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Developing predictive models for palaeoanthropological research: a preliminary discussion

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Abstract

This paper reports on our recent progress in developing an interdisciplinary method to model the spatio-temporal patterns of Neanderthals and modern humans in response to the climate changes. For this purpose, we organised a workshop and lectures in May 2012 to learn the theory, methods, and applications of archaeological predictive modelling. The intensive discussion led us to recognise that it is essential for supra-regional prediction of human niche distribution to evaluate how significantly each environmental variable contributes to the model. The subsequent experiments using MaxEnt, an ecological niche modeller, have provided ideas to improve the models by (1) refined radiocarbon dates of the sites, (2) super-resolved raster data of palaeoclimate, and (3) revised palaeovegetation zoning.

1 Backgrounds

The goal of the palaeoenvironmemt research team of the 'Replacement of Neanderthals by Modern Humans' (RNMH) project is to reconstruct the spatio-temporal progression of the replacement of Neanderthals and anatomically modern humans (AMHs) in response to the climate changes in the Pleistocene [1]. For this purpose, archaeologists, climatologists, geochronologists, geomorphologists, and palynologists are collaborating to develop an interdisciplinary protocol. This paper reports on our recent progress in the development of analytical models through a workshop and discussions.

In the first one and a half year of the project, we designed the workflow of our interdisciplinary research (Figure 1). The first step is to select the palaeoanthropological sites of specific human species or relevant lithic industries from a database. We are developing NEANDAT radiometric sample database by collecting information in published literature and online databases such as PACEA's [2]. The sites are filtered by the time period during which an abrupt climatic change occurred. Then, the principal palaeoclimatic variables—precipitation and temperature—are calculated for the same time period by means of climatic simulator. In parallel with this, geomorphologists create a digital elevation model (DEM) of the relevant period, with taking the sea level change and ice sheet extension into account. Finally, these data are integrated in GIS (Geographical Information Systems) as an information infrastructure to manage, visualise, and analyse these data in geospatial context.

1.1 Ecological niche modeling

We are planning to apply ecological niche models to analyse the spatio-temporal dynamics of the replacement of Neanderthals by AMHs. Ecological niche modelling is a computer-based evaluation of species' geographical range (or ecological niche) expansion or contraction in response to the real or simulated environmental conditions [3, 4]. It can also be applied to palaeoanthropology and archaeology as ecocultural niche modelling (ECNM), because in prrehistory human behaviours were largely influenced by the environmental impact [5, 6, 7].

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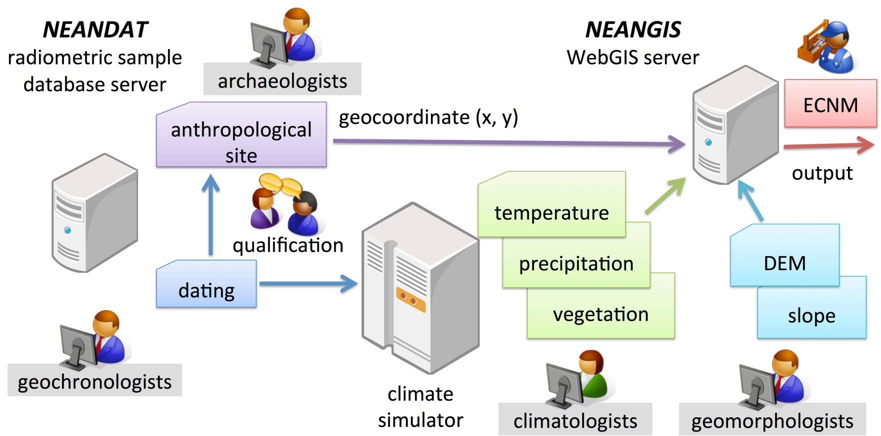

Figure 1: Interdisciplinary workflow to model environmental impacts on palaeoanthropological events.

Among ecological niche models, GARP and MaxEnt are the most commonly applied in current ecological research. Both software programmes are available online at free of charge, and require species' location (x, y), and the environmental variables as inputs. The environmental factors may include both continuous and categorical variables. The continuous variables are more common, including temperature, precipitation, altitude, and slope. On the other hand, categorical variables are exemplified by vegetation and land use. GARP is based on a genetic algorithm for rule-set production [8], and outputs the resultant geospatial matrix (or raster-based map) in binary format (0 or 1). In contrast, MaxEnt employs the maximum entropy model [9, 10, 11], and outputs continuous probabilities of presence ($0 \cdots 1$) for each raster cell. It has been pointed out that these two algorithms tend to yield 'strikingly' different results from the same dataset and parameter settings [12]. The developers of MaxEnt argue its advantage to GARP in the accuracy of prediction [10], although there are some rebuttal opinions in which the geographical extents of the niche predicted by MaxEnt are narrower and more biased than those predicted by GARP [12]. This tendency has also been observed in our comparative experiments using archaeological and environmental datasets of the Japanese Jomon period and the Pleistocene Levant [13].

1.2 Predictive modelling in archaeology

Methods of predictive modelling have been applied for archaeology and cultural resource management (CRM) in Europe and North America for over thirty years [14, 15, 16, 17, 18, 19, 20, 21]. The purpose of archaeological predictive models is to evaluate the probability of presence of unknown archaeological occupations from the location of known sites and environmental variables (as referred to in the previous section). It is a GIS-based approach, and sometimes has expert's judgment incorporated to the model [18]. It seems to share its concepts and direction of approach with ecological modelling. Therefore, it was needed to learn the theory, methods, and applications of archaeological predictive modelling for a better understanding of the applications of ecological models to palaeoanthropological research.

2 Learning predictive modelling

Based on the above-mentioned motivation, the research team invited Philip Verhagen, a specialist of archaeological predictive modelling from VU University Amsterdam (the Netherlands), to Japan for three weeks in May 2012. During his visit at Tokyo Institute of Technology as Visiting Scholar, we organised a workshop and three lectures, as well as intensive discussions on the application of predictive modelling to research RNMH.

Figure 2: A snapshot of the predictive modelling tutorial.

2.1 Workshop

The two-day workshop titled 'Introduction to Archaeological Predictive Modelling' was held at Tokyo Institute of Technology, on May 19 and 20. Kondo coordinated the program with Verhagen. In total 17 researchers and students in archaeology, cultural anthropology, architecture history, ecology, geomorphology, and computer science participated in the workshop.

On the first day, Verhagen gave a three-hour lecture on the theory and methods of predictive modelling with case studies from the Netherlands, France, and the United States. The lecture was designed to provide the participants with basic knowledge on the topic. On the second day, the participants formed six groups, and experienced a four-hour tutorial of predictive modelling, using a dataset of the Rijssen-Wierden area in the Netherlands. The dataset consisted of vector files of archaeological sites for three periods (Palaeolithic-Mesolithic, Late Bronze Age-Early Medieval, and Late Medieval) and raster files of a digital elevation model (DEM), simplified soil map, total viewshed, stream and water areas, and the existing predictive map of the study area. GRASS GIS, an open source GIS software package, was employed for the tutorial.

At the beginning of the tutorial, each group was asked to choose one of the two assignments we prepared—the data-driven model or theory-driven model for one of the archaeological periods distinguished. The data-driven model applied an inductive approach, in which the chi-square test was used to check the significance of the given raster data for site location preference. On the other hand, the theory-driven model is a deductive approach, in which site location preferences were decided by the operators' judgment about where sites should be present. Three groups chose the data-driven model and the other three did the theory-driven. All groups started with reclassifying continuous values of raster files into a smaller number of categories. This manipulation is essential to differentiate geographical features and in this way make prediction more distinctive. Then, participants evaluated in groups whether the reclassification was appropriate, and if not, they discussed what values should be allocated to the reclassification thresholds (Figure 2). The goal of the assignment was to create, interpret, and assess a predictive map. Every team actively asked questions to the tutors in the course of model building, and finally completed the assignment and adequately explained what the team did in a presentation at the end of the workshop.

2.2 Lectures

Besides the workshop, Verhagen gave three lectures on predictive modelling. The first lecture was held at the Center for Spatial Information Science, The University of Tokyo, on May 16, where his latest ideas on object-based landform delineation and classification from DEMs for archaeological predictive mapping [22] were presented to researchers and students in geomorphology and GIS. The lecture was followed by an active discussion on the application of object-based image analysis (OBIA) to LiDAR-based high-resolution DEM.

The second was an invited lecture in the session 'Human Evolution and Climate Change' of the Japan Geoscience Union Meeting 2012, on May 24. Titled 'Predictive modelling of archaeological site location: prospects and challenges', the lecture provided geoscientists with the basic concepts and current issues of archaeological predictive modelling [23].

The third and final public lecture was held at the Faculty of Science, The University of Tokyo, on May 28. The lecture introduced the human factor in archaeological predictive modelling. It has long been excluded from the variables input to models although human behaviour, reflected in site occupation, should be understood in social context. The contribution of human factors was demonstrated by a model including accessibility of the landscape, and was evaluated by means of principal component analysis (PCA) [24].

3 Preliminary discussion

The intensive discussions in the workshop, lectures, and other meetings led us to recognise the advantages and limitations of current archaeological predictive modelling and ecological niche modelling. First of all, the conventional predictive models in archaeology and CRM have focused on relatively small regions up to a few hundred square kilometres. The goals of prediction are to extract some patterns of site location preference in relatively homogeneous environmental settings. In contrast, ecological niche models are usually applied to study areas on the continental scale. It works well to extract significant spatial trends of similarity in diverse environmental settings.

In the RNMH research, we deal with supra-regional ecological niche variability of Neanderthals and AMHs in response to the global climate change, rather than regional patterns of site occupation. Therefore, the machine-learning approach of ecological modelling seems to be more suitable for the project's objectives. Nevertheless, ecological models only take the available variables into account. They are likely to miss some important factors in human evolution such as the effect of individual learning and technological innovation, which are not very well reflected in conventional environmental variables. Thus, it could sometimes happen that the spatial prediction deviates from the researcher's expectations. However, such a result should not be rejected but carefully examined and interpreted because of its possibility to reflect a difference between natural and cultural behaviours. Human factors can also be incorporated to the model, as suggested in the lectures. At this point, we expect that an eco-cultural discrepancy may appear in the statistical reports that some ecological models, including GARP and MaxEnt, output as a byproduct of maps of prediction, and it is important to evaluate how significantly each variable affects species' niche and spatial distribution.

The discussions and thereafter experiments of ECNM [25] have yielded ideas to improve the models by (1) refined radiocarbon dating, (2) high-resolution palaeoclimate models, and (3) revised palaeovegetation zones. We will discuss the methods of improvement more in detail in the RNMH international conference in November 2012 and the next volume of this series. The following summarizes the ideas as of August 2012, with the eco-cultural niche distribution of the Magdalenian culture in Western Europe during the Last Glacial Maximum (LGM) as an experimental study.

3.1 Radiocarbon data analysis and site distribution

Individual radiocarbon dates are represented by the median and standard deviation of probability density. In general, the older date yields the larger standard deviation, and it is almost impossible to date samples older than 50 ka with the current technology. However, it is possible to qualify the dating samples to narrow down the deviation by means of decision-tree models and Bayesian statistics as follows: Firstly,

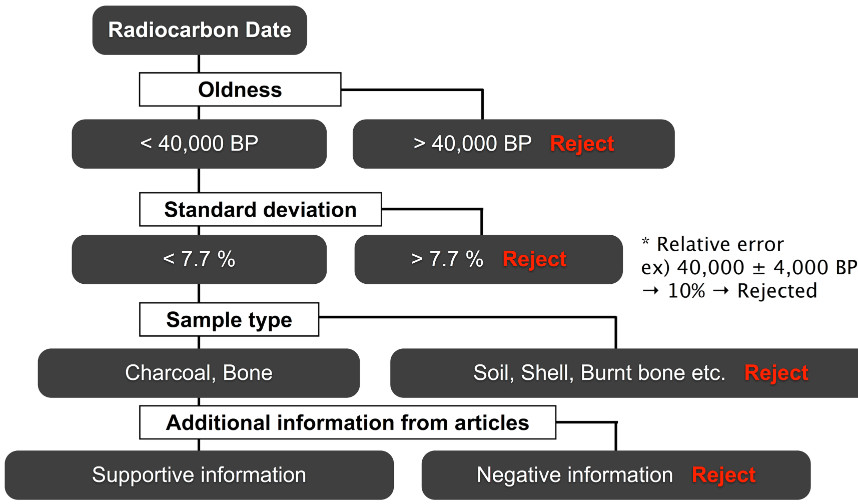

Figure 3: Decision tree to qualify radiocarbon dates.

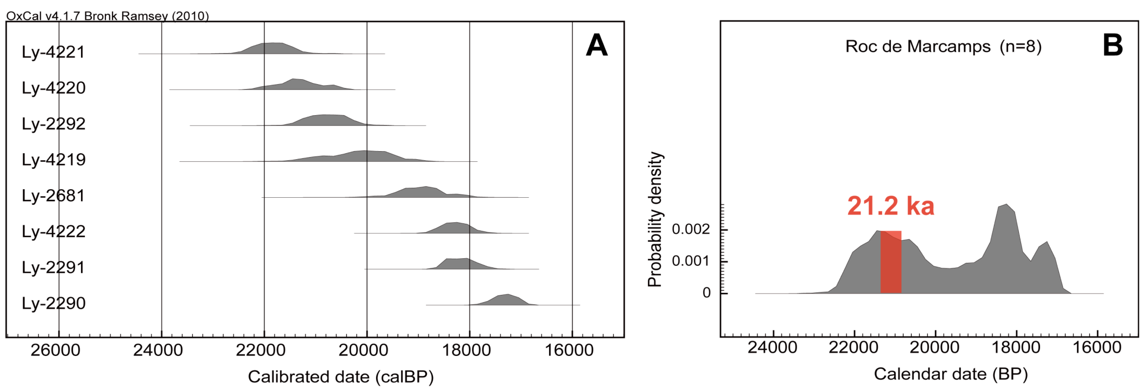

Figure 4: The radiocarbon data processing of the samples from Roc de Marcamps [26, 27].

the original data are screened in terms of technical confidence and adequacy of material type (Figure 3). The reliability of the radiocarbon dates was evaluated as either rejectable or acceptable. Secondly, the probability of the existence of given palaeoanthropological sites are calculated in order to convert radiocarbon age to calendar dates. The accepted data were calibrated by the INTCAL calibration curve [28], and then the calibrated dates were combined for each site using Bayes' theorem (Figure 4). The combined dates express the duration of the sites with its probability. Thirdly, the sites are rated in five grades (1 to 5), with reference to the probability density at the given time period (Figures 6 and 7).

3.2 High-resolution palaeoclimate data

At present, colleagues of the research team are simulating the palaeoclimate for the time periods of our interest at their best resolution. Until the results are provided, we are tentatively using the MIROC 3.2.2 atmosphere-ocean general circulation model in the PMIP 2 protocol [29, 30] for the preliminary experiment. The interval of MIROC data points is 2 arc-degrees. In contrast, the resolution of the GTOPO-1 DEM with bathymetric data is 1 arc-minute (or 0.01667 arc-degrees). It is important for GARP and MaxEnt to match the pixel size of raster-based environmental data prior to the run. Therefore, it is necessary to super-resolve the climatic data. For this purpose, we employ the 30-arc-second (or 0.008335 arc-degrees) climate model of the present day, published by the WorldClim project (`http://www.worldclim.org`).

The procedure of resolution increase is quite simple (Figure 5). First, the difference between the value

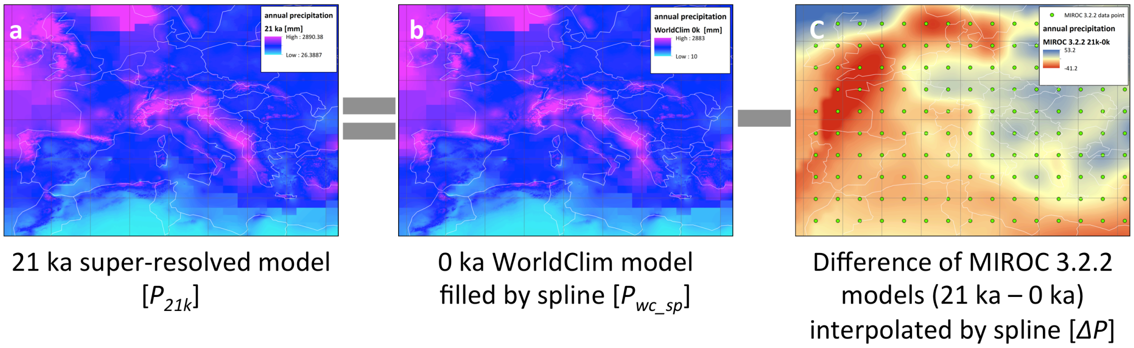

Figure 5: GIS-aided super-resolution of the precipitation data.

of the present day and that of 21 ka was calculated for each data point of the MIROC. For example, the difference in annual precipitation was calculated as:

$$\Delta P = P_{21k} - P_{0k} \tag{1}$$

where ΔP is the difference, and P_{21k} and P_{0k} are the precipitation at 21 ka and the present day (0 ka) respectively. Then, the data points of ΔP were interpolated by a spline algorithm to create a raster surface in 1 arc-minute pixel resolution (Figure 5b). Similarly, null cells (or water surfaces) of the WorldClim data were filled by spline interpolation and downsized to 1 arc-minute pixel (Figure 5a). Finally, the interpolated WorldClim data were converted to the high-resolution LGM data P_{21k_hi} by subtracting the difference ΔP.

$$P_{21k\_hi} = P_{wc\_sp} - \Delta P \tag{2}$$

where P_{wc_sp} is the interpolated precipitation of the WorldClim. The similar method was applied to create the high-resolution raster data of the mean annual, warmest month (or August) and coldest month (or February) temperatures.

3.3 Palaeovegetation zoning

Figures 6 and 7 show the results of MaxEnt's prediction of the geographical extent of the Magdalenian niche at 21.2 ka. Figure 6 is the prediction with the biome, or grouping of ecosystems [31], based on the map suggested by Finlayson and Carrión [32] (hereafter called biome model), while Figure 7 is the prediction without the biome (non-biome model). In both simulations, the same parameter setting was used for both experiments: 500 maximum iterations, $10^{-}5$ convergence limit, and 10 replicate runs, tested by the bootstrap method.

Macroscopically, the two results are similar, particularly in that high probabilities of site occurrence are predicted in the southern part of France, Belgium, the northern half of Switzerland, and the Cantabrian coast of northern Spain. However, there are some differences when we look at details: the high probability areas of the non-biome model (Figure 7) in the west coast of the Iberian Peninsula, the Italian Peninsula, and the northwestern part of the Balkan Peninsula are missing in the biome model (Figure 6). In addition, in the biome model, the boundary of high and low probability zones tends to be sharp in some parts, which is caused by the input of the biome as a categorical value.

It is important in ECNM to understand what environmental factors are influential to human behaviours, which might have different responses to climate change in comparison to other species as a manifestation of emerging 'culture'. The effect of the biome is observed in the percentage of contribution of each environmental variable. In the biome model (Table 1), the biome contributes to the model most significantly (32.4 %). The second most influential factor is annual precipitation (31.1 %), which comes first (36.4 %) in the non-biome model (Table 2). This fact primarily indicates that a revision of the category and geospatial zoning of biome and palaeovegetation, with reference to the plant functional

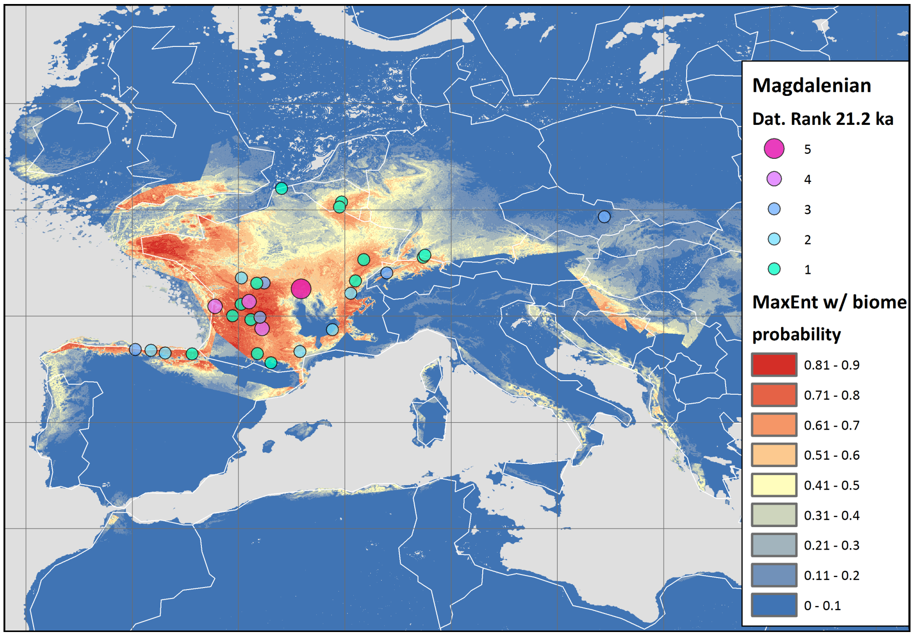

Figure 6: MaxEnt's prediction of Magdalenian niche distribution with the biome input.

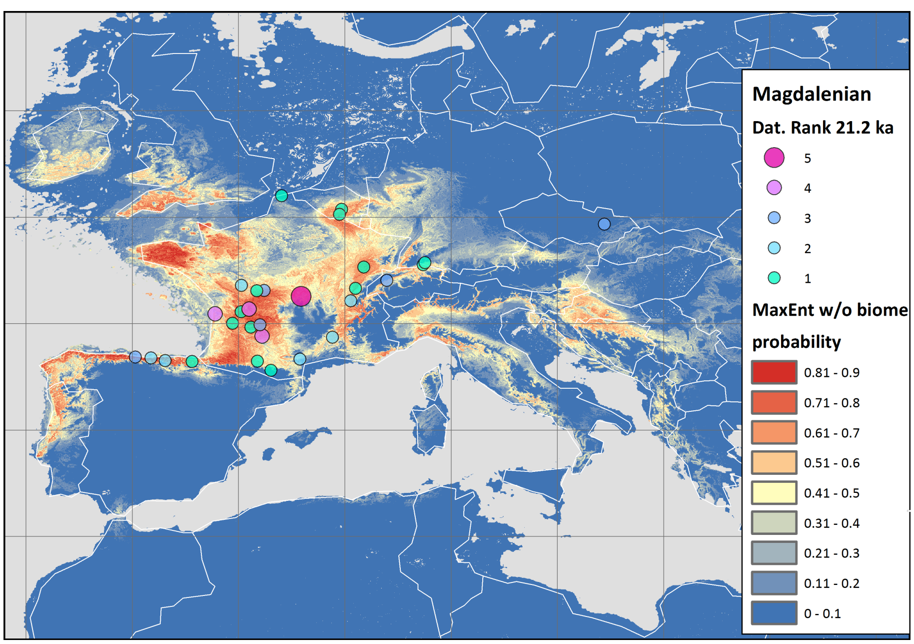

Figure 7: MaxEnt's prediction of Magdalenian niche distribution without the biome input.

Table 1: Percentage of contribution of each environmental variable for the biome model (Figure 6).

Environmental variables	Percentage of contribution [%]	Permutation importance [%]
Biome	32.4	20.1
Annual precipitation	31.1	15.1
Annual temperature	10.5	20.4
February temperature	9.0	9.8
Slope	7.6	2.4
DEM	7.3	10.5
August temperature	2.0	21.7

Table 2: Percentage of contribution of each environmental variable for the non-biome model (Figure 7).

Environmental variables	Percentage of contribution [%]	Permutation importance [%]
Annual precipitation	36.4	13.4
February temperature	17.1	6.0
DEM	16.6	8.4
Annual temperature	12.9	51.5
Slope	11.1	3.6
August temperature	5.9	17.1

type reconstructed from pollen and other palaeobotanical records, is required for a better application of ECNM to RNMH research. In order to reduce the edge effect, each categorical type was separated and converted to a continuous value with fuzzy marginal buffers. Then, the sum of the values at each cell was standardised to 1. This treatment contributes to visualising the boundaries of biome in a more naturalistic manner.

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