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## V.5 New developments in archaeological predictive modelling

*Philip Verhagen,<sup>1</sup> Hans Kamermans,<sup>2</sup> Martijn van Leusen<sup>3</sup> & Benjamin Ducke<sup>4</sup>*

### ABSTRACT

In this paper the authors present an overview of their research on improving predictive modelling into true risk assessment tools. Predictive modelling as it is used in archaeological heritage management today is often considered to be a rather crude way of predicting the distribution of archaeological remains. This is partly because of its lack of consideration of archaeological theory but also because of a neglect of the effect of the quality of archaeological data sets on the models. Furthermore, it seems that more appropriate statistical methods are available for predictive modelling than are currently used. There is also the issue of quality control, a large number of predictive maps have been made but how do we know how good they are? The authors have experimented with two novel techniques that can include measures of uncertainty in the models and thus specify model quality in a more sophisticated way, namely Bayesian statistics and Dempster-Shafer modelling. The results of the experiments show that there is room for considerable improvement of current modelling practice but that this will come at a price because more investment is needed for model building and data analysis than is currently allowed for. It is however doubtful whether archaeological heritage management in the Netherlands will have a true need for this.

### KEY WORDS

*Predictive modelling; archaeological heritage management, expert judgement; uncertainty, statistics*

### 1. INTRODUCTION

Predictive modelling is a technique that at a minimum tries to predict 'the location of archaeological sites or materials in a region, based either on a sample of that region or on fundamental notions concerning human behaviour' (Kohler/Parker 1986, 400). Predictive modelling departs from the assumption that the location of archaeological remains in the landscape is not random but is related to certain characteristics of the (natural) environment. The precise nature of these relations depends very much on the landscape characteristics involved and the use that prehistoric people may have had for these characteristics. In short, it is assumed that certain portions of the landscape were more attractive for human activity than others. If, for example, a society primarily relies on agricultural production it is reasonable to assume that the actual choice of settlement location is, among other things, determined by the availability of land suitable for agriculture.

Archaeological location models have been made with two types of aims in mind. In most academic projects the goal is to model the locational behaviour of different functional, chronological and cultural types of occupations. By contrast, the goal of most archaeological heritage management projects has been to conserve archaeological remains and limit costs by identifying areas with and without these remains, regardless of their nature.

Whilst in theory the academic and heritage management aims might be achieved in different ways, in practice there is little difference between the approaches adopted. Predictive modelling was initially developed in the United States of America in the late 1970s and early 1980s, evolving from governmental land management projects in which archaeological remains became regarded as 'finite, non-renewable resources', and gave rise to considerable academic debate (Carr 1985; Savage 1990). Until the start of the 1990s the emphasis of this debate was on the statistical methods used to evaluate the correlation between archaeological parameters and the physical landscape (e.g. Kvamme 1985; *idem* 1988; *idem* 1990; Parker 1985). European academic interest in predictive models using GIS grew out of its long-standing concern with locational models in general and has been partly directed at an understanding of the modelling process itself. The primary result of this has been a series of papers critical of the inductive AHM-oriented approach common in Dutch predictive modelling (van Leusen 1995; *idem* 1996; Kamermans/Rensink 1999; Kamermans/Wansleeben 1999). At the same time alternative methods and techniques were also explored (Wansleeben/Verhart 1992; *idem* 1997; *idem* 1998; Kamermans 2000; Verhagen/Berger 2001; Verhagen 2006). More recently, researchers have begun to concentrate on the incorporation of social variables into their predictive models (Wheatley 1996; Stančić/Kvamme 1999; Whitley 2005; Lock/Harris 2006).

In general, academic archaeologists have always been sceptical of, and sometimes even averse to, predictive modelling practised in AHM. The models produced and used in AHM are not considered sophisticated enough and many of the methodological and theoretical problems associated with predictive modelling have not been taken onboard in AHM (see e.g. Ebert 2000; Woodman/Woodward 2002; Wheatley 2004; van Leusen *et al.* 2005). At the same time the production and use of predictive models has become a standard procedure in Dutch AHM and it has clearly attracted interest in other countries as well (see e.g. Kunow/Müller 2003).

In post Valletta Convention archaeology, the financial, human and technical resources allocated to archaeology have increased enormously. At the same time these resources have to be spent both effectively and efficiently. Archaeological predictive models will tell us where we have the best chances of encountering archaeology. Searching for archaeology in the high probability areas will pay off as more archaeology will be found there than in low probability zones. It is a matter of priorities, we cannot survey everything and we do not want to spend money and energy on finding nothing. There is also the political dimension, the general public wants something back for the taxpayers' money invested in archaeology. It is not much use telling politicians to spend money on research that will not deliver an 'archaeological return'.

How can we be so sure that the low probability zones are really not interesting? Where do we draw the line between interesting and not interesting? These are difficult choices indeed for those involved in AHM. Archaeologists who do not have to make these choices can criticize the current approach to predictive modelling from the sidelines but do not have to come up with an alternative.

Within the BBO programme we have been trying to provide such an alternative to the archaeological community (see van Leusen/Kamermans 2005; Kamermans/van Leusen/Verhagen 2009). However, after five years of research we have to conclude that we have only been partly successful. In this paper we will briefly explain the research that we have undertaken and venture to offer some explanations for the lack of success of new approaches to predictive modelling in AHM up to now.

## 2. THE DEBATE ON PREDICTIVE MODELLING

Over the past twenty-five years, archaeological predictive modelling has been debated within the larger context of GIS applications in archaeology (see e.g. many of the papers in Lock/Stančič 1995; Lock 2000) and the processual/post-processual controversy that has dominated the archaeological theoretical debate. This debate has centred on the perceived theoretical poverty of what has sometimes been termed ecological determinism, usually contrasted with the theory-laden humanistic approaches advocated by various exponents of post-modernist archaeology. The arguments for and against ecological determinism in the context of GIS modelling were first set out by Gaffney/van Leusen (Gaffney/van Leusen 1995) and the significance of the dichotomy was debated by Kvamme (Kvamme 1997) and Wheatley (Wheatley 1998) in the pages of the *Archaeological Computing Newsletter*. As a dispassionate evaluation of the practical differences in approach between the two sides in this debate shows, the only significant difference is in the use of 'cognitive' variables (see also the brief discussion by Kvamme (Kvamme 1999,182). As such, predictive modelling remains clearly rooted in the processual tradition, with its emphasis on generalization and quantitative 'objective' methods and its lack of interest in the subjective and individual dimensions of archaeology. In itself, this is not a matter of 'bad' versus 'good' archaeology and within the context of AHM, generalized maps are necessary tools to bring back the enormous complexity of archaeology to manageable proportions.

However, the lack of real interest in using spatial technology and statistical methods in post-processual academic archaeology has certainly slowed down the development of predictive modelling as a scientific method. The feeling that processual approaches no longer offered a real contribution to the advancement of archaeological science has left predictive modelling somewhat lost in space. This is a pity because even if we do not want to use predictive modelling in an AHM context, there still is a lot of potential in spatial technologies (GIS) to develop and test theories of spatial patterning of settlements and human activities. Two decades of extensive studies and practical experience in the field of predictive modelling have resulted in some of the most stringent, verifiable and thorough research work known to our discipline (Judge/Sebastian 1988; Zeidler 2001; van Leusen/Kamermans 2005; to name just a few), speaking strongly in favour of predictive models as an essential tool in efficient heritage management.

It appears then that the continuing controversy over whether predictive models actually do anything useful is at least as much about wrong expectations, misunderstandings and maintaining the old processualist vs. post-processualist struggle as it is about real-life performance of the models. One only needs to consult the long-term statistics for projects such as the MN Model to verify that they do indeed achieve their objectives (<http://www.mnmodel.dot.state.mn.us>). While academics have the liberty to limit the space-time scale of the archaeological record to their personal window of interest, AHM's foremost obligation is to assess and preserve the overall archaeological value of the landscape, indiscriminately, under heavy time and money restrictions. Clearly we have here a clash of two very different space-time scales of interest and this includes the choice of methods and practice.

The criticism of predictive modelling in scientific literature has focused on three main issues, statistics, theory and data. In all three areas predictive modelling as it stands today is considered by various authors to insufficiently address the complexity of the matter (see e.g. van Leusen 1996; Ebert 2000; Woodman/Woodward 2002; Wheatley 2004; Whitley 2005). Statistical methods are used uncritically, often using a limited number of techniques that are not the best available. Archaeological theory, especially where it concerns the human and temporal factors in site placement, only plays a marginal role in

selecting the variables used for predictive modelling. Archaeological data, which we all know have various degrees of reliability, are used without much source criticism.

While this is all very much true and many archaeological predictive maps are rather coarse representations of a complex archaeological reality, these criticisms mask a more fundamental question, what is the required quality of a predictive model? This is precisely why models are made that are not very sophisticated from a scientific point of view, they are considered good enough for the purposes they are made for. We do have to wonder however about the demand for more complex models. A commonly held view in science is that the simpler model should be preferred whenever possible as it offers the best interpretability and the least undefined behaviour. It also eases communication of requirements and results. Increased complexity usually serves to compensate for lack of structural knowledge.

### **3. DEVELOPING PREDICTIVE MODELS INTO RISK ASSESSMENT TOOLS**

Our one fundamental problem with predictive modelling is therefore the issue of quality. No one seems to know what constitutes a 'good' model and no tools are available and used to make the quality of the models explicit. This takes us to the mathematical aspects of our framework, necessary to connect critical components like predictive models and survey data into a full risk assessment tool set. A requisite is the incorporation of a formal quantitative notion of uncertainty, such as probability, confidence intervals, residuals or belief values. Within our research project we have tried to focus on these issues by looking at the potential of new statistical techniques for incorporating uncertainty in the predictions (van Leusen/Millard/Ducke 2009) and by studying the best ways of testing the models (Verhagen 2007). Our first foray into the uncharted waters of model quality concerned the role of expert judgement in a quantitative framework. When the first criticisms of predictive modelling appeared in the late 1980s, it quickly became clear that a fully inductive approach was in many cases unsatisfactory (see e.g. Brandt/Groenewoudt/Kvamme 1992; Dalla Bona 1994). The lack of reliable survey data in many areas of the world basically ruled out a rigorous statistical approach unless vast amounts of money were invested in survey. The pragmatic solution therefore was to stop using statistical methods for developing predictive models and instead rely on expert judgement and see if the experts' views were corroborated by the available archaeological data (see e.g. Deeben/Hallewas/Maarleveld 2002). However, in doing so a major advantage of statistical methods was neglected, namely the ability to come up with estimates in real numbers and the calculation of confidence intervals around the estimates. Expert judgement models only classify the landscape into zones of low, medium and high probability without specifying the numbers involved. How many archaeological sites can we expect in a high probability zone? How certain can we be of this estimate with the available data? Statistical methods will provide these numbers, expert judgement will not.

### **4. BAYESIAN STATISTICS**

Bayesian statistical techniques are very well suited to provide numerical estimates and confidence intervals on the basis of both expert judgement and data. Bayesian inference differs from classical statistics in allowing the explicit incorporation of subjective prior beliefs into statistical analysis (see e.g. Buck/Cavanagh/Litton 1996). This makes it an effective method for predictive modelling using expert (prior) opinions. A Bayesian statistical analysis produces an assessment of the uncertainty of the calculated

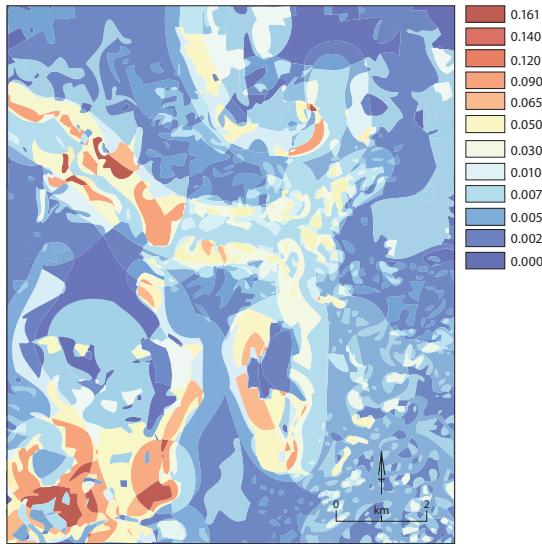


Fig. 1  
An example of Bayesian predictive modelling. *Relative site density according to expert judgement (prior proportions, a cell with a value of 0.12 is twice as likely to contain a site as a cell with a value of 0.06).*

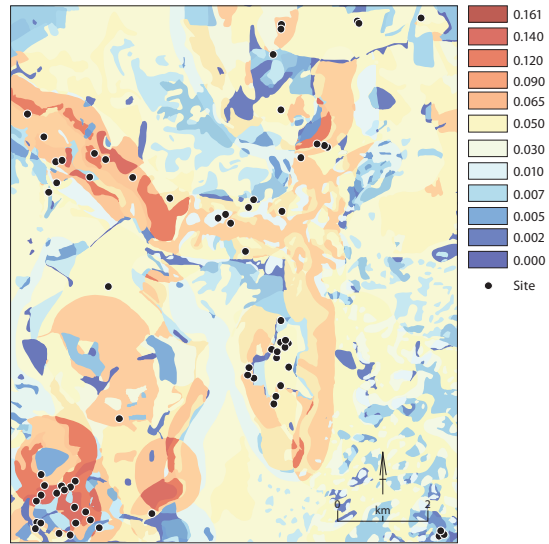


Fig. 2  
Relative site densities following inclusion of 80 observed sites using the same legend as Fig. 1 (*posterior proportions with sites overlaid*).

probabilities in the form of standard deviations and credibility intervals. It also provides a simple framework for incorporating new data into the model.

Bayesian inference, while conceptually straightforward, has only enjoyed widespread application after the advent of powerful computing methods. In archaeology Bayesian inference is predominantly used in 14C dating for calibration purposes. However, up to now it has not been extensively used in predictive modelling. The number of published applications is limited to two case studies (van Dalen 1999; Verhagen 2006). In addition, two other papers (Orton 2000; Nicholson/Barry/Orton 2000) consider survey sampling strategies and the probability that archaeological sites are missed in a survey project given prior knowledge of site density, such as might be gained from a Bayesian predictive model. This lack of application is probably due to the relative complexity of the calculations involved. There are very few archaeologists who can perform these calculations even though computing power is now no longer an obstacle. We have however proved that it can be done (see van Leusen/Millard/Ducke 2009) and we see Bayesian statistics as a very powerful and useful tool for predictive model building. Figs. 1 and 2 show the resulting maps from the pilot study that was done in the area of Rijssen-Wierden, using the opinions of three different experts as input to the model and updating it afterwards with archaeological site data from the area.

## 5. DEMPSTER-SHAFER MODELLING

We also tested the potential of Dempster-Shafer modelling, which has been suggested as an alternative to standard statistical methods. While the results of earlier predictive modelling studies indicated that it performed better than most statistical tools (Ejstrud 2003; *idem* 2005), it has no inherent mechanism to accommodate expert judgement. Furthermore, its conceptual basis is rather complex. We will not go

into detail in this paper (see van Leusen/Millard/Ducke 2009 for more background), but it suffices to say that Dempster-Shafer modelling is more controversial in statistical science than Bayesian statistics and it is more difficult to understand. The Dempster-Shafer Theory of evidence (DST) was developed by Dempster (Dempster 1967) and Shafer (Shafer 1976) and takes a somewhat different approach to statistical modelling. It uses the concept of belief, which is comparable to but not the same as probability. Belief refers to the fact that we do not have to believe all the available evidence and we can make statements of uncertainty regarding our data. The specification of uncertainty is crucial to the application of DST. Unlike Bayesian inference, DST does not work with an explicit formulation of prior knowledge. Rather, it takes the existing data set and evaluates it for its weight of evidence. The reasons for believing the evidence or not may be of a statistical nature (a lack of significance of the observed patterns, for example), or they may be based on expert judgement (like knowing from experience that forested areas have not been surveyed in the past). DST modelling offers a framework to incorporate these statements of uncertainty. It calculates a measure called plausibility, which is the probability that would be obtained if we trust all our evidence. The difference between plausibility and belief is called the belief interval and shows us the uncertainties in the model. Finally, the weight of conflict map identifies places where evidence is contradictory. Different beliefs for different parameters can easily be combined using Dempster's rule of combination.

DST modelling is incorporated in Idrisi and GRASS GIS and is used for a number of GIS applications outside archaeology. In archaeological predictive modelling it has been applied in case studies by Ejstrud (Ejstrud 2003; *idem* 2005). It is better incorporated in GIS and predictive modelling than Bayesian inference. There are clear similarities between DST and (Bayesian) probability theory as both provide an abstract framework for reasoning using uncertain information. The practical difference is that in a DST model belief values do not have to be proper mathematical probabilities and much simpler quantifications, such as ratings, may also work (Lalmas 1997).

## 6. IMPLICATIONS

The results of our modelling exercises show that Bayesian inference and DST modelling are both capable of including and visualizing uncertainty in predictive modelling. Because the DST modelling applied in our case study used different environmental factors from the Bayesian modelling, we could not perform a direct comparison between the two. We can however assume that even with a comparable input the results of the methods will be different, which begs the question of what will be the best approach. The answer should consider practical issues of versatility, robustness, computational performance and interpretability of model results more than mathematical accuracy as the latter is adequate in both cases.

Given the preference of DST modelling for using existing data sets instead of formulating prior knowledge, we can assume that Bayesian modelling will be the most appropriate when few data are available. It will then show us where the experts are uncertain and this could imply targeting those areas for future survey. Bayesian modelling however does not supply a clear mechanism for dealing with (supposedly) unreliable data, while the DST approach implements this by simply stating that these data can only partially be trusted and hence will only have a limited effect on the modelling outcome. The Dempster-Shafer concept of belief supersedes that of mathematical probability and the latter in turn underlies statistical confidence intervals and residuals so that a Dempster-Shafer-based framework could accommodate a Bayesian predictive model, sources of uncertainty and survey information. The

U \ P	High	Medium	Low
High			
Medium			
Low			

Fig. 3. Simplified scheme for representing predicted site density (p) and uncertainty (u) in predictive mapping.

hardest challenge lies in compressing the diverse sources of evidence and uncertainty into one decision criterion. Ideally, there should be a single simple decision map. Anything else would mean a regression in practical applicability.

For practical purposes the results of the models will have to be translated into clear-cut zones. In a simple matrix (Fig. 3) the possible 'states' of the model can be shown, with 9 different combinations of predicted site density and uncertainty. For end users of the models, who have to decide on the associated policies, this means that the number of available choices increases from 3 to 9. A reduction to 4 categories might therefore be preferable, only distinguishing between high and low site density and uncertainty. After all, why do we still need the medium class? Usually, this is the zone where we 'park' our uncertainties so a binary model plus an uncertainty model should achieve the same results. The end users then only need to specify how (un)certain they want the prediction to be.

However, even if tools like Bayesian statistics can build a bridge between expert judgement and quantification, we still need reliable data to have it deliver its potential. The testing issue is therefore of primary importance to predictive modelling. What is probably most problematic in this respect is the lack of attention by archaeologists to the simple statistical principle of data representativity. No matter what statistical method is used, this issue needs to be addressed first before attempting to produce a numerical estimate of any kind. While it is possible to reduce the bias encountered in existing archaeological survey data to an acceptable level, in order to have reliable archaeological predictive models we also need to survey the low probability zones. So here we are facing a real paradox, predictive models are developed to reduce the amount of survey (or even skip it) in low probability zones, yet statistical rigour tells us to do a survey there as well.

Our approach has been to re-assess the value of using statistical methods in predictive modelling. We are convinced that this is necessary and think that it can offer a valuable contribution to AHM. If we can base the models on sophisticated statistical methods and reliable data, then we can really start using predictive models as archaeological and/or economic risk management tools. However, we have not been able to get this message across to the AHM community in the Netherlands. While we have not done an exhaustive survey among our colleagues, we think that the following reasons may be responsible for it:

- The innovations suggested are too complex. While it is sometimes said that statistics are not very difficult, but only very subtle, in practice most archaeologists do not work with them on a daily basis.



Some even have difficulty grasping the most fundamental principles of quantitative methods. This makes it hard to get the message across as it does not really help when we have to bridge a large gap in knowledge between the statistical experts and the people who have to use the end results of statistical models.

- Shifting from the current expert judgement approach to a more sophisticated statistical approach is too expensive. Improving the models in the way we suggest does not replace anything in the current way of dealing with predictive modelling, it only adds to it. So on top of the things we already do, like gathering and digitizing all the available information and interviewing the experts, we now also need to have a statistical expert doing the modelling, a data analysis programme to detect and reduce survey bias and perhaps even a test survey.
- It is irrelevant. While we may be bothered about the quality of the models, most end users are not. They trust the experts. In particular, those responsible for political decision making will not care as they only need clear lines drawn on a map telling them where to survey and where not. If the archaeologists are happy with it, then they are as well.
- This ties in with our last explanation, archaeologists may have reason to be afraid of more transparent methods that will give non-archaeologists insight into the uncertainties of predictive models. When anyone can judge model quality, they will lose their position of power in dealing with politicians and developers.

We may not have been assertive enough in the presentation of our research to our colleagues and we certainly did not have enough time to fully develop these new approaches into practical working solutions. As long as the relevance of these new methods is not acknowledged, it will only remain an interesting approach from a scientific point of view.

## 7. DISCUSSION

Predictive modelling as it stands today is a tool with strengths and weaknesses. Its strong points can be summarized as follows:

- Predictive models are cost-effective tools for archaeological heritage management as they allow us to make transparent and well-founded choices when confronted with the question where to invest money for archaeological research. The approach that is taken in e.g. the United Kingdom, where these decisions are taken on the basis of (expert) knowledge of the *known* archaeological site sample, is in our view an irresponsible approach to AHM. It increases the archaeological risks involved by not taking into account the zones where no previous archaeological research has been done.
- As the models explicitly detail where to expect archaeological remains, they are open to scrutiny and criticism from archaeologists and non-archaeologists. In this way they can also stimulate a debate on how to deal with the areas where uncertainties exist.
- Predictive models, though not often considered as such, are also inherently heuristic tools with a clear scientific value. In the process of constructing a predictive model we are forced to clearly specify and reconsider hypotheses and theories concerning the distribution of archaeological remains and, ultimately, past human behaviour in the landscape.

However, we can also identify some clear weaknesses:

- The models and resulting predictions are only as good as the data and theories that are put into them. The garbage-in, garbage-out principle is relevant to any type of model but becomes even more important for predictive models when they are used for real-world decision-making. Using bad models has potentially undesired consequences for both archaeological research and society. In particular, the lack of attention to testing of the models is, in our view, a serious flaw and the absence of norms with regard to predictive model quality is a worrying aspect of current AHM in the Netherlands.
- Related to this, the emphasis on predicting settlement sites at the expense of other archaeological phenomena means that the use of archaeological predictive models will lead to the protection and investigation of ever more settlement sites, thereby reinforcing the predictions made and leading to a vicious circle of self-fulfilling prophecies. While we want to emphasize that there is no reason why predictive models could not also predict other types of archaeological remains, it is true that current models do not usually take this into account.
- The actual AHM decisions taken on the basis of predictive models may not always be to the archaeologists' liking. We find it hard to judge whether this is a true weakness of the models or of the process by which these decisions are arrived at. In the end, archaeology is only one of the issues that have to be dealt with in spatial planning and in a democratic society it will always be weighed against other interests. We have the impression that some archaeologists feel that predictive models should be used as weapons against the pressures from politics and if this fails they are dissatisfied with the weapons at their disposal rather than with the way in which the decision-making process operates and the role that archaeology plays in it.

There are some interesting developments in the debate on whether to continue developing predictive models and in which direction. The archaeological site as it is traditionally perceived in our discipline is changing its very status from being an object of almost esoteric, clandestine curiosity to a measurable, quantifiable, predictable and assessable resource (see e.g. Verhagen/Borsboom 2009). It will take some effort to establish this notion in general archaeological research. At the same time the definition of the archaeological site itself is under direct attack from modern landscape archaeology that increasingly sees archaeology as the study not only of the places that humans occupied in the past, but also of the landscape that they lived in. In this holistic concept of landscape archaeology, the site itself becomes an almost meaningless entity. Therefore, we can expect a considerable tension between the development towards a better understanding of the physical characteristics of archaeological remains in terms of feature and finds density and size and the fact that a broader vision of landscape archaeology implies that virtually everything in the landscape is worth investigating. In this view, predictive modelling might still be of some use for deciding on the strategy to follow for a survey campaign but it should no longer be used to exempt areas from survey. It is clear that this point of view will create tensions between archaeologists and developers and politicians who would like archaeological research to be manageable in terms of both finance and planning and who currently depend on predictive models to do much of this job for them.

Furthermore, much of the discussion on predictive model quality will probably become less relevant in the future, at least from a practical point of view. Many of the dichotomies debated in archaeological predictive modelling are leftovers from a time when calculations were time-consuming and heading

down the less efficient road could waste precious resources. In the digital age the effects of mistakes and inefficiencies in research design and during the research process have become less severe as models can be re-run, data restructured and results easily updated. Software knows no hard boundaries between data and information, quantity and quality, deduction and induction, belief and knowledge. This has never been more clearly visible than with today's powerful and visually persuasive applications. Anyone who needs proof should try some data mining software. Indeed, archaeology is still in the middle of a digital (read: quantitative) transition where nothing seems uncontested, everything is in flux and many developments will turn out to be dead ends. Considerable stamina is still needed, especially given the small number of archaeologists active in the statistical and computational fields. Nevertheless, with powerful computing technology and mathematical tools at our disposal we are now closer than ever to providing truly efficient, user-friendly (Gibson 2005), reliable archaeological resource management tools and should thus forge ahead.

In our view another important development is the vigorous debate on the merits of regulation of all aspects of archaeological heritage management. In recent years Dutch archaeology has witnessed the birth of national quality norms regarding the execution of excavation, followed by norms for survey, digital data storage and curation and the level of education and experience that archaeologists need to be allowed to do archaeological research. National and local research agendas that try to specify the desired scientific outcome of archaeological fieldwork are recent additions to this expanding web of guidelines, norms and regulations. No doubt there will be more to come and predictive modelling may be one of the issues included. As a matter of fact, we do not see much future in imposing standardized predictive modelling procedures for the whole country. The history of the national Indicative Map of Archaeological Values (IKAW) shows that this is undesirable since a standardized product can never meet local needs (van Leusen *et al.* 2005, 48-51). Nevertheless, we do think that clear norms are necessary where it concerns the correct use of input data, the methods applied and the required output of the models. However, experience shows that more regulation does not necessarily imply a better quality of work and we will therefore have to see how Dutch public archaeology will cope with the tension between taming its bureaucracy and maintaining professional integrity in a fiercely competitive market.

#### NOTES

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