the probability density function of the mixel,

$m_{pj}=\sum_{c=1}^{N}\alpha_c\, m^*_{cj}$ is the average of the mixel,

$\sigma^2_{pj}=\vec{\alpha}^t\cdot S_j\cdot\vec{\alpha}$ is the variance of the mixel,

$S_j=\mathrm{diag}\,(\sigma^{*2}_{1j},\ \sigma^{*2}_{2j},\ \cdots,\ \sigma^{*2}_{Nj})$ is the diagonal matrix of the variance of the mixel,

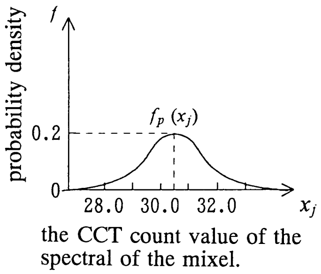
and $\vec{\alpha}=(\alpha_1,\cdots\alpha_N)$ is the occupancy of the landcover classes, respectively.

Figure 1 shows an example of membership function in the proposed method. Fig. 1 (a) shows probability density function $f_p(x_j)$ and Fig. 1 (b) shows membership function $\mu_p(x_j)$ according to above definition.

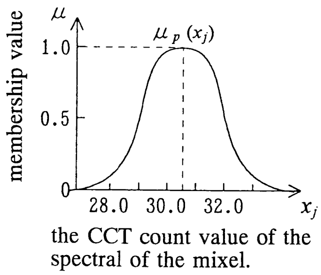
2) Distinction between mixels and pure pixels

One pixel of a satellite image offers the integrated information on the resolution area of the TM sensor. The landforms of the middle and lower Amazon, which is the study area in this work, are relatively extensive and horizontal. It is therefore assumed that the difference of the CCT count value corresponds to the optical characters of the landcovers. As a result, it is reasonable to suppose that the CCT count value of pixels in the boundary area has changed in a drastic way. On the other hand, it is assumed that the CCT count value of pixels in the same landcovers has little changed.

Figure 2 shows an example of the relation between the mixel and the pure pixel. There



a) probability density function



b) membership function

Fig. 1 Example of probability density and membership function.

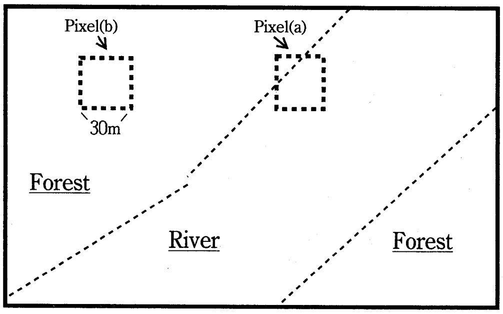


Fig. 2 An example of the relation between mixel and pure pixel.
One pixel of a satellite image offers the integrated information on the resolution area of the TM sensor. When the pixel exists in the boundary area like pixel (a), it is assumed to be a mixel. Otherwise, when the pixel exists in the Forest area like pixel (b), it is assumed to be a pure pixel of the Forest class.

are two landcover classes : forest and river in the figure. When the pixel exists in the boundary area like pixel (a), it can be expressed as a mixel of the Forest class and River class. Otherwise, when the pixel exists in the Forest area like pixel (b), it can be expressed as a pure pixel of the Forest class.

When landcover classification is conducted, it is important to distinguish mixels from pure pixels for accurate classification. An edge pixel means the boundary of the landcovers. The edge pixel can be defined as a mixel and calculated with local filters (Takagi and Shimoda, 1991). Therefore, the local filters are used to calculate the change of the CCT count value of each spectral band data. They are shown in Fig. 3.

When the value of any spectral band in a pixel is larger than the threshold value, the pixel is assumed to be a mixel. In addition, the neighbor pixels (eight pixels) surrounding the noticed mixel are also assumed to be mixels considering the characteristics of local filters.

Next, if the largest occupancy of the pixel

$$\begin{matrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{matrix} \qquad \begin{matrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{matrix} \qquad \begin{matrix} 0 & -1 & -1 \\ 1 & 0 & -1 \\ 1 & 1 & 0 \end{matrix} \qquad \begin{matrix} 1 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -1 \end{matrix}$$

(a) (b) (c) (d)

Fig. 3 Local filter.
(a) is used for the direction from west to east.
(b) is used for the direction from north to south.
(c) is used for the direction from northeast to southwest.
(d) is used for the direction from southeast to northwest.

is more than the threshold value T ($T=0\sim1$), the pixel is classified into the landcover class with the largest value. In other words, the classified pixel is assumed to be a pure pixel. The case of $T=0.8$ was used in this paper.

If the pixel is assumed to be a mixel, the occupancy of each component classes of the mixel is estimated with the fuzzy estimation method. The estimated value means the each landcover classes in mixel.

III. Rrmote Sensing Data

1) Study area

TM image (Path-Row : 229-062) taken from the Landsat 5 satellite on August 4, 1989, was used in this study. This data consists of seven bands and their cell size is $30\,m\times30\,m$ except for band 6 (its cell size is $120\,m\times120\,m$). Fig. 4 shows the outline of study area A located to the West of Parintins-city (56°44′W, 2°30′S), Brazil. Fig. 5 shows study area A with about 30 km in length and about 30 km in width.

2) Training data

Figure 6 shows the local landscape in study area A taken in July 1995. In the figure, the dark green colored part corresponds to upland (terra firme forest) and light green colored part corresponds to várzea areas, which is flooded by sediment. An example of várzea areas is shown in Fig. 7 and terra firme

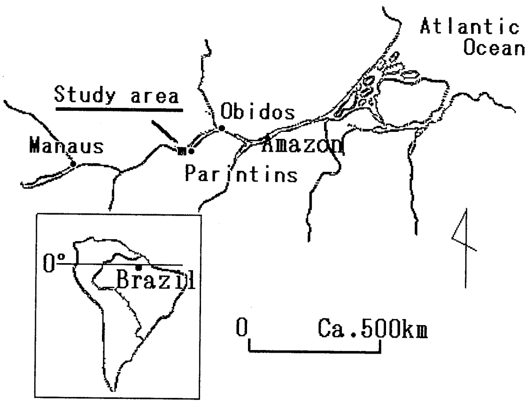


Fig. 4 Map around the study area.
Study area A is located to the West of Parintins-city, Brazil.

Fig. 6 Landscape in study area A (July, 1995).
In the figure, the dark green colored part is correspond to upland (terra firme forest) and the light green colored part is corresponding to várzea areas, which is flooded by sediment.

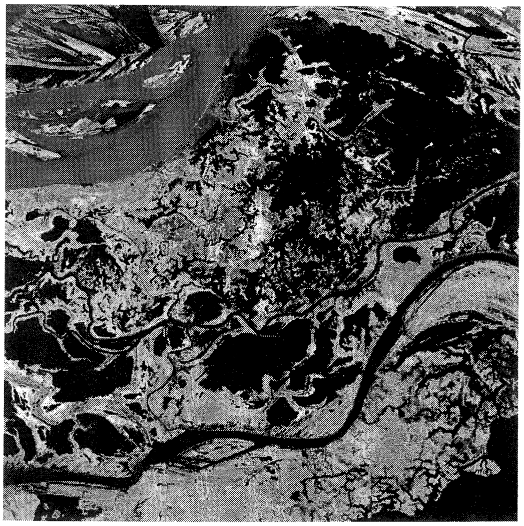


Fig. 5 Study area A.
The image with about 30 km in length and about 30 km in width was taken from the Landsat 5 Satellite on August 4, 1984 (Path-Row : 229-062).

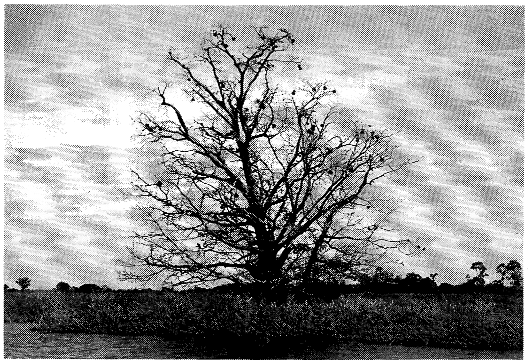


Fig. 7 An example of várzea areas in study area A (July 1996).
The water level in the study area is decreasing in July and it is observed that várzea areas can be flooded at high levels.

forest is shown in Fig. 8, respectively. Both was taken in July 1996. Water level at Manaus, Brazil reaches its highest in June (Hida *et al.*, 1997), and the water level in the study area is decreasing in July. It is observed that várzea areas can be flooded at high levels in June, and terra firme forest can be never under water at flooded periods. Therefore, it is evident that the change in the water level effects the landcover condition.

When supervised classification is conducted in the proposed method, training data in estimating landcovers is needed. Therefore, five training classes (water-1, water-2, várzea, forest, other classes) were selected on the basis of the actual landcovers as follows :

1) Water-1 is nutrient-rich water called white water river.

2) Water-2 is nutrient-poor water called black water river.

3) Várzea is the area that goes under water at high levels and become land areas at low levels.

4) Forest is the area well grown with the terra firme forest and can be never flooded even at flooded periods.

5) Other classes include clearing, roads, thick clouds and others.

A training class data composed of three hundred pixels taken out by the operator in each classes. They were sampled from the study area, and each class information was extracted from them. The average and standard deviation of the CCT count value of the TM bands in each training class in Fig. 9. The figure shows the patterns of the landcover classes on a spectral space.

Fig. 8 An example of terra firme in study area A (July 1996).
It is observed that terra firme forest can be never under water at flooded periods.

IV. Analysis Result and Discussion

1) Classification result

The occupancy of five landcover classes in each pixel unit was estimated with the proposed method, and then landcover classification in the overall study area A was conducted.

Figure 10 shows the classification result based on the occupancy of five landcover classes. Estimation ratio has a range from 0 to 1. It is difficult to show all fractional combinations of the component classes in the image, and hence in the paper, three groups showing the classification result were made. They are "pure pixel", "nearly pure pixel" and "mixel consists of two classes". For instance, when the percentage of "water-1" in a pixel is more than 80 %, the pixel is represented as "water-1". Similarly, the percentage of "water-1" is from 60 % to 80 %, the

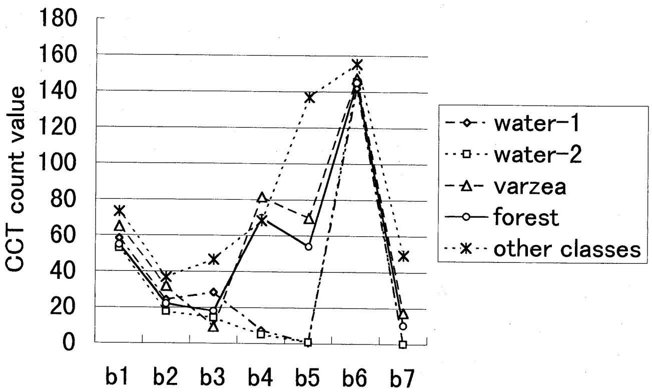


Fig. 9 The average of CCT count number of training data.
A training class data composed of three hundred pixels were taken out by the operator.

pixel is represented as "nearly water-1" and the total percentage of the two classes ("water-1" and "water-2") is from 40 % to 60 %, the pixel is represented as "water-1 +water-2". Here, the percentage means the occupancy of the landcover classes in each pixel.

It is reported that the white river (water-1) and the black river (water-2) have run without mixing with each other in some areas (Hida *et al.*, 1997), and the situation can be observed in Fig. 10. It is also observed várzea areas exist between water areas (water-1 and water-2) and forest (upland). Landcover classification taking both mixels and pure pixels into consideration was conducted. There are many mixels in the figure classified to "várzea+forest", "water-1+ várzea" and others. Compared with conventional methods, it seems reasonable to conclude that this classification result shows the condition of the landcovers in detail.

Special attention has been paid to várzea areas in Fig. 11 and the classification result of várzea areas is shown on the basis of its occupancy at 20 % intervals.

2) Estimation maps

Landcover conditions are estimated with one Landsat-TM data, and we tried to draw estimation maps of water areas for high and low levels using the occupancy of the landcover classes. In this paper, it is defined that várzea areas can go under water at high levels and then can become land area at low levels. Therefore, the ratio of water areas at high levels can correspond to the total ratio of three classes (water-1, water-2 and várzea). On the contrary, the ratio of water areas at low levels can correspond to the total ratio of two classes (water-1 and water-2). Estimation maps at high and low levels are shown in Figs. 12 and 13, respectively. The occupancy of water areas on estimation maps is made at 20 % intervals. When the total percentage of water areas in a pixel is more than 80 %, the pixel is represented as "the water area". Similarly, when the percentage is between 60 % and 80 %, the pixel is represented as "the nearly water area", when the total percentage of either water areas or land areas is between 40 % to 60 %, it is also represented as "the water and land area".

It is physically impossible to evaluate the accuracy of the estimation maps with the proposed method at this point. However, the comparison of the estimation results with actualities obtained in the ground survey can be effective. Therefore, we try to discuss for study area A. The ground survey was carried out in November 1995, February and July 1996, and the condition of landcovers in the study area was obtained as follows :

1 : South area, lower part of this image, is well grown with terra firme forest (upland) and never under waters even at high levels.

2 : The area located in center area can go under water at high levels.

3 : There are banks in várzea areas and they can be never flooded at high levels.

Figure 14 shows the area corresponding to the above issues in study area A. Lower part in Fig. 12 is estimated as the land area or nearly land area even at high levels. Next, the center area is estimated as a land area at low levels (Fig. 13), and the same area is estimated as water areas at high levels (Fig. 12). In addition, "water area+land area" can be seen at high levels (Fig. 12) and the same area is estimated as land area at low levels (Fig. 13). The extraction of the bank area may be limited considered cell size (sensor's resolution). But the estimation result

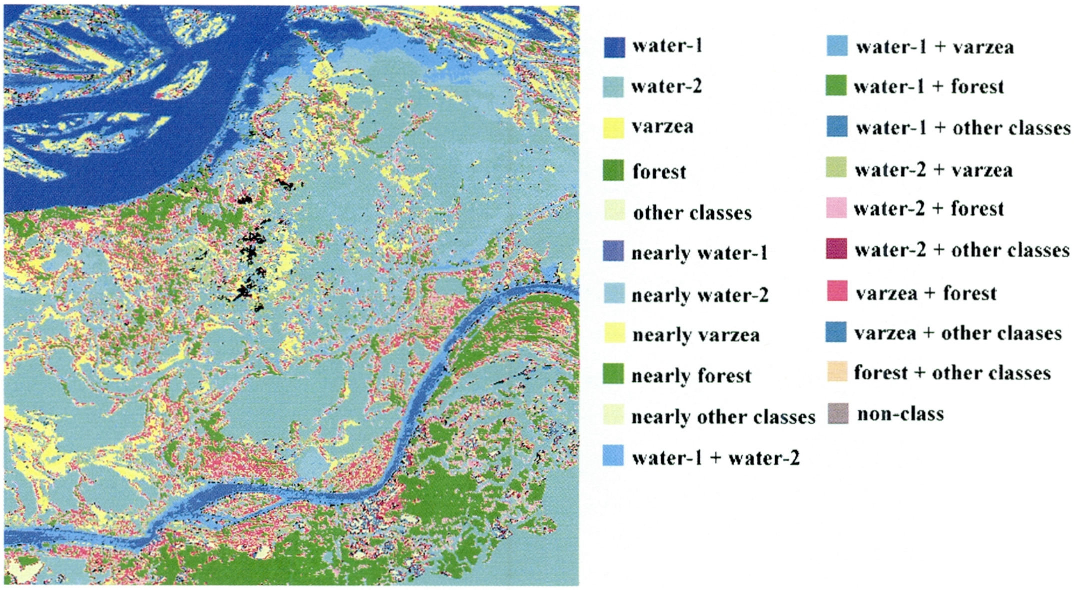


Fig. 10 Classification result in study area A with the proposed method.
Groups as "pure pixel", "nearly pure pixel" and "mixel consists of two classes" are made, and the classification results are displayed. For instance, when the percentage of "water-1" in a pixel is more than 80 %, the pixel is represented as" water-1. Similarly, the percentage of "water-1" is from 60 % to 80 %, the pixel is represented as "nearly water-1" and the total percent age of the two classes ("water-1" and "water-2") is from 40 % to 60 %, the pixel is represented as "water-1 + water-2".

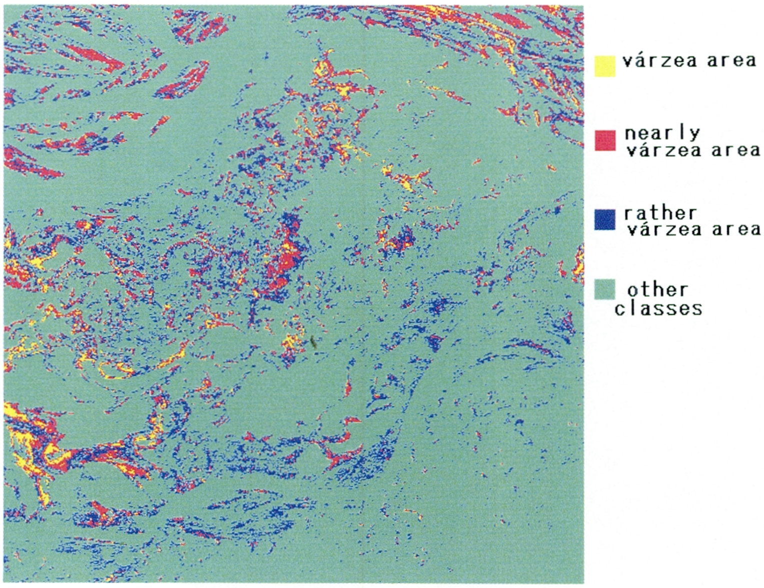


Fig. 11 Estimation result of the várzea area in study area A.
The percentage of the várzea area is more than 80 % : the pixel is represented as "várzea area", the percentage is from 60 % to 80 % : the pixel is represented as "nearly várzea area", the percentage is from 40 % to 60 % : the pixel is represented as "rather várzea area", the percentage is less than 40 %: the pixel is represented as "other classes".

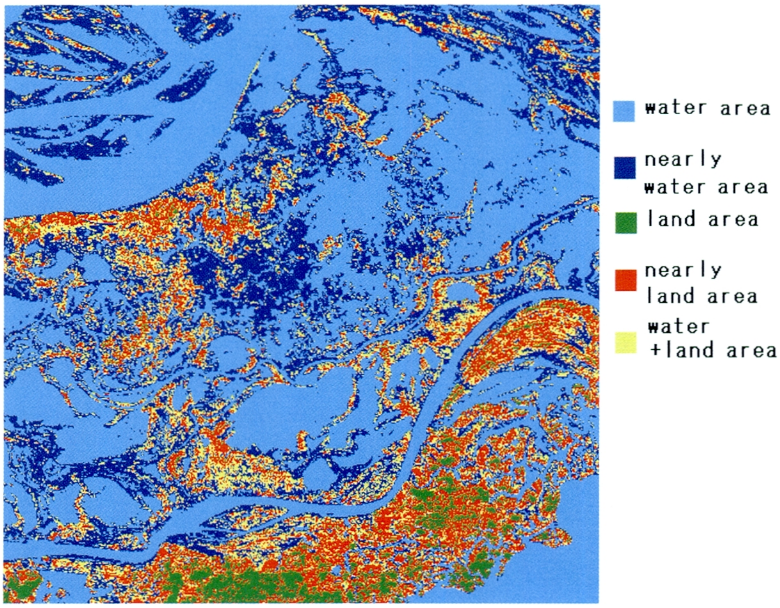


Fig. 12 Estimation map of the water area at high levels in study area A.
The total percentage of water areas at high levels is more than 80 % : "water area", the percentage is from 60 to 80 % : "nearly water area", the percentage of either water areas or land areas is 40 %～60 % : "water and land area".

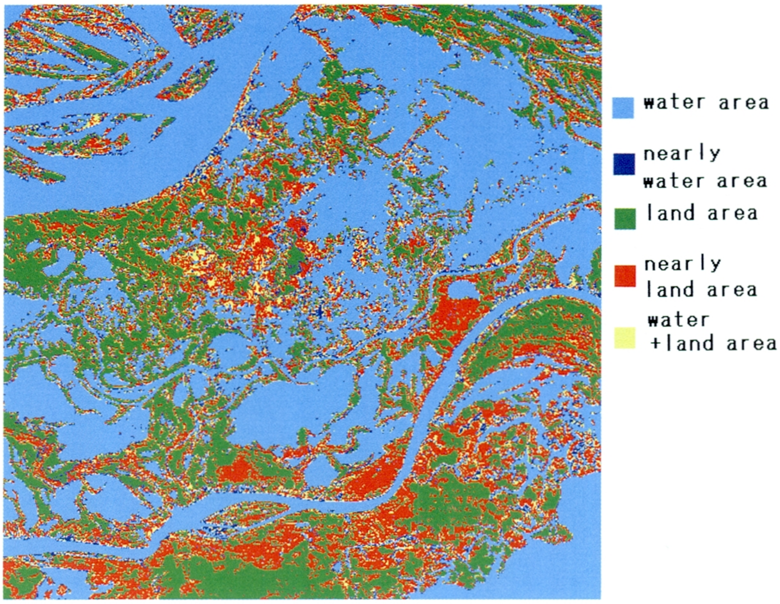


Fig. 13 Estimation map of the water area at low levels in study area at low levels in study area A.
The total percentage of water areas at low levels is more than 80 % : "water area", the percentage is from 60 to 80 % : "nearly water area", the percentage of either water areas or land areas is 40 %～60 % : "water and land area".

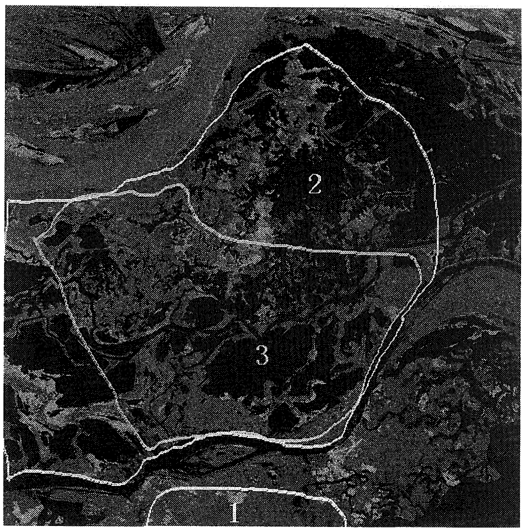


Fig. 14 The area correspond to the knowledge obtained by the ground survey in study area A.
The ground survey was carried out in November 1995, February and July 1996.

with the proposed method is allowed to estimate the occupancy of the landcover classes in a mixel. As a result, it is likely that bank is displayed as "water area+land area".

Judging from the above issues, it is clear that the distribution of the estimation maps correspond to the condition obtained in the investigation. It can be concluded that the results of estimation maps at high and low levels considering the várzea areas match the actualities there.

3) Twelve study areas

We tried to see local condition in perspective from the full scene image data taken by Landsat 5, with about 170 km in length and about 185 km in width. A mesh in 8×8 pixel was made, and then landcover classification was conducted. Fig. 15 shows the classification results with the proposed method. While there is some influence of thin clouds in above right and below left on the image, it seems reasonable to conclude that the result shows the condition of landcovers in this area.

To obtain detailed landcover conditions, especially, water areas in the Amazon, twelve study areas were selected including study area A. Fig. 16 shows the study areas A to L. The occupancy of five landcover classes was estimated in each study area. Table 1 shows the estimation results for the occupancy of five types landcover classes of each study area. The estimation ratio of the várzea area is roughly from 12 % to 33 %. As a result, the várzea area occupies about 21 % in the study areas. The total ratio of water areas at high levels is about 57 % ; the sum of three classes (water-1, water-2 and várzea), and the total ratio of water areas at low levels is about 36 % ; the sum of two classes (water-1 and water-2). Namely, water areas around Parintins-city, Brazil at high levels is an increase of about 58 % compared with water areas at low levels. The proposed method is only applied to this particular area (twelve study areas) and the occupancy of the landcover classes may not be directly extrapolated to other regions in the Amazon. Using Landsat-TM image data obtained in large sphere, this approach can be applied to larger water areas including várzea areas. Therefore, it is confirmed that the proposed method is very useful to estimate water areas in the Amazon by using the optical remote sensing images.

V. Conclusion

This paper has presented the estimation result of water areas in the Amazon with the optical remote sensing data. The approach uses the fuzzy estimation method and edge data in analyzing mixels.

It has been common that multi-temporal image data are used to estimate the flooded

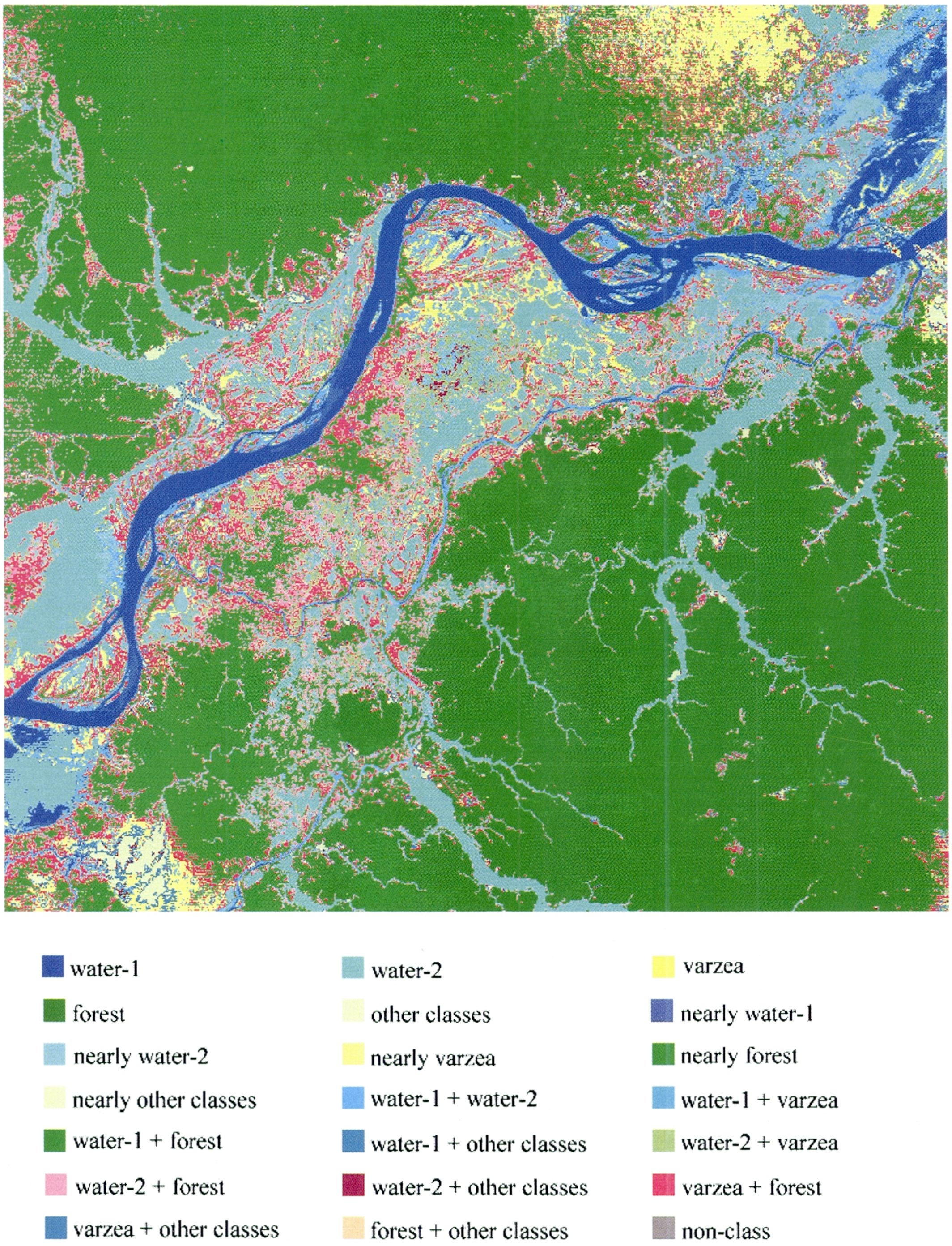


Fig. 15 Classification result for the full scene image with the proposed method.
Groups as "pure pixel", "nearly pure pixel" and "mixel consists of two classes" are made, and the classification results are displayed. For instance, when the percentage of "water-1" in a pixel is more than 80 %, the pixel is represented as "water-1". Similarly, the percentage of "water-1" is from 60 % to 80 %, the pixel is represented as "nearly water-1" and the total percent of the two classes ("water-1" and "water-2") is from 40 % to 60 %, the pixel is represented as "water-1 + water-2".

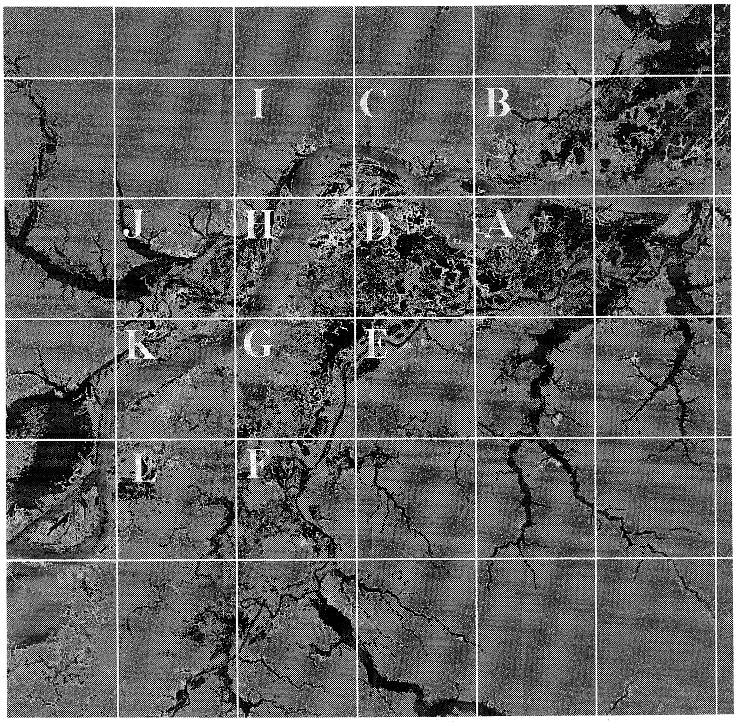


Fig. 16 Twelve study areas (Study area A to L).

Table 1 Estimation result for the occupancy of five landcover classes.

Study area	Water-1	Water-2	*Várzea*	Forest	Other classes
A	0.181	0.402	*0.185*	0.203	0.029
B	0.202	0.149	*0.204*	0.386	0.059
C	0.153	0.118	*0.120*	0.584	0.025
D	0.143	0.416	*0.283*	0.126	0.032
E	0.028	0.183	*0.108*	0.647	0.034
F	0.042	0.281	*0.171*	0.470	0.036
G	0.075	0.301	*0.269*	0.321	0.034
H	0.208	0.274	*0.266*	0.201	0.051
I	0.126	0.128	*0.126*	0.590	0.030
J	0.036	0.358	*0.218*	0.330	0.058
K	0.206	0.089	*0.330*	0.363	0.012
L	0.045	0.212	*0.216*	0.493	0.034
Average	0.121	0.242	*0.208*	0.393	0.036

The occupancy of five landcover classes was estimated in each study area. The total ratio of water areas at high levels is about 57%; the sum of three classes (water-1, water-2 and várzea), and the total ratio of water areas at low levels is about 36%; the sum of two classes (water-1 and water-2). Namely, water areas around Parintins-city, Brazil at high levels is an increase of about 58% compared with that at low levels.

areas. Optical sensors such as Landsat-TM may be limited by their inability to penetrate cloudcover in the Amazon region. However, they have been well stocked in comparison with SAR image data and are useful to classify landcovers. Therefore, the method that uses only one image data to estimate the várzea area was proposed in this paper.

Distinction between pure pixel and mixed pixel was conducted, and then the occupancy of landcover classes in the study area was estimated by a fuzzy estimation method. In addition, landcover classification was conducted using the occupancy of landcover classes. We tried to estimate water areas at a specific time when the data was not obtained, and estimation maps of the water areas at high and low levels have been drawn from the results. Comparing estimation maps with the condition on a basis of a ground survey, it has been observed that the estimation results correspond to the local situation.

As a result of this work, the estimation ratio indicate that water areas around Printins-city, Brazil is an increase of about 58 % at high levels compared with water areas at low levels in the twelve study areas. The approach is applied only to particular regions (twelve study areas) and the occupancy of the landcover classes may not be directly extrapolated to other regions in the Amazon. Using the Landsat-TM image data obtained in large sphere, this approach can be applied to larger water areas including várzea areas. Therefore, it is confirmed that the proposed method is very useful to estimate water areas in the Amazon by using the optical remote sensing images.

It is anticipated that classification result can be improved with the SAR data. We will investigate the analysis of the relation between Landsat-TM data and SAR data for estimating water areas in the Amazon and the result will be submitted to this journal in near future.

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ランドサットTM画像を用いたアマゾン川における水域の推定

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アマゾン川中下流の河川水位の変動差は，例えば，アマゾン川河口から約1,300 km上流に位置するManaus付近では年平均約10 mに達し，高水位時に水没する氾濫原はvárzeaと呼ばれている。várzeaは土壌の更新性，漁獲量および優れた輸送条件などといったさまざまな利点を備え，アマゾン川流域においてもっとも人間活動に密着している地域である。

本研究は，アマゾン川中下流域においてvárzea域に代表される水没範囲の変化などといった水文環境の変化を念頭に置き，リモートセンシング技術を用いたvárzea域の面積推定を目的としている。várzea地域のような季節により土地被覆状況が変化する地域を推定する場合，多時期に得られた複数の画像を用いることが一般的とされているが，土地被覆状況に着目することで，várzea域を含む水域の推定が可能になると思われる。アマゾン川流域周辺は雲量が多いため，SAR（Synthetic Aperture Rader）データを用いた解析方法も報告されているものの，データ量および時系列的な観測といった点を考慮すると，光学センサであるランドサットTM（Thematic Mapper）センサにより取得された画像を用いて水域を推定する手法を確立する必要がある。

そこで，本研究では土地被覆状況に着目することにより，1枚のTM画像からアマゾン川における水域の面積推定を試みた。具体的には，エッジデータと各画素におけるクラス占有率からミクセルとピュア画素の判別を行ない，クラス分類を行なった。クラス占有率の推定には種々の「あいまいさ」を表わすのに適するとの考えから，簡略化ファジィ推論法を用いた。次に，解析結果に基づいて高水位時および低水位時における水域の推定分布図を作成し，データが得られなかった高・低水位時における水域の分布状況をTM画像上から推定した。さらに，解析領域を広域とし，その範囲においても同様の処理を施してvárzea域の推定を行なった。その結果，本研究で設定した解析領域（Parintins周辺）における水域は，低水位時に比較すると高水位時では約58 %増加する可能性のあることが示された。

キーワード：リモートセンシング，várzea，ファジィ推論，エッジデータ，水位変動，ミクセル，土地被覆クラス

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