Geostatistical Modeling for Forest Management Using IKONOS Imagery

Takeshi SHIKAMA, Mamoru KUBO, Ken-ichiro MURAMOTO*

Graduate School of Natural Science & Technology, Kanazawa University
Kakuma, Kanazawa 920-1192 Japan
*corresponding author: email: muramoto@t.kanazawa-u.ac.jp

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Abstract

This paper proposes a procedure for modeling tree density by geostatistical method using high spatial resolution forest image. We calculate sample data set of tree density using tree locations extracted at sample areas selected from IKONOS image at Arimine area. We calculate experimental variogram using sample data set and variogram model was fitted. We were able to describe spatial variation of tree density using parameters of variogram model and created prediction map of tree density using variogram model. In this result, the sill and range were effective parameters to modeling the structure of forests at Arimine area.

1. Introduction

Remote sensing is a very effective technology for forest management on a large scale. Ecologists interested in forest dynamics at the individual tree level are only now beginning to explore the potential uses of high spatial and high spectral resolution remote sensing. In high spatial resolution images like an aerial image or IKONOS image, individual crowns can be distinguished [1].

Forests play an important role in maintaining environmental conditions suitable for life on the earth. Strengthening of forest management is necessary to clarify absorption mechanism of CO_2 and forest ecosystem. Details of forest condition can be obtained by ground-base research, but it is difficult to measure large areas constantly and it needs high

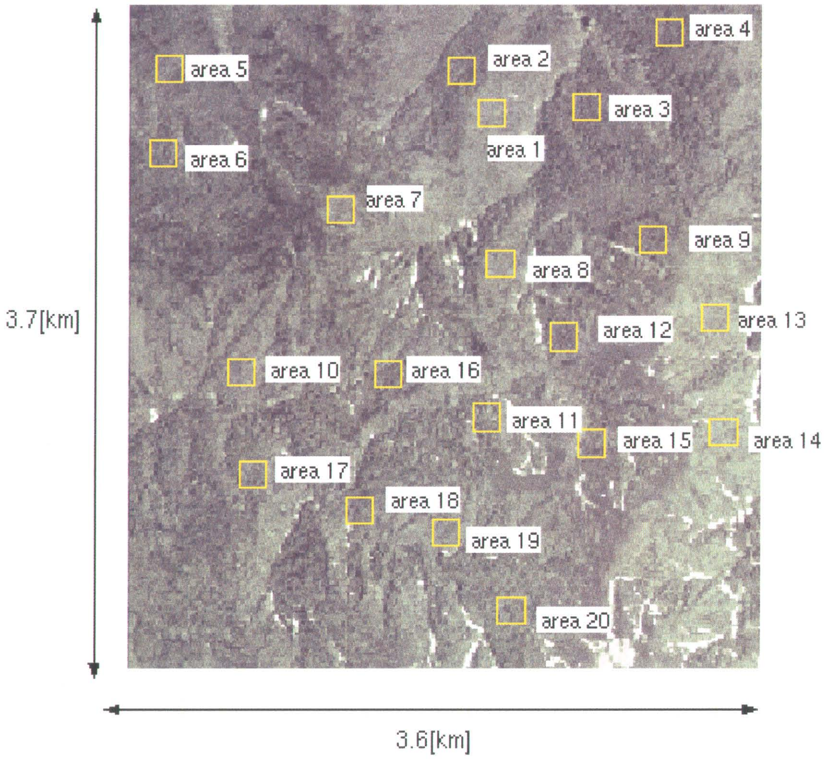

Fig. 1 IKONOS image at Arimine area.

cost and strenuous effort. These problems can be solved by satellite remote sensing image. The tree density map is important information for forest management.

Recently, geostatistical methods have been introduced for mapping. This method has evolved considerably during the last few decades, since its beginning in the early 1970s [2]. Kriging in geostatistics is a useful technique to predict values at un-sampled locations. A first step in kriging consists of computing variogram to describe the spatial variation. This function must be obtained from sample data. In a second step, variogram model is fitted to the variogram. A final step consists of predicting values using variogram model.

In this study, we purpose modeling spatial variation of tree density using variograms and we analysis the forest at large area using parameters of variogram.

2. Remote Sensing Data

2.1 IKONOS Image

In this study, we use an IKONOS pan-sharpened multi-spectral image in forest at Arimine area in Toyama prefecture, Japan on June 1st, 2002. Multi-spectral images represent four bands in the visible and near-infrared spectrum. The spatial resolution of

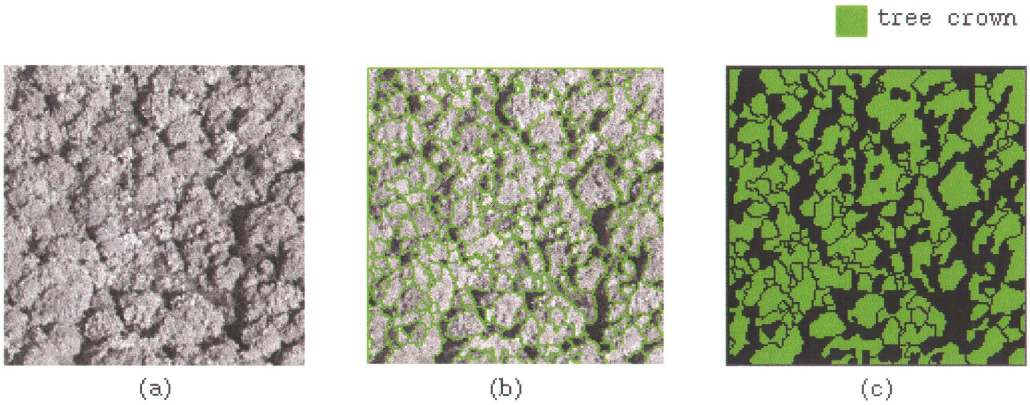

Fig. 2 (a) Principal component of 4 bands of IKONOS data, (b) the result of segmentation by image processing, (c) the image of tree crown.

analysis image is 1 m, and enable an individual tree crown whose radius is more than 3 or 4 m to be discriminated and identified. There are abundant natural forests at Arimine area. The dominant vegetation type in the study area is hardwood forest. Other vegetation types are shrub and conifer. Fig. 1 shows IKONOS image used in this study and the size of image is 3.6 km by 3.7 km. We analyze sample areas shown in Fig. 1. Each area size is about 150 m by 150 m and the total number of study area is 20. Sample area is selected the forest which could be discriminated by eyes except to areas such as grass or shrub.

2.2 Tree Crown Delineation

Tree crown delineation in the IKONOS image has been developed [3]. The brightness reflected from tree crown is higher than other areas. This algorithm detects tree crown by spreading of high brightness areas in image. Fig. 2(a) and (b) shows analysis image and tree crown delineated in the study area. The tree crown classified by K-means algorithm using mean brightness value of segments is shown in Fig. 2(c)

3. Methods

3.1 Tree Density Data

Tree density was calculated at all tree location for sample data set. As shown in Fig. 3, the number of tree within 20 m was counted, and divided by area of circle which haves radius of 20 m. The measure of density is the number par square meter.

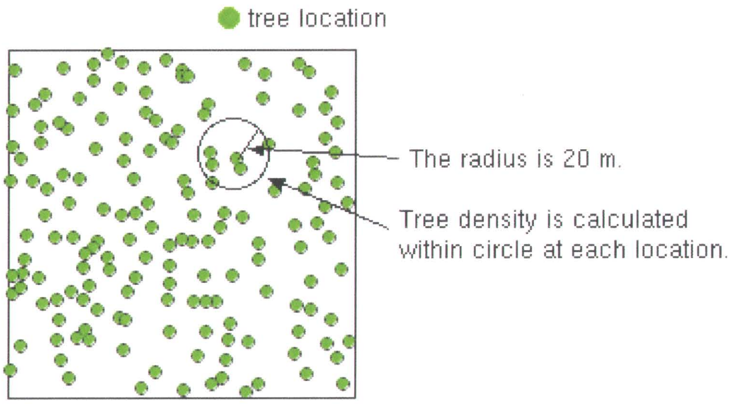

Fig. 3 Calculation of tree density.

3.2 Variogram

Sample data set $\{z(x), x = x_1, x_2, \ldots, x_n\}$ is obtained. Here, x is a tree location and n is the number of sample data set. If two sample data $z(x)$ and $z(x+h)$ of a variable are separated by a distance h, they usually are assumed similar when the distance h is very small. This similarity usually becomes weaker as separation distance h increases, and finally disappears. This is called spatial continuity and variability of a variable [4],[5]. The spatial variability can be measured using

$$\gamma^*(h_k) = \frac{1}{2n_c}\sum_{\alpha=1}^{n}(z(x_\alpha + h) - z(x_\alpha))^2 \tag{1}$$

where n is the number of data, $\gamma^*(h_k)$ is called experimental variogram. The experimental variograms can be fitted using models. For example, a spherical model is

$$\gamma(h) = \begin{cases} c_0 + c_1\left[\frac{3}{2}\frac{h}{a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right], & if \;\; h \le a \\ c_0 + c_1, & if \;\; h > a \end{cases} \tag{2}$$

where c_0 is called nugget, $c_0 + c_1$ is called sill parameter and a is range parameter. This model is shown in Fig. 4. The nugget is the positive y-intercept of the model and corresponds to discontinuity of the density variable. Usually the nugget will arise from errors of measurement or if a sampling interval is too coarse. The range is the separation

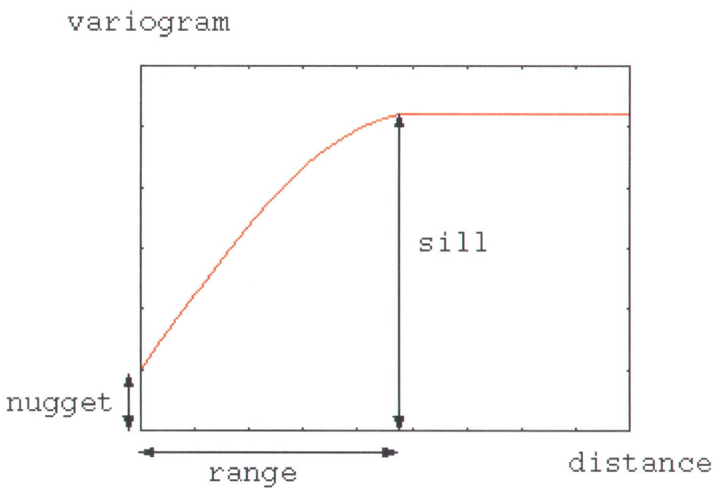

Fig. 4 Variogram model.

distance where points are no longer spatially correlated. The sill is the point where the curve levels out and this equals the priori variance of the variable [6].

3.3 Fitting Variogram

There are several different ways to fit models to sample variograms, including from completely automatic fitting to fitting by eye. Almost inevitably the best solution is a compromise between these two where the user chooses a type of variogram model, and then obtains a fit for these choices using the weighted sum of squares approximation is

$$WSS = \sum_{k=1}^{K} w(h_k) \cdot (\gamma^*(h_k) - \gamma(h_k))^2 \tag{3}$$

where $\gamma^*(h_k)$ and $\gamma(h_k)$ are experimental variogram and variogram model. k is the number of experimental variogram. An alternative that gives more weight to the first lags consists of dividing the number of data pairs by the squared model value: $N(h_k) / [\gamma(h_k)]^2$ [7].

3.4 Ordinary Kriging

Ordinary kriging is the most general method of the kriging. The existence of model of spatial dependence allows one to estimate attribute values at un-sampled locations using the neighborhood sample values. Ordinary kriging estimator is

$$z^*(x_0) = \sum_{\alpha=1}^{n} \lambda_\alpha z(u_\alpha) \tag{4}$$

where x_0 is a location to be estimated, n is the number of sample data, γ_α is the weights, z^* is prediction value at a location x_0. For the weights, a system consisting of $n + 1$ linear equations containing the variograms must be solved. The ordinary kriging system is expressed in terms of variograms as

$$\begin{cases} \sum_{\beta=1}^{n} \lambda_\beta \gamma(\mathbf{x}_\alpha - \mathbf{x}_\beta) + \mu = \gamma(\mathbf{x}_\alpha - \mathbf{x}_0) \\ \sum_{\beta=1}^{n} \lambda_\beta = 1 \end{cases} \quad \alpha = 1,\ldots n \tag{5}$$

where μ is a Lagrange multiplier. The ordinary kriging variance is equal to

$$\sigma^2 = \mu - \gamma(\mathbf{x}_0 - \mathbf{x}_0) + \sum_{\alpha=1}^{n} \lambda_\alpha \gamma(\mathbf{x}_\alpha - \mathbf{x}_0) \tag{6}$$

Ordinary kriging is exact interpolator. If predicted location corresponds with sampled location, predicted value equals to sample data at the location.

4. Results and Discussion

Fig. 5 shows tree position calculated using tree crown image. Mean number of tree was 165 and area 13 had maximum number of tree crowns and area 9 has at least. In distribution at area 2, there were coarser than the other areas. At area 1 and area 13, tree distribution was dense all over area. Tree distribution of area 9 was sparse. In area 11 and 14, trees were distributed unevenly compared with the other areas.

Fig. 6 shows the experimental variogram and variogram model and parameters of variogram model is shown in Table 1. The variogram model of area 11 had a largest sill parameter, implying highest variability of tree density of all areas. The variogram model of

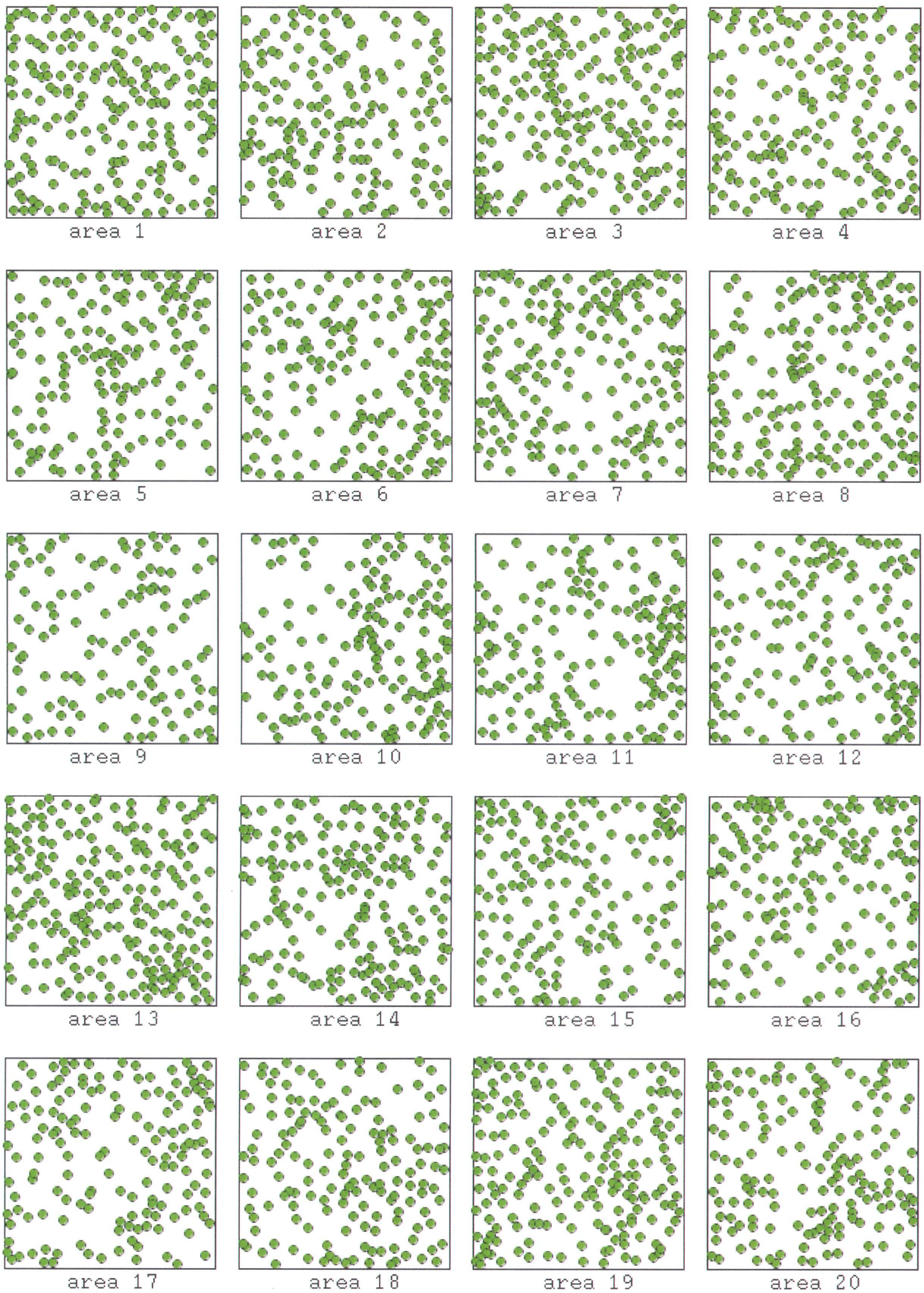

Fig. 5 Tree position at each study area.

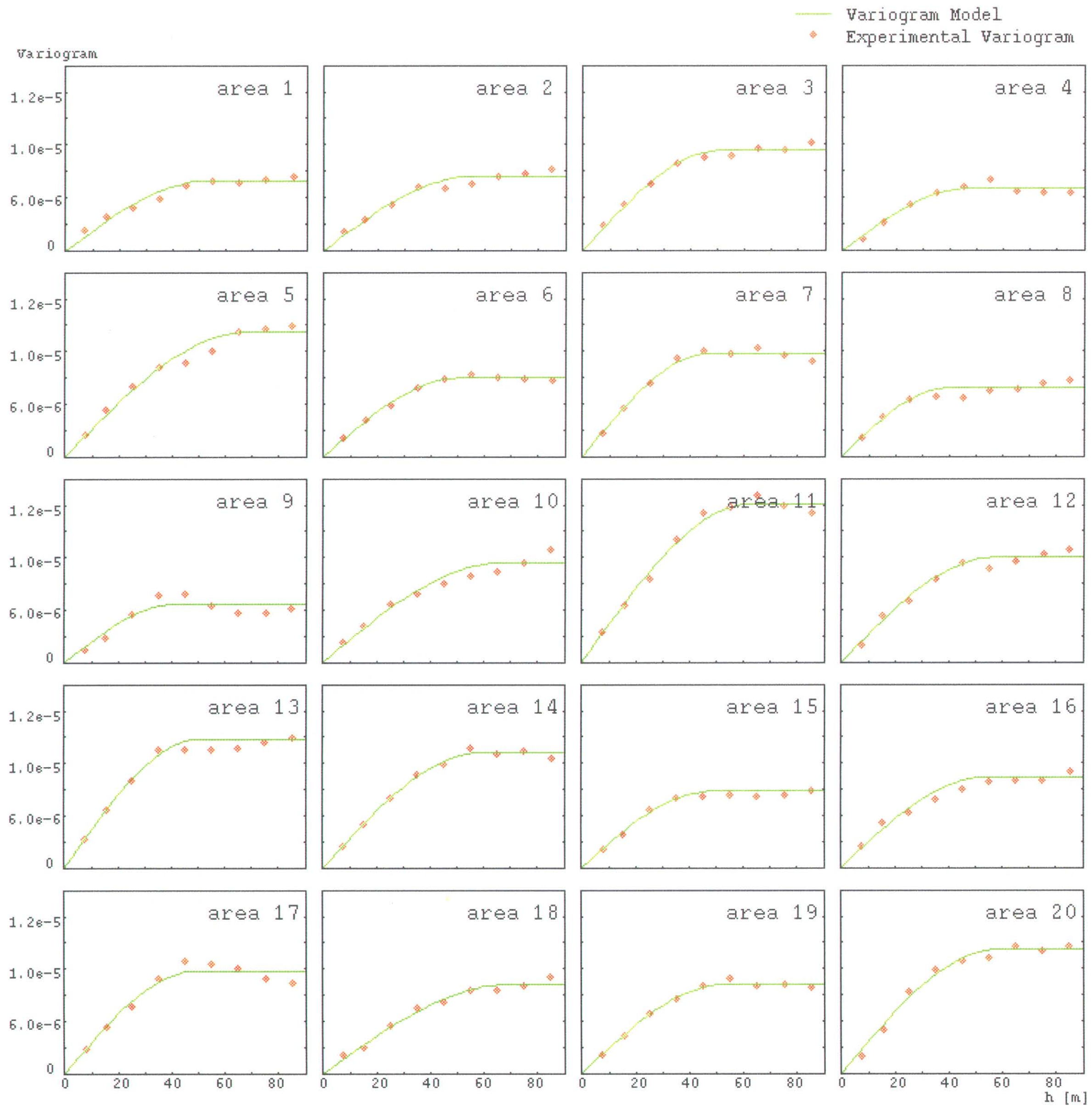

Fig. 6 Experimental variogram and variogram model.

area 18 had largest range parameter, indicating a greatest distance within which the values of the area 18 were spatially correlated.

Prediction maps of tree density using ordinary kriging are shown in Fig. 7. These results led to be reflected characteristic of tree spatial distribution of each area shown in Fig. 5. The areas which has large sill parameter were prediction map of high variability such as areas 11 and 5. The areas of small sill parameter such as area areas 8 and 9 had low variability. The prediction maps of large range parameter such as areas 5, 11 and 18 showed a few of dense regions and simply distribution compared with the other areas. In areas of low range parameter such as areas 8 and 9, prediction map had several dense regions of separate and areas of dense regions clustered was larger range parameter like areas 4 and 7. These results indicate that the sill parameter represented variability of tree density and range parameter represented spatial aspect of dense regions.

Fig. 8 shows sill and range parameters at sample areas overlaid a digital elevation model (DEM) with a grid spacing of 50 m and vertical resolution of 1m. The elevation of study area becomes higher as going to south. Both range and sill parameters changed smoothly. This indicates that variability and spatial variation of tree density shifted smoothly. The sill

Table 1 Parameters of variogram model.

No. of sample area	sill	range[m]
1	5.22E-06	52.13
2	5.60E-06	55.13
3	7.57E-06	51.36
4	4.64E-06	46.93
5	9.48E-06	67.35
6	5.98E-06	50.5
7	7.84E-06	47.35
8	5.21E-06	40.08
9	4.40E-06	40.99
10	7.56E-06	65.78
11	1.21E-05	62.69
12	7.99E-06	56.58
13	9.84E-06	50.23
14	8.78E-06	58.27
15	5.85E-06	47.67
16	6.93E-06	53.88
17	7.84E-06	48.96
18	6.82E-06	69.64
19	6.82E-06	53.21
20	9.47E-06	58.38

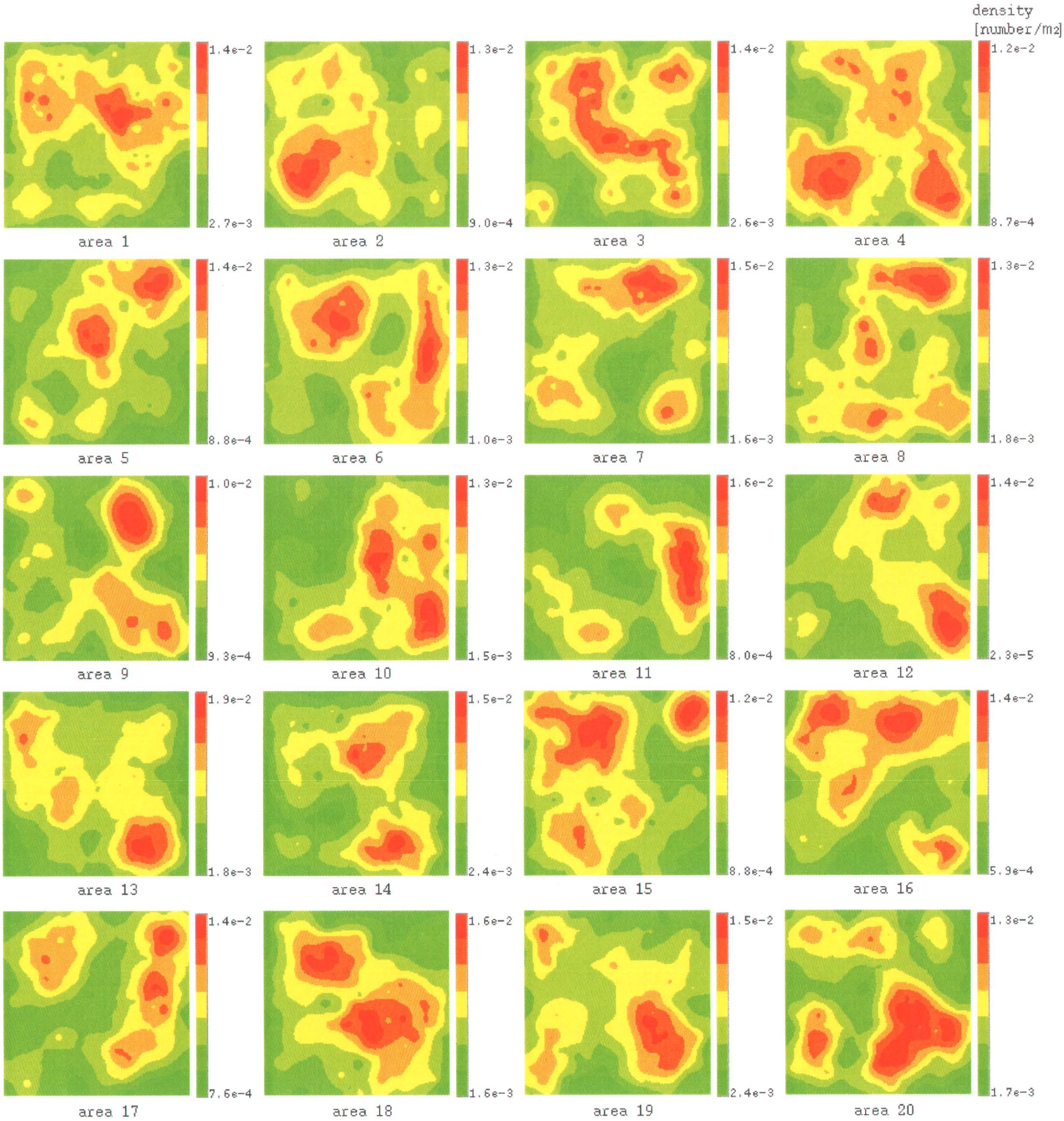

Fig. 7 Prediction maps of tree density using ordinary kriging.

parameter showed high value at southeast of study area and low value at northeast. In this result, tree density of southeast area had high variability compared with northeast area. The range parameter showed low value near the center of study area and high value at north and south area. This result showed that tree density of north and south was unevenly distribution and center was evenly. Compared with DEM, variability of tree density became higher as elevation become higher.

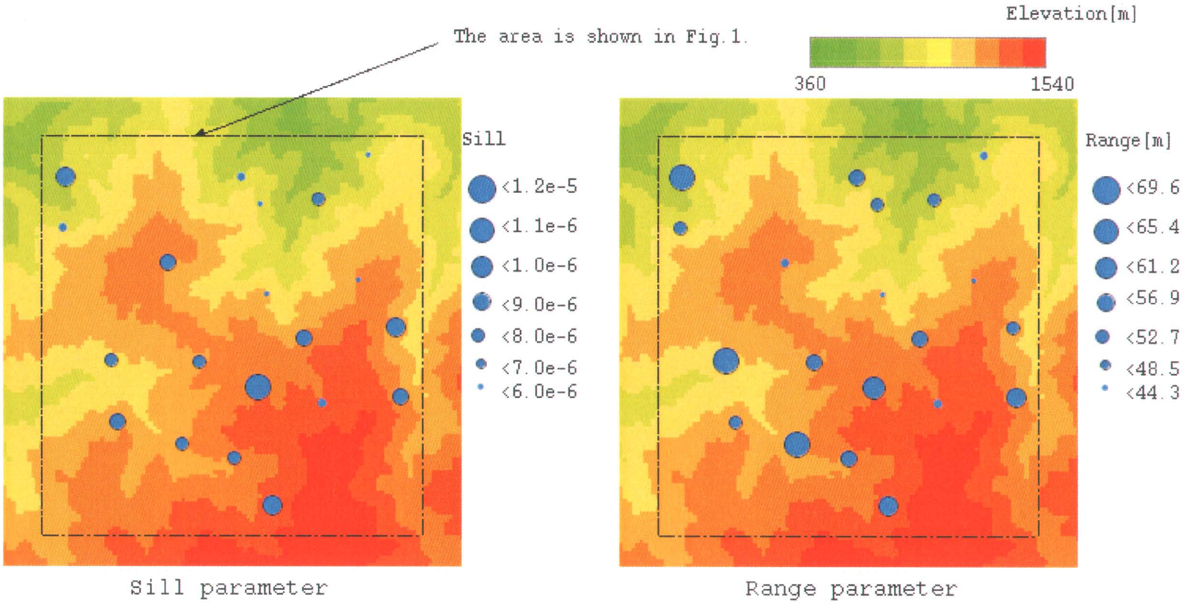

Fig. 8 Sill and range parameters at each study area overlaid digital elevation model.

5. Conclusion

Analysis areas of the number of 20 whose size is 150 m × 150 m were sampled from IKONOS image in forest at Arimine area. We calculated tree locations using tree crown delineated from IKONOS image. We created sample data set of tree density that was calculated at all tree locations.

We modeled the distribution of tree density using variogram model and created prediction map of tree density by ordinary kriging using variogram model. Spatial variation of tree density was characterized by sill parameter and range parameter in study area. We found that the sill parameter represented variability of tree density and the range parameter represented spatial aspect of dense regions.

We analyzed change of sill and range parameters using DEM at study area. In the result, we found that tree density of southeast area had high variability compared with northeast area and north and south was unevenly distribution and center was evenly. Compared with DEM, we found that variability of tree density correlated with elevation. The analysis using sill and range parameters are effective method to represent the structure of forest and we expect to apply to forest management.

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