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Integration of Observational Data and Behavioral Models for Spatio-Temporal Interpolation —Application to Reconstructing Long-Term Land Use and Land Cover Changes

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Abstract—Spatio-temporal interpolation to generate voxel-field data in a space-time domain from observational data is indispensable to many spatio-temporal reconstruction and visualization of dynamic spatial phenomena. However, only very primitive interpolation methods such as nearest neighbor interpolation based on a Voronoi diagram are proposed for nominal or "class variable" data such as land use or land cover data. In interpolating nominal data with these primitive methods, we cannot make use of knowledge on spatial or temporal patterns or behavior of the object. The authors propose a spatio-temporal interpolation scheme for generating a voxel-field of nominal data under the framework of optimization of likelihood. The likelihood is computed from the fitness to both observational data and expected patterns/behavior described by a behavioral model or rules specific to the object. Any model which provides likelihood or probability to a given spatio-temporal pattern can be used in this framework. For the optimization of likelihood, a genetic-algorithm (GA) was combined with the Hill-Climbing (HC) method to increase the efficiency and reliability of optimization. Through some experiments, it is demonstrated that the GA/HC based interpolation method can generate voxel-fields which fit both the observational data and to the knowledge of its behavior and that the reliability of interpolation can be evaluated quantitatively in terms of the maximal likelihood. Finally, the method is applied to the reconstruction of long term land cover changes from BC 7500 to present.

BACKGROUND AND OBJECTIVES

Temporal or dynamic analysis of spatial data is needed in various fields such as environmental systems analysis. A fundamental problem faced by users is the difficulty in generating spatio-temporal data fields (3D or 4D voxel field) through interpolation of observational data. This comes from the fact that observational data from multi-sources often have sparse or biased distributions, and different forms (point, edge, polygon and solid in a spatio-temporal space), resolutions and accuracy/reliability.

In several fields, to improve the reliability of spatio-temporal interpolation/extrapolation in generating quality data, models and/or equations describing a mechanism and structure underlying a spatial or behavioral pattern are integrated with observational data.

Integration methods for data and models have been mainly developed for continuous variables such as temperature and precipitation in meteorological and oceanographic studies. These methods are known as 4DDA (Four Dimensional Data Assimilation).

For nominal or class variables such as land use types, only relatively primitive interpolation methods have been made available, such as nearest neighbor interpolation. We propose a method of integrating models and nominal observational data from multiple sources under the framework of the optimization of likelihood of spatio-temporal events. For optimizing the likelihood, a genetic algorithm (GA) is combined with the classical "Hill-Climbing" method. Experimental results demonstrate that GA with HC can be successfully applied to the integration.

GENETIC ALGORITHMS (GA) AND NOMINAL VARIABLE INTERPOLATION

Introduction of genetic algorithm (GA)

Genetic algorithms have been developed by John Holland and his colleagues as an approach to optimization problems. The search algorithms are based on the mechanisms of natural selection and evolution of natural genetics. The approach combines survival of the fittest among string structures with a structured but randomized gene exchange to form a search algorithm with some innovative flair for human search (Goldberg, 1989).

Genetic algorithms are computationally simple and powerful in their search without restrictive assumptions about search spaces. In a simple genetic algorithm, five basic aspects should be considered; the representation or coding of the problem, the initialization of the population, definition of the evaluation function, the definition of genetic operators, and the determination of parameters.

Optimization scheme for nominal variable interpolation

Most natural properties in magnitude vary along a continuous scale. Spatial continuity and temporal continuity are intuitive assumptions that provide rationale for interpolating observational data (Olover, 1990). However, knowledge and rules governing spatio-temporal patterns and behavior of geographic objects (e.g., environmental systems) are now being rapidly accumulated and represented by many simulation models. They can provide more robust and quantitative basis for interpolating observational data, though many of the models still may not be sufficiently accurate and reliable. On the other hand, it can be said that reliability of results estimated from model simulation can be improved by combining reliable observational data. Integration of observational data and models (GCM etc.) is conducted in meteorology as a daily routine. There has been no such attempt to extend the idea of integration to more generic geographic objects.

It is reasonable to assume that spatio-temporal events or the “voxel-field” of nominal variables which are estimated should maximize likelihood under given observational data and behavioral models, if we suppose that observation is a probabilistic event and that behavioral models are structured and probabilistic of a priori knowledge on the behavior of the object phenomenon. Observational data and behavioral models/rules can be integrated in the process of maximizing the likelihood of spatio-temporal events.

Because searching for the most likely spatio-temporal voxel-field of nomimal data is a typical combinatorial optimization problem, we introduce the genetic algorithm as a optimization scheme.

APPLICATION OF GA FOR INTEGRATING BEHAVIORAL MODELS AND OBSERVATIONAL DATA TO CLASS VARIABLE INTERPOLATION

Three dimensional (3D) representation of an individual (coding)

In the following discussion, a 3D array is defined to represent an individual (Fig. 1) in a space-time domain. The horizontal plane represents 2D space and the vertical dimension represents temporal dimension.

Initialization of population

An initial population for a genetic algorithm is usually chosen at random; one random trial is made to produce each individual. All members of the initial population are chosen automatically by the same procedure so that the expected value of each member of the initial population is same. In addition, we use cubes of $1 \times 1 \times 1$, $2 \times 2 \times 2$ and $3 \times 3 \times 3$ pixels as the initial unit for the initialization of population to increase the efficiency of the procedure.

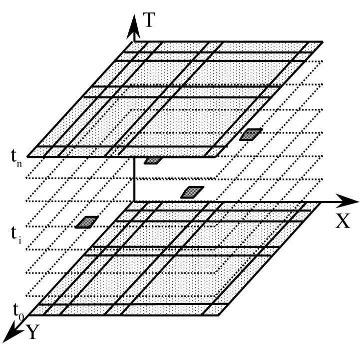

Fig. 1.

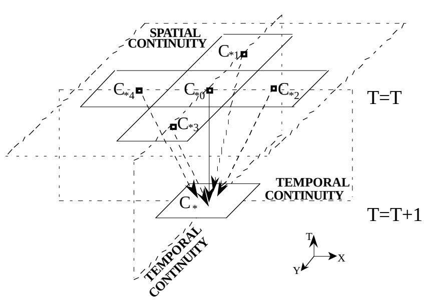

Fig. 2.

Fig. 1. Representation of individual.

Fig. 2. 3D spatio-temporal relation of pixel-based class variable data.

Definition and computation of an individual's fitness

Spatio-temporal behavioral models/rules of class variable data

Any type of behavioral models can be used for the GA-based interpolation if they can determine the probability of every possible behavior/transition of nominal or class variables. For nominal variable data, possible changes in a class at one pixel are basically defined by the probability of the changes from one class to another. A simple example is a Markov chain, where transitional probability is determined only by the previous class. In addition, the probability can also be affected by the combination of classes in the neighborhood. In this study, we used a model where transitional probability is determined by the combination of classes in the neighborhood. The test data have five classes.

In our experimental model, spatial and temporal relations affect the transitional probability in three ways (Fig. 2). The first is "spatial continuity", based on the assumption that the same class data tends to continue in the spatial dimension. The second is temporal continuity, which is an extension of the spatial continuity to the temporal domain. The third is expansion-contraction relations based on the assumption that some data classes have a higher possibility of expanding their area at the next time-slice, while others tend to contract. The temporal change in a non-contractible class pixel will be determined by the pixel class itself. The temporal land use changes in contractible type pixels will be determined by the class of the pixel and classes of its expansible neighbors.

Definition and computation of fitness of an individual

Fitness of an individual is defined by the combination of behavioral fitness and observational fitness. Behavioral fitness is defined as the combined probability of a change in events of nominal variables under the condition that these changes follow a given probabilistic behavioral model or rule.

Observational fitness can be defined as the combined probability that the observational nominal values occur under probabilistic functions of observational errors or uncertainties. Observational probability can be determined by accuracy, resolution and frequency of observation. Overall fitness can be computed by multiplying behavioral fitness and observational fitness. Thus, behavioral/

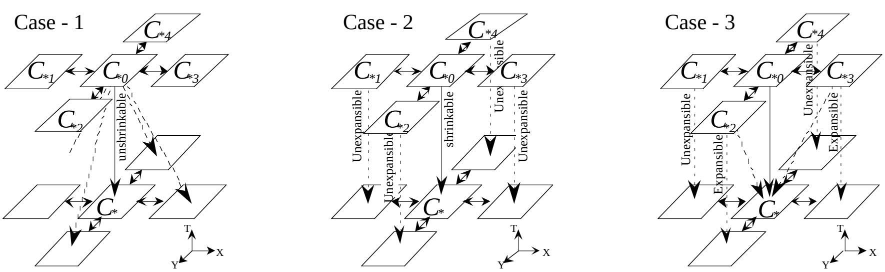

Fig. 3. Possible change patterns of land use classes in temporal and spatial distribution.

structural models and observational data can be integrated by optimizing the overall fitness.

1) Behavioral Fitness: As shown in Fig. 2, let $P_V(C_{P,T}, C_{P,T+1})$ as the probability of changes from land use class $C_{P,T}$ or C_{*0} to land use class $C_{P,T+1}$ or C_* considering both the temporal continuity and the expansion-contraction effect of its neighbors ($P_V(C_{*0}, C_*)$), and ($P_{SC}(C_{*0}, C_{*1}, C_{*2}, C_{*3}, C_{*4})$) as the probability of spatial continuity. If we assume that $P_V(C_{*0}, C_*)$ and $P_{SC}(C_{*0}, C_{*1}, C_{*2}, C_{*3}, C_{*4})$ are independent, we can compute behavioral fitness of each individual according to the following formula:

$$\underset{\text{(behavioral fitness)}}{\text{FITNESS}} = \prod_{P=1}^{N_P}\left\{\prod_{T=1}^{N_T} P_V\left(C_{P,T}, C_{P,T+1}\right)\right\}$$
$$= \prod_{P=1}^{N_P}\left\{\prod_{T=1}^{N_T} P_{TC}\left(C_{*,0}, C_*\right) P_{SC}\left(C_{*,0}, C_{*1}, C_{*,2}, C_{*3}, C_{*,4}\right)\right\} \tag{1}$$

where

N_P: is the pixel number,

N_T: is the temporal slice number,

$C_{P,T}$: is the land use class of the cell on the Pth pixel at the T time-slice.

For the class change probability with spatial continuity, $P_{SC}(C_{*0}, C_{*1}, C_{*2}, C_{*3}, C_{*4})$, we set values according to the following five neighboring pixels' status along the spatial dimension, which form a set of behavioral rules: 1) whether classes in all neighboring pixels are equal; 2) whether classes in the 4 neighboring pixels are equal; 3) whether or not classes in 3 neighboring pixels are equal; 4) whether classes in the 2 neighboring pixels are equal; 5) whether all classes in the 5 pixels are unequal.

Table 1. Behavior of class changes in Case 3.

Invasion C_{*i1}	Invasion C_{*i2} (Value of C_*)	C_{*i1} $P_M(C_{*0}, C_{*i1})$	C_{*i2} $P_M(C_{*0}, C_{*i2})$	$C_{*i1} = C_{*i2}$ $P_M(C_{*0}, C_{*i1})$	Others $P_M(C_{*0}, C_*)$
Yes ($\alpha_{C_{*i1}}$)	Yes ($\alpha_{C_{*i2}}$)	0	0	Invasion	0
Yes ($\alpha_{C_{*i1}}$)	No ($1-\alpha_{C_{*i2}}$)	Invasion	0	Invasion	0
No ($1-\alpha_{C_{*i1}}$)	Yes ($\alpha_{C_{*i2}}$)	0	Invasion	Invasion	0
No ($1-\alpha_{C_{*i1}}$)	No ($1-\alpha_{C_{*i2}}$)	Markov Chain	Markov Chain	Markov Chain	Markov Chain

Notice: 1> Supposed C_{*i1} and C_{*i2} are expansible (i1, i2 = 1 ~ 4) ;
2> $\alpha_{C_{*i1}}$ and $\alpha_{C_{*i2}}$ are defined as expansion speed of C_{*i1} and C_{*i2} ;

To calculate the probability of class changes under the temporal continuity/ expansion-contradiction effect, three possible changing patterns of land use classes in spatial-temporal distribution are selected and listed in Fig. 3. The probabilities of those cases can be determined by integrating the probability of class changes in a Markov chain, and the expansion probability of the class-types into neighboring pixels (Table 1).

2) Observational Fitness: Observational fitness can be computed with the following formula:

$$\text{Observational Fitness} = \prod_{n=1}^{N_O} P_{\text{Obs.}}\left(C_{P,T}, C_{P,T,\text{Obs.}}\right)$$

$$P_{\text{Obs.}}\left(C_{P,T}, C_{P,T,\text{Obs.}}\right)\text{: Probability that observational value } C_{P,T,\text{Obs.}} \text{ is given when actual value is } C_{P,T}. \quad (2)$$

Observational probability can be determined mainly by the accuracy of observation. Observational location and time/frequency can be represented by locating an observational pixel in the two-dimensional string. Spatio-temporal resolutions can be represented by setting an aggregation formula over the range of observation.

3) Total Fitness: Total fitness is computed from behavioral fitness and observational fitness by the following formula:

$$\text{Total fitness} = \text{Behavioral fitness} \cdot \text{Observational fitness},$$
$$\text{or } \ln(\text{Total fitness}) = \ln(\text{Behavioral fitness}) + \ln(\text{Observational fitness}). \quad (3)$$

Definition of operators

Reproduction

Reproduction is a process in which individual strings are copied according to their objective function values or the fitness values. Copying strings according to their fitness values means that strings with a higher value have a higher

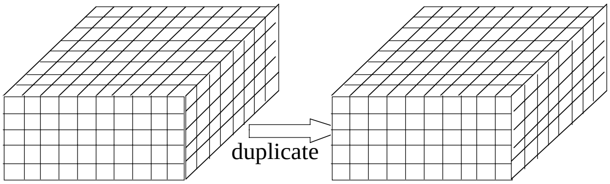

Fig. 4. Reproduction of an individual.

probability of contributing one or more offspring in the next generation (Fig. 4). This operator may be viewed as an artificial version of natural selection, a Darwinian survival of the fittest among string creatures.

There are several proposals for selecting survival individuals. The most basic schemes are the roulette wheel scheme, the deterministic sampling and the elitist scheme. In order to efficiently find the best solution in the search space, we adopted the selection scheme based on the combination of the deterministic sampling and the elitist scheme. The selected survival possibility in next generation of each individual is calculated as in the deterministic sampling. The best individual is kept into the next generation as in the "elite" scheme.

Crossover

The crossover operator first randomly mates newly reproduced individuals in the mating pool. It then randomly locates a window of random size for a pair of individuals. Finally, the contents of the individuals within the window are swapped to create new individuals (Fig. 5).

Mutation

A mutation operator plays a secondary role in the simple GA by occasionally altering the value in an individual position (Fig. 6).

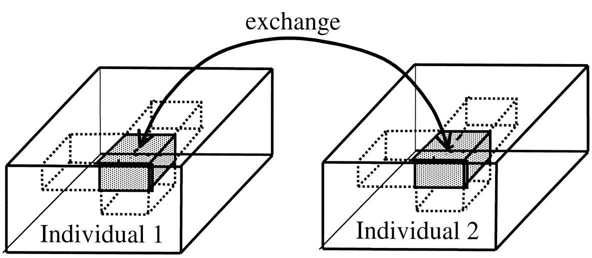

Fig. 5. Crossover of individuals.

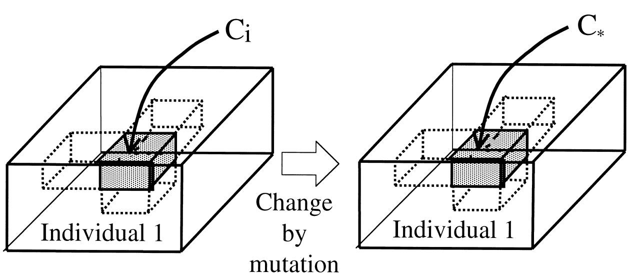

Fig. 6. Mutation of an individual.

IMPROVEMENT OF THE SEARCH IN GENETIC ALGORITHM (GA)

Hill-climbing (HC) method to improve the efficiency of genetic algorithm (GA)

Searching a complex space of problem resolutions often involves a tradeoff between two apparently conflicting objectives: exploiting the best solutions currently available and robustly exploring the space (Lashon Booker, GA&SA). Generic algorithms have been regarded as a class of general purpose search strategies that strike a reasonable balance between exploration and exploitation. The power of these algorithms is derived from a very simple heuristic assumption: that the best solutions will be found in regions of the search space containing relatively high proportions of good solutions. The problem is that, if the complex space of problem resolutions become larger and larger, the population size and the generation size have to be increased at same time. The efficiency of GA is one of the obstacles to real world applications of the GA.

Hill-Climbing (HC) is a good example of a search strategy that exploits the best among known possibilities for finding an improved solution. Although HC strategies are easily trapped in one of the local maxima farther away from the optimal solution, it is a very good search strategy that exploits the best among known possibilities for finding an improved solution. In our research, we investigated the potential for combining the HC strategy with GA.

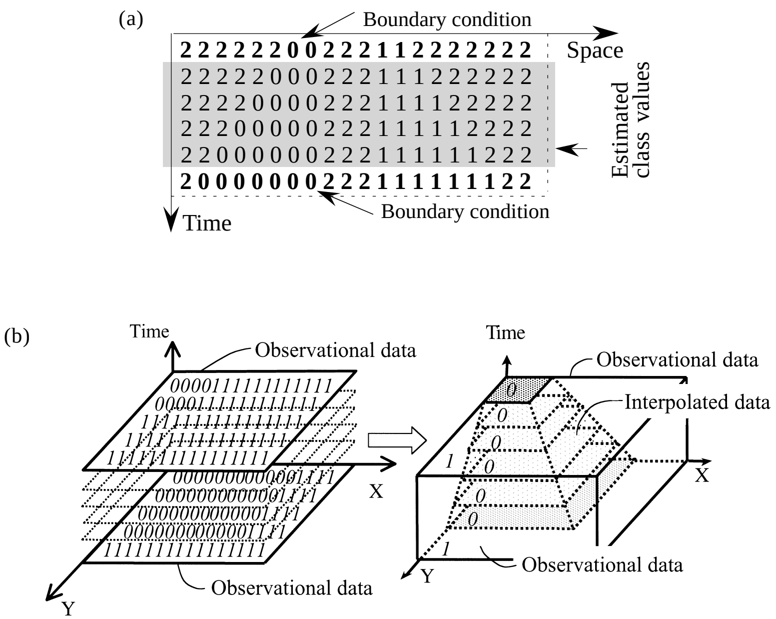

Fig. 7. (a) Results of GA/HC (2D case). (b) Results of GA/HC (3D case).

Maintenance of population diversity

Despite the demonstrated advantages of GA and the high performance of most implementations, it still fails to live up to the high expectations engendered by the theory. The problem is that any implementation uses a finite population or set of sample points. Estimates based on finite samples inevitably have a sample error associated with them. Repeated iterations of an algorithm compound the sample error and lead to search trajectories much different from those theoretically predicted. The most serious phenomenon is premature convergence.

Premature convergence is caused by early emergence of an individual that is better than the others in the population, although far from optimal. Copies of this structure may quickly dominate the population. Search continues then but is concentrated in the vicinity of this structure and may miss much better solutions elsewhere in the search space.

To avoid premature convergence, one has to avoid the loss of population diversity. Although reducing the reproduction number cannot always eliminate premature convergence, it can be used as a simple way to reduce rapid convergence. In our research, we therefore limited the duplicated number of individuals less than two; if the individual's expected duplicated number is larger than two, we set it equal to two.

EXPERIMENTS

The test program of GA/HC for spatio-temporal interpolation of pixel-based land use data was coded in C language and was run on SPARC/station2. Small

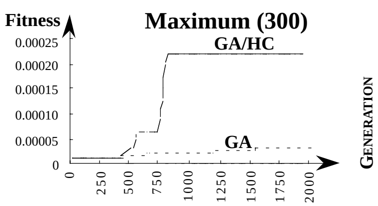

Fig. 8. Comparison of GA with GA/HC.

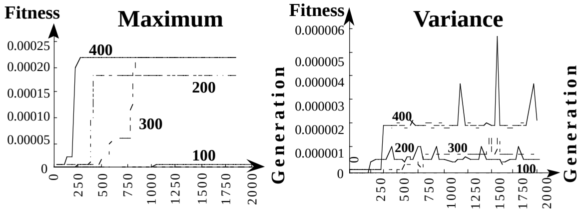

Fig. 9. Effect of population and generation size.

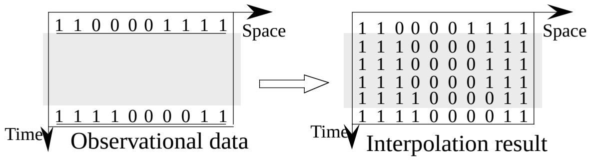

Fig. 10. Interpolation result (overlapping case).

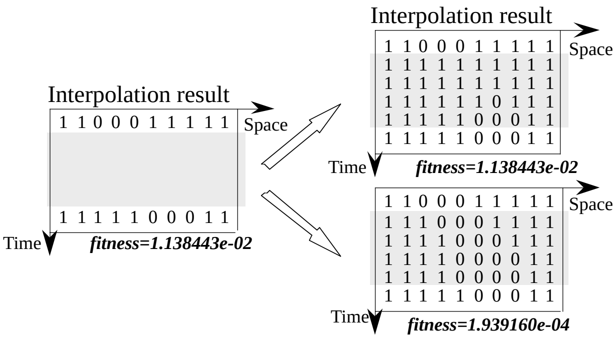

Fig. 11. Interpolation results in non-overlapping case.

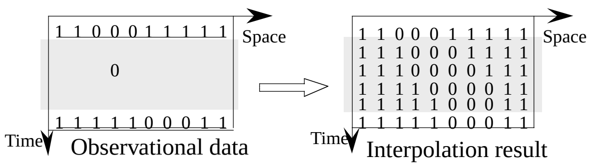

Fig. 12. Interpolation results with additional observation data.

spatio-temporal datasets are used in the experiment to check the behavior of the GA/HC based interpolation under different conditions. The size of an individual had been defined with 20 pixels × 6 time-slices for a 2D case and 11 lines × 11 columns × 6 time-slices for a 3D case. The first and last time-slice in the individual are supposed to be sample (observational) data and all middle time-slices should be estimated by the interpolation. In these experiments, we set the generation size of GA/HC to 2000, which was large enough to obtain stable results. The probability of crossover operation was defined as 0.7, while the probability of mutation operation was relatively small in the natural population, so that we used 0.01 as the probability of mutation. 2D and 3D experimental results of GA/HC, in which the individual has the largest fitness value are presented in Fig. 7. In the model used for this experiment, smooth transition/ expansion has the largest fitness or likelihood.

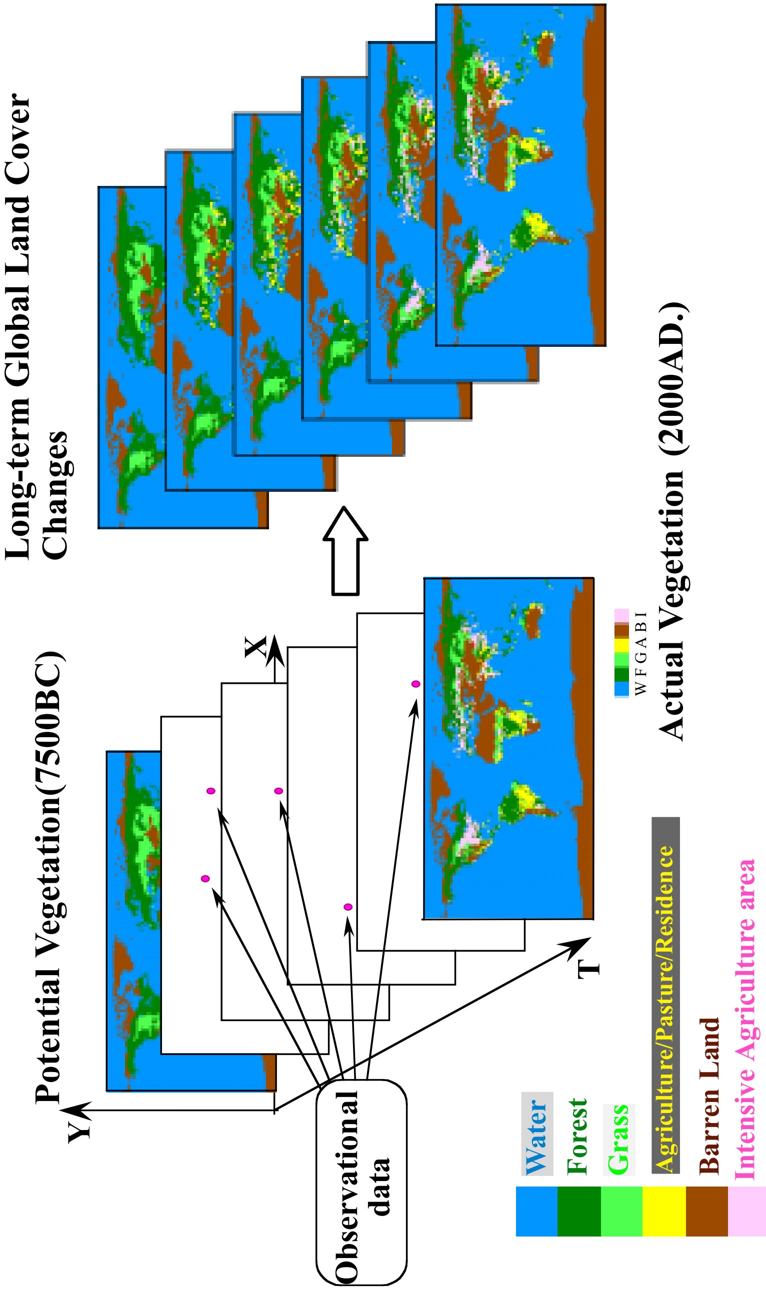

Fig. 13. Applying GA-based interpolation method to reconstructing long term land use and cover change.

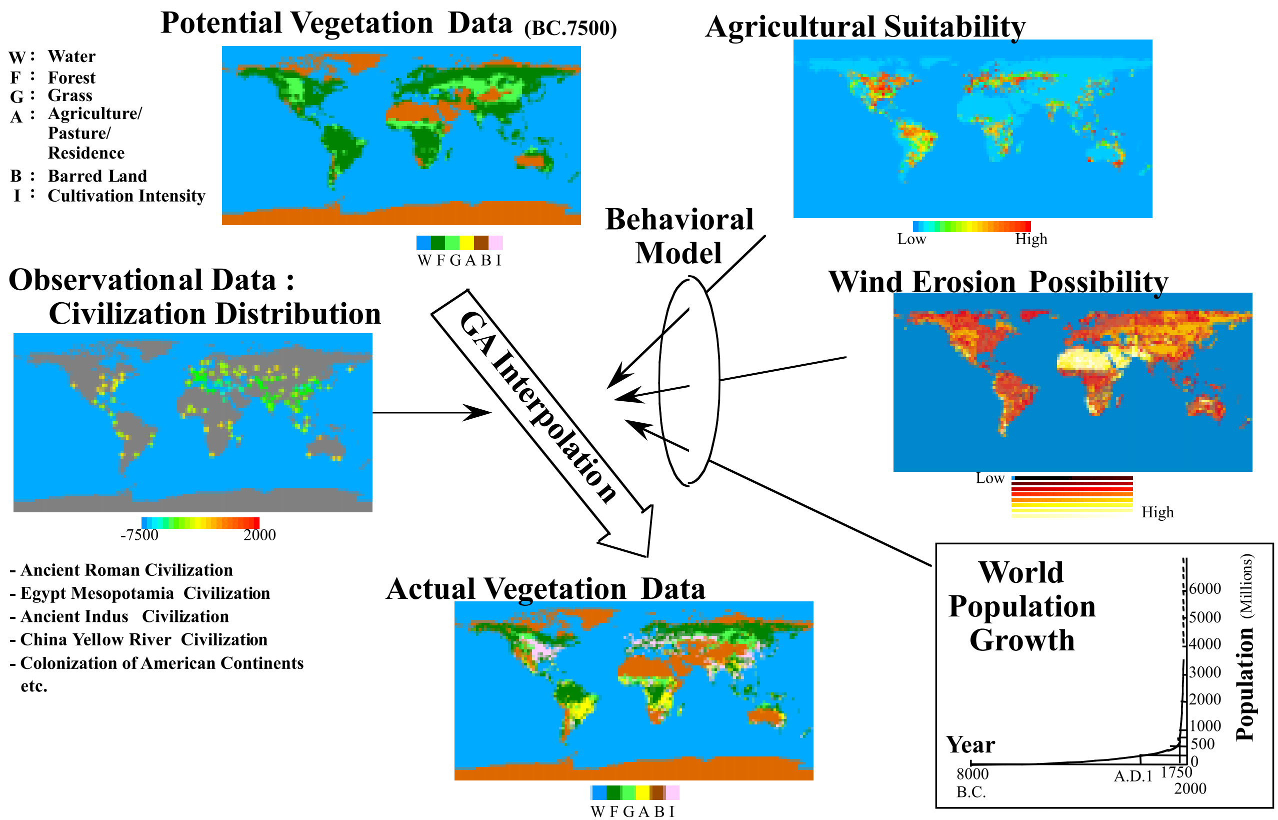

Fig. 14. Data and behavioral models used in the interpolation.

Several experimental results are compared in Fig. 8. Based on this figure, we can find that the larger the population size is, the faster a stable result can be obtained, and the closer the stable result tends to be the best solution. Comparison of GA/HC with GA for spatio-temporal interpolation of land use class variable data is presented in Fig. 9. GA/HC has a much higher efficiency than GA for spatio-temporal interpolation because a much higher fitness value can be obtained in younger generations.

In Fig. 10, the observed location of class “0” in the first time-slice and the last time-slice are overlapping spatially. The interpolation result naturally merges class “0” together, forming a band of class “0”. On the other hand in Fig. 11, although class “0” is not overlapping, it is demonstrated that the most likely interpolation does not connect class “0” together and that a case forming a band of class “0” apparently has lower likelihood, though it appears reasonable. In Fig. 12, other observational data are given at the middle. In this case, the most likely spatio-temporal pattern of class changes has a band of class “0”. These variations in the resulting patterns suggest that the interpolation method integrating observational data and behavioral models/rules can estimate the most likely voxel field under different conditions.

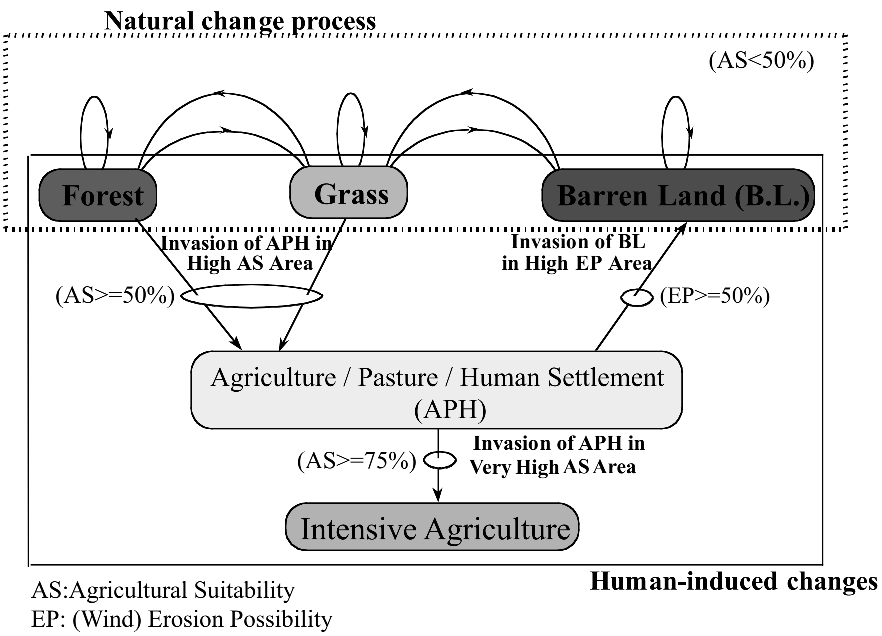

Fig. 15. Behavioral model of land cover changes used in the interpolation.

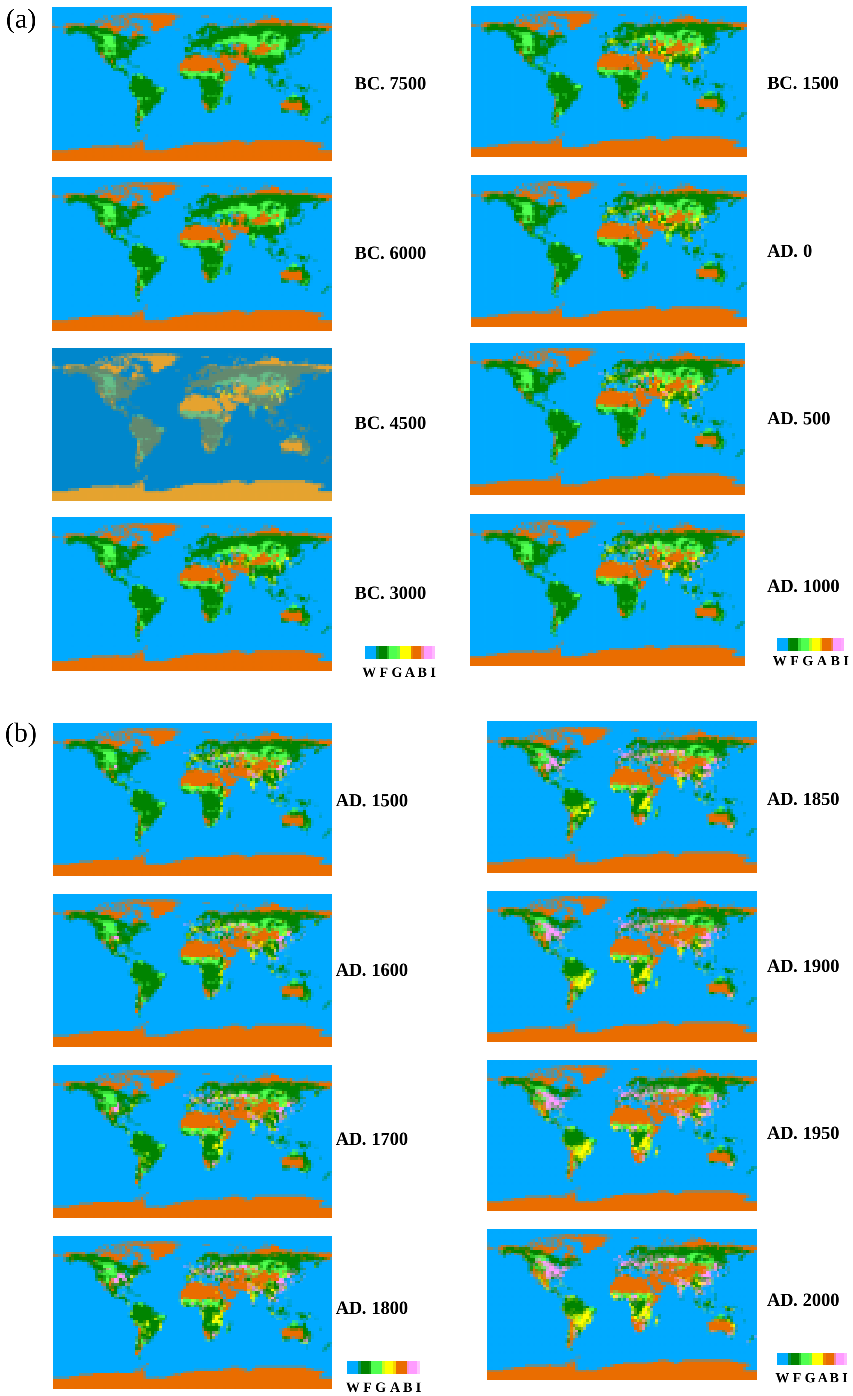

Fig. 16. Reconstructed long-term global land use and cover changes.

APPLICATION TO RECONSTRUCTING LONG-TERM LAND USE AND COVER CHANGES

In this section, the results of applying the interpolation method to long-term reconstruction of land use and land cover changes. Although the long-term land use and land cover changes are important for global environmental studies, only fragmentary data on those changes have been available from historical documents and pollen analysis and so forth. The interpolation method is applied to demonstrate the possibility of reconstructing long-term land use and land cover changes by combining fragmentary data and quantitative knowledge of the changes.

The period of the reconstruction is from BC 7500 to present. Only for the start and end years, land use and land cover data are provided while point-based observational data are given in between the start and end. It is assumed that patterns or rules of land use and land cover changes are given in terms of transitional probability (Fig. 13).

BC 7500 is chosen as the start year, because agricultural activities were assumed to start in around BC 7500. Spatial resolution of the reconstructed land use and land cover data is 0.5 degree, while temporal resolution varies from 1500 years at the beginning of the period to 50 years near 2000.

The following observational data are used in the application (Fig. 14).

1) Land cover (vegetation) data at the start year: global potential natural vegetation data (Box, 1995) were used. The global potential natural vegetation was generated from the present climate data, because the global climate data over the past 9500 years is not available. This means that some of the vegetation distribution (e.g., forest in the Sahara desert) are neglected in the reconstruction process.

2) Land use and land cover data in 2000: Cultivation intensity data (Matthews, 1983) are overlaid on global vegetation data (Tateishi and Kajiwara, 1991) to represent the impact of agricultural activities.

3) Point-based observational data were collected from the World Historical Pictorial Handbook (1993). Many of the data are on the emergence of cities which suggest the existence of agricultural areas around them.

4) The total area of the agricultural area is strongly correlated with the total population. Global population growth data are from Durand (1967). In the interpolation, a constraint condition should be taken into account in which the total agricultural area should be proportional to the total population. However, the computational load can be very heavy if the constraint condition is explicitly taken into account. To avoid this, the interval of the time-slice in the interpolation is determined so that the population growth rate becomes constant between neighboring time-slices, which results in an almost constant growth rate of agricultural area expansion between the neighboring time-slice. Thus, knowledge on the land use and land cover changes can be very much simplified.

In addition, the following knowledge on land use and land cover changes is assumed (Fig. 15).

1) Knowledge on the land use and land cover changes is given in terms of transitional probability from one class to another.

2) The transitional probability varies according to regional conditions. In areas which are climatologically suitable for high agriculture, the transitional probability from forest or grassland to agricultural areas is relatively high. In areas where the possibility of wind erosion is high, the transitional probability from grassland to barren or desert areas is relatively high. In areas with a very high suitability of agriculture, ordinary agricultural areas are likely to change to intensive agricultural areas.

Figure 16 shows the reconstructed results of the long-term land use and land cover changes. Because long-term changes in climatologic variables are ignored and the number and quality of the point-based observational data are limited, the reconstructed results cannot be validated against the other observational data. Nevertheless, the reconstructed results show a reasonable fitting both to the observational data and the knowledge of the changes. It can be concluded that by applying more accurate and reliable scientific data and knowledge of climate changes, long-term land use and land cover changes can be reconstructed more accurately.

CONCLUSIONS AND FUTURE PROSPECTS

In this study, a spatio-temporal interpolation scheme is proposed for raster or grid-based nominal data to integrate observational data with behavioral models under the framework of the maximum likelihood of spatio-temporal events. Genetic-Algorithm/Hill-Climbing can be successfully applied to the combinatorial optimization of nominal voxel-field data. Our conclusions are summarized as follows:

1) GA/HC can be very rigorous because it can generate the most likely spatio-temporal distribution of class variables under observational data and a behavioral model.

2) The Hill-Climbing method can be an effective method for greatly improving the efficiency of GA;

3) The interpolation method can be applied to the reconstruction of dynamic phenomena such as long-term land use and land cover changes from fragmentary observational data and knowledge of the changes.

REFERENCES

Box, E. O. (1995): Global Potential Natural Vegetation: Dynamic Benchmark in the Era of Disruption, Proceedings of the 8th Toyota Conference, “Toward Global Planning of Sustainable Use of Earth—Development of Global Eco-engineering”, Elsevier Science, Amsterdam, pp. 77–96.

Bramlette, M. F. (1991): Initialization, Mutation and Selection Methods in Genetic Algorithms for Function Optimization, Proc. of the 4th Conf. on GA, R. K. Belew and L. B. Booker (Editors), July, 1991, pp. 100–107.

Burrough, P. A. (1986): Methods of Spatial Interpolation, Principle of GIS for Land Resource Assessment, Monograph on Soil and Research Survey, No. 12, 1989, pp. 147–166.

Davis, L. (1987): Genetic Algorithms and Simulated Annealing, Pitman Publishing, 128 Long Acre, London WC2E 9AN.

Durand, J. D. (1967): The Modern Expansion of World Population, Proceeding of the American Philosophical Society, III-3.

Eshelman, L. J. and J. D. Schaffer (1991): Preventing Premature Convergence in Genetic Algorithms by Preventing Incest, Proc. of the 4th Conf. on GA, R. K. Belew and L. B. Booker (Editors), July, 1991, pp. 115–122.

Gold, C. M. (1989): Surface interpolation, spatial adjacency and GIS, Three Dimensional Applications in Geographic Information System, J. Raper (Editor), Taylor & Francis Ltd., pp. 22–35.

Huang, S. B. and R. Shibasaki (1995): Development of Generic Algorithm/Hill-Climbing Method for Spatio-temporal Interpolation, 6th Symposium on Functional Graphics and Geographic Information Systems, IIS, Univ. of Tokyo.

Matthews, E. (1983): Global Vegetation and Land Use; New High Resolution Data Bases for Climate Studies, *Journal of Climatology and Applied Meteorology*, **22**, 474–487.

Shibasaki, R., T. Ito and Y. Honda (1993): Integration of Remote Sensing and Ground Observation Data for Developing Global GIS, Proc. of SEIKEN Symposium, Vol. 12, Aug. 1993, pp. 263–277.

Shibasaki, R., M. Takaki and Y. Honda (1994): Spatio-temporal Interpolation Using Multi-Source Data for Global Dataset Development, COMMISSION III, IGWG III/IV.

Shibasaki, R., S. Murai, T. Endo and B. Xuemei (1995): Global Planning for the Sustainable Use of the Earth Based on Land Suitability Analysis, Proceedings of the 8th Toyota Conference, “Toward Global Planning of Sustainable Use of Earth—Development of Global Eco-engineering”, Elsevier Science, Amsterdam, pp. 301–314.

Tateishi, R. and K. Kajiwara (1991): Land Cover Monitoring in Asia by NOAA GVI Data, *Geocarto International*., **6**, No. 4, 53–64.

World Historical Pictorial Handbook (1993): Hamashima Publishing Company.

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