On the Use of Integrated Process Models to Reconstruct Prehistoric Occupation, with Examples from Sandy Flanders, Belgium

Ann Zwertvaegher,[1,*] Ilke Werbrouck,[2] Peter A. Finke,[1] Jeroen De Reu,[3] Philippe Crombé,[3] Machteld Bats,[3] Marc Antrop,[2] Jean Bourgeois,[3] Mona Court-Picon,[1] Philippe De Maeyer,[2] Philippe De Smedt,[4] Joris Sergant,[3] Marc Van Meirvenne,[4] and Jacques Verniers[1]

[1]*Department of Geology and Soil Science, Ghent University, Krijgslaan 281, 9000 Ghent, Belgium*
[2]*Department of Geography, Ghent University, Krijgslaan 281, 9000 Ghent, Belgium*
[3]*Department of Archaeology, Ghent University, Sint-Pietersnieuwstraat 35, 9000 Ghent, Belgium*
[4]*Department of Soil Management, Ghent University, Coupure Links 653, 9000 Ghent, Belgium*

Intensive archaeological investigations in Sandy Flanders (Belgium) revealed sites dating from the Final Paleolithic to the Neolithic, showing a discontinuous spatial and temporal distribution. To improve the understanding of these occupational patterns, a paleolandscape reconstruction is proposed. A major problem in paleolandscape reconstruction is that basic data are scattered in the temporal and spatial sense. Therefore, we propose an interdisciplinary approach to the application of different process models to soil–water–landscape reconstruction. The process models used include a digital elevation model, a hydrological, a pedogenetic, and a land-evaluation model. The result is a modeling framework in which these discipline-specific models, which provide input to each other, are integrated. Outcomes of the different models are still preliminary, because of the ongoing calibration and application of the models. The paper focuses on the methodological aspects of constructing the modeling framework and the questions one needs to answer in advance to facilitate the integration of the model results. Furthermore, errors within each individual model need to be accounted for and ideally are propagated into the next modeling step. Because of model complexity and runtime this is presently unfeasible. Alternatively, we propose to repeat the last step of the model framework (the land-evaluation procedure) for perturbations of the parameters reflecting the estimated model errors. We emphasize the difficulties occurring when integrating these different models, such as those relating to scale differences and error propagation. © 2010 Wiley Periodicals, Inc.

*Corresponding author; E-mail: Ann.Zwertvaegher@ugent.be.

Geoarchaeology: An International Journal, Vol. 25, No. 6, 784–814 (2010)

Published online in Wiley Online Library (wileyonlinelibrary.com). DOI:10.1002/gea.20332

INTRODUCTION

Geoarchaeological research is often motivated by the desire to understand observed occupational patterns. A major question is how strong the evidence for these occupational settlement patterns actually is. Data- and knowledge-driven predictive mapping techniques are valuable tools in addressing this question. If predictive mapping based on field data and the current landscape does not provide strong evidence for any occupational pattern, possible reasons may be: (1) non-systematic recording of presence/absence of finds; (2) biased sampling; (3) current landscape attributes do not explain old occupational patterns; (4) the landscape attributes used for predictive mapping do not give a physical explanation for occupational preferences; and (5) a deterministic approach based on the physical landscape cannot explain occupational patterns completely. Reason (3) would motivate a paleolandscape reconstruction; (4) would motivate a search for biophysical factors that, with the land use at that time, give a physical-deterministic explanation for occupational patterns; (5) would motivate the inclusion of social, economic, cultural, ideological, and ritual drivers that explain occupational patterns (Jordan, 2001; Thomas, 1993; Tilley, 1994, 2004; Zvelebil, 2003). By using the word occupation we emphasize that the localization of favored areas for prehistoric land uses is equally important in this study as the localization of actual settlements. In situations where data collection possibilities are limited because of the available time and funds, dealing with issues (3) to (5) of the above list appears to offer the best perspective to improve understanding of occupational patterns.

In this paper we focus on landscape reconstruction methods and the derivation of relevant landscape attributes to tackle problem (3). We propose land-evaluation methods to obtain a motivation for occupational patterns (4) and to decide which landscape attributes are relevant. Land evaluation includes the human factor (e.g., the cropping system reflects the farm size and the knowledge level of the farmer). It also includes the human perception of the landscape (e.g., the workability of the land). Therefore, issue (5) is also partly considered. With Kamermans (2006), we see land evaluation as a form of deductive predictive modeling, and our working hypothesis is that land evaluation based on reconstructed landscapes and land use will outperform predictive modeling based on the current landscape in the assessment of past occupational patterns.

Landscape is defined by Berendsen (2005) as the part of the earth's surface functioning as an integrated entity with both static and dynamic equilibria between its components. A landscape can be characterized by its appearance (physiognomy), its structural components such as soil and vegetation types, and by their interrelations, dynamics, and evolution. With landscape reconstruction in an archaeological context, we mainly consider the evolution of properties and interrelations of the components soil, relief, and vegetation over time and pay less attention to the physiognomic evolution, which is hard to assess without historical maps. However, historical maps can be used to filter the current cultural landscape to obtain the relief of the preexisting near-natural landscape. Hence, part of the landscape reconstruction can be considered as a deconstruction of the current landscape. The preceding

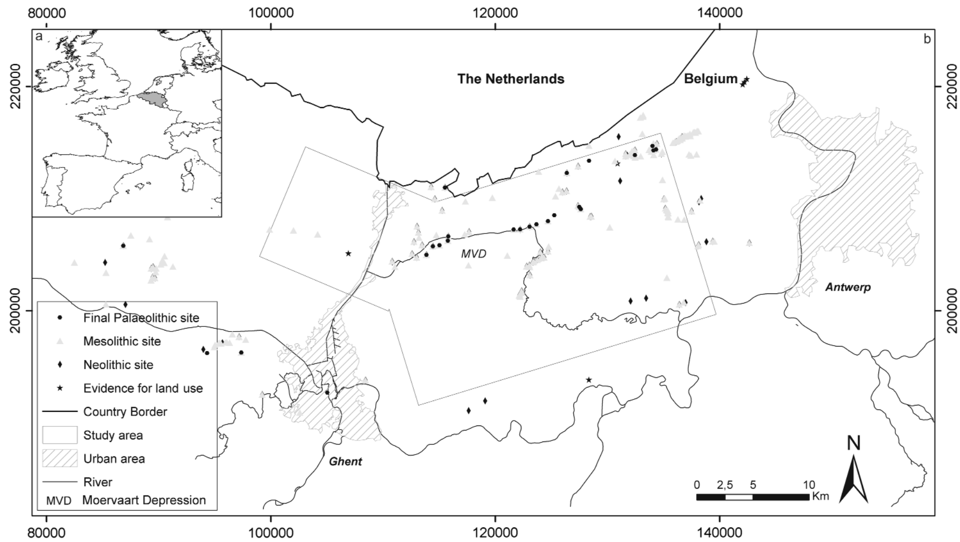

Figure 1. The study area. (a) Location of Belgium within Europe. (b) Delineation of the study area within Sandy Flanders (NW Belgium) and the distribution of known archaeological sites for the Final Palaeolithic, the Mesolithic, and Neolithic. Sites with evidence of land use are also located on the figure.

genesis of the natural landscape must be analyzed with a forward temporal arrow, starting from an assumed initial landscape, taking the natural (deconstructed cultural) landscape as final reference and using local reconstructions based on sedimentological, paleoecological, and pedological research as benchmarks in space and time. Some models calculate the production and redistribution of soil material in (mainly alluvial) landscapes (Schoorl, Veldkamp, & Bouma, 2002; Minasny & McBratney, 2001) and deal with some but not all aspects of the above landscape definition. Most landscape reconstructions, however, are knowledge assemblages.

The method of landscape reconstruction proposed here will be applied to the area of Sandy Flanders (NW Belgium). This area is situated at the southern limit of the lowland coversand region of the NW European plain, and it is one of the most intensively surveyed areas of NW Europe (Sergant, Crombé, & Perdaen, 2009). More than three decades of archaeological investigations, mainly by means of systematic field surveys and excavations, revealed sites dating from the Final Paleolithic to the Neolithic (Figure 1). An inventory of the data collected (Sergant, Crombé, & Perdaen, 2009) shows a geographically and chronologically discontinuous site distribution, possibly implying that the population and exploitation of the region during prehistory was intermittent (Crombé & Verbruggen, 2002; Crombé, Perdaen, & Sergant, 2008). During the Late Pleniglacial and the Late Glacial, numerous, generally small but elongated sand dunes, shallow mires, and wet depressions were formed. The largest paleomire is called the Depression of the Moervaart, which is ca. 15 km long and 2.5 km wide. At the onset of the Early Holocene, the depressions and mires probably dried out as a result of increasing vegetation and evaporation (Heyse, 1983; Verbruggen, 1999; Verbruggen, Denys, & Kiden, 1996).

Several attempts at reconstructing the paleolandscape have already been undertaken in the study area on the scale of settlements (Bats, 2007; Crombé, 2005). When looking at occupational distributions, it is necessary to cover a larger research area. With this in mind, we have delineated an area of 584 km^2 (Figure 1).

We approach landscape reconstruction as a spatio-temporal mapping problem based on the prediction of spatial patterns of variables at different time slices that are determinants for occupational patterns in a biophysical (deterministic, process-based) sense. A time slice is a representative year for a certain period that is considered homogeneous in a climatic and archaeological sense. The relevant variables follow from the data requirements of the land evaluation. They need to be defined, and methods must be developed to map these values in the spatial and temporal domain of interest. We define a model as a set of equations or decision rules that mimic the behavior of a system—for example, the landscape—or subsystems such as the soil–vegetation or the groundwater–atmosphere system. The advantage of using models with data instead of only data is that environments that change with varying speed—for instance, in response to climatic variations—can be more reliably described with models built on process knowledge than with simple assumptions on, for example, linear change between dates on the time axis. Additionally, models apply the relationships between variables such as precipitation, vegetation, water and nutrient uptake, soil moisture, and leaching of soil components, while the prediction of spatio-temporal patterns of these variables on a one-by-one basis may result in loss of covariation. Therefore, we propose a model framework based on the integration of different models. The end product is not one single model, but a framework incorporating different models providing input to each other. Certain questions need to be answered in advance in order to facilitate the integration of the model results. Furthermore, errors occurring within each individual model can also propagate into the next modeling step and need to be accounted for. The focus of this paper lies on the methodological aspect of constructing the model framework and the difficulties occurring when integrating these different models.

METHODS

Predictive Modeling

Predictive modeling based on the current landscape is applied to formalize the state of knowledge at the onset of the project. It is not a part of the proposed model framework, but the results will be compared in a later stage, with a deductive predictive model obtained after the land evaluation, which is the last step in the model framework.

Predictive modeling is the activity that results in rules describing the geographical patterns of archaeological finds of predefined type. Often the end product is a map (Westcott & Brandon, 2000) displaying the expected pattern of find occurrences, which can be considered to be an extrapolation of scattered finds to a presumed occupational pattern. The rules are based on inference that may be of statistical nature, but may also be the condensation of expert judgment or a mixture of both.

Usually, the type of inference gives the predictive modeling its name (Kamermans et al., 2004):

- The inductive approach is entirely data-driven and constructs inference using occurrence patterns of archaeological finds in combination with full-cover maps that describe, for example, soil, landscape, and infrastructure.
- The deductive approach is knowledge-driven, as experts formulate the rules that link attributes such as soil, relief, and infrastructure to the occurrence of finds. Evidently, expert knowledge is to some extent based on field data as well, but it may originate from different geographical areas and is usually of a more informal kind. Predictive maps based on a land evaluation (suitability maps) would be the result of a deductive approach.
- Mixed approaches are also conceivable (Finke, Meylemans, & Van de Wauw, 2008), where experts identify the geographic attributes that are of presumed relevance, but the classification of continuous values, such as wetness, grouping of nominal values (e.g., soil texture class), or the weighing of different attributes is optimized using field data and statistical techniques.

Ideally, expectation maps are evaluated with independent field observations before publication. Depending on the statistical part of the inference, it may be possible to display only those parts of the map that are strongly supported by evidence (Finke, Meylemans, & Van de Wauw, 2008), which may be wise in contexts that are politically sensitive.

In the case study at hand, a mixed approach to predictive modelling was applied, using Bayesian inference and the current landscape to obtain probabilities for archaeological finds for typical combinations of environmental attributes ("strata"), as described by Finke, Meylemans, and Van de Wauw (2008). One stratum can be a combination of one soil drainage class, one wind exposure class, and one altitude class, for example. The expectation maps for the Final Paleolithic, the Mesolithic, and the Neolithic periods were produced, based on a number of 27, 193, and 91 find spots, respectively. A total of 151 non-find spots were also taken into account. This information was combined with present-day full-cover auxiliary information on different variables, such as altitude, slope, wetness index, wind exposure, visibility, distance to open water, natural drainage class, and texture class. In order to allow for Bayesian prediction, each of the chosen variables was divided into classes. Chi-squared statistics were used to check each class for its efficiency in distinguishing between presence and absence of find spots. Classes with nonsignificant chi-squared statistics were merged with adjacent classes and only variables with two or more significant classes were retained to perform the rest of the predictive modeling. Based on this method, the altitude, slope, drainage and texture class, wetness index, distance to open water, and wind exposure variables were selected for the Meso- and Neolithic. Based on the chi-squared statistics, the same variables, except wind exposure, were chosen for the Final Paleolithic. After selecting these variables and converting them into attribute maps, the prior, the conditional, and the posterior probabilities were calculated for each grid cell in the chosen study area. The prior probability reflects the degree of belief in a certain event, for example, the occurrence of an archaeological find. The conditional probability represents the likelihood of the hypothesis to be true given the evidence. The outcome of the applied predictive modeling is the posterior probability, which is calculated using both prior and likelihood. Furthermore, an evidence filter was used. This filter is applied in order to display only those patterns that are strongly supported by the field evidence. Results that do not meet this standard are not shown on the map.

Model Framework for an Integrative Model-based Landscape Reconstruction

Rationale

The major problem in reconstructing past landscapes is that the basic data usable for inference are scattered in both the temporal and geographical sense. Thus, to obtain a continuous or even a fragmented picture of past landscapes, methods are required to interpolate landscape characteristics in both space and time. Such interpolation can be entirely data-based (e.g., space-time kriging; Kyriakidis & Journel, 1999), but when information on rates of change and speed of processes is available, for example, it can also be used. When rates of change obey physical laws, process models can be particularly useful as deterministic interpolators in time and sometimes also in space (Heuvelink et al., 2006). We therefore propose the application of process-based models in the reconstruction of soil–water landscapes to improve the understanding of occupational patterns as far as these can be explained by biophysical factors. The complexity of soil–water–vegetation processes and their interaction in the landscape requires a multidisciplinary approach. Due to the multiple disciplines involved, no single model can be used, but a modeling framework must be defined in which various discipline-specific models are integrated.

Therefore, we developed a conceptual framework for the purpose of an environmental reconstruction in a postglacial and mainly alluvial landscape with mostly shallow water tables in Flanders. The next sections contain a description of the development of this framework and its model components with some examples. Additionally, attention is paid to the transfer of inputs and outputs between the various models and associated issues of scale that have to be addressed.

Approach

As stated above, the final objective is to predict, by using models, spatial patterns of biophysical variables that are considered to be of influence on occupational patterns at various time slices. A generic seven-step approach is proposed to reach this goal:

1. Define biophysical attractors for human occupancy and associate these with variables to be predicted by models. Examples of biophysical attractors are “suitable places for hunting,” “good soils for a particular type of agriculture,” or “a sheltered place that does not flood.” The third example corresponds to places with low wind exposure, where in the wet season the groundwater

table does not reach the surface and where stream floods do not occur. These places can be identified if the land qualities "wind exposure," "wetness," and "flooding hazard" can be mapped for the landscape in the relevant time slice. We propose land-evaluation methods to translate these biophysical attractors into land qualities.
2. Define a modeling framework that can provide the variables. In the above example, wind exposure and drainage pattern can be mapped with a temporal digital elevation model (DEM), while a hydrological model can calculate the water-table fluctuations and flood-occurrence maps using the drainage pattern.
3. Define model dependencies in terms of data and knowledge flows at various scales. A hydrological model requires elevation data as an input, but computational limitations may require them to be at lower resolutions than the DEM can provide. This integration may involve upscaling activities before and during the hydrological modeling and downscaling of the obtained model results afterwards.
4. Prepare the individual models to run. The model components must be optimally defined to produce plausible results. Wherever possible, the individual models must be calibrated using existing data and maps. Model results should be evaluated with independent and preferably measured data. Additionally, model input data (which can be of spatial or of temporal nature) must be generated, possibly using other components from the modeling framework.
5. Run the models within the framework to obtain space-time coverage with the required variables identified in the first step.
6. Integrate the results so that the selected biophysical attractors are mapped and the reconstructed landscapes at various time slices can be evaluated for optimal places to live, to hunt, to fish, or to farm.
7. Matching of the resulting maps with the occupational data from archaeological finds to identify to what extent biophysical deterministic reconstructions can explain these patterns, and to what extent other, socioeconomic attractors play a role.

The modeling framework presented in the next sections illustrates the above generic approach in the context of a landscape reconstruction in Flanders. The studied period stretches from Final Paleolithic to the Iron Age and the Roman Period and thus covers a variety of climates, vegetation (Verbruggen, Denys, & Kiden, 1996), and types of land use (Crombé, 2005). The biophysical attractors to be defined in step 1 of the above approach should reflect the variety of environmental conditions and land use. By analyzing the data needed to perform an evaluation of the land-utilization types at the various time slices, these attractors and associated land qualities are revealed at the parameter level (step 1). Table I lists these biophysical attractors and their land qualities, together with the parameters that explain them. The source for each of these parameters is defined, which motivates the use of the model instruments inside the model framework (step 2). The framework includes a temporal DEM, a hydrological and pedogenetic model, and needs reconstructed climate data.

Table I. Parameters needed for land evaluation (ordered by biophysical attractors and land qualities). Additional characteristics per parameter: source (model), indication of accuracy of model estimates in test area, spatial grain. P = pedogenetic model; D = temporal digital elevation model; H = hydrological model; NR = not relevant in study area; RC = reconstructed climate data.

Biophysical Attractors (in bold) and Associated Land Qualities (in italics)	Parameter																
	Annual Precipitation	Annual Evapotranspration	January Temperature	July Temperature	Mean Lowest Water Table	Mean Highest Water Table	Soil Texture	Bulk Density	Stoniness	Calcium Carbonate Content	Organic Carbon Content	Base Saturation	pH	Reduced Conditions in Rooted Zone	Surface Water Presence	Slope	Altitude
Rain-fed agriculture—potential production			X	X													
Moisture availability	X	X			X	X	X										
Oxygen availability	X	X			X	X	X										
Workability								X	X								
Nutrient availability										X	X	X					
Rootability								X	X								
Germination							X	X	X								
Flooding hazard	X	X													X		
Toxicity													X	X			
Erosion hazard																X	
Soil degradation hazard							X			X	X		X				
Hunting, fishing																	
Surface water															X		
Visibility																X	X
Gathering																	
Ecological diversity					X	X	X			X			X		X	X	
Settling																	
Wind exposure																X	X
Wetness						X									X	X	X
Fresh water															X		
Parameter source (model)	RC	RC	RC	RC	H	H	P	P	NR	P	P	P	P	H	H	D	D
Accuracy (units)	<50 mm	<50 mm	2°C	2°C	<40 cm	<40 cm	<5 mass%	<0.25 kg/dm^3	NR	<2 mass%	<1 mass%	40%	<1 units	20% of cases	20% of cases	<1%	<0.5 m
Spatial grain (m^2)	10^8	10^8	10^8	10^8	10^4	10^4	1	1	NR	1	1	1	1	10^4	10^4	4	4

The next two sections address these model instruments—including also the land-evaluation method, explaining in more detail the choice of the biophysical attractors—and their linkage in the landscape-reconstruction study in Flanders (steps 3–6).

Components of the Model Framework

Elevation Model

Conditions affecting occupation, such as wind exposure and wetness, or hunting conditions such as visibility, are highly influenced by the relief. Thus, a DEM should be incorporated into the modeling framework. Since the relief has changed over time by natural and anthropogenic actions, it is necessary to not only take the current topography, but also paleotopographies into account.

The DEM for the chosen study area was generated based on high-precision airborne LiDAR (Light Detection and Ranging) data with an average sample density of one point per 2 m^2. The altimetric accuracy ranges from 0.07 m on a concrete surface to 0.20 m on vegetation cover (AGIV, 2003), which is significantly better than the planimetric accuracy with a typical value on the order of 0.50 m (Drosos & Farmakis, 2006). This exceptional accuracy at centimeter level and the regular scan pattern allows the production of a high quality DEM (Lohr, 1997; Axelsson, 1999; Drosos & Farmakis, 2006; Liu, 2008). In this paper, the term DEM is used in the context of a raster DEM that represents the relief as a two-dimensional regular grid, where each grid cell contains one elevation value. Given that a higher ground resolution results in an increasing ability to record features but also increases the size of the data sets, a resolution of 2 m $\times$ 2 m was chosen to obtain an optimal combination of efficiency and accuracy of terrain representation. However, the DEM derived from the original LiDAR data contains data points representing not only terrain elevation but also topographical objects like vegetation and buildings, as well as current disturbances of the natural topography by artificial features such as road banks and waste dumps, which are no part of the natural topography. To generate a DEM exclusively representing the natural topography, three filtering steps were executed involving the use of topographical vector maps and aerial photographs for the filtering, slope analysis for identifying remaining extreme non-natural relief features, and interpolation to refill the grid.

During the first step the LiDAR data were filtered for topographical objects. This is the most critical and difficult step in LiDAR-data processing (Liu, 2008), because it creates filtering artifacts, and some buildings and vegetation still remain. Also, artificial features disturbing the natural topography are not removed by this filtering method, as visible in Figure 2a.

In order to meet these problems it is crucial to conduct a second filtering of the LiDAR using ground-point data to remove the filtering artifacts and the remaining artificial features (Figure 2b). This second filtering is conducted automatically using topographical vector data. As no automated filtering procedure is completely accurate, additional manual editing was necessary (Chen, 2007) to remove remaining artifacts. This step was based on aerial photographs (Figure 2c). The filtering resulted in masked areas where new elevation values were created through interpolation

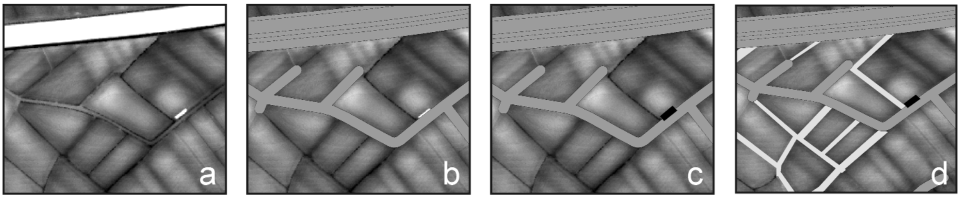

Figure 2. Removal of topographical objects from a LiDAR DEM. (a) Filtering major objects from point LiDAR data. (b) Filtering by overlay with topographic vector maps (indicated in gray). (c) Manual filtering by comparison with aerial photographs (indicated in black). (d) Filtering of non-natural relief by slope analysis (indicated in white). After stages c and d, interpolations are performed to refill the grid.

using two different methods. Small confined areas were interpolated using surrounding data points with inverse distance weighted interpolation. The elevation values of large areas were estimated from contour lines on historical topographical maps of 1863 showing the landscape before the infrastructures were created.

A third filtering of the elevation data aims to extract small artificial elements in the DEM, such as small drainage ditches, remnants of former ditches bordering fields, and convex shaped fields produced by circular plowing. These remaining features are too small and too numerous to be removed manually during the second filtering step. The third filtering step implies a slope analysis followed by a removal of the elevation values for which the rate of the maximum change in z-value in a predefined radius of surrounding cells exceeds a defined threshold (Figure 2d). To avoid the removal of natural slopes, certain confined regions in the study area, exposing natural inclines exceeding this threshold, are assigned an adjusted threshold.

This filtered DEM corresponds to the post-medieval landscape. Creating a temporal DEM involves taking into account landscape changes occurring earlier. In the case study, these changes were reported to be the transition of a Pleniglacial alluvial landscape into a landscape with niveo-eolian deposits and coversands from the Pleniglacial and Late Glacial (Crombé, 2005). These changes were associated with the formation of Late Glacial lakes and changed drainage patterns. At various point locations, such genesis can be reconstructed by paleoecological research on undisturbed soil cores. At these points, the altitude and approximate dates of stable surfaces can be identified. By lithostratigraphic correlation of these undisturbed cores to georeferenced soil-profile descriptions, the number of point locations can be extended. These profiles include descriptions from the Flemish database on subsurface information, archaeological investigations and other literature sources (Figure 3). They facilitate interpretation and correlation of layers over larger areas. A total of 5,574 point locations have been collected, although not all of them contain dated surfaces and not all are equally well described. Therefore, a selection of useful point locations needs to be made. The temporal DEM can be constructed with space-time interpolation methods using the full-cover current natural landscape DEM and the point reconstructions. Examples of such space-time interpolation methods are spatio-temporal kriging (Heuvelink et al., 1997; Kyriakidis and Journel, 1999) and space-time Kalman

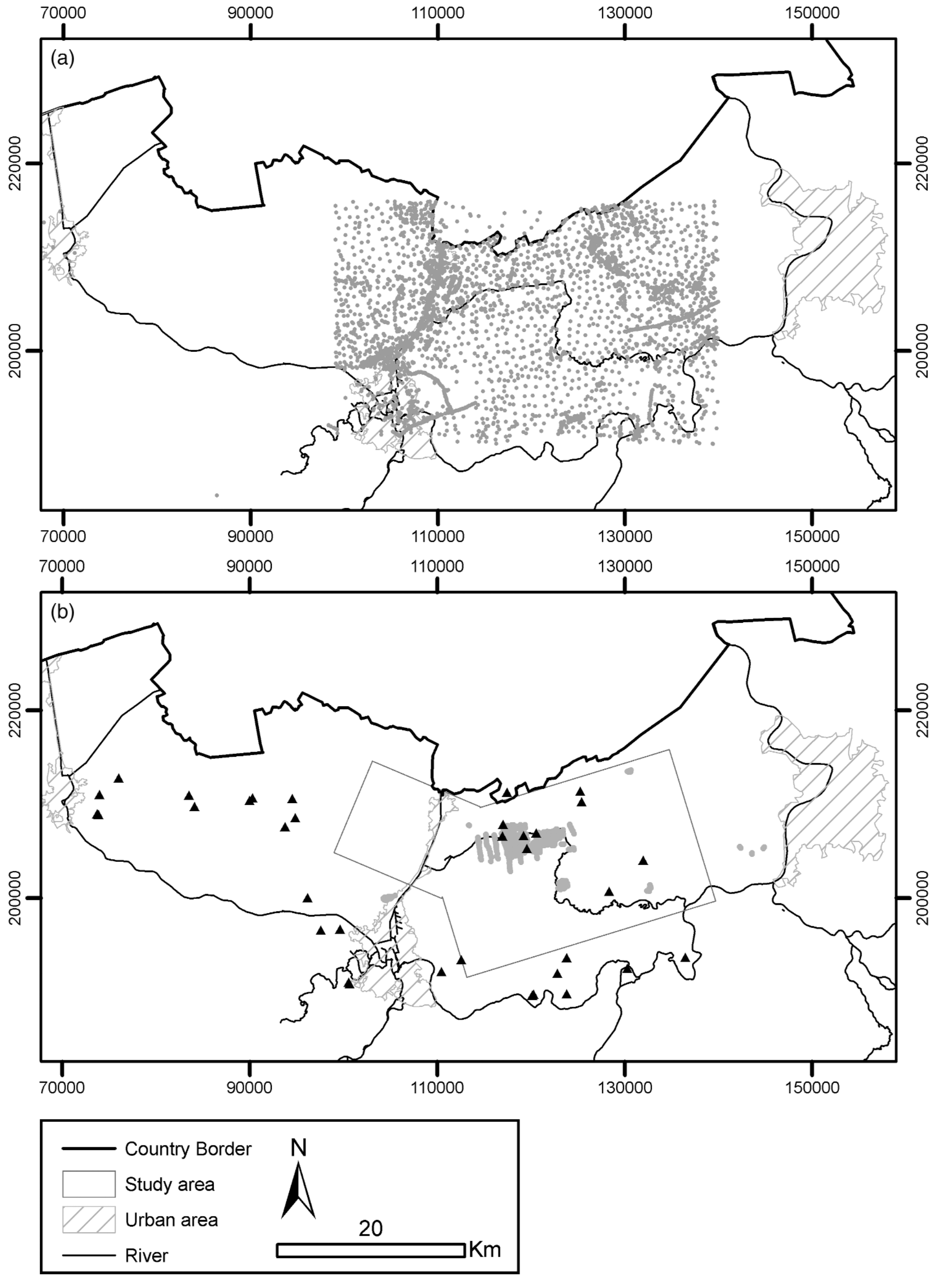

Figure 3. Maps of the point locations with described profiles used for the reconstruction of a temporal DEM. (a) Data provided by the Flemish database on subsurface information. (b) Data collected from literature and coring performed inside the project, with dated surfaces (dark gray triangles) and without dated surfaces (pale gray circles).

filtering (Heuvelink et al., 2006). Alternatively, process-based models describing landscape evolution (Schoorl, Veldkamp, & Bouma, 2002) can be calibrated to the point reconstructions, although existing models mostly focus on the effects of tectonic and alluvial processes and less on eolian landscape-forming processes such as those occurring in the research area.

Hydrological Model

In areas with shallow groundwater tables, such as Sandy Flanders, environmental processes such as pedogenesis and vegetation development are strongly influenced by water-table dynamics. The hydrological model supplies information directly to the pedogenetic model and therefore, indirectly to the land-evaluation model. The model also provides input directly to the land-evaluation model (Table I). Wetness, for example, is influenced by the mean highest water table provided by the hydrological model.

The hydrological model used is MOCDENS3D (Oude Essink, 1998), which is based on the three-dimensional finite-difference groundwater model MODFLOW, which has a worldwide distribution (Viaene et al., 1998) and is known as the standard code for simulating groundwater flow in saturated zones (Schwartz & Zhang, 2003). In order to simulate groundwater flow, distributed information on topography, drainage pattern, subsoil properties, and recharge to the water table is required as a model input. In a first step, a steady state simulation is performed, with a user-specified head as an initial estimation. This procedure only affects the number of iterations required to converge to an acceptable approximation of the solution of the steady state flow equation and has no effect on the solution itself (Harbaugh, 2005). As a result, a mean water-table elevation for every cell of the study area is produced. This elevation gives information on the average wetness of a site through time, which will partly determine the suitability for settlement. Monthly minimum and maximum fluctuations influence soil formation and determine if a site is seasonally wet. These fluctuations are calculated during a non–steady state flow simulation, in which the specific yield or storage coefficient near the water table, derived from soil characteristics, and the monthly recharge to the groundwater reservoir, obtained from meteorological data such as precipitation and evapotranspiration, are also taken into account. This simulation leads to the production of monthly mean lowest and mean highest water-table maps.

Because of the large temporal extent of the period of interest, computational limitations and constraints on data availability are encountered. To overcome these problems, water-table dynamics are calculated for time windows of 30 years, which correspond to a climatic period (Finke et al., 2004). Afterwards, a continuous set of groundwater heads is obtained by means of interpolation. Furthermore, the spatial units considered are set to $100\,\text{m} \times 100\,\text{m}$ grid cells. Data availability is mainly limited to present-day groundwater heads, which implies that calibration can practically only be performed on the present-day time window. Furthermore, calibration of the entire area based on measured heads proves to be hard because of the size of the study area and the restricted spatial distribution and temporal extent of the available data. Full-cover information, however, is present as drainage classes on the soil map of Flanders (scale 1:20,000), which was mapped during the 1950s. During this survey, as well as soil profile and texture, information on the groundwater dynamics was recorded and translated into drainage classes. These drainage classes are related to mean highest and mean lowest water table (Van Ranst & Sys, 2000), expressed as classes of depths below the surface. By means of a recent drainage-class map of part of the study area (Zidan, 2008), average values of the mean highest and mean lowest water tables are calculated per drainage class, and a mean water-table map is derived. By comparing the results of the steady state simulation of the present time window with this mean water-table map and the results of the transient or non–steady state flow with the mean highest and mean lowest water-table maps, the model can be calibrated for the present time. By means of paleoecological observations at different locations, simulated groundwater heads for previous time windows can be tested.

Another consideration that has to be made is that topography, river network, and climate are variable, considering the long time periods involved. This variability is opposed to the geological strata and their hydrogeological properties, which are assumed to be continuous for the time period considered. In order to take the changing climatic factor into account, present-day meteorological measurements are combined with paleoprecipitation (Davis et al., 2003) and paleoevapotranspiration series based on pollen data. As a consequence, a reconstruction of paleotopography and paleodrainage pattern, which is derived from the paleotopography, is required for each time window, which again reveals the close interconnection between the different models.

Pedogenetic Model

The main reason to include a pedogenetic model in the framework is that the natural chemical and physical fertility of the soil determines to a large extent the suitability for Neolithic and later types of agriculture. Liming was only introduced in the Iron Age. The suitability is determined in the land-evaluation model, but this model needs information on, among other factors, soil pH, soil texture, calcium carbonate content, and organic matter content at the relevant time slices. For a more detailed list of the model parameters and the associated land qualities, see Table I. A pedogenetic model is then needed to reconstruct these variables. Such a model should take into account the effects of (changing) climate, vegetation, topographic position, parent material, and human influence such as plowing and erosion on the soil properties mentioned above. Soil processes involved include flow of water, chemicals and heat, chemical equilibration, carbon sequestration, physical and chemical weathering, and perturbation of the soil by soil organisms and by plowing. The model SoilGen, described in detail by Finke and Hutson (2008), has these abilities and produces annual values of the required variables for desired depths in the soil profile at a point location.

The model needs initial values of soil properties at the starting year, which can be taken from chemical and physical analysis of C horizons in the current soil. Furthermore, for the whole simulated period, values for precipitation, potential evapotranspiration, temperature, water-table depth, and type of vegetation must be available. Meteorological data can be generated using climate reconstructions based on quantitative analyses of pollen data like those of Davis et al. (2003) to obtain annual values for precipitation, evapotranspiration, and January and July temperatures. The data of Davis et al. (2003) were calculated for six regions based on more than 500 sites covering Europe. These can be downscaled to local and daily values using a reference series based on local current measurements (Finke & Hutson, 2008). In this study, the local measurements originated from Uccle (Belgium). Vegetation types can be reconstructed with local pollen diagrams (Verbruggen, Denys, & Kiden, 1996), and water-table depths come from the hydrological model. Additionally, the model handles erosion and sedimentation events, which can be derived from point-scale reconstructions using the temporal DEM and results from on-site pedological and paleoecological research.

The reliability of the model outputs needs to be maximized. The underlying hypothesis is that if process rates and final state of the soil are well reproduced by the model, it is a suitable interpolator in time; that is, it can give a reasonable estimate of soil conditions at different points in time. Model reliability is therefore maximized by (1) calibrating the model on measured soil data and (2) by calibrating process rates to reproduce literature values (Egli & Fitze, 2001). Furthermore, individual model components such as water- and chemical-flow routines, decalcification rate, and carbon sequestration need to be calibrated and evaluated. The above-mentioned model components in SoilGen have been well tested (see Addiscott & Wagenet, 1985; Smith et al., 1997; Jalali & Rowell, 2003; Dann et al., 2006; Jabro et al., 2006; Finke & Hutson, 2008). Ideally, the calibrated model is evaluated at independent test locations in the study area as well. As the runtime for such model for temporal extents in the range of 15,000 B.P. to present is quite long, the number of geographic data points that can be simulated is limited. Therefore, the simulated values must be spatially interpolated to obtain a complete spatial coverage.

Land-Evaluation Model

The aim of the land-evaluation model is to delineate areas where, in a chosen part of the temporal extent, the conditions for concomitant uses of land were optimal. Land evaluation is defined as "the process of collating and interpreting basic inventories of soil, vegetation, climate and other aspects of land in order to identify and make a first comparison of promising land use alternatives in simple socio-economic terms" (Brinkman & Smyth, 1973: 7). Early examples of land evaluation in archaeology were reported by Kamermans, Loving, and Voorrips (1985) and Finke and Sewuster (1987); they focused mostly on the agricultural aspect, but this need not be the case. Here, like Kamermans (2006), we take a broad interpretation of land use, including the use of land for hunting and gathering and as a comfortable place to live. The resulting maps provide a biophysical motivation for occupational patterns and can be considered as deductive predictive maps.

The first activity in an archaeological land evaluation is careful evaluation of the archaeological and paleoecological record for evidence of land uses, for example, pollen, plant macroremains, artifacts, and archaeological traces in the soil. This record should, in combination with knowledge on the socioeconomic organization, lead to identification of land-use objectives and subsequent definition of land-utilization types. The next step is identification and mapping of relevant basic land properties (called "land characteristics," e.g., soil pH) and compound land properties (called "land qualities," e.g., moisture-supply capacity). These properties must in our approach largely be derived from the models described earlier, and they actually define the desired model functionality. The requirements of the land utilization type are then formalized and matched with the land characteristics and qualities at the considered period to result in maps indicating the suitability for the defined land utilization types. In instances where a fairly complete overview of the possible land utilization types is acquired and reasonable assumptions on the socioeconomic system can be made, it is possible to make assessments of the population carrying capacity based on the suitability maps. Land evaluation has since the 1970s undergone an evolution from qualitative evaluation approaches toward approaches that quantify crop production with models and use trade-off analysis to define land-use systems in detail (Stoorvogel et al., 2004). We consider such analysis as extensions of the proposed approach but do not pursue it in the case study at hand.

Concepts of Scale

When different models are to be connected for integrated studies such as geoarchaeological studies, it should be realized that the various models in the framework may not have the same spatial or temporal scale and may or may not cover the whole research area or time frame. In the context of scale, three concepts are of relevance (Bierkens, Finke, & De Willigen, 2000):

1. The *grain*, being the largest area (or volume) or time interval for which the property of interest is considered homogeneous. For example, in a DEM of $5\,\text{m} \times 5\,\text{m}$, the spatial grain is $25\,\text{m}^2$, and the temporal grain of our civil calendar is one day. If a modeling framework contains models with different grains, and these models have to be connected, upscaling or downscaling methods must be applied to obtain results at the target grain.
2. The *extent* is the total area or time interval considered in a study. If two or more model components do not have the same extent, extrapolation (or singling out) is necessary to obtain results for equal extents.
3. The *coverage* is the fraction of the extent for which there are data values (for a chosen grain). If a model operates on a small spatial grain, then many model runs must be carried out to obtain full coverage. In this case, the runtime of the model may be a limiting factor. If the applied models do not have the same coverage, then interpolation is necessary to obtain equal coverage. The choice for a grain affects the variability of the target property. At any grain, the within-grain variability is ignored as only the grain average is considered. At a large spatial grain, less variability can be displayed on a map but one is more certain about the average values. Inversely, a small spatial grain allows displaying variability in detail, but it may not be certain at all if these patterns are true. Ideally, the spatial grain is chosen based on an acceptable uncertainty threshold.

In practice, choice of grain, spatial as well as temporal, is determined by the available data and analytical instruments such as models.

RESULTS

Predictive Modeling

Figure 4 shows the results of the predictive modeling with and without evidence filter for the Final Paleolithic, the Mesolithic, and Neolithic, based on the current landscape. By using the evidence filter, only those patterns that are strongly supported by field evidence are displayed, while patterns supported by less strong evidence are not shown on the map. The non-filtered (no evidence filter used) maps display the entire area investigated with the predictive modeling. The filtered (with evidence filter) map of the Final Paleolithic also displays the entire area, while the filtered maps of the Mesolithic and Neolithic only display 3.3% and 49.7% of the modeled area, respectively. All three filtered maps display only low probabilities for findings. Given the data at hand, however, these probabilities appear to be the most reliable. The highest values on the filtered map of the Final Paleolithic (Figure 4a) are located alongside river courses and the borders around the Depression of the Moervaart. However, these values are still very low. The filtered map of the Mesolithic (Figure 4b) displays certain but low probabilities for findings in the polder areas in the west and alongside the borders of the Depression of the Moervaart. Other regions show higher Bayesian probabilities, which appear to be less certain, since they are not displayed on the filtered map. The map for the Neolithic shows a different pattern (Figure 4c), in which a much broader area of low probabilities is displayed. The non-filtered version shows higher probabilities for the topographically higher regions. However, these probabilities appear to be highly uncertain because they are not displayed on the filtered map. Certain but low probabilities appear in the lower-lying regions, which would suggest less occupation in these parts of the landscape during the Neolithic.

Components of the Model Framework

Elevation Model

As stated above, several DEMs are generated while processing the different steps of the construction of the temporal DEM, as can be seen on the flowchart in Figure 5. Each DEM represents the terrain elevation for a different time slice. Starting from the original LiDAR data and after removal of vegetation and buildings, an elevation map of the current time ($t = T$) is provided. The resulting DEM has a $2\,\mathrm{m} \times 2\,\mathrm{m}$ resolution, and an accuracy equal to the one of the original data set, which is $0.5\,\mathrm{m}$ in planimetrical view (x, y) and ranging between 0.07 and $0.20\,\mathrm{m}$ in altimetrical view (z). This high-resolution DEM derived from the airborne LiDAR data proves to be useful to detect archaeological and paleoenvironmental features such as paleochannels or filled ditches, even when other data sources show no evidence for these features. The DEM is also useful for geophysical and paleoecological field sampling and

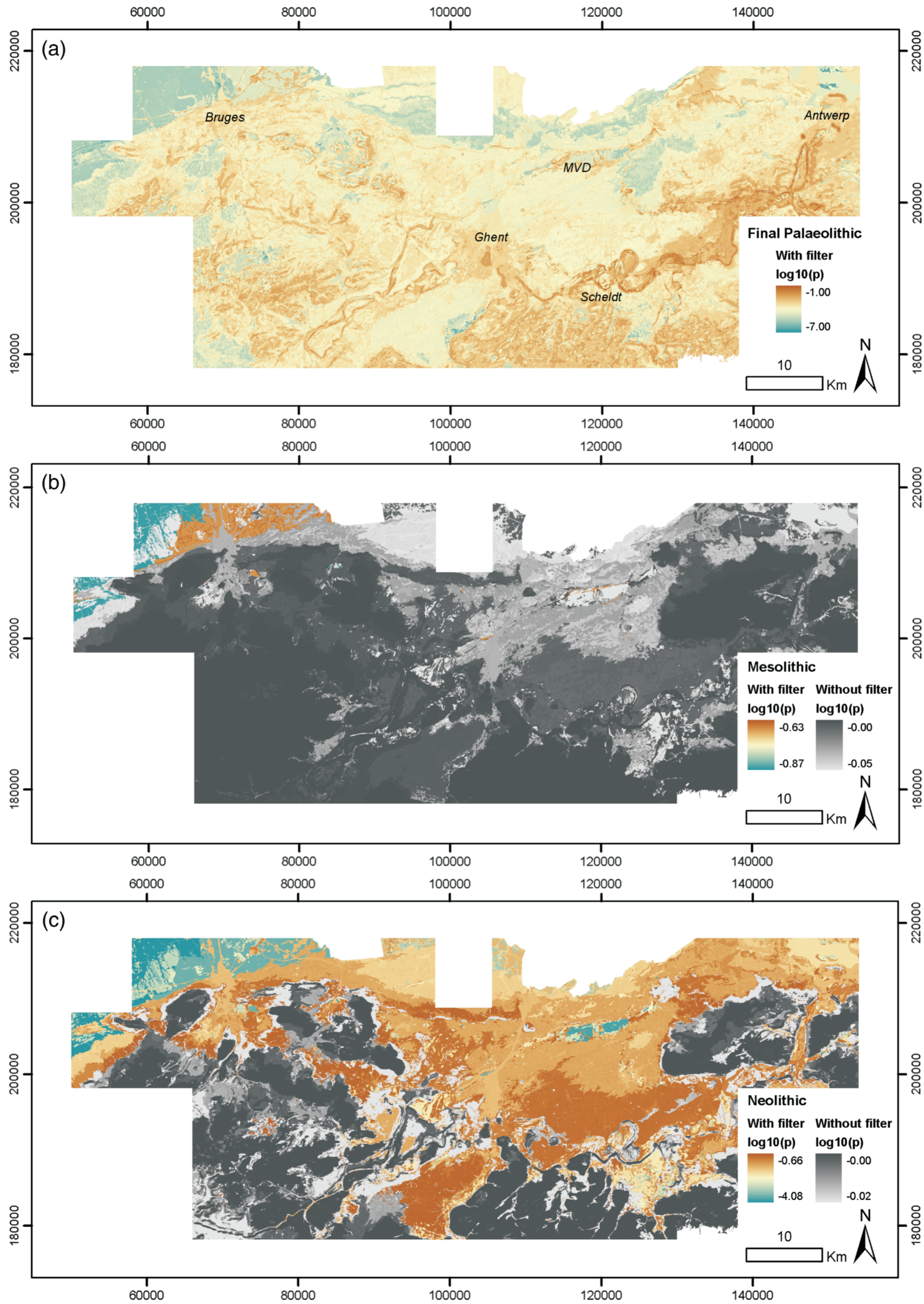

Figure 4. Maps with evidence filter (color scale) and without filter (gray scale) of the (log-transformed) probability of finds obtained by Bayesian modeling for the Final Paleolithic (a), Mesolithic (b), and Neolithic (c). The maps with the evidence filter only display probabilities strongly (p = 0.001) supported by field evidence. The maps without evidence filter display the probabilities for the entire study area. Scale bars for the maps without filter are adjusted for better visualization: Lowest values for the Mesolithic and the Neolithic are, respectively, –1.09 and –4.68. (MVD = Moervaart Depression.)

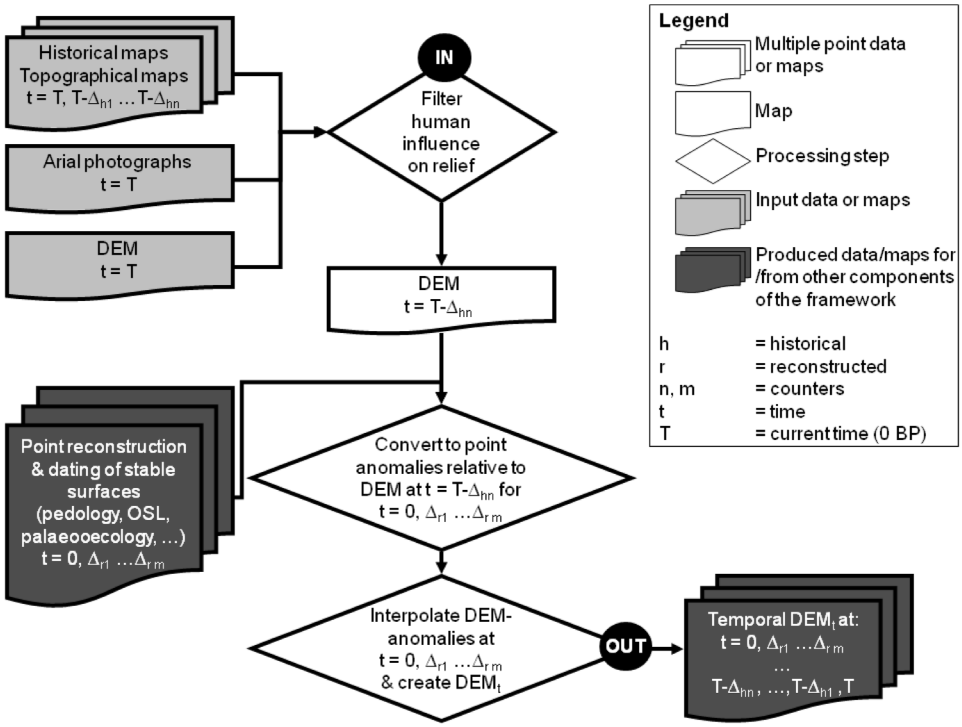

Figure 5. Flowchart for the construction of a temporal DEM, containing the legend applicable to the following flowcharts. Solid lines indicate data flows, dotted lines indicate information flows (for model calibration and evaluation).

archaeological prospection. Furthermore, it is used in calibrating the hydrological model to present time data.

By performing the stepwise filtering, a DEM exclusively representing the natural topography is generated ($t = T - \Delta_{hn}$). Accuracy again equals the accuracy of the original LiDAR data, except in the interpolated parts where the minimum accuracy is 1 m. This is the maximum equidistance of the contours on the historical maps used for interpolation. The resulting DEM represents the natural topography free of artifacts caused by modern objects and infrastructures, corresponding to the post-medieval landscape.

Hydrological Model

The flowchart of activities needed to run the hydrological model is given in Figure 6. The results discussed below are preliminary, because of the ongoing calibration of the model. The calibration time window is situated between 1947 and 1976, a 30-year time frame covering the period in which the soil survey in the area was executed (1949 to 1953; Van Ranst & Sys, 2000).

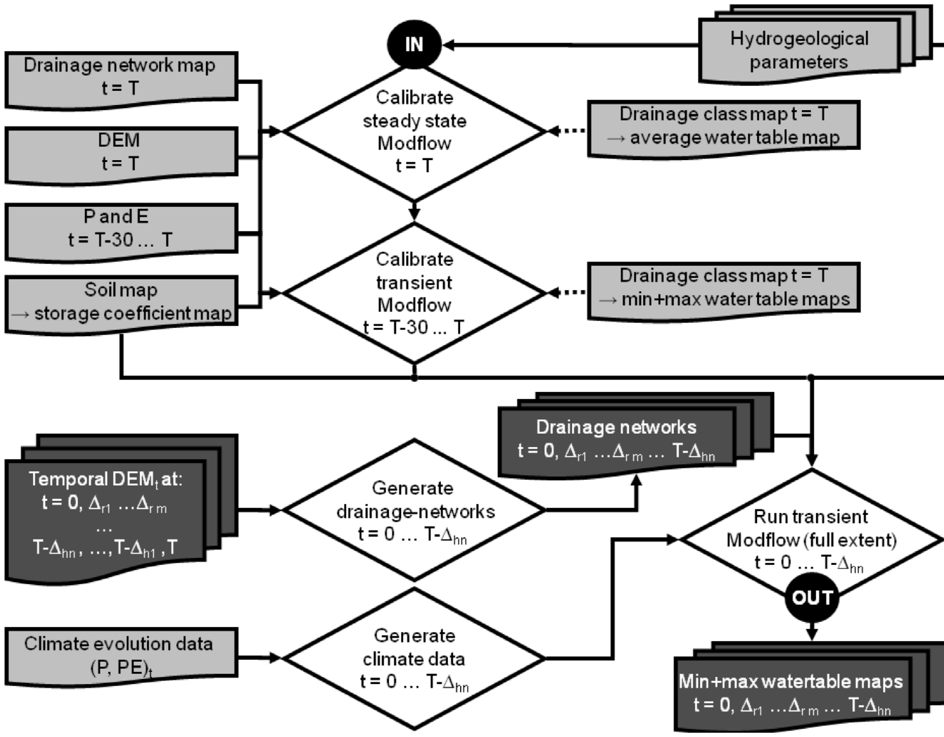

Figure 6. Flowchart for the construction of the hydrological model. Note the necessary input from, among others, climate data and the temporal DEM. For the legend, see Figure 5. Solid lines indicate data flows, dotted lines indicate information flows (for model calibration and evaluation).

A steady state flow simulation is performed for this time window, with the average value of precipitation and evapotranspiration for the period of 1947 to 1976, calculating groundwater levels for cells of 100 m × 100 m. This simulation results in a map of the average water table, expressed in m TAW (Figure 7). "TAW" is the reference for the Belgian altimetry. The height of 0 m TAW equals the average sea level at low tide at Ostend (Belgium). As an outcome of the transient flow simulation, maps of the groundwater level are given for each month, covering the 30-year time window. For each year, the three months with the highest and with the lowest groundwater levels are selected and their 30-year average is calculated, giving maps of the mean highest and mean lowest water tables.

Pedogenetic Model

The flowchart of activities needed to run the model for soil reconstruction is given in Figure 8. Obtaining meteorological input data from general climate-evolution data is essential for running the model, as pedogenesis is strongly influenced by fluctuations in precipitation, evapotranspiration, and temperature. In the flowchart, these

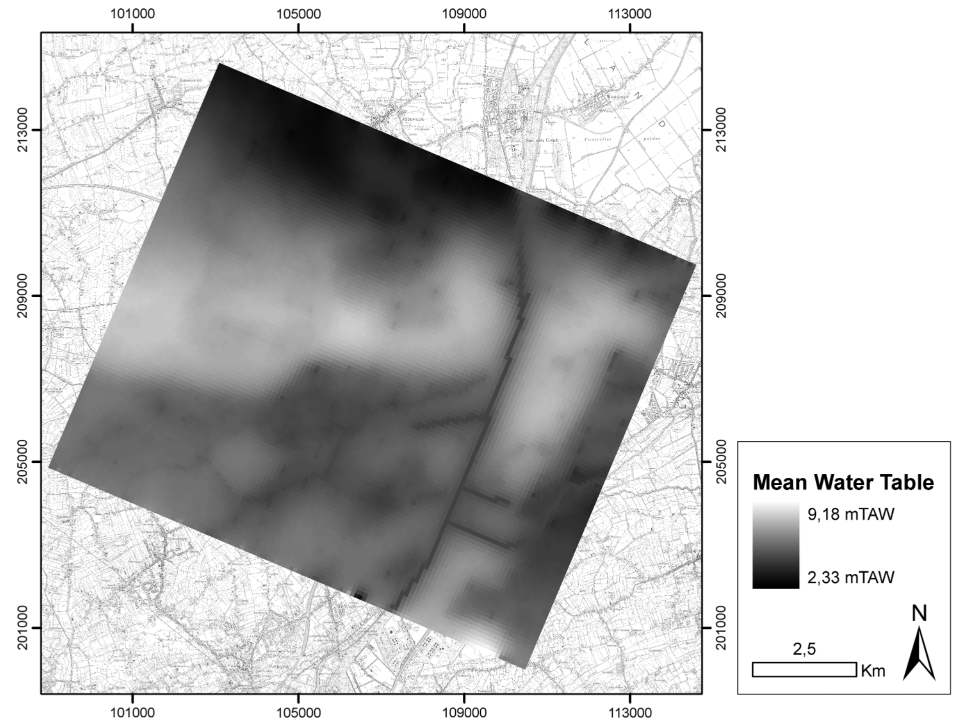

Figure 7. Simulated average water level in the most western part of the hydrological modeling, expressed in mTAW. "TAW" is the reference for Belgian altimetry. The height of 0 m TAW equals the average sea level at low tide at Ostend (Belgium).

data are considered as available input data, which was the case for the present model run, but may be laborious to obtain in other cases. As an example of the output of the pedogenetic model at the 1 m × 1 m spatial grain and one year temporal grain, Figure 9 shows the evolution of soil pH in soil depth and time. The effects on soil pH of calcareous eolian dust additions in the Older and Younger Dryas periods are clearly visible. In deeply drained soils, the high Belgian precipitation surplus in combination with acidity produced by organic matter decomposition rapidly decalcifies the soil, especially in the Holocene. In such soils, the conditions for agriculture without fertilization in the form of liming were already unfavorable from the start of the Neolithic. This effect is less marked in soils with shallow water tables. Other output data include the organic matter content and bulk density, which are important to assess the chemical and physical soil fertility in the land-evaluation model.

Land-Evaluation Model

The flowchart for land-evaluation modeling is depicted in Figure 10. Apart from the procedure, no results from the case study can yet be shown as this model is applied near the end of the modeling chain, when the other model outputs are available.

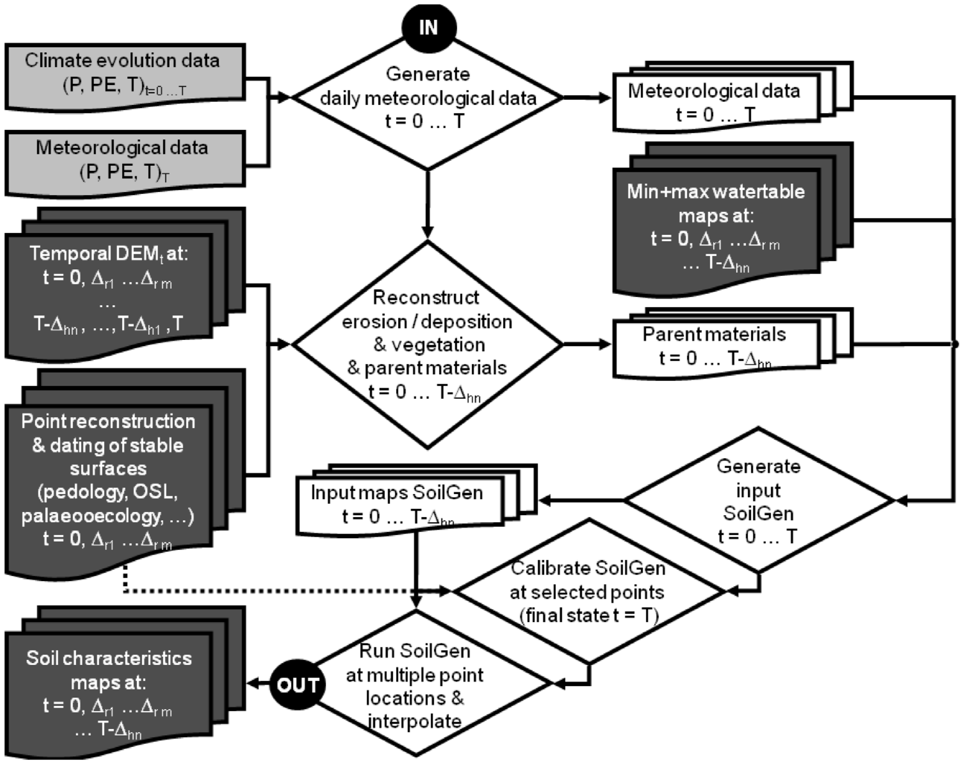

Figure 8. Flowchart of the pedogenetic model. For the legend, see Figure 5. Solid lines indicate data flows, dotted lines indicate information flows (for model calibration and evaluation).

Current emphasis is on evaluation of archaeological and paleoecological evidence for more precise definition of land-use types in the form of pollen, plant macroremains, and archaeological artifacts and features. The earliest possible indication for agriculture within the area of Sandy Flanders was found at the site of Doel "Deurganckdok-sector B" (Bastiaens et al., 2005). One charred cereal grain of *Triticum aestivum* (bread wheat) was recovered on the top of a sand dune, underneath a peat layer (Crombé & Vanmontfort, 2007). The beginning of the peat growth was dated around 5050 ± 55 B.P. (sample KAI-12075: 3840 ± 130 cal. B.C.; Crombé, 2005). Artifacts linked with agricultural land-use activities were discovered at Kluizen and Zele. In Kluizen, three ard shares were reused in the revetment of a well, dated in the Early Iron Age (Laloo et al., 2009), while in Zele, two fragments of an ard were found in a Late Iron Age well (Bourgeois, De Clercq, & Laloo, 2009). At the excavations of Bronze and Iron Age sites at Sint-Gillis-Waas, pollen of *Cerealea* were collected in wells, indicating agricultural activities in the vicinity (Gelorini, 2001). The locations of these finds are shown in Figure 1. Based on these observations, the parameters needed for the land evaluation were identified (Table I). We presumed three broad land-utilization types: rain-fed agriculture, hunting and fishing, and

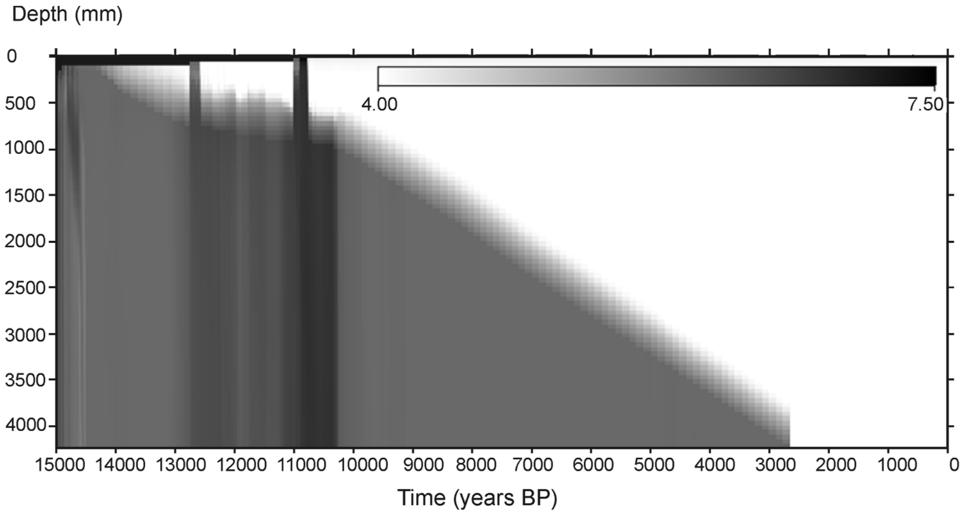

Figure 9. Simulated soil pH as a function of depth and time in a deeply drained silt loam soil in Flanders. The pH value corresponding with each color is indicated in the color bar (upper right of the figure). The figure shows a drop of the pH through time and through the profile. The effects on soil pH of calcareous eolian dust additions in the Older and Younger Dryas periods are also clearly visible.

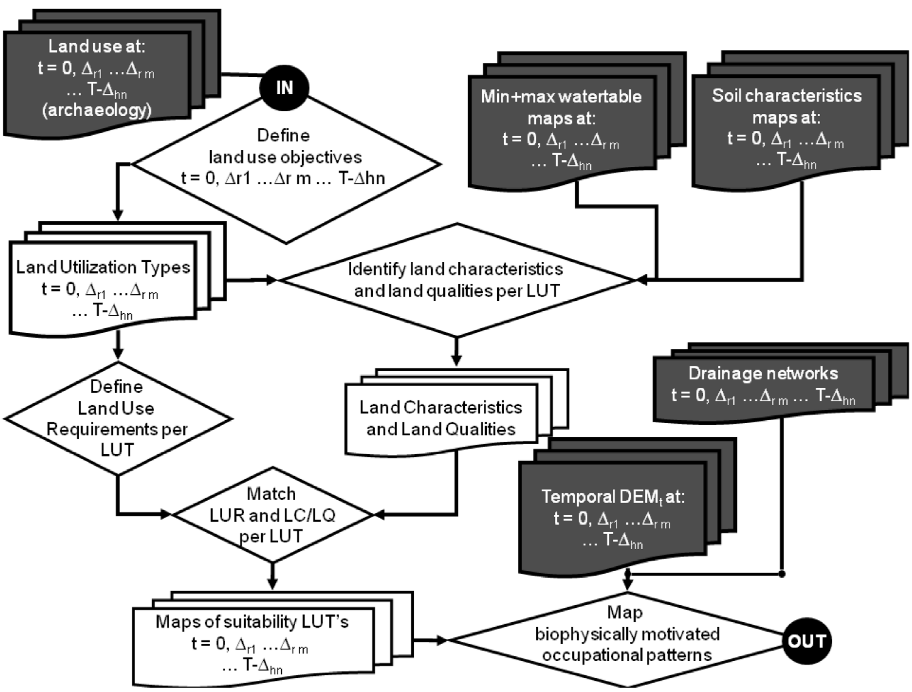

Figure 10. Flowchart of the land-evaluation model. For the legend, see Figure 5. Solid lines indicate data flows, dotted lines indicate information flows (for model calibration and evaluation).

gathering, and also formulated criteria relevant for occupation. For rain-fed agriculture we defined the data needs for ten land qualities that were used in previous land evaluations (Finke & Sewuster, 1987; Kamermans, 1993; Van Joolen, 2003: 26) for emmer, spelt, and barley. For hunting and fishing we based the data needs on the land qualities "presence of surface water" and "visibility." For gathering we defined an attractor "ecological diversity" with associated landscape characteristics. Finally, for housing we defined the comfort-related qualities "wind exposure," "wetness," and "nearby fresh water." Table I shows the associated parameters, of which practically all can be provided by the hydrological model, pedogenetic model, and temporal DEM. Additionally, climate-reconstruction data (notably annual precipitation, potential evapotranspiration, and January and July temperatures) need to be known. These data can be obtained using studies such as that of Davis et al. (2003). The spatial object of land evaluation should correspond to the smallest unit of land use or land management, assuming this management was homogeneous. We consider agricultural fields of 40 m × 40 m reasonable. A period of one year is considered a reasonable temporal scale as the crop growth, hunting, and gathering cycles take one year to complete.

Modeling Framework and Component Integration

The proposed general modeling framework (Figure 11) connects four models in a sequence: DEM : hydrological model : pedogenetic model : land-evaluation model. This sequence was actually designed in the reverse order to ensure that all the data needed by the land-evaluation model can be generated with the model instruments earlier in the modeling chain. The identified model components cannot be directly connected because of scale issues: As the grain sizes of the DEM, hydrological model, pedogenetic model, and land-evaluation model differ, upscaling and downscaling steps must be added to the chain. Furthermore, interpolation is necessary to obtain full coverage with soil properties. Thus, the modeling framework is integrative in the sense that it combines process knowledge from various disciplines and integrates the result to predictive maps with chosen spatial and temporal grains. From such a framework, protocols can be derived that specify data and information flows between research groups involved, which will be of great value when several disciplinary groups cooperate. The modeling framework is generic in the sense that it is portable to other landscapes, especially in regions with shallow water tables. However, the processes to be included (or not) in the various models partly depend on the geographic setting. For instance, the construction of a temporal DEM in a tectonically active area or an area undergoing strong erosion may involve inclusion of additional processes.

DISCUSSION

Predictive Modelling

A predictive modeling was conducted based on a mixed inductive–deductive approach, with Bayesian inference used to evaluate typical combinations of

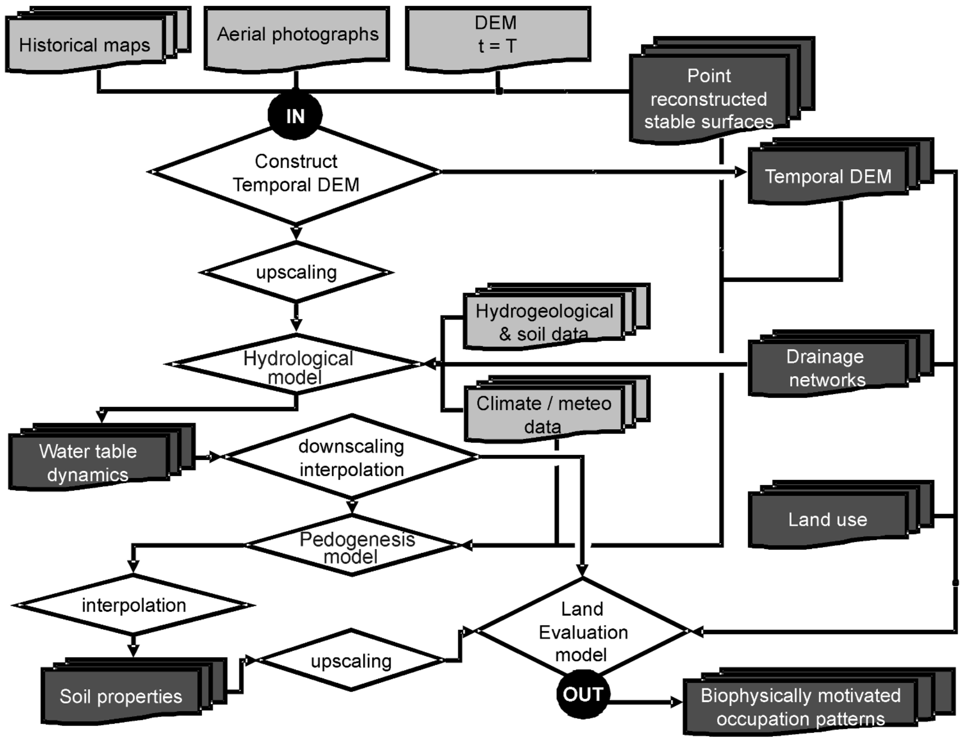

Figure 11. Modeling framework incorporating the different models (DEM, hydrological model, pedogenetic model, and the land-evaluation model). The legend and detailed activities are given in Figure 5.

environmental attributes of the current landscape. Both absence and presence of finds were recorded and the data were geographically scattered and clustered per surveyed field. This last configuration causes poor performance of geostatistical methods but does not hinder the prediction to geographical strata. Based on this data configuration, a mixed inductive–deductive approach to predictive modeling was chosen. This approach has proven to be the most favorable for a similar data configuration in another study area (Finke, Meylemans, & Van de Wauw, 2008). The predictive modeling resulted in filtered maps displaying only certain but very low probabilities for archaeological findings. The observed site distributions did not match the predictive maps based on our knowledge of the current landscape and the chosen biophysical attractors. In this way, more insight was obtained into the state of knowledge at the beginning of the project. This has led to the motivation of an integrated landscape reconstruction.

Model Linkage over Different Scales

In this study, we assume that all models must produce their final outputs at full extent (the complete study area), full coverage (no empty areas), and at the spatial

Table II. Spatial and temporal grain and coverage of the DEM, hydrological, pedogenetic and land-evaluation models. The region of interest covers an area of 584 km² and a period of 15,000 years; n is the number of time slices.

Model	Spatial Grain	Spatial Coverage	Temporal Grain	Temporal Coverage
DEM	$4\,m^2$ ($2\,m \times 2\,m$)	100%	4 years	0.027% * n
Hydrological model	$10{,}000\,m^2$ ($100\,m \times 100\,m$)	100%	1 month	0.2% * n
Pedogenesis model	$1\,m^2$ ($1\,m \times 1\,m$)	0.000017%	1 day	100.00%
Land evaluation model	$1600\,m^2$ ($40\,m \times 40\,m$)	100%	1 year	100.00%

and temporal grains of the land evaluation model. The spatial and temporal grains and coverages of the different models mentioned above are listed in Table II. Most of the model instruments operate over the entire coverage of the study area. The pedogenetic model is the exception here, since it simulates pedogenesis at the point scale. Because of the long runtime of this model, it is only possible to perform simulations at a restricted number of locations. The same restrictions obtain for the DEM and the hydrological model, concerning their temporal coverage. A simulation with the hydrological model is restricted to 30 years, and this only for a certain amount of time windows. To reach the grain of the land evaluation model, up- and downscaling actions are necessary, where the full coverage is attained by interpolation, as illustrated in Figure 12. This figure is a simplification of reality since the models do not contribute only to the land-evaluation model but also to each other, which may involve more upscaling, downscaling, and interpolation activities. We refer to Heuvelink and Pebesma (1999) and Bierkens, Finke, and De Willigen (2000) for an extensive review of upscaling and downscaling methods in the context of modeling. The latter publication also gives protocols for choosing appropriate scale transfer methods for specific situations.

In the context of upscaling, the choice of method depends on the question whether the model responds linearly to its input parameters. If this is the case, one can upscale (e.g., spatially average) the model inputs and run the model at the coarser grain to directly obtain results at the target grain. Usually, in hydrological and pedogenetic models, this is not the case, so that the model has to be run at many locations at a fine grain, and the model results have to be upscaled. The latter method has the disadvantage that many more model runs need to be made, which can be time consuming.

In the context of downscaling, one can utilize fine-grain auxiliary information to obtain plausible patterns at the finer grain. The auxiliary information should then be relevant for the process studied.

For modeling purposes, the DEM with the $4-m^2$ grain needs to be resampled to the resolution of the hydrological model, which is $100\,m \times 100\,m$. Taking into account possible remaining peaks in the DEM, the median value is used to upscale the grid size. As the DEM exclusively represents the natural terrain elevation, it can also be used for downscaling the results of the hydrological model in a later phase, because the water-table depth is known to be related to micro-relief.

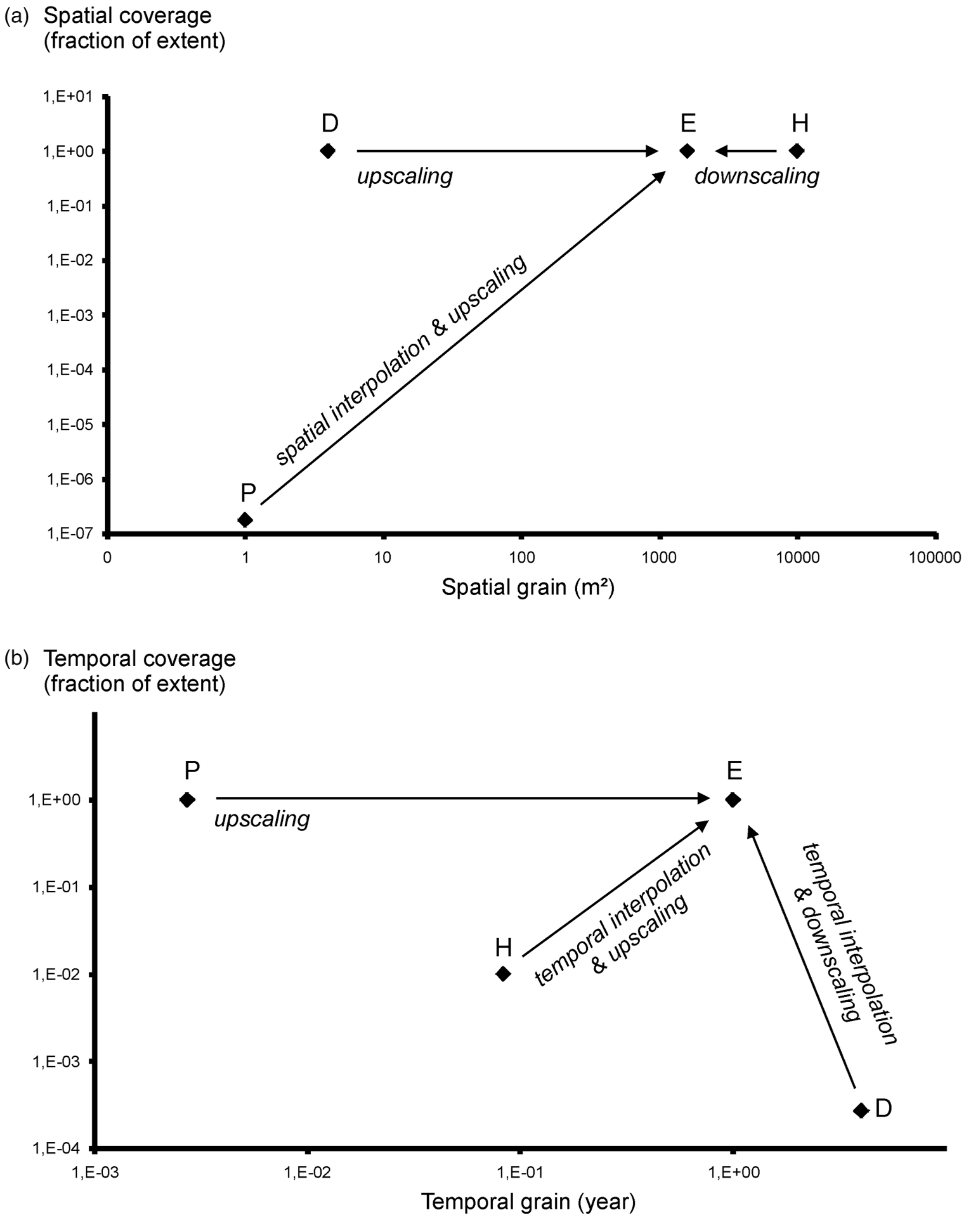

Figure 12. Spatial (a) and temporal (b) grain versus coverage of model components in this study. Temporal coverages of the DEM and the hydrological model are dependent on the number of time slices and need to be multiplied by the number of time slices to get the correct value. Spatial and temporal up- and downscaling are necessary to bring the model outputs to the same grain as the land evaluation. Spatial and temporal interpolations bring the model outputs to the 100% coverage. P = pedogenetic model; D = temporal digital elevation model; H = hydrological model; E = land-evaluation model.

Model Errors and Error Propagation

The accuracies of the different models are listed in Table I. These values are derived from studies (Finke & Hutson, 2008; AGIV, 2003; unpublished studies) where model results were confronted with measurements. Within each individual model, errors occur and propagate into the next step. For the DEM, accuracy of the original LiDAR data is reduced after filtering and interpolation. Interpretation and correlation of profiles involve uncertainties that are enhanced in a later step of space-time interpolation when creating the full-cover temporal DEM. Within the hydrological model, errors are already present in the input, derived from the DEM, the soil map, and the climate data. Even after calibration, uncertainties are present, because the calibration is based on the drainage classes of the soil map, made in the 1950s, instead of present-day measurements of the water-table level. Using the soil map, however, allows estimations of the water-table dynamics on a full-cover scale. Furthermore, using current data should impose current activities of pumping and draining on the model, while a natural situation without these activities is pursued. The soil map represents a seminatural situation, close to the intended situation. In the pedogenetic model, soil parameters are simulated at different depths through the profile, starting from a parent material and going forward in time. A good assessment of the characteristics of the parent material is therefore of great importance for the outcome of the simulations. However, this is not always feasible, for example, in the case of the initial calcite content of the soil-parent material.

It is clear that even after calibration, models are not free from error. As a result, the land evaluation is subject to uncertainty as well. This would, however, be equally true for less formal ways of landscape reconstruction, where errors would be unquantifiable. Ideally, the propagation of errors through the chain of models and upscaling, downscaling, and interpolation steps would be studied by techniques such as Monte Carlo analysis (Heuvelink, 1998). Given the complexity of the models and their runtime, this is currently unfeasible. A more realistic option would be to estimate model errors such as given in Table I and repeat the land-evaluation procedure for perturbations of the parameters that reflect these errors. This approach would allow the identification of persistent patterns in suitability for the land use given the model errors.

CONCLUSIONS

The identification of occupational patterns benefits from landscape reconstructions, since the current landscape often does not provide essential information, as may result from evidence-filtered predictive modeling. The development and subsequent application of models provide the tools to interpolate various landscape characteristics in space and time, using process knowledge supplemented by empirical interpolation methods. This approach allows the prediction of spatial patterns of biophysical variables that are considered to influence to occupational patterns at various time slices. A land-evaluation method is proposed, in order to translate these biophysical attractors into parameters, which can be provided by models. The first step of the approach is thus to define the requirements of the land evaluation, followed by the choice of the models that can provide the necessary parameters. We propose the following components as model tools for landscape reconstruction:

1. A temporal DEM derived from a current DEM, historical maps, point reconstructions of paleosurfaces, and interpolation methods;
2. A hydrological model applied at various time slices to reconstruct the water-table dynamics and flood-hazard areas;
3. A pedogenetic model applied at various point locations to reconstruct relevant soil characteristics such as pH and organic matter content, followed by spatial interpolation of the results for time slices; and
4. A land-evaluation model to identify areas of land per time slice that provided favorable conditions for the land uses at that time.

All these model components need input data that only paleooecological, sedimentological, and pedological field research, preferably on-site, can provide. Next to this, the model components also provide input to each other. Since the model components operate at different spatial and temporal grains and coverages, upscaling and downscaling methods as well as interpolation methods should be part of the integrated framework. Errors are present in the initial input data and in the model instruments, and these propagate through the model framework. As a result, the land evaluation is subject to uncertainty. The quality of model results needs to be estimated to assess how uncertain the land evaluation results are. It is clear that errors are present in this kind of landscape reconstruction, but this is equally true for other methods of landscape reconstruction, where errors would be unquantifiable.

The authors gratefully acknowledge UGent Integrated Project BOF08/GOA/009, "Prehistoric Settlement and Land-Use Ssystems in Sandy Flanders (NW Belgium): A Diachronic and Geoarchaeological Approach," for financially supporting this work. We are thankful to the Flemish government, more specifically the Department of Environment, Nature, and Energy, for sharing the data from the Flemish database on subsurface information. We are also grateful to the reviewers for their detailed comments toward the improvement of this manuscript.

REFERENCES

Addiscott, T.M., & Wagenet, R.J. (1985). Concepts of solute leaching in soils: A review of modelling approaches. Journal of Soil Science, 36, 411–424.

AGIV. (2003). Digitaal hoogtemodel Vlaanderen. Nieuwsbrief GIS Vlaanderen, 16, 3–21.

Axelsson, P. (1999). Processing of laser scanner data: Algorithms and applications. ISPRS Journal of Photogrammetry and Remote Sensing, 54, 138–147.

Bastiaens, J., Deforce, K., Klinck, B., Meersschaert, L., Verbruggen, C., & Vrydaghs, L. (2005). Palaeobotanical analysis. In P. Crombé (Ed.), The last hunter-gatherer-fishermen in Sandy Flanders (NW Belgium): The Verrebroek and Doel excavation projects, Part 1: Palaeo-environment, chronology and features (pp. 251–278). Ghent: Academia Press.

Bats, M. (2007). The Flemish wetlands: An archaeological survey of the valley of the River Scheldt. In J. Barber, C. Clark, M. Cressy, A. Crone, A. Hale, J. Henderson, R. Housley, R. Sands, & A. Sheridan (Eds.), Archaeology from the wetlands: Recent perspectives. Proceedings of the 11th WARP conference, Edinburgh 2005 (pp. 93–100). Edinburgh: Society of Antiquaries.

Berendsen, H.J.A. (2005). Landschap in delen: Overzicht van de geofactoren. Assen: Van Gorcum.

Bierkens, M.F.P., Finke, P.A., & De Willigen, P. (2000). Upscaling and downscaling methods for environmental research. Dordrecht: Kluwer Academic Publishers.

Bourgeois, I., De Clercq, W., & Laloo, P. (2009). Onderdelen van een eergetouw op de vindplaats Zele—Zuidelijke Omleiding (provincie Oost-Vlaanderen, België). Lunula, Archaeologia Protohistorica, 17, 217–220.

Brinkman, R., & Smyth, A.J. (Eds.). (1973). Land evaluation for rural purposes. Wageningen: ILRI Publication 17.

Chen, Q. (2007). Airborne LiDAR data processing and information extraction. Photogrammetric Engineering and Remote Sensing, 73, 109–112.

Crombé, P. (Ed.). (2005). The last hunter-gatherer-fishermen in Sandy Flanders (NW Belgium): The Verrebroek and Doel excavation projects, Part 1: Palaeo-environment, chronology and features. Ghent: Academia Press.

Crombé, P., & Vanmontfort, B. (2007). The neolithisation of the Scheldt basin in western Belgium. Proceedings of the British Academy, 144, 263–285.

Crombé, Ph., & Verbruggen, C. (2002). The Lateglacial and early Postglacial occupation of northern Belgium: The evidence from Sandy Flanders. In B.V. Eriksen & B. Bratlund (Eds.), Recent studies in the Final Palaeolithic of the European plain, Proceedings of a UISPP Symposium, Stockholm, 14–17 October 1999 (pp. 165–180).

Crombé, P., Perdaen, Y., & Sergant, J. (2008). La transition du Mésolithique ancien au Mésolithique moyen/récent dans le nord-ouest de la Belgique: quelques réflexions concernant l'occupation du territoire. In J.-P. Fagnart, A. Thévenin, Th. Ducrocq, B. Souffi, & P. Coudret (Eds.), Le début du Mésolithique en Europe du Nord-Ouest. Actes de la table ronde d'Amiens, 9 et 10 octobre 2004, Mémoires de la Société Préhistorique Française, 45, 195–204.

Dann, R.L., Close, M.E., Lee, R., & Pang, L. (2006). Impact of data quality and model complexity on prediction of pesticide leaching. Journal of Environmental Quality, 35, 628–640.

Davis, B.A.S., Brewer, S., Stevenson, A.C., Guiot, J., & Data Contributors. (2003). The temperature of Europe during the Holocene reconstructed from pollen data. Quaternary Science Reviews, 22, 1701–1716.

Drosos, V., & Farmakis, D. (2006). Airborne laser scanning and DTM generation. In E. Manolas (Ed), Proceedings of the 2006 Naxos International Conference on Sustainable Management and Development of Mountainous and Island Areas, Greece (pp. 206–218).

Egli, M., & Fitze, P. (2001). Quantitative aspects of carbonate leaching of soils with differing ages and climates. Catena, 46, 35–62.

Finke, P.A., & Hutson, J. (2008). Modelling soil genesis in calcareous löss. Geoderma, 145, 462–479.

Finke, P.A., & Sewuster, R.J.E. (1987). A soil survey and land evaluation in a Bronze Age context for the central Gubbio basin, Italy. Amsterdam: University of Amsterdam, Laboratory for Physical Geography and Soil Science.

Finke, P.A., Brus, D.J., Bierkens, M.F.P., Hoogland, T., Knotters, M., & de Vries, F. (2004). Mapping ground water dynamics using multiple sources of exhaustive high resolution data. Geoderma, 123, 23–39.

Finke, P.A., Meylemans, E., & Van de Wauw, J. (2008). Mapping the possible occurrence of archaeological sites by Bayesian inference. Journal of Archaeological Science, 35, 2786–2796.

Gelorini, V. (2001). Protohistorische waterputten palynologisch bekeken: Site Sint-Gillis-Waas/Kluizenmolen. VOBOV-Info, 53, 2–12.

Harbaugh, A.W. (2005). MODFLOW-2005: The US. Geological Survey modular ground-water model—the ground-water flow process. U.S. Geological Survey, Techniques and Methods No. 6-A16.

Heuvelink, G.B.M. (1998). Error propagation in environmental modelling with GIS. London: Taylor and Francis.

Heuvelink, G.B.M., & Pebesma, E.J. (1999). Spatial aggregation and soil process modelling. Geoderma, 89, 47–65.

Heuvelink, G.B.M., Musters, P., & Pebesma, E.J. (1997). Spatio-temporal kriging of water content. In E. Baafi & N. Schofield (Eds.), Geostatistics Wollongong '96, Vol. 1 (pp. 1020–1030). Dordrecht: Kluwer Academic Publishers.

Heuvelink, G.B.M., Schoorl, J.M., Veldkamp, A., & Pennock, D.J. (2006). Space-time Kalman filtering of soil redistribution. Geoderma, 133, 124–137.

Heyse, I. (1983). Preliminary results of the study of a Vistulian late glacial drainage pattern in the Scheldtbasin (Belgium–Flemish Valley–Moervaart Depression). Quaternary Studies in Poland, 4, 135–143.

Jabro, J.D., Jabro, A.D., & Fox, R.H. (2006). Accuracy and performance of three water quality models for simulating nitrate nitrogen losses under corn. Journal of Environmental Quality, 35, 1227–1236.

Jalali, M., & Rowell, D.L. (2003). The role of calcite and gypsum in the leaching of potassium in a sandy soil. Experimental Agriculture, 39, 379–394.

Jordan, P. (2001). Ideology, material culture and Khanty ritual landscapes in western Siberia. In J.J. Fewster & M. Zvelebil (Eds.), Ethnoarchaeology and hunter-gatherers: Pictures at an exhibition (pp. 25–42). BAR International Series 995. Oxford: Archaeopress.

Kamermans, H. (1993). Archeologie en landevaluatie in de Agro Pontino (Lazio, Italië). PhD dissertation (in Dutch), Universiteit van Amsterdam.

Kamermans, H. (2006). Problems in Paleolithic land evaluation: A cautionary tale. In M. Mehrer & K. Wescott (Eds.), GIS and archaeological predictive bodeling (pp. 97–122). Boca Raton, FL: CRC Press.

Kamermans, H., Deeben, J., Hallewas, D., Van Leusen, M., Verhagen, Ph., & Zoetbrood, P. (2004). Deconstructing the crystal ball: The state of the art in predictive modelling for archaeological heritage management in the Netherlands. In W. Börner and W. Stadtarcheologie (Eds.), Enter the past: The e-way into the four dimensions of cultural heritage (pp. 175–200). BAR International Series 1227. Oxford: British Archaeological Reports, Archeopress.

Kamermans, H., Loving, S.H., & Voorrips, A. (1985). Changing patterns of prehistoric land use in the Agro Pontino. In C. Malone & S. Stoddart (Eds.), Papers in Italian archaeology, Vol. 4, Part 1: The human landscape (pp. 53–68). BAR International Series 243. Oxford: British Archaeological Reports.

Kyriakidis, P.C., & Journel, A.G. (1999). Geostatistical space-time models: A review. Mathematical Geology, 31, 651–684.

Laloo, P., De Clercq, W., Crombé, P., Deforce, K., Haneca, K., & Perdaen, Y. (2009). Drie eergetouwscharen uit een ijzertijdwaterput te Kluizen (Evergem, Oost-Vlaanderen, België): Beschrijving van de vondsten en vergelijking met enkele andere mogelijke eergetouwonderdelen uit Vlaamse contexten. Lunula, Archaeologia Protohistorica, 17, 131–136.

Liu, X. (2008). Airborne LiDAR for DEM generation: Some critical issues. Progress in Physical Geography, 32, 31–49.

Lohr, U. (1997). Digital elevation models by laser scanning. Photogrammetric Record, 16, 105–109.

Minasny, B., & McBratney, A.B. (2001). A rudimentary mechanistic model for soil production and landscape development II: A two-dimensional model incorporating chemical weathering. Geoderma, 103, 161–179.

Oude Essink, G.H.P. (1998). Simuleren van 3D dichtheidsafhankelijke grondwaterstroming: MOCDENS3D. Stromingen, 4, 5–23.

Schoorl, J.M., Veldkamp, A., & Bouma, J. (2002). Modelling water and soil redistribution in a dynamic landscape context. Soil Science Society of America Journal, 66, 1610–1619.

Schwartz, F.W., & Zhang, H. (2003). Fundamentals of ground water. New York: John Wiley and Sons.

Sergant, J., Crombé, P., & Perdaen, Y. (2009). Mesolithic territories and land-use systems in north-western Belgium. In S. McCartan, R. Schulting, G. Warren, & P. Woodman (Eds.), Mesolithic horizons: Papers presented at the Seventh International Conference on the Mesolithic in Europe, Belfast 2005 (pp. 277–281). Oxford: Oxbow Books.

Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov, O.G., Coleman, K., Franko, U., Frolking, S., Jenkinson, D.S., Jensen, L.S., Kelly, R.H., Klein-Gunnewiek, Komarov, A.S., Li, C., Molina, J.A.E., Mueller, T., Parton, W.J., Thornley, J.H.M., & Whitmore, A.P. (1997). A comparison of the performance of nine soil organic matter models using datasets from seven long term experiments. Geoderma, 81, 153–225.

Stoorvogel, J.J., Antle, J.M., Crissman, C., & Bowen, W. (2004). The tradeoff analysis model: Integrated bio-physical and economic modelling of agricultural production systems. Agricultural Systems, 80, 43–66.

Thomas, J. (1993). The politics of vision and the archaeologies of landscape. In B. Bender (Ed.), Landscape: Politics and perspectives (pp. 19–48). Providence, RI: Berg.

Tilley, C. (1994). A phenomenology of landscape: Places, paths and monuments. Oxford: Berg.
Tilley, C. (2004). The materiality of stone: Explorations in landscape phenomenology. Oxford: Berg.
Van Joolen, E. (2003). Archaeological land evaluation: A reconstruction of the suitability of ancient landscapes for various land uses in Italy focused on the first millennium BC. PhD dissertation, Universteit Groningen.
Van Ranst, E., & Sys, C. (2000). Eenduidige legende voor de digitale bodemkaart van Vlaanderen (Schaal 1:20000). Laboratorium voor Bodemkunde. Gent: Universiteit Gent.
Verbruggen, C. (1999). Quaternary palaeobotanical evolution of Northern Belgium. Geologica Belgica, 2, 99–110.
Verbruggen, C., Denys, L., & Kiden, P. (1996). Belgium. In B.E. Berglund, H.J.B. Birks, M. Ralska-Jasiewiczowa, & H.E. Wright (Eds.), Palaeoecological events during the last 15000 years: Regional syntheses of palaeoecological studies of lakes and mires in Europe (pp. 135–143). Chichester: John Wiley and Sons.
Viaene, P., Vlieghe, C., Bellon, J., Buysse, M., & De Smedt, P. (1998). Vergelijking van vier softwarepakketten voor de modellering van grondwaterstroming. Water, 101, 101–106.
Westcott, K.L., & Brandon, R.J. (Eds.). (2000). Practical applications of GIS for archaeologists: A predictive modelling kit. London: Taylor and Francis.
Zidan, Y.O.Y. (2008). Mapping the phreatic water tables to update the drainage class map 1:20,000 in the Scheldt Valley near Ghent. Unpublished masters thesis, Department of Geology and Soil Science, University of Ghent, Belgium.
Zvelebil, M. (2003). Enculturation of Mesolithic landscapes. In L. Larsson, H. Kindgren, K. Knutsson, D. Loeffler, & A. Åkerlund (Eds.), Mesolithic on the move: Papers presented at the Sixth International Conference on the Mesolithic in Europe, Stockholm 2000 (pp. 65–73). Oxford: Oxbow Books Ltd.

Received 17 October 2009
Accepted for publication 12 June 2010
Scientific editing by the guest editors