UNIVERSITY OF BIRMINGHAM

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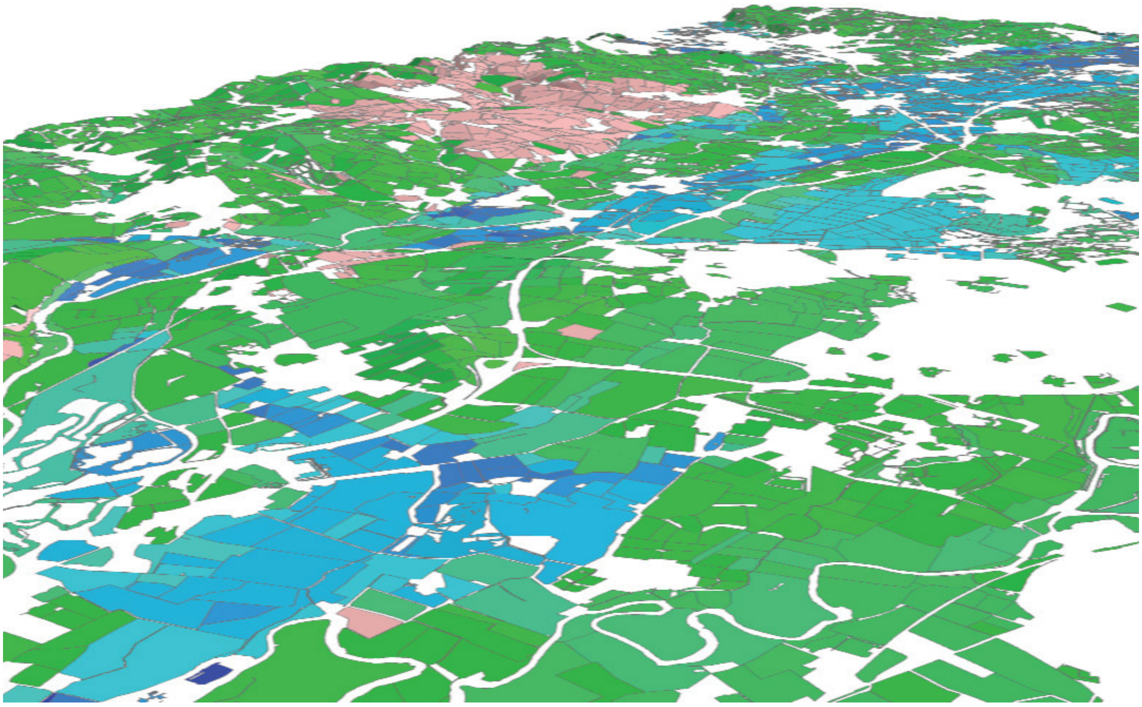
EXPERIMENTAL MAPPING OF THE RISK OF ENCOUNTERING BURIED ARCHAEOLOGY IN AGGREGATE LANDSCAPES

FINAL REPORT



PN5700
March 2011

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EXECUTIVE SUMMARY

- This document is a Summary Final Report for the project entitled '*Mapping the risk of encountering buried archaeology in aggregate landscapes*' (PNUM 5700).

- It is intended as a summary statement of results and will be superseded in due course by a more comprehensive final statement, the Final Report.

- The project builds on a number of significant aggregate related projects funded in the Trent Valley under previous rounds of the ALSF. The significant corpus of archaeological knowledge gathered for this valley floor provides arguably the best (national) opportunity to develop and test a model for archaeological decision making with respect to risk and for the direct transfer of this knowledge to planning authorities and the minerals industry.

- In simple terms the project has addressed the construction of GIS-based spatial models which will allow a first level of understanding of the likely archaeological value of land parcels within the study area.

- Work has developed a set of robust algorithms that are based on personal perceptions and empirical scientific data to model archaeological risk/potential at the level of individual land parcels. The completed models provide per parcel scores for:

    - The predicted archaeological potential of all land parcels.
    - The aggregate bearing potential and value of all land parcels.
    - The susceptibility of individual land parcels field evaluation techniques.
    - The likely physical condition of buried cultural remains.
    - The risk of encountering buried waterlogged organic remains.
    - The importance of archaeology in the light of regional priorities.
    - The likely mitigation needs in the light of PPG 16 guidance.

- Models have been validated through feedback from stakeholders; discussion of validation is reserved for the Final Report.

- This Summary Final Report includes discussion on appropriate methods of dissemination of the results of work of this sort, although it is recognised that the results of the work as it stands are not suited for nor were intended to be widely disseminated.

- The Summary Final Report also includes an outline critique of the work undertaken, its strengths and weaknesses and some pointers towards appropriate future and complimentary research.

INTRODUCTION

1 INTRODUCTION

1.1 PREAMBLE

This document comprises a Summary Final Report for the project entitled '*Mapping the risk of encountering buried archaeology in aggregate landscapes*' (PNUM 5700). It will be superseded in due course by a more comprehensive final statement, the Final Report. The work described herein has built on a number of significant aggregate related projects funded in the Trent Valley under previous rounds of the ALSF (see TVG.org.uk). The significant corpus of archaeological knowledge gathered for this valley floor provides arguably the best (national) opportunity to develop and test a model for archaeological decision making with respect to risk and for the direct transfer of this knowledge to the minerals industry via the regional HERs.

In simple terms, such models should allow any mineral operator, or other non-archaeological stakeholder, to identify a parcel of land for aggregate extraction, consult the HER and to gain a first level of understanding of the likely archaeological value of that land (and hence an assessment of mitigation costs).

It is anticipated that the development of such an approach will provide the following benefits to both the aggregates industry and heritage management community:

- An easily accessible, interactive resource that can be the focus of query based interrogation
- A rapid first order assessment of the level of risk (and hence mitigation demands for both developers and heritage managers)
- An easily up-datable resource, which can be refreshed as new data become available. New data fields could also be added which provide additional information about archaeological resource management (e.g. groundwater conditions).
- A generic approach, which if the subject of successful trial in the Trent Valley, could be up-scaled to a national level.

1.2 REPORT STRUCTURE

The Summary Final Report is divided into seven sections: Section one comprises introductory material on the context of the work and the locations of the study areas; Section two is a précis discussion of predictive modelling within archaeology and provides an academic context for the work; Section 3 outlines the aims and objectives of the work (somewhat modified through experience from those set out in the project design); Section four provides method statements for the work undertaken and the modelling approaches adopted; Section five reviews the results of the modelling work; Section six provides critical discussion of the meaning of the results achieved, and Section seven provides a bibliography of the published sources consulted during the research. Two appendices provide additional data not included within the report text.

1.3 CONTEXT

The concept of archaeological risk is not new and has been explored conceptually in previous ASLF projects (e.g. Walker and Challis, 2004). Work by Ursilla Spence, the County Archaeologist for Nottinghamshire County Council, considered methods to devise spatially continuous indices of risk, while at York Archaeological Trust, Walker and Challis (2004) considered concepts of risk and risk management related to the success or otherwise of archaeological field evaluation from a number of perspectives. However, this is the first time a project has been developed where risk has been modelled and mapped within an interactive GIS framework. As such, this project has been designed in direct response to the needs of both the cultural resource management (CRM) profession and the aggregates industry.

With the increasing costs of archaeological mitigation (evaluation and excavation) in aggregate bearing landscapes and the demonstrable archaeological wealth of these environments (Needham and Macklin, 1992; Needham, 2000; Sidell *et al.*, 2000), greater emphasis than ever is being placed by regional and national heritage managers in England and other parts of the UK on the collation, interrogation and interpretation of both published and unpublished archaeological datasets, which allow the characteristics of any landscape to be assessed and hence inform Cultural Resource Management (Bishop, 2003; Catney and Start, 2003; Knight and Howard, 2004).

The understanding of the character and distribution of the archaeological resource engendered by a comprehensive characterisation exercise carries with it the potential to understand the **risk** of encountering archaeological deposits, both in areas where such deposits are already documented and in so-called “blank” areas, where archaeological remains might be anticipated, but are not documented by existing survey or intervention. The risk of encountering archaeological remains, the types of remains likely to be encountered and the applicability of appropriate prospection methodologies are all questions of considerable importance to the minerals industry since they will directly affect extraction costs. Such questions are of equal importance to cultural heritage professionals when designing the most appropriate mitigation strategies for their clients in response to archaeological planning briefs.

Reliable, rapid quantification of the risks associated with encountering archaeological remains is a concern for the aggregates industry and many other development led organisations. Similarly, the ability to provide such information in a robust, easy to interpret manner is a concern for heritage professionals who often have to make informed judgement on a rapid basis.

The research described here was designed to meet the broad research objectives for studying and assessing the risks to historic assets and devising responses set out by English Heritage in their Research Agenda (**Criteria D**; English Heritage 2005).

The project directly addressed the English Heritage corporate objective 1D, ‘Develop New Approaches Which Improve Understanding and Management of the Historic Environment’, and specifically the sub-programme number 14171.310, “Fresh Toolkits: Methodological and theoretical research and innovation” (English Heritage, 2008). Research used innovative approaches to predictive modelling in order to improve the efficiency and ability of cultural resource management, therefore closely meeting the intended scope of this particular SHAPE programme. Although here focused on the problems and peculiarities of aggregate bearing landscapes the techniques and methodologies established may potentially have wider archaeological relevance on a national scale.

The research has also directly addresses the ALSF funding priority **1.2:**

- Research and development of practical new techniques to locate hidden historic environment assets in aggregates landscapes;
- to improve our understanding of direct and indirect impacts of extraction on such assets and landscapes;
- to develop practical ways of mitigating such impacts to enhance conservation and management of the resource

1.4 STUDY AREAS

Research has been actively supported by the stakeholders represented by Trent Valley GeoArchaeology and in particular by the archaeological officers of Nottinghamshire, Derbyshire and Lincolnshire, within which counties the three study areas were located.

Study areas were deliberately selected to encompass part of the Trent Valley in each county as well as a range of landscapes encountered within the valley.

The following three areas were selected for this research (Figure 1); in each case a study window of approximately 500km2 was investigated.

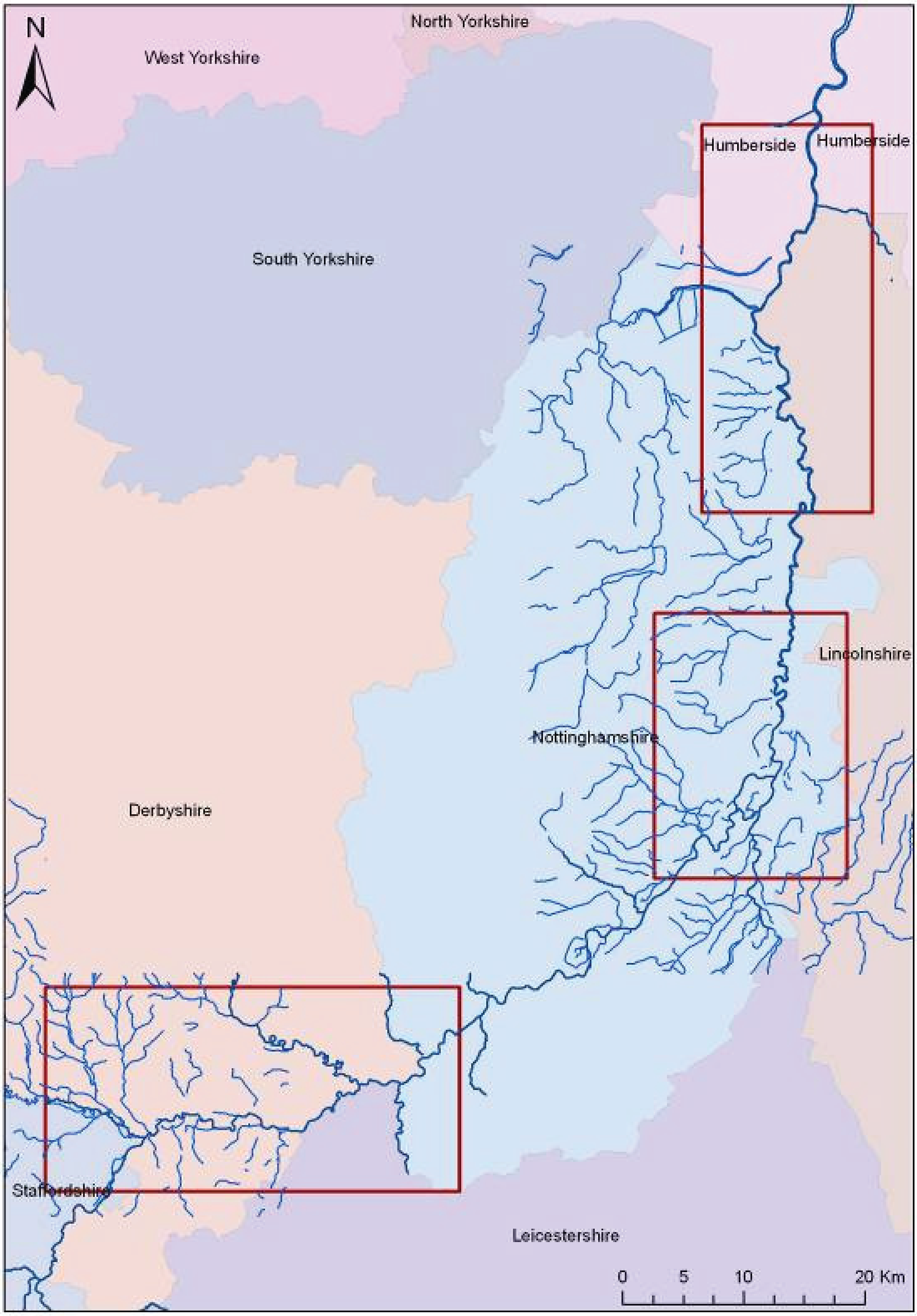


Figure 1. The Trent Valley showing the locations of the three study areas.

1.4.1 Study Area 1: The middle Trent Valley in Derbyshire from the Dove to the Derwent

In this part of the Trent Valley, the river has high levels of energy and is geomorphologically active, primarily because of the large volumes of floodwater that it receives from the uplands of the Peak District. This results in the river migrating back and forth across its valley floor and regularly switching channel by sudden movements (avulsion). Such lateral migration activity results in the burial of archaeology and the preservation of palaeochannels on the floodplain.

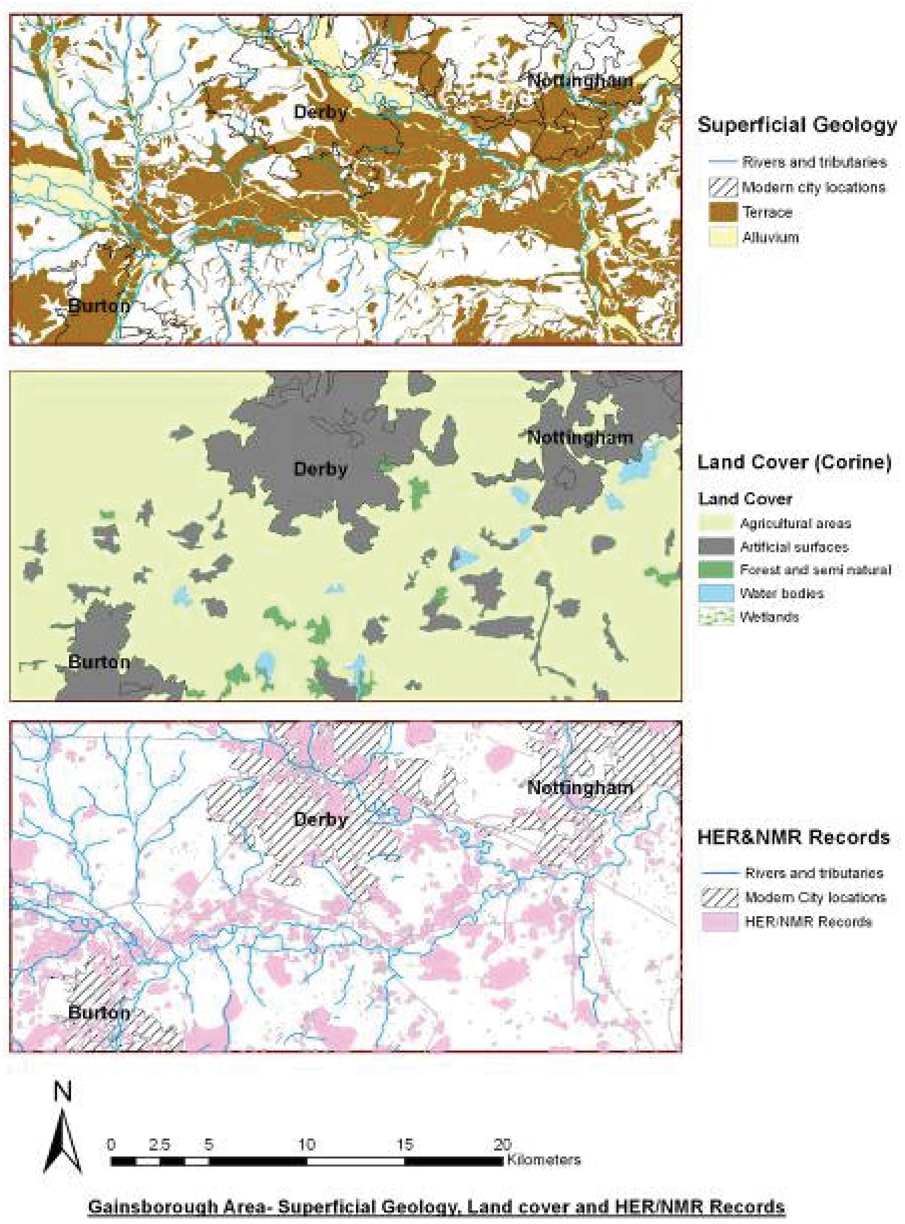


Figure 2. The Middle Trent in Derbyshire from the Dove to the Derwent showing (top) superficial geology, (middle) landcover, (Bottom) HER records.

1.4.2 Study Area 2: The Lower Trent Valley in Nottinghamshire between Newark and Girton

In this part of the Trent Valley, the river has a lower gradient and less energy, but quarry exposures such that gravel movement is still important, possibly because of high energy levels created by funnelling of water through the Trent Trench, immediately upstream of Newark. Therefore, this area marks a transition zone between the piedmont system viewed in the Middle Trent and the true lowland system further downstream (see below). The result is a valley floor that displays characters of both (i.e. overbank alluviation, but also lateral reworking of the valley floor).

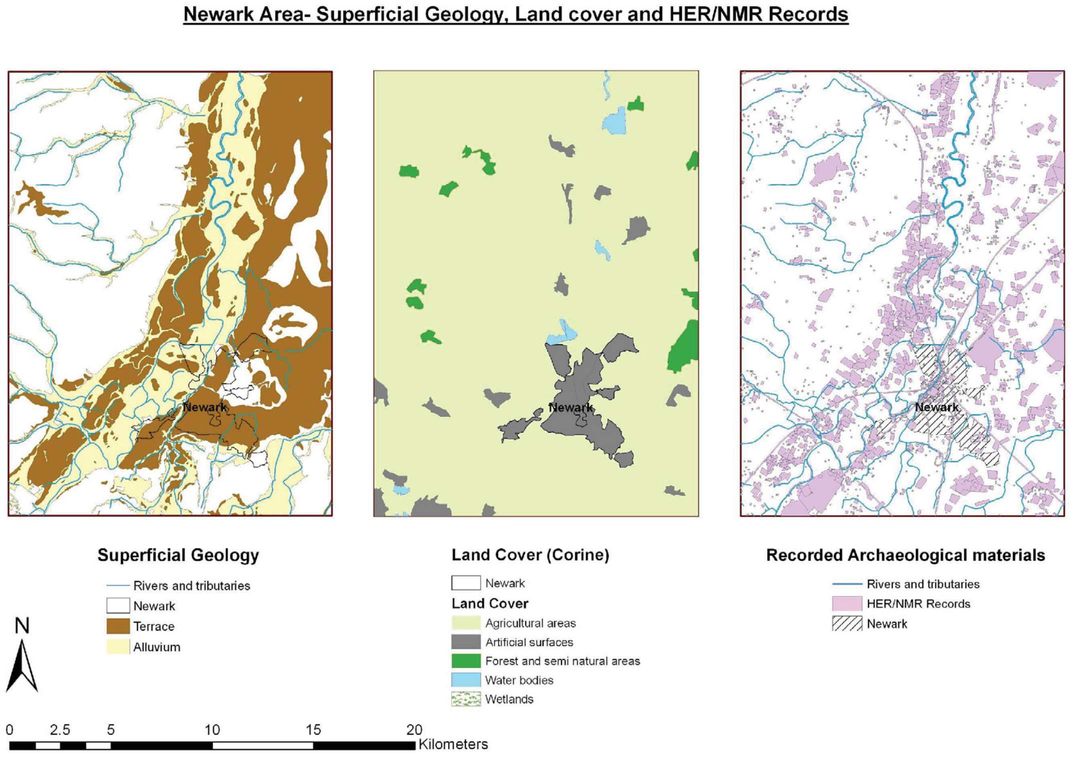


Figure 3. The Lower Trent in Nottinghamshire between Newark and Girrton showing (left) superficial geology, (middle) landcover, (right) HER records.

1.4.3 Study Area 3: The Lower Trent Valley in Lincolnshire around Gainsborough

This part of the Trent Valley floor is characterized by a true lowland river with significant levels of overbank alluviation within a stable channel zone. Vertical accretion masks the archaeology beneath blankets of fine sediment and relatively high water tables create excellent conditions for preservation. Within this zone, there is also the potential influence of tidal processes on landscape evolution.

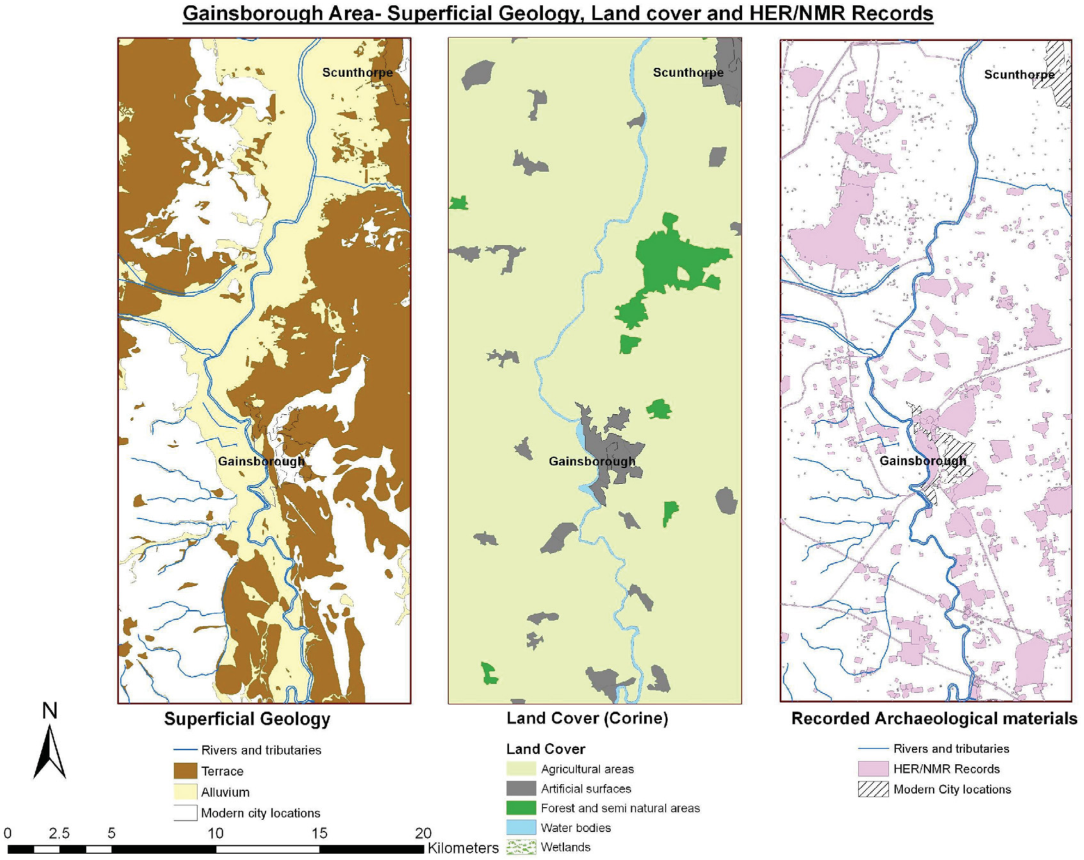


Figure 4. The Lower Trent in Lincolnshire around Gainsborough showing (left) superficial geology, (middle) landcover, (right) HER records.

PREDICTIVE MODELLING IN ARCHAEOLOGY: A REVIEW OF APPROACHES

2 PREDICTIVE MODELLING IN ARCHAEOLOGY: A REVIEW OF APPROACHES

2.1 A REVIEW OF PREDICTIVE MODELLING IN ARCHAEOLOGY AND KEY CONTENTIONS

Archaeological predictive modelling arises conceptually from spatial geographical studies during the latter half of the twentieth century, and in part from theoretical approaches advanced by processual (or ‘new’) archaeological theory during the 1960’s (Verhagen 2007). Whilst processual theory gave rise to the conceptual birth of the field however, its utility within the embrace of the post-processual approach has also developed (Witcher 1999 provides a discussion of the post-processual applications of GIS), and the development of the field overall has been facilitated by the step-changes in computing power and availability which occurred during the late 1980’s and the continued exponential advances in these areas.

Active discussions within the archaeological academic community as to applications of predictive modelling have traditionally largely been focused upon uses of spatial modelling for prediction of potential site locations. This discussion, and the adoption of the predictive modelling approach, has been particularly prevalent in the United States, where large spatial extents requiring planning policy assessment which considers the archaeological record, coupled with the reduced visibility of pre-conquest/colonial archaeological materials within the landscape, has driven an industry of state and local modelling processes. Typically these models attempt to pre-define the archaeological potential of areas for targeting further investigation, and planning consideration. The Netherlands has also been a focus of predictive modelling studies for use in planning policy, somewhat following the American approach (P. M. Van Leusen 2002; Verhagen 2007; Brandt et al. 1992), and (in regards to the published record) has grown to rival the US in terms of developing methodologies and approaches. Wider Europe, and particularly Britain, has been comparably conservative in regards to predictive modelling approaches, with a much reduced scale of academic interest, an emphasis upon cautionary and conceptual discussion, and with predictive models not (to date)an established element of UK planning policy procedures.

Typically predictive modelling exercises have involved the use of diverse data (although somewhat with an emphasis towards material environmental characteristics) to analyse potentially favourable or unfavourable conditions for site location and to use observed potential relationships to extrapolate further likely site locations within a landscape. The manner and chronological breadth of sites which have been the focus of predictive modelling is broad, however particular emphasis has been placed upon the location of potential prehistoric sites, particularly within the US. Typically existing data regarding site locations within the landscape of investigation is examined to statistically explore potential correlations between site locations and particular combinations of environmental characteristics. Potential correlations are then used to form the basis for the assignation of a value to non-sampled locations within the landscape which is considered to reflect the suitability of that location for the presence of a site. Processes to sum weighted variables (with weighting derived either from model-creator deduction, or based on the relative strengths of correlations observed during the pre-analysis phase) are then followed to produce an overall model which allocates all locations within the landscape a value reflective of potential for archaeological presence. Model validation or testing may then be performed, typically through 'jack knife' sampling where a proportion of the original archaeological data sample, which was removed from consideration during the analysis phase, is compared with the modelled data to assess the level to which the model has accurately predicted site locations.

A range of methodologies around this theme have developed over time, and several key methodological elements have become widely adopted. Principal amongst these is the concept of 'gain', developed by Kvamme (1988) which allows the assignation of a value allowing cross-model comparisons, and has been widely used, although criticised as often being portrayed as a performance indicator rather than a measure of internal model consistency by Wheatley (2004). Logistic regression analysis to determine correlation between variables has also been commonplace, as have numerous statistical methods for further defining model accuracies.

However, as work has progressed, numerous conceptual arguments (critical since the entire investigative framework utilised in predictive modelling is conceptual in origin and formulation) have arisen in terms of how PM is devised and approached, with some discussion indeed of whether such exercises have any value at all, or instead simply serve to lend undue cumulative weight to entirely conceptual unconfirmed hypotheses (Wheatley & Gillings 2002; Wheatley 2004). Critical evaluations of the nature of current approaches to predictive modelling and of specific models as planning tools, frequently updated over time, have been prolific (Van Leusen 2002; Kamermans 2008; Whitley 2003; Ebert 2000). In brief summary (interested readers are recommended to investigate the bibliography and the significant volume of academic literature regarding predictive modelling) two overarching emphasises are recurrent within this debate. The first regards the categorisation of the activities performed within the field, whilst the second concerns the validity of the conceptual approaches implied by many predictive modelling exercises.

The first recurrent emphasis, regarding the classification of approaches, primarily results not from desire to label different methods, but more from a desire to outline and reinforce that predictive modelling is a conceptually driven exercise, with numerous assumptions implicit to its use, regardless of the approach taken. Therefore the requirement for detailed recognition of these assumptions and their implications towards model suitability and validity by the model creators is repeatedly emphasised point, and it is the desire for clarification of these tacit implications, both for potential model builders, and potential model end-users, which has driven much of the discussion of how different approaches are classified.

The second recurrent emphasis regards significant theoretical issues perceived in regards to how the data and methods used in predictive modelling derive predictions and the level to which these predictions reflect past decisions regarding location choice. A prominent exemplar of this discussion is concern regarding the underlying level to which varying approaches can be branded as deterministic, particularly in terms of environmental determinism; argued to represent a conceptual approach to landscape which may be significantly divorced from likely past considerations and cognition (Gaffney & Van Leusen 1995). Environmental determinism is but one of several key contentions, with many authors having signified considerable concerns regarding the core nature of predictive modelling exercises and recent practices (Gaffney & Van Leusen 1995; Ebert 2000; Wheatley & Gillings 2002; Wheatley 2004).

Whilst being drawn at depth into the classifications of modelling approaches is beyond the remit of this summary, a brief description of principle classifications which have been held (although potentially erroneously) to be in dichotomy shall be presented.

Differences have been traditionally emphasized between American (and to some degree, Dutch) approaches to predictive modelling, and European (and particularly British) approaches. Van Leusen (2002) has discussed at length perceived dichotomies in approaches taken within the field which have largely been grouped as opposing viewpoints under these geographic banners. American approaches have been seen to largely focus upon approaches emphasizing site prediction for CRM, using inductive (or 'data-driven'), somewhat ecologically (or environmentally in the terms of Gaffney & Van Leusen, 1995) deterministic methods. These methods focus upon derivation of suitability from a combination of environmental factors which are considered to make a location more or less favourable in comparison to others (such as distance to watercourses, slope, proximity to resources, etc).This has been mirrored in the Netherlands by the work of Verhagen and others on large-scale modelling for cultural resource management (Brandt et al. 1992; Verhagen 2007). In contrast, British or wider European approaches have been traditionally regarded to emphasize deductive, or 'rule-based' modelling approaches where a hypothesis regarding the manner in which people determined locations for activity based upon the wider archaeological or ethnographic record is used to determine relevant site suitability variables. However, in reality it seems that in recent years any line of geographical categorisation between approaches has been blurred to the point of questionable utility, with extensive work in developing the predictive modelling approach utilising perspectives from both sides of these perceived dichotomies over recent years (Wescott & Brandon 2000; Verhagen 2007). Indeed Van Leusen (2002) has argued convincingly that many approaches held formally to be in opposition are not dichotomies, and Ebert (2000) has argued for the utilisation of approaches which are rooted in a 'mixed' approach and for recognition that even modelling formerly classified as inductive in fact is deductive to some level.

One classification which has a high level of importance is that of end-use. Strong distinctions have been drawn between *correlative* models with the purpose of CRM (using observed patterns in the correlation of archaeological data to readily definable variables to identify further potential archaeological *discovery* locations and thereby determine relative levels of archaeological mitigation and management which may be appropriate across a landscape) and those which are academic and *explanatory*, and seek to understand and explain site location patterning and causality.

Whilst as previously, some grey area lies between these purposes, it has been argued that CRM may be a more valid application for predictive approaches, as many of the theoretical issues discussed above relate to what is inferred regarding past site location strategies from the archaeological data. For CRM models it has been suggested that the important consideration is not whether the model is able to explain site location, site location strategies, multi-temporality or former landscape perceptions, but rather simply whether the prediction is correct to a to a reasonable degree of accuracy (Connoly & Lake 2006). Additionally, it has been posited that for CRM correlative modelling can be conceptualised as in fact modelling likely locations for future archaeological discovery (operating on the assumption that the combinations of environmental and human factors which in the past led to the discovery of the current archaeological dataset will continue into the future and yield further discoveries), rather than directly modelling the presence of materials in the ground (Van Leusen 2002). This is a viewpoint strongly in accordance with that of this project. However, as a cautionary point, the potential for such models becoming a self-fulfilling prophecy in regard to CRM, since non-site locations may not be investigated, or may be cleared for development with minimal archaeological mitigation, therefore resulting in an artificial enforcement of the model results, has also been raised (Wheatley 2004).

Overall the majority of approaches taken within published exercises have been ‘possibilistic’ (i.e. indicating how suitable an area is for the modelled activity) rather than ‘probabilistic’ (measuring how likely it is that the modelled activity will be present in a given area) according to Van Leusen (2002). However an increasing number of models are seeking to factor uncertainty into models through the application of Boolean Logic (Stancic & Kvamme 1998), and more recently concepts of ‘Fuzzy data’ and the creation of probability surfaces through use of Dempster-Schafer theory (Canning 2005; Boos et al. 2010). To contextualise our study in regards to this background, this project could be seen to be ‘weakly probabilistic’ according to the definitions Van Leusen (2002) proposes, as it provides relative measures of the potential level of archaeologically-associated economic risk associated with given land parcels, without extensive probabilistic assessment.

In summary, academic debate regarding predictive modelling has been intensive, and at times heated. Numerous approaches and potential conceptual and functional pitfalls have been classified, and although a broad division has been drawn between predictive modelling for site explanation and modelling for CRM, the reality is that these areas have for much of the time utilised common approaches with differing nuances of method and concept which renders clear distinction more difficult. Perhaps the most pertinent consistent point arising from the debate is an admonishment that predictive modelling exercises should always be entered into with a clear understanding of the conceptual framework which is implied at their inception and by their end function, and that a full considered examination at each stage of the method of the multi-scalar conceptual and functional implications of each new aspect of the modelling, as it is applied, is critical. Providing clear measures of model validation, discussion of the limitations of validation approaches, and a reliable assessment of model accuracy is also pivotal. A model purporting to define real-world location of archaeological materials to a given level of accuracy must provide a validated measure of that accuracy, whilst a model measuring (for example) the relative risk of archaeological interventions being required within a particular area must include careful validation strategies and also define the comparable accuracy of its predictions.

2.2 RISK AND THE PROBLEMS OF PREDICTIVE MODELLING IN ARCHAEOLOGY

Despite the demonstrable threats to aggregate related archaeology (Darvill and Fulton, 1998; French, 2004), little attempt has been made by the archaeological community to use the often detailed spatial information available to develop indicative risk maps. Such mapping has often been seen to rely on the vexed technique of predictive modelling for its development. In essence predictive models seek to predict the probability of a particular phenomena (for example, an archaeological site of a particular type) occurring at an unsampled location based on a quantitative assessment of the locational characteristics of known examples of the same. Predictive models rely on a four step process, from data collection through statistical analysis, model application and validation, and the application of complex statistics.

The patchy uptake of such techniques in archaeology is due to the ambivalent attitude amongst archaeological practitioners and academics in the UK to the development of predictive models. Reasons for this ambivalence are manifold, but often focus on the essentially environmental deterministic nature of predictive models and are typified by the view of Gaffney and Van Leusen (1995) who caution that the reliance on such models may actually create an unacceptable potential for the destruction of cultural heritage. Key academic texts skirt the issue of predictive modelling (eg Wheatley and Gillings 2002) although a number of recent studies have demonstrated useful applications in a variety of domains (Coulthard et al., 2007; Bunting et al., 2008) and Connolly and Lake (2006, 180) assert their usefulness at least in the field of cultural resource management.

It is suggested that more inductive approaches to predictive modelling , rather than simply the distribution of a particular class of site, typified for example by the whole landscape approach of historic landscape characterisation (eg Clark *et al* 2004) will often prove more profitable.

Fortunately, the field of geoarchaeological landscape assessment has seen a number of useful recent studies adopting such inductive, landscape focused approaches. For example in the UK and USA, relatively small reaches of Holocene valley floor have been zoned into areas of varying archaeological potential on the basis of their geomorphic evolution (Bettis and Hajic, 1995; Mandel, 1995; Passmore and Macklin, 1997; Howard and Macklin, 1999a; Bettis and Mandel, 2002; Passmore *et al*., 2002; Stafford and Creasman, 2002). As part of the research undertaken by Trent Valley GeoArchaeology in the Nottinghamshire Trent Valley, a study undertaken by the University of Newcastle devised a risk map for the valley floor based on an analysis of geological and geomorphological units (Yorke *et al* 2004).

More recently, a significant advance has been made by Ward *et al* (2009) who have demonstrated the value of mapping the physical and chemical characteristics of soil as an index of archaeological preservation potential in aggregate landscapes.
It is key at this juncture to categorise how this project relates to this overall academic framework and to prior works.

This modelling project differs distinctly from the majority of archaeological predictive modelling exercises. The models being created seek primarily not to statistically predict the location of potential archaeological sites, but rather *to predict the interpretations which would be reached regarding a given parcel of land by an informed archaeological resource manager using typical available data*. This is a significant distinction, which warrants more detailed explanation and characterisation.

The created models are to be a tool which predicts *how CRM management choices in aggregate landscapes are created*, and which provides a prediction at the pre-planning and even pre-enquiry stage for stakeholders in aggregate extraction as to the level of archaeological investigation which will be required for a given location should exploitation be proposed. As such, whilst the project indirectly models a relative risk of discovering archaeological materials (following a correlative approach as discussed in Van Leusen 2002), it more directly maps the *economic risk* in regards to archaeological mitigation requirements which would be attached to extraction proposals in a given location. By characterising these risks in relation to aggregate concentrations and existing extraction sites, this serves to provide a tool whereby the archaeological potential of a location *as inferred by the present corpus of information* can be contrasted with its aggregate-bearing potential to make informed decisions. In contrast to many traditional predictive modelling approaches, the detailed statistical assessment of combinations of environmental characteristics attached to known archaeological locations within the study area, and the creation of probabilistic models of archaeological location based upon the incidence of comparable cumulative characteristics is **not** being pursued beyond the levels which are suggested to be performed by cultural resource managers during an assessment exercise. Rather, the model seeks to predict the conclusions which would be reached regarding a given land parcel, if an informed archaeological interpretive process were to be followed by an archaeological planning officer, using the typically available existing data. This process will include the assessment of landscape characteristics, however these will primarily relate to factors confirmed to influence the likely preservation level of any archaeological materials which may be present within a given area (for example, Soil PH), and to characteristics which reduce/enhance the potential for the presence of materials.

Many discussions have been made regarding the pitfalls surrounding the use of existing archaeological data in predictive models, given that data is biased in both character and location (being a product of investigative foci, development locations, preservation and visibility), and is not a representative sample of the total (unknown) corpus of material in a given area. However, in CRM models such as this, contrastingly, limited suggestions have been made that this bias may in fact be of value (Hill et al. 2006).

'The importance of a representative sample rests on an assumption that it is past land use we desire to explain. However, if our goal is to model the *articulation of past land use with current and future land use*, the existing sample may be appropriate for our needs. While it is not a random sample, it is *representative of recent and contemporary interest in the landscape from a development point of view*. The distribution of known sites and modern archaeological surveys in this region are a good reflection of the range of interest it has received over the last several decades.

The variable scrutiny received by different areas is an indication of how much activity has occurred and is likely to occur in the near future.'

'The goal of producing a sensitivity map suggests a desire to identify cultural resources that are subject to imminent effect by development, and modeling sensitivity requires consideration of both the resources and development trends. *Bias inherent in much existing archaeological data produced by CRM may essentially be considered a weighting factor for threat level*. Rather than apply techniques to correct for this bias, we chose to use it strategically, emphasizing those areas most likely to be impacted by developments in the near future.'
(Hill et al. 2006) (emphasis added).

The above statements, with qualification, could be seen to fit the models being produced during this project. The threat level for materials proximal to known materials may indeed be seen to be relatively high, as the presence of the investigations which identified the known materials is typically indicative of the suitability of these areas to an extractive or developmental threat (with the exception of data derived from non-commercial research). This exploitation suitability is likely to extend beyond the archaeologically assessed area, and therefore proximal locations to the existing archaeological data may be considered favourably by developers for future exploitation, as the logistical challenges proximal to areas which have already been exploited are likely to be less, to be known, or to have previously been addressed.

However, a cautionary point should be made here. An elevated threat level proximal to prior investigations is a point-in-time measure at the time of the model production. There is therefore the potential (following the availability of the model to development agencies) for threat to become decoupled from prior foci of interest, as parties using these models seek to take advantage of areas indicated to be both suitable for development, and low in archaeological decision-related economic risk.

Since the assessed risk level is influenced by the results of prior investigations, this means that models of course *cannot account for completely un-indicated archaeology*, and make no attempt to locate this in the manner of traditional predictive models. This is not to say that areas currently recorded as blank in the HER will not be characterised archaeologically, as spatial autocorrelation and spatial statistics in relation to existing materials (in combination with numerous other variables) will be used to characterise the potential incidence and form of archaeological materials in areas for which no materials are known. It is simply important conceptually to acknowledge that, in areas which are indicated by this inductive approach as being low-risk, whilst the risk of expense associated with pre-planning archaeological intervention is likely to be low, the economic risk from *mid-development encounters* with archaeological materials which are completely un-indicated by the current record (and the subsequent economic risk associated with these) remains unquantifiable. This is a ‘known unknown’ associated with any data-driven interpretive approach.

The approach and question chosen means that the model also side-steps some of the concerns regarding environmental determinism that have been a key point of contention within the field (Gaffney and Van Leusen 1995). The produced models are not inductive per se since they leave aside academic questions regarding how choices are made in regard to how activities are sited, and instead focus upon modern decision-making regarding classification, investigation, likely preservation of, and risk of encountering archaeological materials. This is in accordance with Van Leusen's (2002) suggestions as to the value of correlative modelling in CRM. In order to avoid confusion, it may even be appropriate to refer to the overall model as a model characterising and facilitating likely archaeological intervention choices, rather than the somewhat historically-loaded term 'archaeological predictive model'.

In summary, whilst embracing the principles, lessons and approaches developed by the majority of archaeological predictive modelling, this project applies them to answer a somewhat different theoretical question, and stands alone from the majority of prior works.

2.3 TOPSIGHT: OUR APPROACH

The work undertaken for this project builds on and expands the concepts of Ward *et al* (2009) to address concepts of archaeological risk and to develop a robust, repeatable methodology for quantifying the economic risk associated with encountering cultural heritage in aggregate bearing landscapes.

We have adopted a landscape-focused, inductive methodology, rather than a deductive, deterministic, predictive model based approach. Such an approach has allowed us to capture data and judgements on the value of aggregate bearing landscapes to industry as well as effectively modelling value and risk associated with the known and anticipated archaeological resource to all stakeholder groups.

In many ways our work seeks to digest and simplify complex, often opaque (to the non-specialist) existing data into an easily comprehended overview. The concept of "Topsight" coined by Harvard computer scientist David Gelernter in his seminal 1992 book *Mirror Worlds or the Day Software Puts the Universe in a Shoebox...How It Will Happen and What It Will Mean* is particularly relevant here. In Gelernter's paradigm, Topsight in computer generated models of the complexity of the real world provides an understanding of the big picture coupled with the ability to rapidly test multiple hypotheses, and fail softly -- without a loss of face.

Although the project aimed to primarily model risk based on an inductive (data-driven) approach, it is inescapable that all work such as this contains at least a certain number of theoretical deductive assumptions based on the experience and knowledge of the project team. For example, it is considered 'general knowledge' in the profession that the typical form, function and distribution of archaeological sites will differ markedly between particular time periods or regions. This knowledge forms an unavoidable subjective decision-making framework for many of the models in question.

This theoretical framework has been made as explicit as possible in the accompanying report, in particular by documenting the scores assigned to model layers and the data driving the scoring (whether derived from spatial modelling, inductive analysis of data or user estimation) in order for users of the information to fully understand how and why particular weightings or decisions have been reached. It is fully acknowledged that such archaeological knowledge is to some extent subjective. However, it is also important to ensure that models can be adapted as knowledge of the archaeology of a particular area increases. In a final commercial sense this subjective decision-making is best conducted through detailed discussions with a specialist in the regional archaeology in question, especially in light of the increasing presence of large multi-regional contractual archaeological units working throughout the country.

AIMS and OBJECTIVES

3 AIMS AND OBJECTIVES

The overall aim of the research reported herein has been to devise a robust, repeatable methodology for quantifying the risk (and hence the potential economic consequences) of encountering cultural and environmental archaeological remains in aggregate bearing landscapes using case study areas from the Trent Valley. Such an overarching objective takes into account:

- An assessment of the known archaeological record and its preservation potential
- The potential for finding further unknown remains
- The potential for dealing with those remains within the framework of mitigation offered under PPG 16 (i.e. preservation *in situ* or preservation by excavation record).

In order to meet the aims of this project, a number of objectives were defined in the project design:

A. To review attitudes to risk and risk management in relation to cultural heritage within the aggregates industry in order to identify appropriate metrics for quantifying and describing risk.

B. To develop a set of robust algorithms that are based on both personal perceptions / attitudes and scientific data to quantify the archaeological risk at the level of individual land parcels. It is anticipated that the completed models will provide per parcel scores for:

    B1 The known and predicted archaeological potential of all land parcels.
    B2 The aggregate bearing potential and value of all land parcels.
    B3 The susceptibility of individual land parcels to yield archaeological information using a standard range of archaeological field evaluation techniques (aerial photography, field walking, test-pitting, trial trenching ground based geophysics)
    B4 The likely physical condition of buried cultural remains based upon physical and chemical ground conditions.
    B5 The risk of encountering buried waterlogged organic remains including palaeoecological deposits.
    B6 The level of impact that different forms of extraction may have on the archaeological record (e.g. dry or wet extraction)
    B7 Consideration of the importance of archaeology in the light of regional priorities as described in English Heritage sponsored regional research framework.
    B8 Consideration of the likely mitigation needs in the light of PPG 16 guidance and national and regional priorities (e.g. full excavation etc).

C. The validation of model results through feedback from stakeholders.

D. The dissemination of project results to the wider stakeholder and academic community.

These objectives, and any necessary modifications to them occasioned by the process of research, are briefly reviewed here.

3.1 OBJECTIVE A: DEFINING RISK METRICS

The nature of the risk associated with archaeological remains depends on the point of view from which one approaches those remains and will vary across stakeholder groups. Aggregate companies, or others engaged in the development and exploitation of the landscape, will often see the presence of archaeological remains as a risk of potential hindrance, delay and cost. Heritage professionals view risk associated with those same remains from a different perspective; risk is that associated with the incomplete understanding of the significance of remains, or the unexpected discovery of material for which no mitigation provision exists. Useful work on defining how different stakeholder perceive risk was accomplished by Walker and Challis (2004) and the present work will build on their dual perception of risk, broadly considering risk from the perspective of those engaged in development (to whom archaeology is generally perceived as a limiting factor) and heritage professionals (largely concerned with strategic resource management and resource allocation).

Within the bounds of this research, we have used informal discussion with stakeholder groups to define and develop a consensus for metrics to describe risk associated with encountering archaeological remains from the dual perspective of the aggregates industry and heritage professionals.

3.2 OBJECTIVE B: CONSTRUCTING RISK MODELS

3.2.1 B0: A GIS Framework for Assessing Risk

The mapping and modelling work undertaken as part of this project has been carried out within a common geographical information system (GIS) based framework, developed using ESRI's ArcGIS 9.3. The GIS model for the study areas was constructed using data from stakeholders, the Ordnance Survey (via Edina), the Trent Valley GeoArchaeology archive and other appropriate sources. Details of the data used in individual modelling task are provided in the relevant method statements.

3.2.2 B1. The predicted archaeological potential of all land parcels

Work has established scores for the cultural archaeological potential of all non built-up land parcels of greater than 1ha extent within the study areas defined on Ordnance Survey MasterMap digital mapping

3.2.3 B2. The aggregate bearing potential and value of all land parcels

Work has established scores for the aggregate bearing potential of all non-built up land parcels of greater than 1ha extent within the study areas defined on Ordnance Survey MasterMap digital mapping. The intention is to provide data on the mineral value of land parcels to both stand alongside and inform other risk measurement.

3.2.4 B3. The susceptibility of individual land parcels to field evaluation techniques

Work will seek to establish scores for the susceptibility of all non-built up land parcels of greater than 1ha extent within the study areas defined on Ordnance Survey MasterMap digital mapping to archaeological evaluation with a range of standard techniques. The intention is to provide stakeholders with rapid guidance on the suitability of different techniques in different landscape areas and additionally to assist in determination of a confidence factor for the modelling of land parcels presently devoid of known archaeological remains.

3.2.5 B4. The likely physical condition of buried cultural remains based upon physical and chemical ground conditions

Work has established scores for the likely physical condition of a range of buried archaeological materials in all non-built up land parcels of greater than 1ha extent within the study areas defined on Ordnance Survey MasterMap digital data.

The intention is to provide stakeholders with rapid guidance on the range of likely preservation environments across the landscape. This information will also be used to inform models of the impact of extraction, importance of archaeological remains and likely mitigation requirements.

In the event, rather than further duplicate modelling this project task was adapted from its original intention to provide a local interpretation of the modelling work of Ward et al (2009) presented within the data and landscape framework common for all project results.

3.2.6 B5. The risk of encountering buried waterlogged organic remains

Work has established models for the likelihood of encountering buried waterlogged organic remains in all non-built up land parcels greater than 1ha in extent within the study areas defined on Ordnance Survey MasterMap digital.

The intention is to provide stakeholders with rapid guidance on the range of likely preservation environments across the landscape. This information will also be used to inform models of the impact of extraction, importance of archaeological remains and likely mitigation requirements.

3.2.7 B6. The level of impact that different forms of extraction may have on the archaeological record

Work sought to establish the likely impact of differing forms of aggregate extraction on archaeological and palaeoenvironmental remains within the study areas. In the event, given the likely future focus on exclusively wet working or aggregate resources this project task was abandoned as unnecessary and is not further discussed.

3.2.8 B7. The importance of archaeology in the light of regional priorities

Work has established a model for the anticipated importance assigned to varying archaeological remains in the light of regional and national research agendas. The intention is to provide stakeholders with rapid guidance on the importance of results reported by other modelling stages, rather than necessarily to map archaeological importance at a landscape scale.

3.2.9 B8. Likely mitigation needs

Work has established models for the likely mitigation needs for varying archaeological areas at the resolution of individual MasterMap polygons of greater than 1ha in extent. The intention is to provide stakeholders with rapid guidance on a range of likely mitigation requirements, rather than to second guess the considered professional opinions of other professionals.

3.3 OBJECTIVE C: VALIDATION AND FEEDBACK

3.3.1 C1. Validation and Testing

Validation of predictive models traditionally follows the control sample concept favoured by English Heritage, whereby a proportion of the data being used is held back until a working model has been created and then introduced to provide a check on how accurate the model appears to be.

This approach, while applicable to deductive models based on statistical analysis of data, is problematic when applied to the inductive landscape modelling approach employed in the present research. The application of statistical test techniques to predictive models is at best problematic and at worse lends spurious credibility to the often tenuous framework of assumption and inference on which models are built. In the real world of archaeology and planning, models will work and gain credibility if they are able to mirror the knowledge-based assumptions made by planning archaeologists.

In the present research we have adopted an approach based on expert validation of model results. In essence this approach requires independent expert assessment of case studies, each equivalent in area to a typical planning application. Experts (from within the sphere of planning and contract archaeology) provided a summary of their expectations of the archaeological potential, significance and likely actions required in each case which were subsequently compared to model results both by the same experts and the project team. The experts also provided qualitative feedback on the models.

METHOD STATEMENTS

4 METHOD STATEMENTS

This section provides a discussion of the methods adopted for mapping and model building as part of the project.

4.1 B0: A GIS FRAMEWORK FOR ASSESSING RISK

4.1.1 GIS Choice

All mapping and modelling work took place within a common GIS framework developed using ESRI's ArcGIS 9.3. ArcGIS was chosen because of its familiarity to the project team, its use in earlier Vista projects, its compatibility with systems operated by HER involved in the project and its ability to provide output for use in standalone viewing software and/or via web-based mapping.

4.1.2 Building Spatial Models

The modelling work undertaken as part of the project was carried out using the raster data model and the spatial modelling and analysis tools provided by ArcGIS.

Raster based spatial modelling involved the conversion of most original input data from its native vector format to a raster equivalent (Table 1). Raster models were built at a standard resolution of 50m (ie the standard raster cell was 50x50m, so input vector data was degraded or amalgamated to form new raster data at this resolution; in this way each 500km2 study area comprise approximately 200k cells.

Data Source	Native Vector	Native Raster
OS MasterMap	x	
OS DTM		x
OS Historic Mapping		x
Corine Land cover	x	
Agricultural Land Classes	x	
NMP Mapping		x
NMR Amie	x	
HER	x	
SAM	x	
MLP Constraints	x	
Geology	x	
Soils	x	
Palaeochannels	x	
Thickness of Overburden		x
Thickness of Aggregate		x
Groundwater		x
Soil pH		x

Table 1. Matrix of data sources and native digital formats.

4.1.3 MasterMap: A Spatial Framework

The fundamental spatial framework for presentation of results from modelling was provided by Ordnance Survey MasterMap vector mapping.

Models were built to provide output data at the resolution of land parcels mapped by MasterMap as it is felt that this provides the most useful real-world spatial framework for querying underlying spatial models. MasterMap was chosen for this purpose as its Topography layer includes useful integrated information on landscape character and because each topographic polygon has a nationally unique identifying tag (TOID), an essential feature for building spatial models that work on the scale of real-world land parcels.

Thus, the output from raster models was devolved back to vector MasterMap data by generating neighbourhood statistical summaries of raster model values using the MasterMap topography layer as the template for neighbourhood polygons, thus each MasterMap TOID acquires one or more new attributes as a result of each modelling process.

One significant advantage of this method is that output data from models can be provided to end-users as ASCII text tables of TOID and attribute groupings, to be reconstructed into MasterMap attributes in their own systems, thus avoiding the need to negotiate the supply of polygons based on Ordnance Survey data to end users.

4.1.4 Documenting Modelling Algorithms

The algorithms behind each model are documented using standard process model diagrams and accompanied by tables of model input weights so that assumptions made in each model and their impact on the modelling process are transparent and open to later critique.

4.1.5 Quantifying Risk

Perhaps the most significant challenge faced by the project was the uniform quantification of risk. Models based on statistical analysis are able to provide indices of confidence derived from the statistical tests used. In general such statistical referencing is not likely to be available using the methods proposed herein. Rather we have adopted assigning calculated risk to a series of pre-defined classes, via a number of metrics (Table 2) able to cope with statistical definitions of likelihood, qualitative value judgement and ordinal status and translated to maps via a simple numerical score, for example to control a colour ramp in a colour shaded map.

Numerical Score (for mapping)	**Risk Category**	**Frequency**	**Free Text Explanation**
5	Very High Risk	> 95%	A factor is known to exist in the land parcel in question (eg parcel encompasses a SAM)
4	High Risk	More than 75% (upper quartile)	A factor is more than 75% likely to occur in the land parcel in question
3	Medium Risk	25-75%	A factor is between 25 and 75% likely to occur in the land parcel in question
2	Low Risk	less than 25% (lower quartile)	A factor is less than 25% likely to occur in the land parcel in question
1	Very Low or Unknown Risk	< 5%	Insufficient information to judge

Table 2. Matrix of risk values and meanings.

4.2 METHOD STATEMENTS FOR INDIVIDUAL MODELS

The sections below provide individual method statements for the various modelling tasks undertaken. Since it would be both tedious and repetitious to describe each modelling task in full, the stages involved in the generation of the models of archaeological potential are discussed in detail as a guide to the processes adopted throughout. This method statement is amplified for subsequent tasks only where it varies.

4.3 B1. THE PREDICTED ARCHAEOLOGICAL POTENTIAL OF ALL LAND PARCELS

Models constructed in this project stage are intended to provide continuous coverage scoring the archaeological potential of all non built-up land parcels.

4.3.1 Source Data

Data for this model was provided from the following sources:

- Historic Environment Records
    - County Sites and Monuments Record
    - English Heritage AMIE Database
- Geological Survey Mapping
- OS Panorama Topographic Mapping
- TVG Palaeochannel Mapping

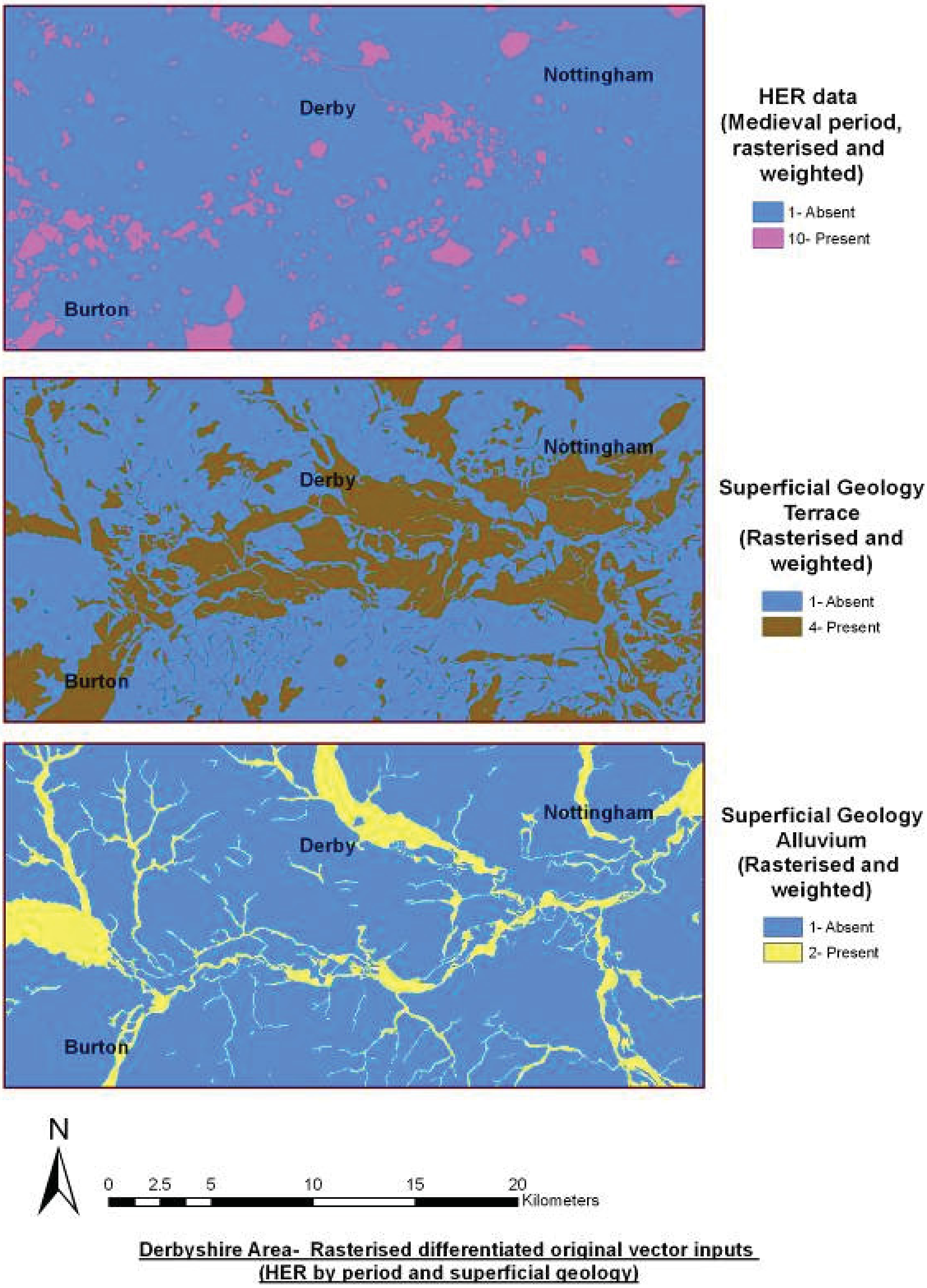


Figure 5. Examples of rasterised versions of original vector data.

HER data required considerable "cleaning" to provide suitable model input. Since in general models were concerned with period based classification, rather than other attributes,County and National HER data were merged to form a single database and a matrix of fields indicating period classifications was appended to this new database. The period matrix allowed the entry of binary (yes/no) values against each period field in the new database, thus a single record could have multiple period entries, accommodating multi-period sites.

Data of different types (point/polygon) were merged by converting all data types to polygons; points were converted to polygons by creating an arbitrary buffer of 30m diameter (in order to ensure feature visibility following conversion to raster format) and assigning the point attributes to each new buffer polygon.

It was decided not to attempt to model type or intensity of activity, since the information provided in the HER was considered insufficiently comprehensive or reliable to determine this with certainty. In addition it was recognised that an HER record of a simple find spot could (on field investigation) resolve itself into anything from an insignificant maturing scatter of material to a complex nationally important site. HER in general do not provide the data to determine such transformations and therefore to attempt to model them from such data is unreliable.

It should be noted that some cases of duplication of HER records, or multiple records with precisely the same information, location and spatial extents, but different ID numbers were observed within the data. Where observed (and clearly representing duplicate entries) such data was removed, however significant ambiguity in whether records were distinct was present and a comprehensive data sorting procedure and contacting providers to attempt to rectify such issues was beyond the remit of the project and would have required a prohibitive timescale. Differences in classification of archaeological periods and in the manner in which sites were assigned a period was also observed within base data from different HER's, and whilst attempts have been made to produce a standardised base dataset to work from, there does remain the potential for some misclassification (for example in one case a Roman road record was classified as prehistoric, with potential, because of how the models are generated, for this to erroneously alter local predictions relating to prehistoric materials). It should be noted that the *models produced can only be considered as reliable as their base data*, and where issues such as duplication and differential classification across providers are present this has the potential to impact upon model predictions erroneously in any given location. Should such large-scale cross-HER boundary modelling be frequently desired in the future, then regional or national standardisation and integration may be beneficial.

Geological mapping data were divided by drift geology classification (the Lex Rock field of BGS data) in essence creating a classification separating floodplain alluvium from terrace, which was further subdivided into in situ Pleistocene terrace and that material reworked in the Holocene (the so-called Hemington Sand and Gravels in the Trent).

Ordnance Survey topography was divided into a simple binary classification of low-lying valley bottom areas and all other areas (both terrace and non-terrace) based upon natural statistical breaks (jenks) within the data for each area.

TVG palaeochannel mapping was undifferentiated, since the source data contain no classification by period, but was rather used to indicate areas potentially with river frontage in any period and weighted appropriately.

4.3.2 Raster creation

All vector source data were converted to raster format, with a 50m cell size, using the convert to raster option in ArcGIS 9.3. Vector data were separated into their constituent elements before conversion, thus HER data was divided by period, geology and soil mapping by type, etc.

In recognition of the relatively limited capacity of HER data to distinguish records by period we have restricted ourselves to a relatively simple classification distinguishing Palaeolithic, Mesolithic, Neolithic, Bronze Age, Iron Age, Prehistoric (where HER's used this classification for material of uncertain prehistoric date), Roman, Medieval, Post-Medieval and Modern (20th century) only. As discussed above, the periods assigned in the original HER data have been taken at face value, no attempt has been made validate, cross-check or correct HER data, which process was beyond the scope of our research.

Where small vector entities were missed by the conversion algorithm (an apparently inexplicable feature of ArcGIS is that some small vector features appear to be randomly excluded from conversion to raster data of any granularity) the source features were assigned vector buffers (to which attributes were transferred) to ensure that they were of sufficient dimension not to evade conversion.

4.3.3 Assigning Raster Weights

The resulting raster data was assigned weights on an integer scale between 1 (low) and 10(high) based on a range of factors, an example of which is discussed below and tabulated in table 3.

The per-period HER raster data were assigned weights based on presence (10) or absence (1) of a recorded site in each cell. Since it was recognised that single cells in the raster model could contain more than one recorded site of each period a further graduated presence by period raster was developed to reflect this. A spatial query was used to determine the number of intersecting HER records of each period within each 50m raster cell. A new raster layer was created holding these gradiated presence values, which were assigned appropriate weight (cf table 3)

Cells in the geology mapping raster were assigned values by calculating the proportion of total sites of each period that fell within each geology class and assigning weights appropriately.

Cells in the palaeochannel raster were assigned a value depending on whether they were within a channel (low score for most periods; elevated score for Bronze Age to account for well-documented ritual deposition within channels of the Trent), proximal (within 100m) to a channel (elevated score as evidence suggest that river channels served as a focus for activity in most period) or distant from a channel (neutral score).

Cells in the topography raster were assigned a value based on the binary elevation classification, with higher ground being considered as marginally more likely to harbour remains of all periods.

Finally, in an attempt to model a very limited degree of spatial autocorrelation (it remains our assertion that one is likely to encounter material adjacent to known remains since the boundaries of a site are rarely clearly determined by the HER) an Euclidean distance raster was created for each period based layer, with a marginally elevated weight assigned to cells proximal (within the closest region defined by a ten-class equal interval classification) of a known site and a neutral value to all other cells. In effect this attempts to model fuzzy edges to sites.

An example of the weights employed in one modelling stage are shown in table 3; full tabulated details of the weights employed for all models of all periods are provided in Appendix 1.

4.3.4 Weighted Raster Models

Once weights were assigned, raster models were generated by a simple arithmetical process. For each cell within the overall raster model the sum value of all weights derived from each raster layer was calculated and assigned to a new raster layer.

These sum weights were then reclassified to a simple five point scale (1=low 5=high) by examining the statistical properties of the entire dataset and dividing the sum scores into quartile ranges. Very high values (above the 95th percentile) scored 5 and very low values below the 5th percentile) scored 1, the lower quartile scored 2 and the upper quartile 3 and the middle quartiles (between 25 and 75%) 3. This process of reclassification was adopted for all raster models as it provides a uniform qualitative assessment of the model results which is dependant on the actual sum scores, but presents them on a comparable range from low to high risk/potential.

Iron Age

Dataset	Potential classes	Weights
Period Differentiated Presence (for each period)	Presence Absence/no data	10 1
Gradiated Presence by period IA- TEST MODEL	1 feature 2 features 3 features 5 features 10 features 12 features 15 features no data/absence of features	2 3 4 5 7 8 9 1
Terrace 58/95 features on terrace	no data/absence of features Presence	1 7
Alluvium 17/95 on alluvium	no data/absence of features Presence	1 2
Topography	Valley- Ie lowest ground for Gains Upland- ie slightly higher ground for Gains	2 5
Euclidean Distance	Currently classified by distance In 10 classes- class 1-9 (distant) class 10-proximal	1 2
Palaeochannels	Channel Proximal (within 100m) to channel no data/absence of features	2 5 1

Table 3. Example of archaeological presence model weights for the Iron Age in Derbyshire

4.3.5 Deriving Scores to OS TOIDS

The reclassified raster data were used to derive scores for each Ordnance Survey MasterMap land parcel classified as non-urban and above 1ha in extent. This qualification was required to render the use of MasterMap computationally feasible and is rationalised by the recognition that urban (or built up) land parcels are not likely to be considered candidates for aggregate extraction and the vast majority or rural land parcels (with the exception of gardens adjoining properties) are more than 1ha in extent.

Land parcels were assigned scores using the ArcGIS Neighbourhood Statistics function. This process derives a statistically determined value for each vector land parcel by determining the arithmetic mean of all values of all raster cells falling within the vector feature. Output is in the form of a table comprising a unique ID for each vector entity (the OS TOID), and statistics (minimum, maximum, mean and standard deviation).

Clearly a single land parcel, particularly a large one, may take in a significant number of cells from the original raster data, which may display a considerable range of values (conceivably including both very high and very low values). For this reason the vector results often appear somewhat at odds with the original raster data. We have argued that since consideration of risk within the planning process tends to be at the per land parcel basis this simplification of results is justified and in general our mapping of vector values has employed the mean value, suitably reclassified to a five point scale using the same metrics as employed on the original raster data. However, in an attempt to visualise the variation within source raster data within a single land parcel the standard deviation may also be mapped as it provides a convenient index of that variation.

Full results of this modelling stage are reviewed in section 5.1.

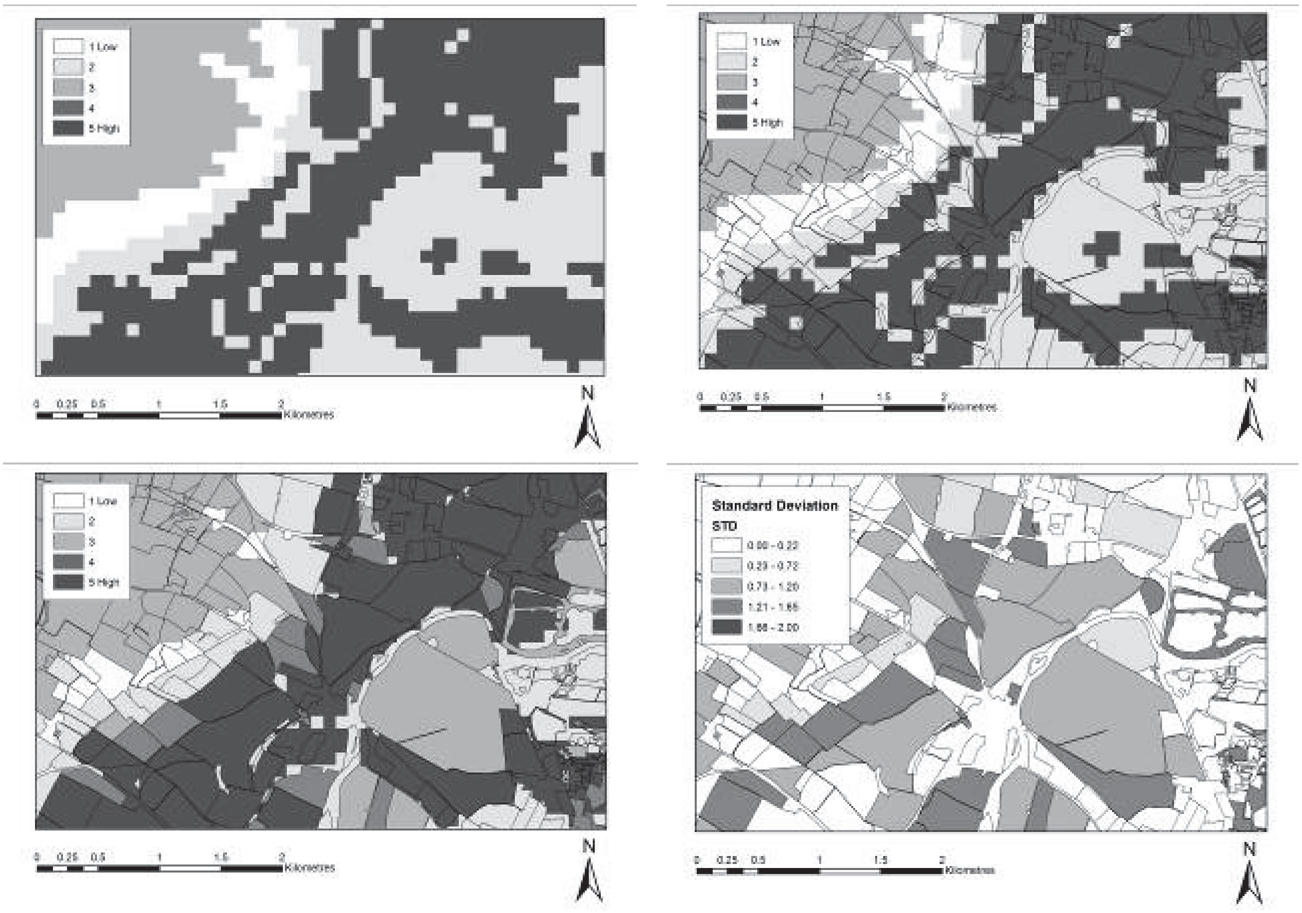


Figure 6. Examples of model output in various guises, showing (top left) raster model output (top right) raster with MasterMap overlay (bottom left) model scores propagated to MasterMap using zonal statistics (bottom right) standard deviation by toid.

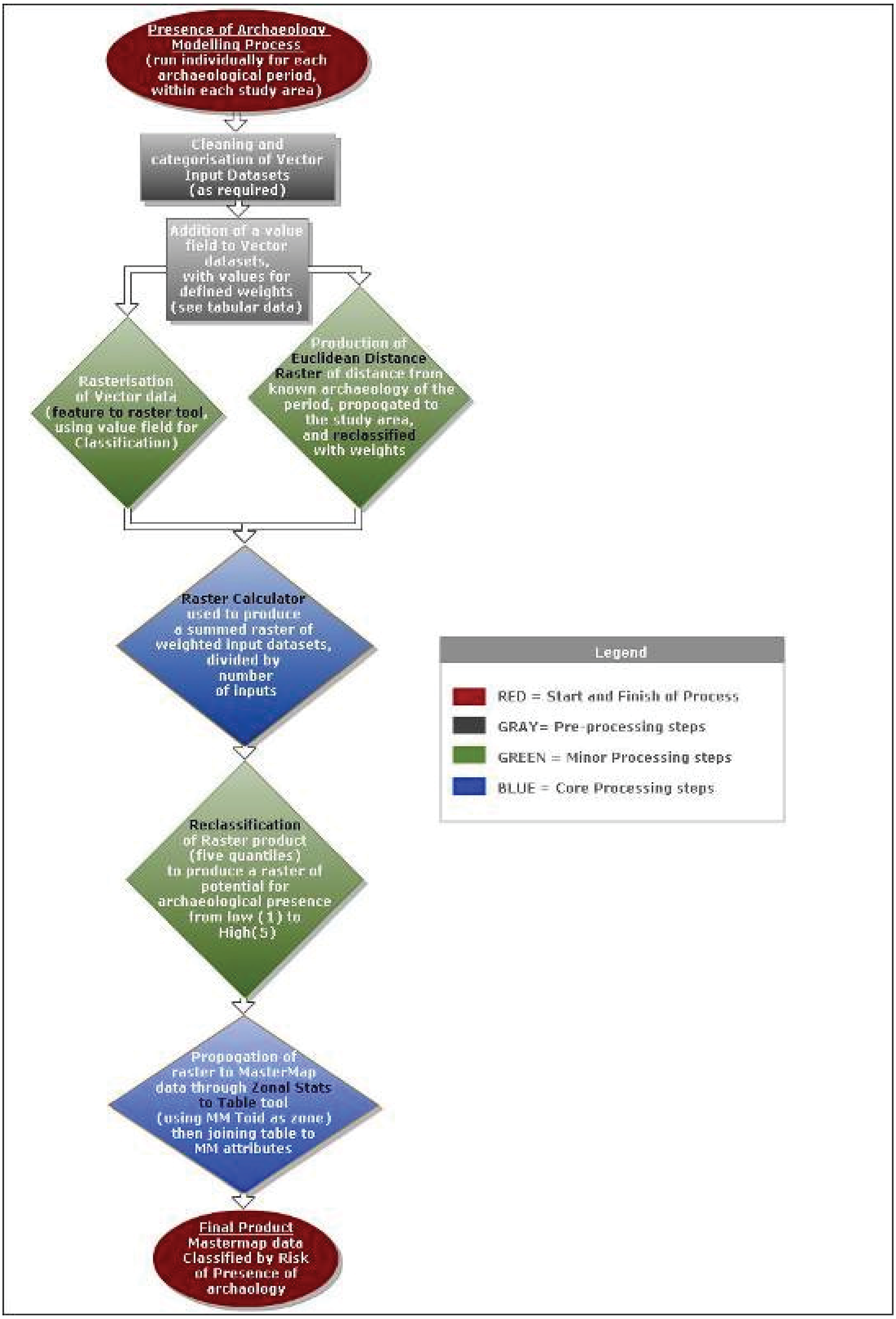


Figure 7. Process model illustrating the steps comprising an single archaeological presence model.

4.4 B2. THE AGGREGATE BEARING POTENTIAL AND VALUE OF ALL LAND PARCELS

Models constructed in this project stage provide continuous coverage scoring the aggregate bearing potential of all non built-up land parcels. Models were derived from appropriately weighted raster datasets derived from analysis of four key landscape characteristics:

- Geology
- Thickness of overburden (derived from modelling of borehole data)
- Thickness of aggregate (derived from modelling borehole data)
- Groundwater

Source data were rasterised and weights assigned using the method described in section 4.3. Individual class weights are set out in table 4, and are based on empirical judgement of appropriate weighting.

A thickness of aggregate layer was derived from the gravel thickness field of the TVG borehole database, interpolated to a continuous raster of 50m cell size using a kriging interpolation function. Separate rasters were created for thickness of terrace aggregate and thickness of aggregate beneath alluvium, which were subsequently merged to a single raster layer representing overall aggregate thickness. These data were reclassified to 5 classes before assigning appropriate weights with non aggregate areas being assigned a nodata value.

A thickness of overburden raster was created from the alluvium thickness field of the TVG borehole database, again interpolated to continuous raster with a 50m cell size using a kriging interpolator. These data were reclassified to 5 classes before assigning appropriate weights, with non alluvial areas being assigned a nodata value.

Depth to groundwater was interpolated from the mean depth below ground level observations in the British Geological Survey grounwater data. A grid of 50m cell size was created using a kriging interpolator and the resulting data reclassified to 3 classes and weighed appropriately, with the assumption that higher groundwater levels reduce aggregate value by increasing the economic cost of recovery.

Dataset	**Potential Classes**	**Weight**
Geology	Solid Geology Terrace Alluvium	No Data 10 2
Thickness of Aggregate	5m+ 4m 3m 2m 1m	10 7 5 3 1
Thickness of Overburden	1m 2m 5m+	1 3 5
Depth to Groundwater	3m+ 2m 1m	5 3 1

Table 4. Model weights for aggregate bearing potential

The sum raster model was reclassified to five classes using the method described in section 4.3 and the raster scored propagated to MaterMap Toids for examination. A selection of the results of this modelling stage are reviewed in section 5.2

4.5 B3. THE SUSCEPTIBILITY OF INDIVIDUAL LAND PARCELS TO FIELD EVALUATION TECHNIQUES

Models constructed in this project stage provide continuous coverage indicating the predicted susceptibility of land parcels to a variety of field evaluation. Modelling takes account of a variety of environmental factors including:

- Soils
- Geology
- Land cover

Source data were rasterised using the methodology described in section 4.3. CORINE landcover data (sourced from the European Environment Agency) were subdivided into six simple classes, based on landcover properties considered most likely to have an impact of archaeological investigation.

Similarly, soil and geology data were subdivided and classified based on properties likely to affect archaeological work.

An example of the weights employed in one modelling stage are shown in table 5; full tabulated details of the weights employed for all models are provided in Appendix 2.

Ground Penetrating Radar (GPR) Survey

Dataset	Potential classes	Weight
CORINE Land Cover	Built-up	2
	Arable	5
	Pastoral	5
	Woodland	2
	Mineral	2
	Other	5
Soilscape (texture)	Clayey	1
	Loamy	5
	Sandy	5
Terrace	present	4
	absent	1

Table 5. Example of model weights for GPR survey.

The sum raster model was reclassified to five classes using the method described in section 4.3 and the raster scores propagated to MasterMap Toids for examination. A selection of the results of this modelling stage are reviewed in section 5.3

4.6 B4. THE LIKELY PHYSICAL CONDITION OF BURIED CULTURAL REMAINS BASED UPON PHYSICAL AND CHEMICAL GROUND CONDITIONS

Models constructed in this project stage are intended to provide continuous coverage indicating the predicted physical condition of a variety of *in situ* buried cultural materials for all non built-up land parcels.

The original project design envisaged modelling a variety of preservation scenarios based on the available source data and weights determined by examination of published literature. In the event the work of Ward et al (2009) rendered this project stage all but unnecessary. Since the results of the modelling undertaken by Ward were provided by National Soil Resources Institute as an added data table accompanying the soilscape digital soils mapping for the study areas it was considered inappropriate to attempt to duplicate this work, particularly given the limited resources and expertise available to the project team, in comparison to that of Ward's study.

Instead, the model results determined by Ward (which provide a three-point aggregated score for likely physical condition of a range of archaeological material for each soil survey polygon, were raterised using the method described in section 4.3 and the raster scores propagated to MasterMap Toids for examination. A selection of the results of this modelling stage is reviewed in section 5.4. In particular we make comparison between Ward's predicted preservation of organic materials and our own, separately undertaken, models.

4.7 B5. THE RISK OF ENCOUNTERING BURIED WATERLOGGED ORGANIC REMAINS

Models constructed in this project stage provide continuous coverage indicating the predicted risk of encountering buried waterlogged organic remains in all non built-up land parcels. Models were built using a variety of environmental variables, including:

- Geology
- Palaeochannels
- Known organic deposits (from borehole records)
- Groundwater (Soil Wetness)

Source data were rasterised using the methodology described in section 4.3. Geology mapping was classified into a simple division between terrace (low potential) and alluvium (high potential). Soil wetness was derived from the drainage field of the soilscape NATMAP soil mapping data classified to distinguish wet, impeded and dry soils. The presence of known organic remains was determined by extracting records of organic sediments from the TVG borehole database, TVG palaeochannel data was used without further classification on the basis that all palaeochannels provide an increased likelihood of encountering waterlogged and anaerobic conditions.

Dataset	**Potential Classes**	**Weight**
Geology	Terrace Alluvium	3 9
Soil Wetness	Dry Impeded Wet	2 5 10
Known Organic Remains	Present Absent	10 1
Paleochannels	Present Absent	9 1

Table 6. Model weights for potential for waterlogged organic remains.

The sum raster model was reclassified to five classes using the method described in section 4.3 and the raster scores propagated to MaterMap Toids for examination. A selection of the results of this modelling stage are reviewed in section 5.5

4.8 B7. THE IMPORTANCE OF ARCHAEOLOGY IN THE LIGHT OF REGIONAL PRIORITIES

Models constructed in this project stage provide continuous coverage indicating the predicted importance of archaeological remains in the light of regional and national research priorities for all non built-up land parcels. Models were built using a variety of previously modelled variables, including:

- Archaeological Period

- Archaeological Importance [principally whether granted statutory protection]
- Archaeological Rarity [determined from statistical analysis of HER]
- Palaeoenvironmental Potential
- Physical Condition of Buried Remains

Source data were rasterised using the methodology described in section 4.3.

Dataset	**Potential Classes**	**Weight**
Archaeological Importance	World Heritage Scheduled Ancient Monument Other HER	10 10 5
Archaeological Rarity	Range	10-1
Predicted Organic Preservation	Range	5-1
Predicted Physical Condition of Materials	Range	3-1

Table 7. Model weights for regional archaeological importance.

The sum raster model was reclassified to five classes using the method described in section 4.3 and the raster scores propagated to MasterMap Toids for examination. A selection of the results of this modelling stage are reviewed in section 5.6

4.9 B8. LIKELY MITIGATION NEEDS

Models constructed in this project stage provide continuous coverage indicating the likely mitigation requirements for archaeological remains in all non built-up land parcels. Models were built using a variety of previously modelled variables, including:

- Archaeological Importance [principally whether granted statutory protection]
- Regional Importance

Source data were rasterised using the methodology described in section 4.3.

Dataset	**Potential Classes**	**Weight**
Archaeological Importance Model	Per period	Range from 1-5
Scheduled Ancient Monuments	Presence Absence	5 1

Table 8. Model weights for likely mitigation needs.

The sum raster model was reclassified to five classes using the method described in section 4.3 and the raster scores propagated to MasterMap Toids for examination. A selection of the results of this modelling stage are reviewed in section 5.7.

4.10 VALIDATION AND TESTING

Testing and validation of the models was based on a combination of basic visual error checking by the project team, coupled with expert validation of model results.

4.10.1 Error Checking

Visual error checking comprised the careful scrutiny of model results for anomalies and the examination of these results in the light of what was anticipated. Potential problems this identified were investigated by examining the integrity of source data, derived data at each modelling stage and the weights applied to each data layer in the final model. In several cases this process lead to the modification of models to remove inappropriate or redundant data or to modify the modelling process (for example it quickly became clear that use of Euclidian distance to simulate fuzzy edges to known sites was not wholly successful and the influence of the distance raster in the final model was modified by changing its weighting factor.

An attempt at more quantitative checking of modelling results was made for a selection of archaeology models from each of the three study areas. In each area Iron Age, Roman and Medieval models were recalculated after removing a randomly selected 10% sample of the original source HER data.

The models thus generated were compared both with the correctly computed models and with the full source data to assess the robustness of the modelling approach.

The results of this work will be discussed more fully in the full final report.

4.10.2 External Validation

A number of experts from within the sphere of planning and contract archaeology have independently assessed single case studies. The experts provided a summary of their expectations of the archaeological potential, significance and likely actions required in each case study using a pro-forma answer sheet.

In each instance the assessors' results were compared to modelled predictions both by the same experts and the project team. A series of scoring metrics assessed how well model and expert match.

The results of this work will be discussed more fully in the full final report.

RESULTS

5 RESULTS

5.1 INTRODUCTION

Results for the seven modelling task undertaken are provided in the following section. The report includes full output for each archaeological period and locale for the presence of archaeology models (section 5.22) as this is considered key to assessing the project outcomes.

For other models a representative selection of outputs, usually for a single study area, are provided and stand for the whole. Since the intention of this work is to act as a proof of concept and an experiment in methodological development it was not felt necessary to include full results for the non archaeology models, which comprise aggregate bearing potential (section 5.3), susceptibility to field evaluation (section 5.4), preservation of anthropogenic archaeological material (section 5.5), presence of organic/waterlogged deposits (section 5.6), importance of remains (section 5.7) and mitigation needs (section 5.8).

Presentation of results focuses on the final raster models rather than data propagated to MasterMap Toids as this approach provides a higher resolution view of the results of modelling without the generalising effect of the generation of zonal statistics by Toid.

In several cases we have included examples of both the raster data and the data propagated to Toid using zonal statistics in order to illustrate this process.

In all instances results are presented atlas style, with minimal accompanying text. Where it is appropriate a more comprehensive commentary on individual model results will be provided in the full final report.

5.2 PRESENCE OF ARCHAEOLOGY

5.2.1 Study area 1: Middle Trent Valley Around Derby (Figs. 8-12)

The models highlight the essentially geologically determined bias of the chosen approach, with the presence of mapped river terrace in particular acting to elevate archaeological potential in all periods. The spatial autocorrelation function appears rather overrepresented in several of the models, producing islands of elevated potential rather than the fuzzy edges to known sites anticipated.

The overall patterns that appear to emerge from the modelling reflect received wisdom about changes in activity foci between different period, for example a change in focus away from the valley bottom and terraces in the Anglo-Saxon period.

Further close examination of the modelled results is required to determine the usefulness of these models *in toto*.

5.2.2 Study Area 2: Middle Trent Valley Around Newark on Trent (Figs. 13-17)

Once again drift geology appears to play a significant role in determining modelled archaeological potential in each period. In particular the elevated potential of island sof terrace within the floodplain is closely modelled (and to a large extent reflect the received view).

There are clear distinctions in potential of the same geological unit from period to period, which seems to suggest that the models are able to distinguish variations in the spatial component of settlement and activity choice over time.

The spatial autocorrelation function is again over represented, particularly in the chronologically early models.

5.2.3 Study area 3: Lower Trent Valley Around Gainsborough (Figs. 18-22)

The essentially geologically determined nature of modelled potential is again clear in the final models for this area. Large expenses of geologhicaly homogeneous (at lease as far as mapping goes) alluvium in the lower Trent highlight variations in potential introduced by other factors, such as the presence of known sites, for example particularly in the Bronze Age (Figure 20).

Again, there is variation in modelled potential for the same geographical unit from period to period, which suggests a degree of success in representing landscape change over time.

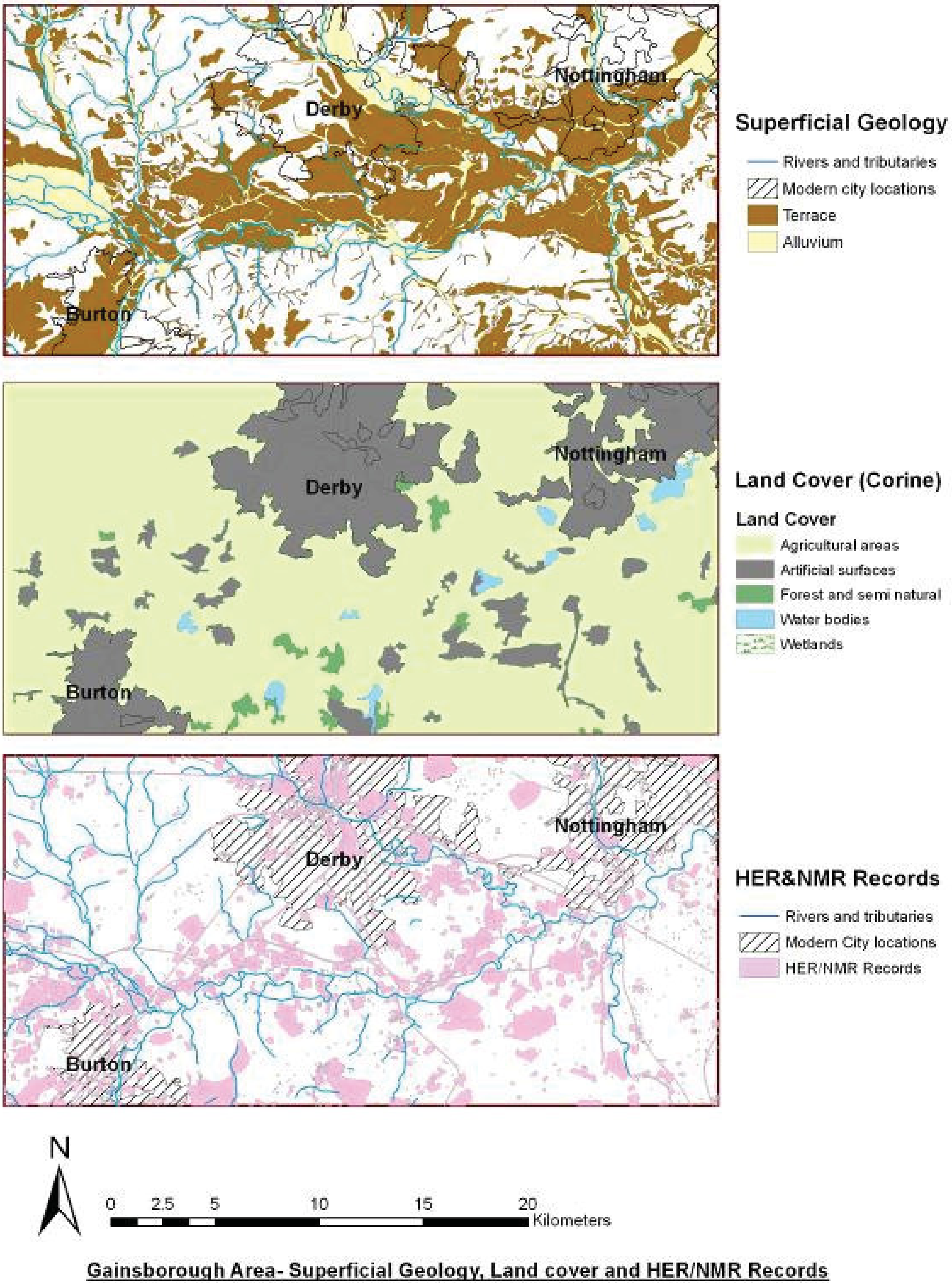


Figure 8. The Middle Trent in Derbyshire from the Dove to the Derwent showing (top) superficial geology, (middle) landcover, (Bottom) HER records.

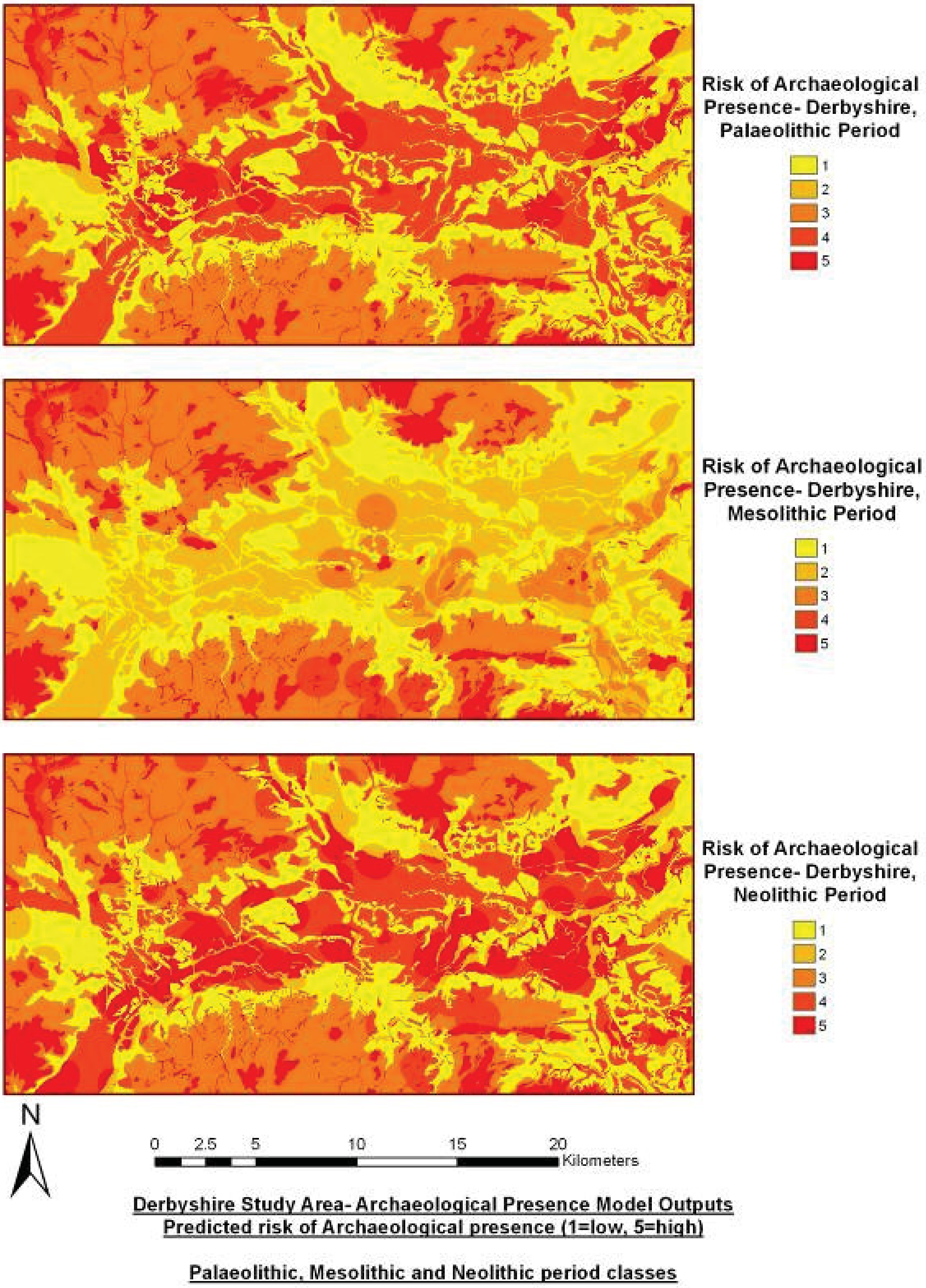


Figure 9. The Middle Trent in Derbyshire from the Dove to the Derwent showing (top) Palaeolithic, (middle) Mesolithic, (Bottom) Neolithic model results.

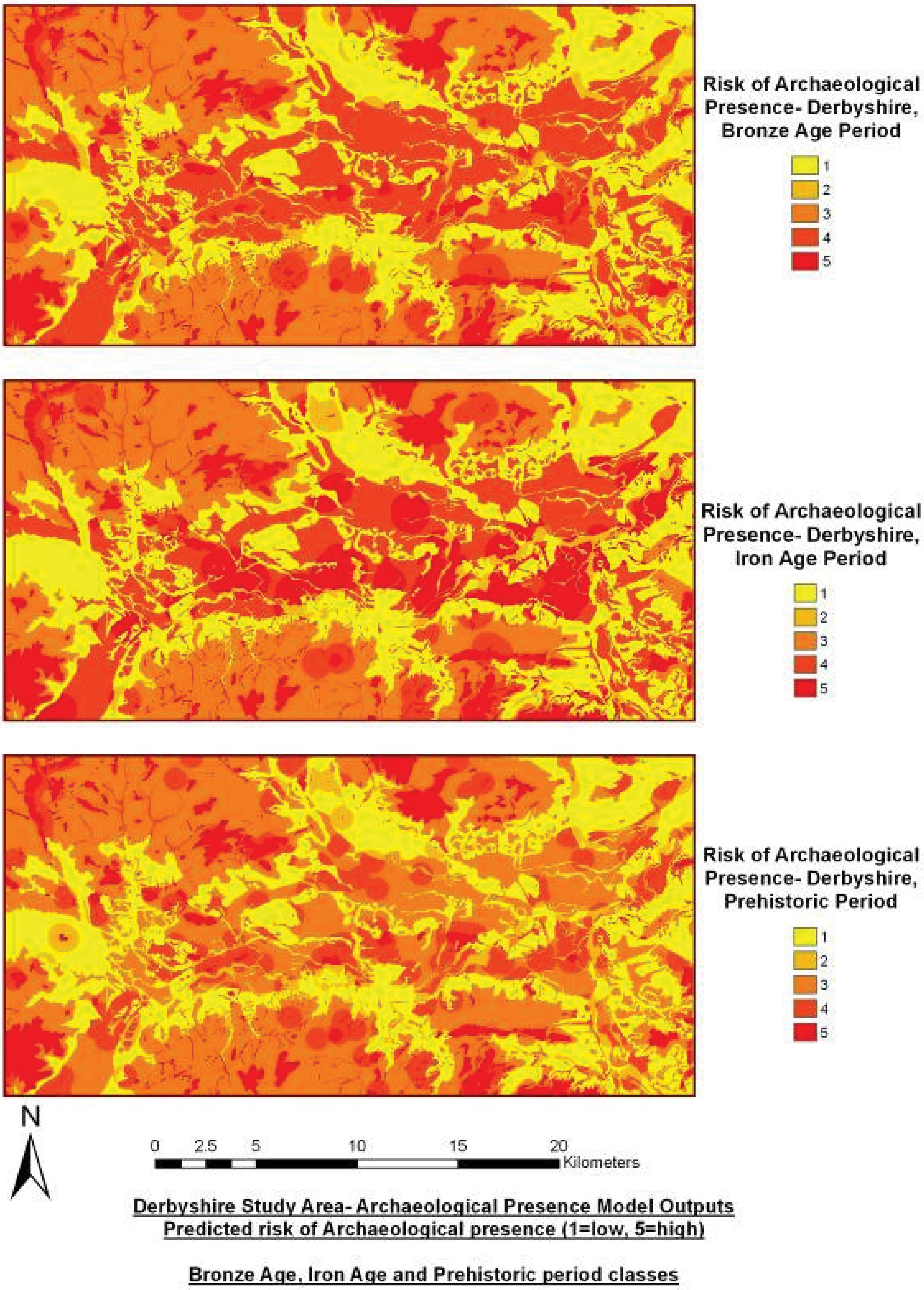


Figure 10. The Middle Trent in Derbyshire from the Dove to the Derwent showing (top) Bronze Age, (middle) Iron Age, (Bottom) general prehistoric model results.

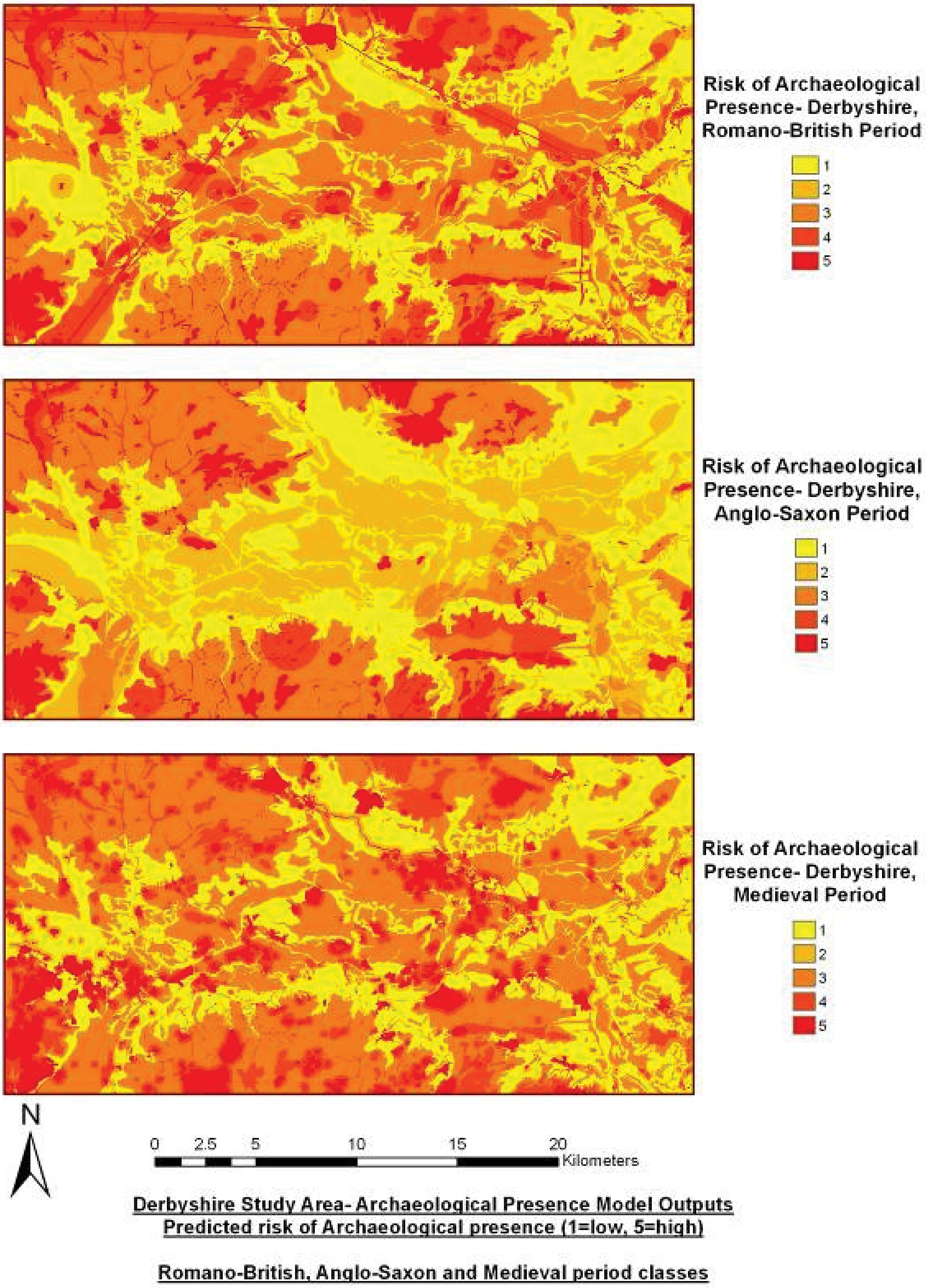
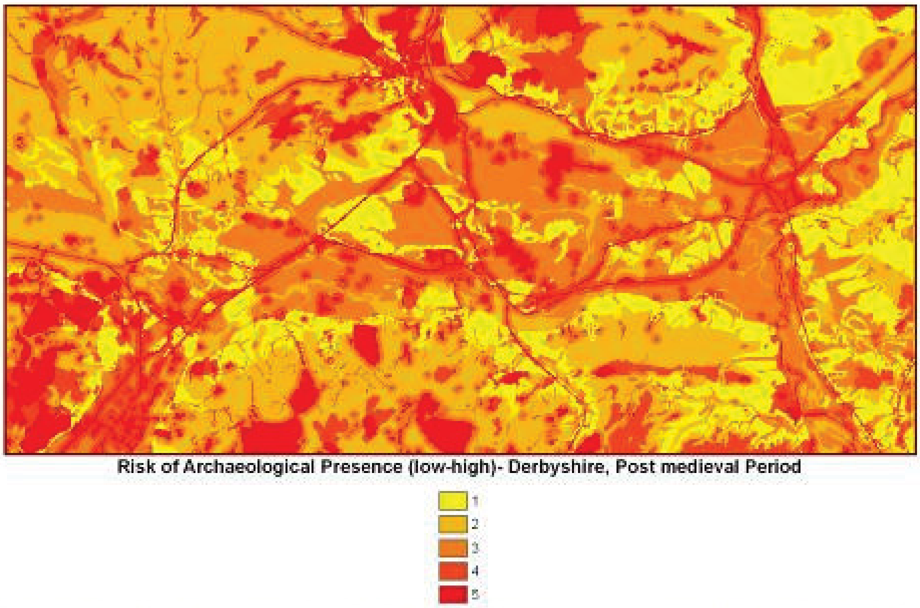
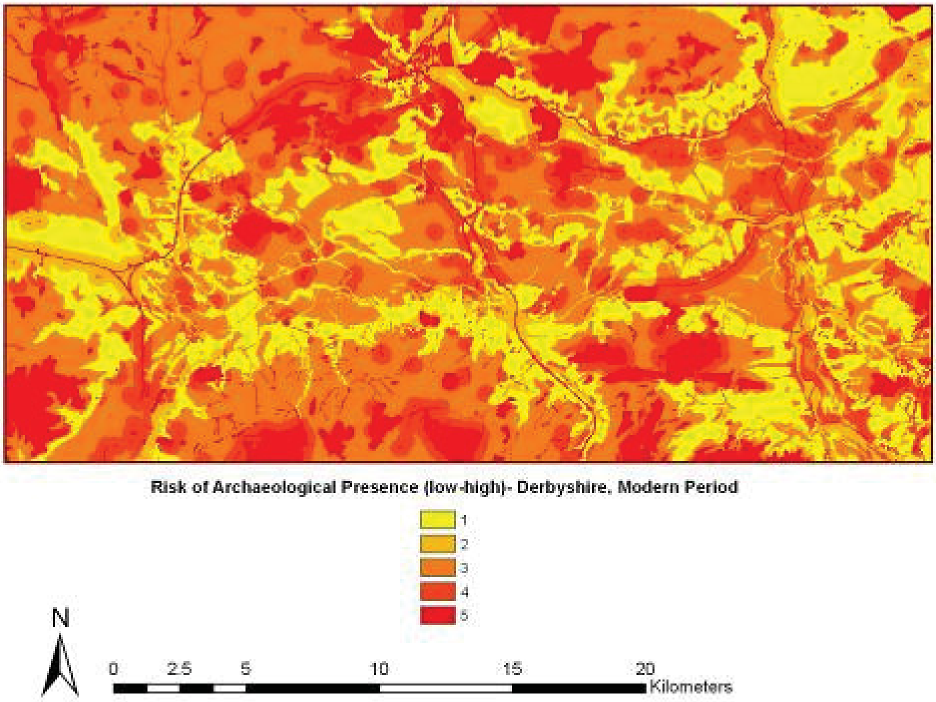


Figure 11. The Middle Trent in Derbyshire from the Dove to the Derwent showing (top) Romano-British, (middle) Anglo-Saxon, (Bottom) Medieval model results.


Risk of Archaeological Presence (low-high)- Derbyshire, Post medieval Period


Risk of Archaeological Presence (low-high)- Derbyshire, Modern Period

Derbyshire Study Area- Archaeological Presence Model Outputs
Romano-British, Anglo-saxon & Medieval period classes

Figure 12. The Middle Trent in Derbyshire from the Dove to the Derwent showing (top) Post-Medieval, (Bottom) Modern model results.

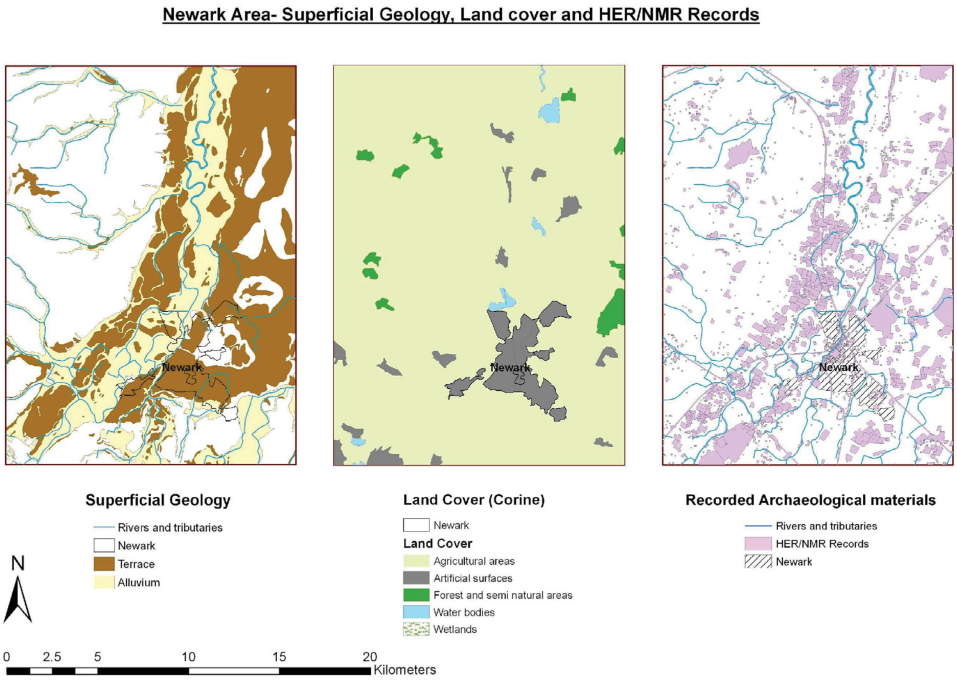


Figure 13. The Lower Trent in Nottinghamshire between Newark and Girrton showing (left) superficial geology, (middle) landcover, (right) HER records.

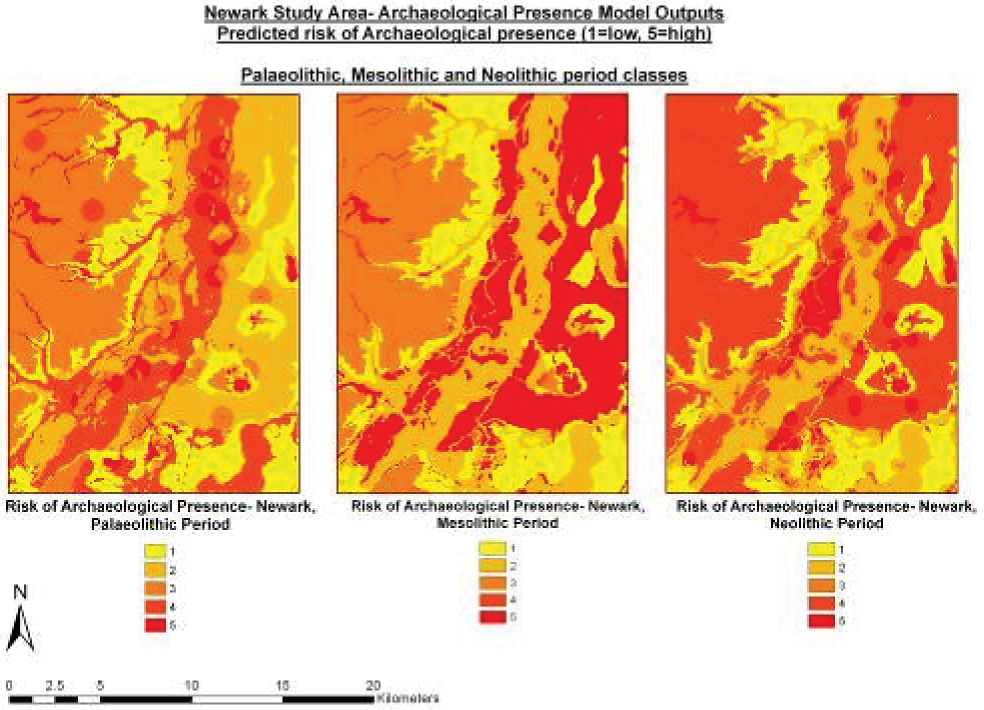


Figure 14. The Lower Trent in Nottinghamshire between Newark and Girrton showing (left) Palaeolithic, (middle) Mesolithic, (right) Neolithic model results.

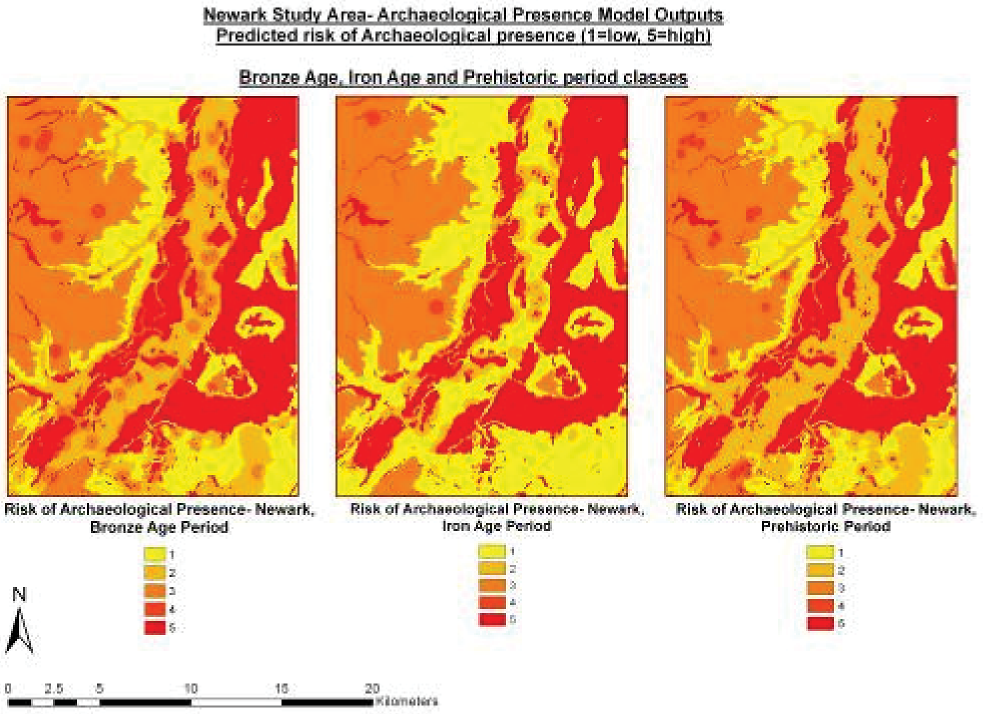


Figure 15. The Lower Trent in Nottinghamshire between Newark and Girrton showing (left) Bronze Age, (middle) Iron Age, (right) general prehistoric model results.

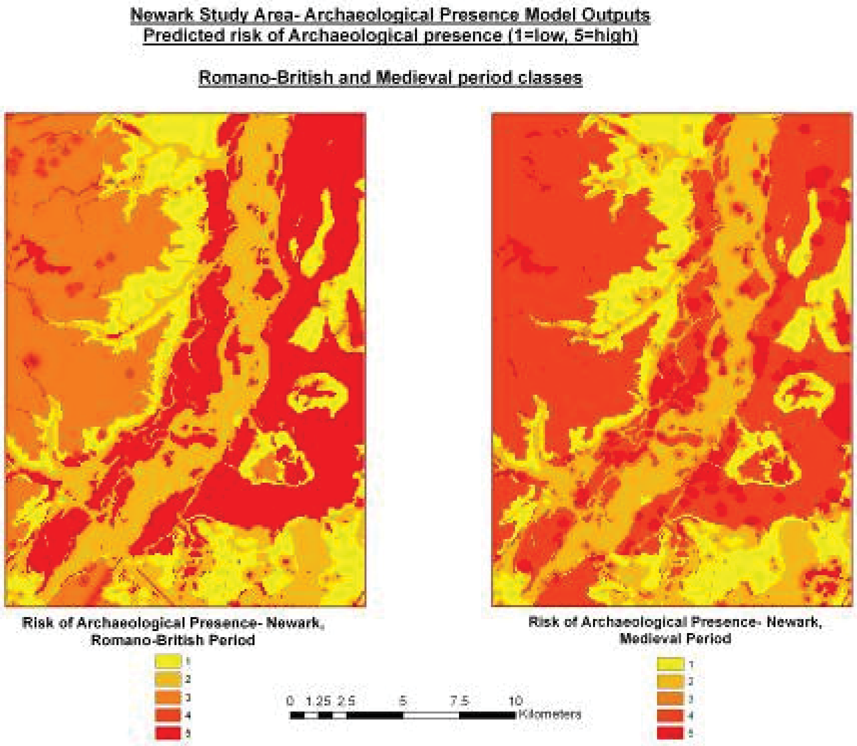


Figure 16. The Lower Trent in Nottinghamshire between Newark and Girrton showing (left) Romano-British, (right) Medieval model results.

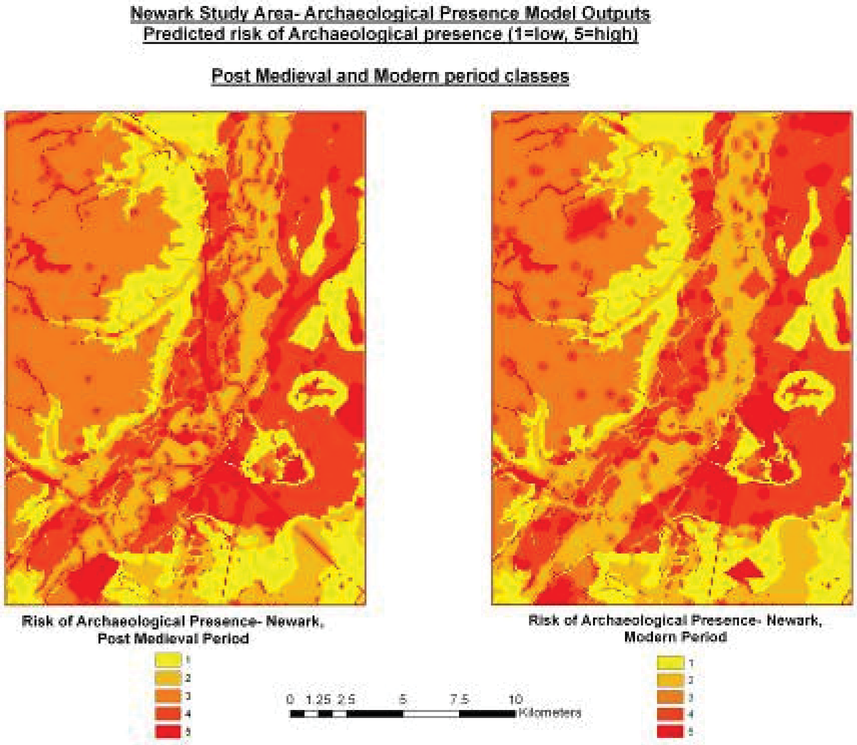


Figure 17. The Lower Trent in Nottinghamshire between Newark and Girrton showing (left) Post-Medieval and (right) Modern era model results.

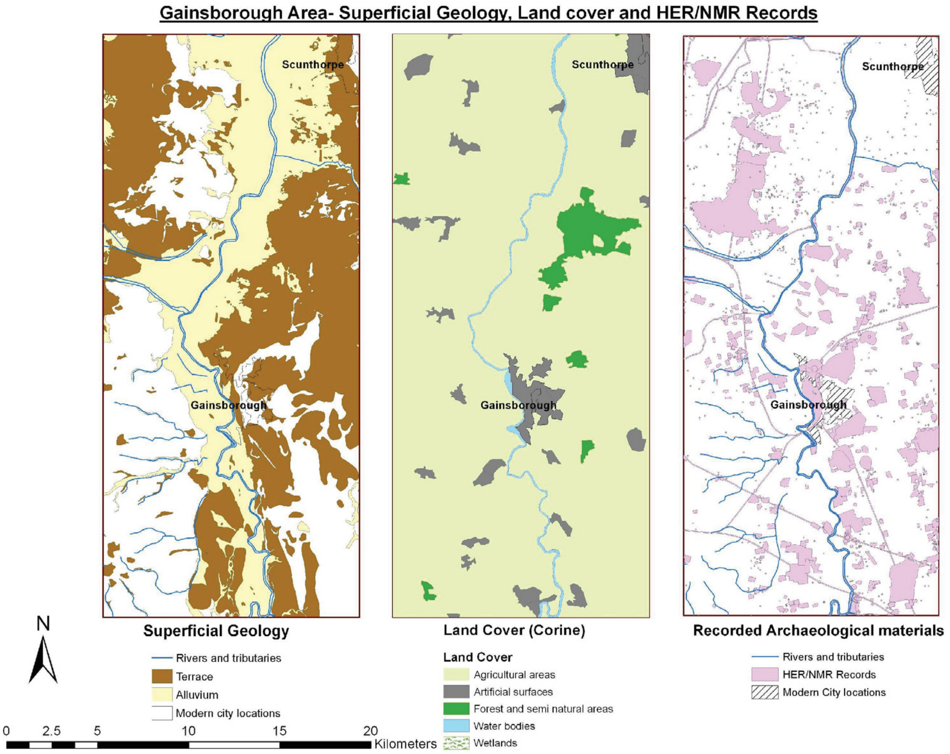


Figure 18. The Lower Trent in Lincolnshire around Gainsborough showing (left) superficial geology, (middle) landcover, (right) HER records.

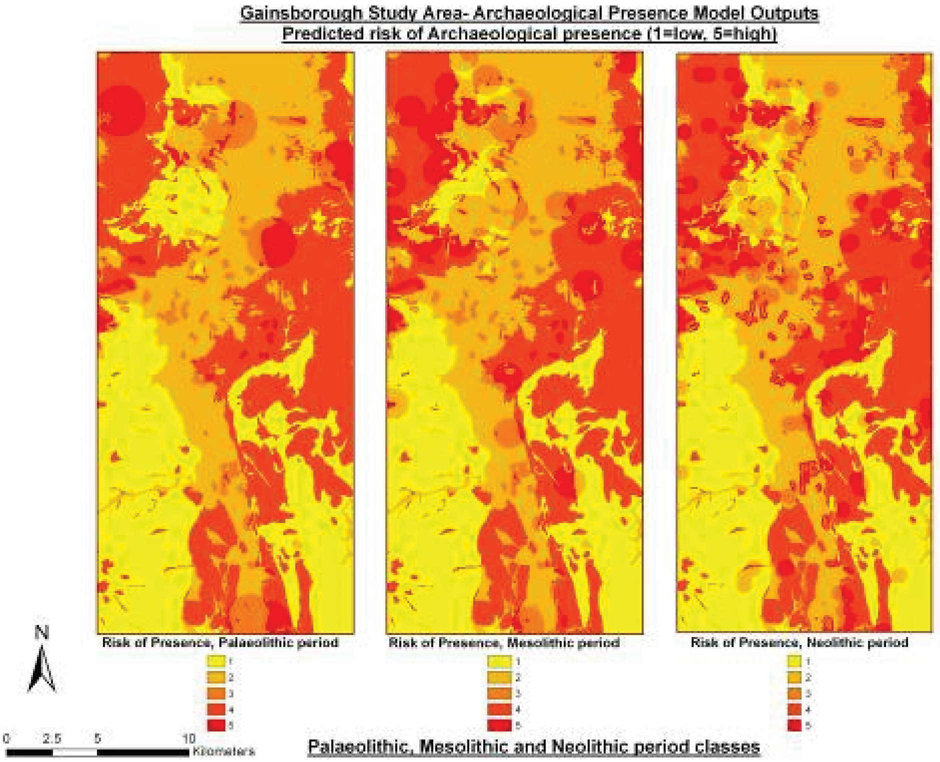


Figure 19. The Lower Trent in Lincolnshire around Gainsborough showing (left) Palaeolithic, (middle) Mesolithic, (right) Neolithic model reesults.

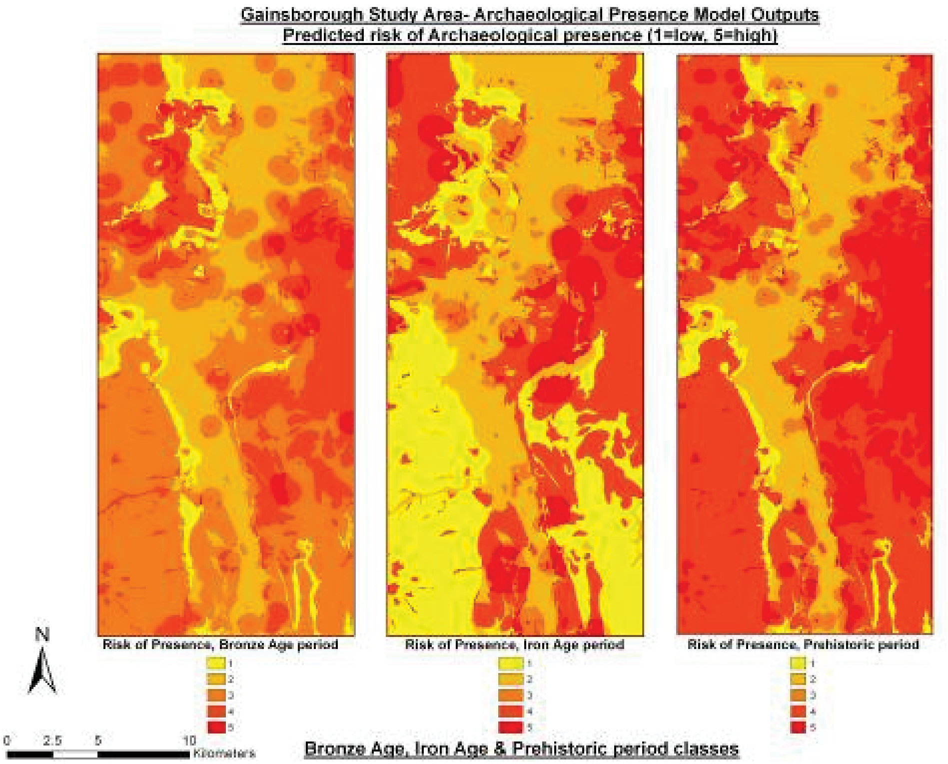


Figure 20. The Lower Trent in Lincolnshire around Gainsborough showing (left) Bronze Age, (middle) Iron Age, (right) general prehistoric model results.

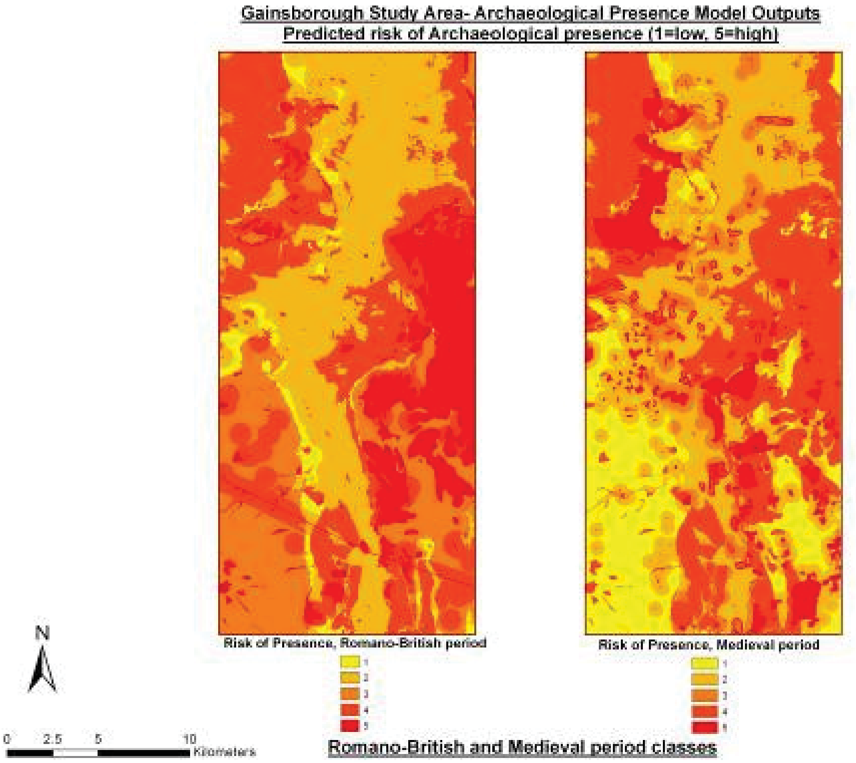


Figure 21. The Lower Trent in Lincolnshire around Gainsborough showing (left) Romano-British, (right) Medeival model results.

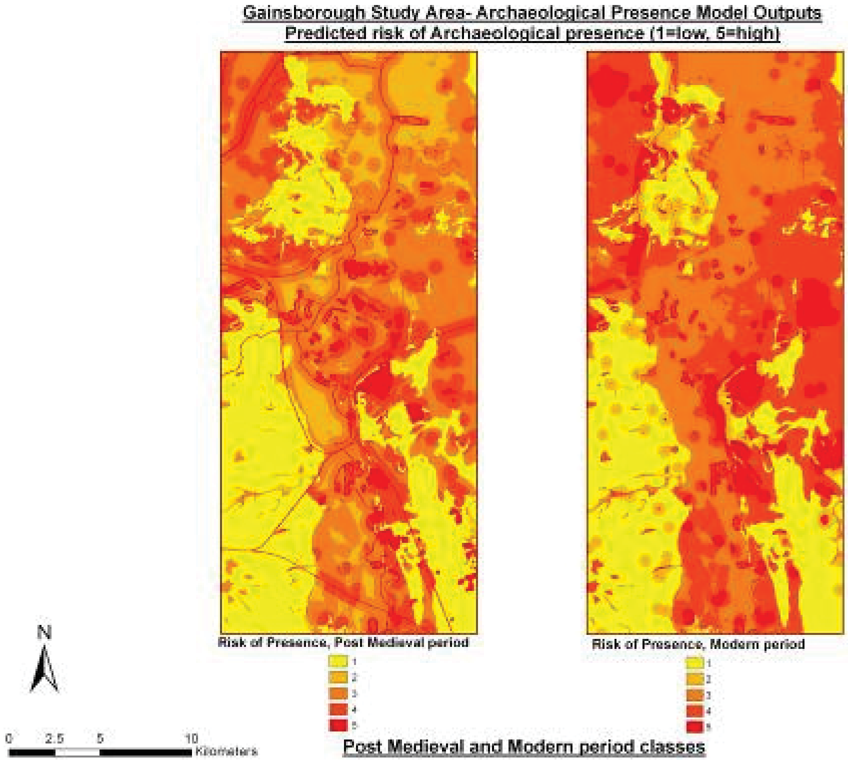


Figure 22. The Lower Trent in Lincolnshire around Gainsborough showing (left) Post-Medieval, (right) modern era model results.

5.3 AGGREGATE BEARING POTENTIAL

These models proved complex to calculate and open to criticism due to the poor quality and sparseness of input data, in particularly that relating to groundwater, and the lack of information about commercial quality the aggregate reserves modelled.

In general the modelled rasters for aggregate and overburden thickness appear to reflect anticipated spatial variations in these physical properties, albeit in a much generalised form.

The final model of aggregate bearing potential (Figure 26) while not unfeasible is of insufficient precision and lacking information on the character, quality and economic character of aggregate.

The simple raster of modelled aggregate thickness has some value, both to those seeking sand and gravel reserves and to archaeologists, but it appears that further modelling deviates too far from what is required in the real world of aggregate prospection to be of nay value.

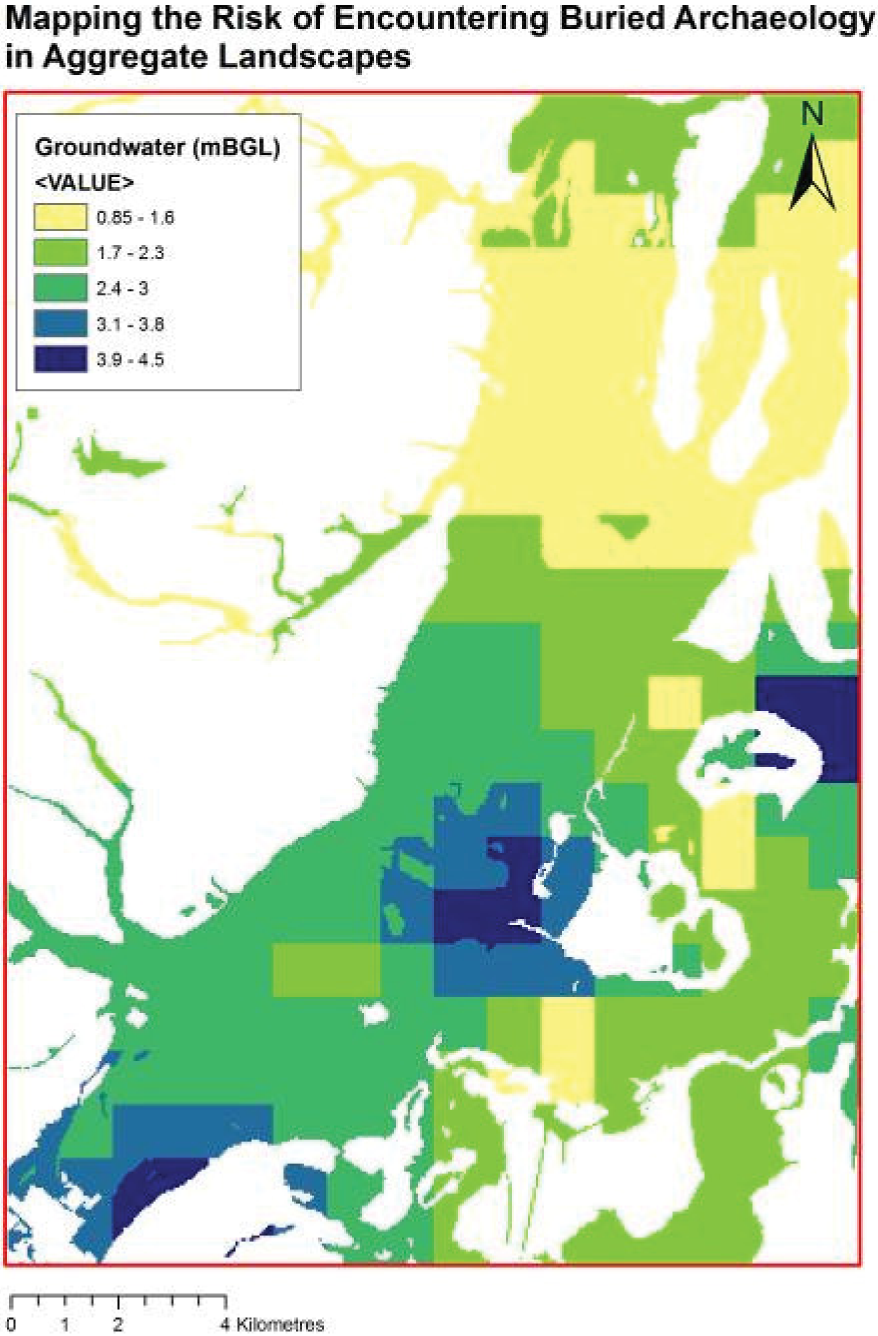


Figure 23. The Lower Trent in Nottinghamshire between Newark and Girrton showing modelled groundwater levels in metres below ground level.

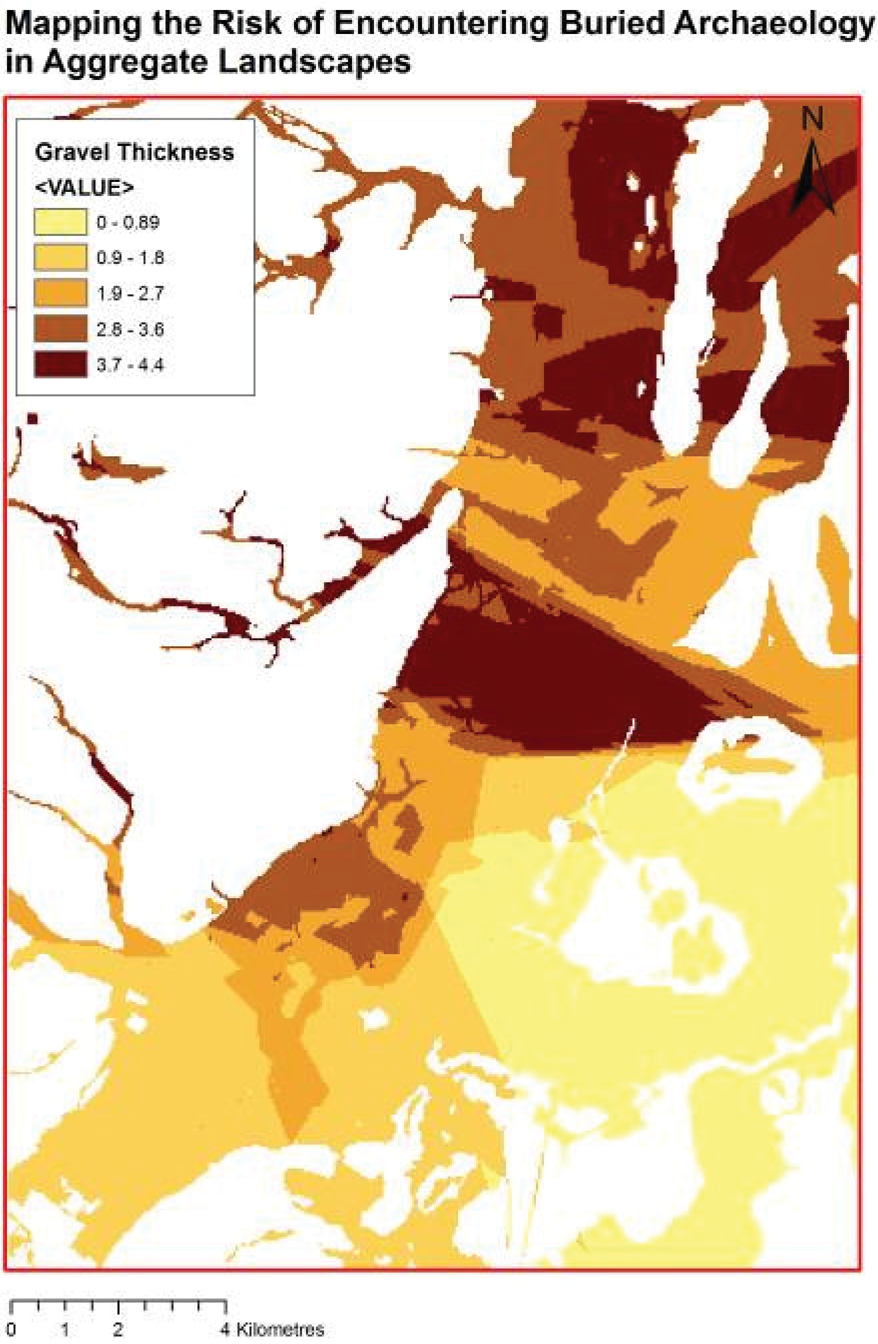


Figure 24. The Lower Trent in Nottinghamshire between Newark and Girrton showing aggregate thickness in metres.

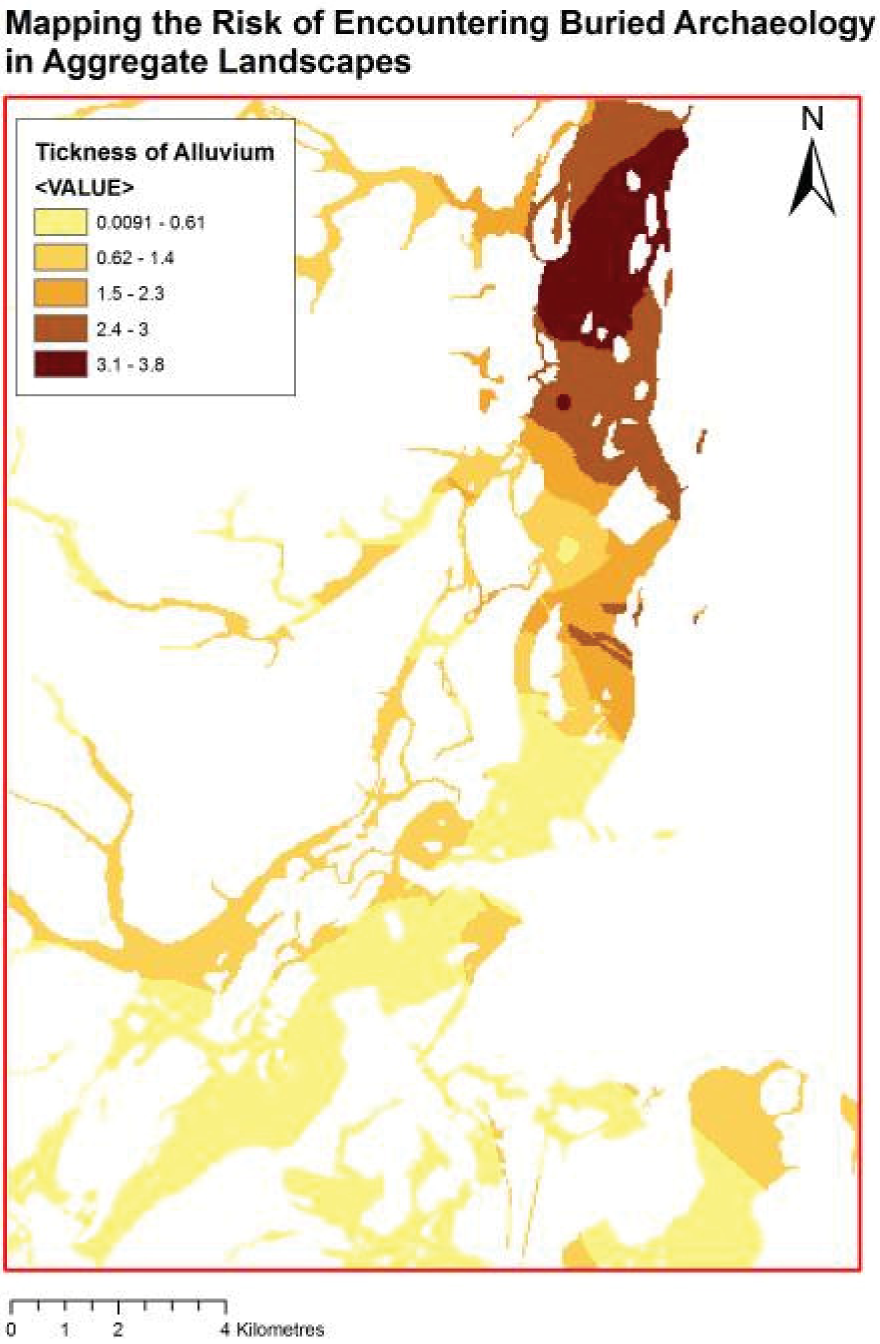


Figure 25. The Lower Trent in Nottinghamshire between Newark and Girrton showing modelled overburden (alluvium) thickness in metres.

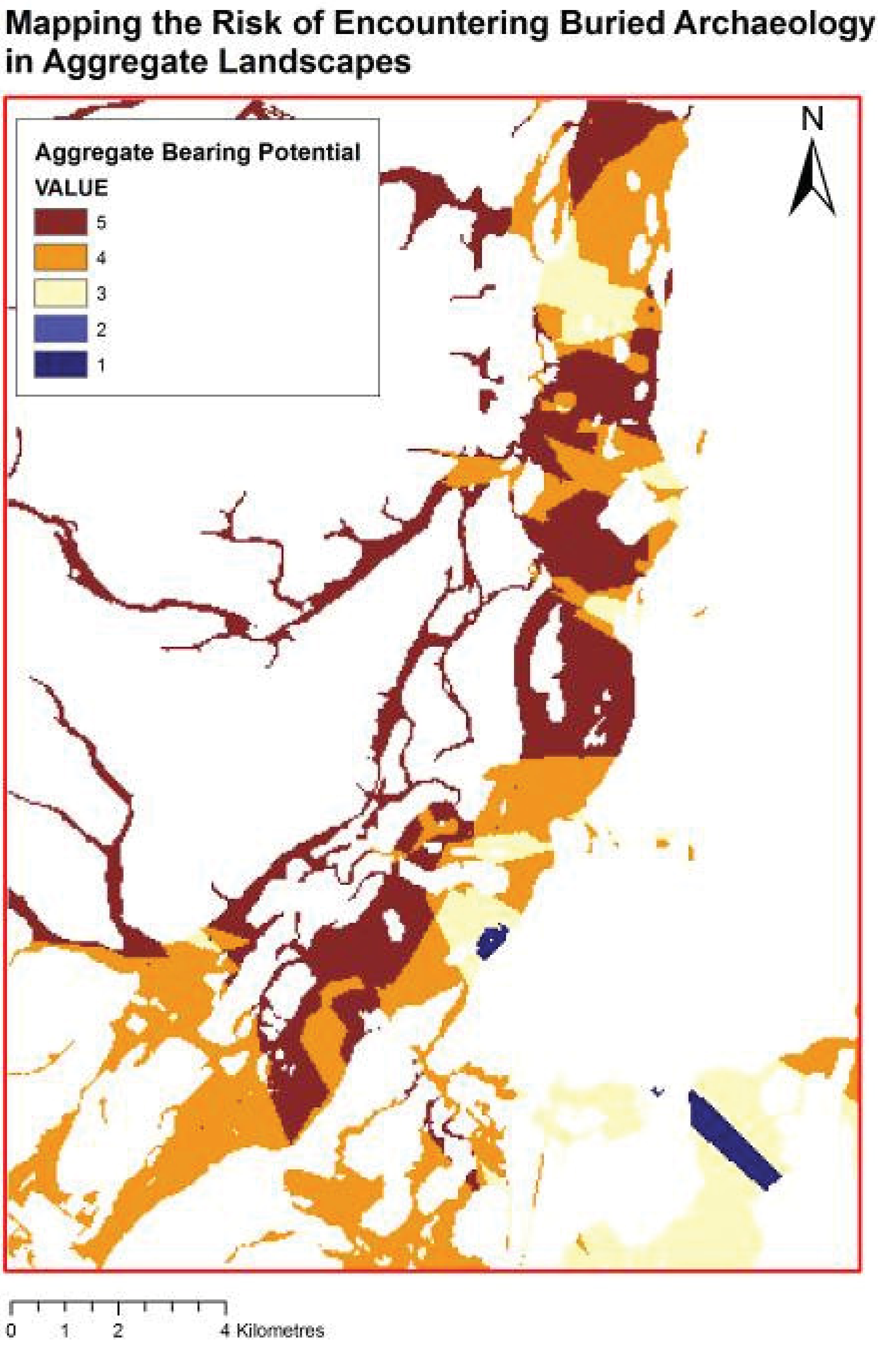


Figure 26. The Lower Trent in Nottinghamshire between Newark and Girrton showing modelled aggregate bearing potential.

5.4 SUSCEPTIBILITY TO FIELD EVALUATION

Models for susceptibility to field evaluation are intended to act as a first look guide to what techniques might be appropriate in what areas. As such they are heavily influenced by geology, soils and present land use.

Clearly some models are problematic, for example that for susceptibility to cropmark formation is weighted too heavily in favour of contemporary land use and so fails to model the crucial effect of geology on cropmark formation.

The relatively low spatial resolution of the available land use data is also problematic, rendering the models inappropriately generalised.

All models bear closer scrutiny, and in some cases adjustment of weightings, and while it is felt that they have only a limited use, they may provide a helpful guide alongside information on know archaeology and archaeological potential for scoping field investigation.

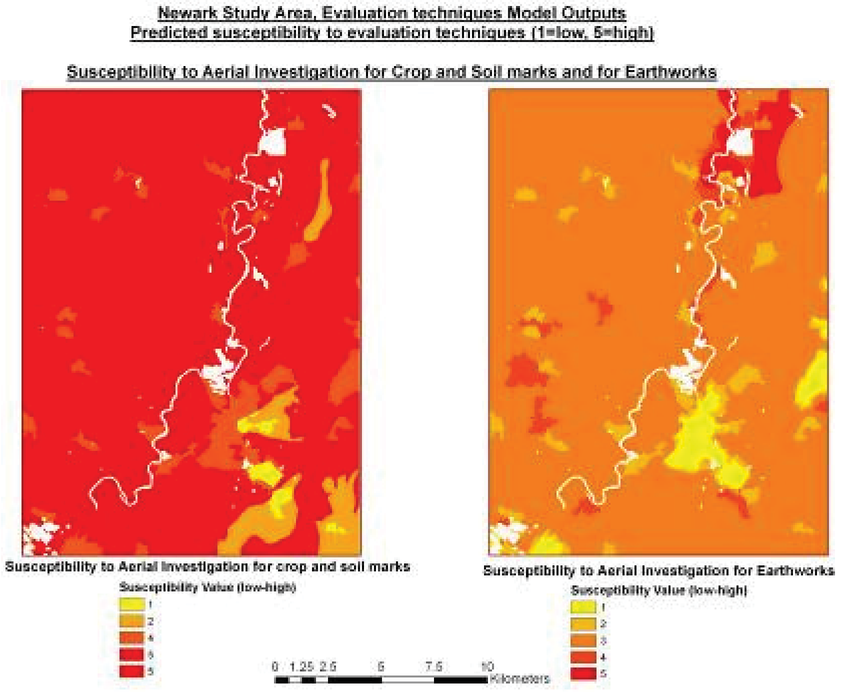


Figure 27. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) susceptibility to crop and soilmark formation and (right) susceptibility to earthwork formation.

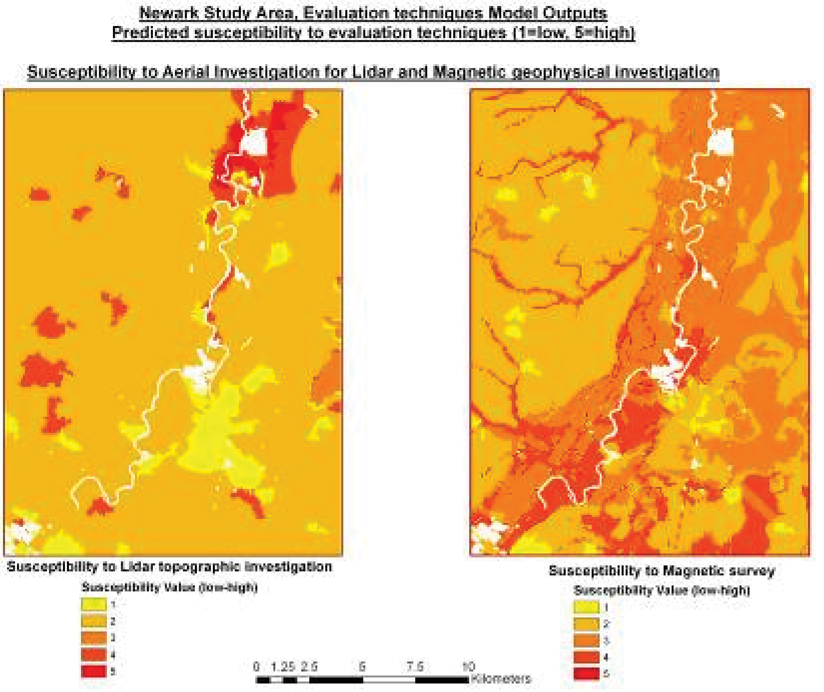


Figure 28. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) susceptibility to lidar investigation and (right) susceptibility to magnetic survey.

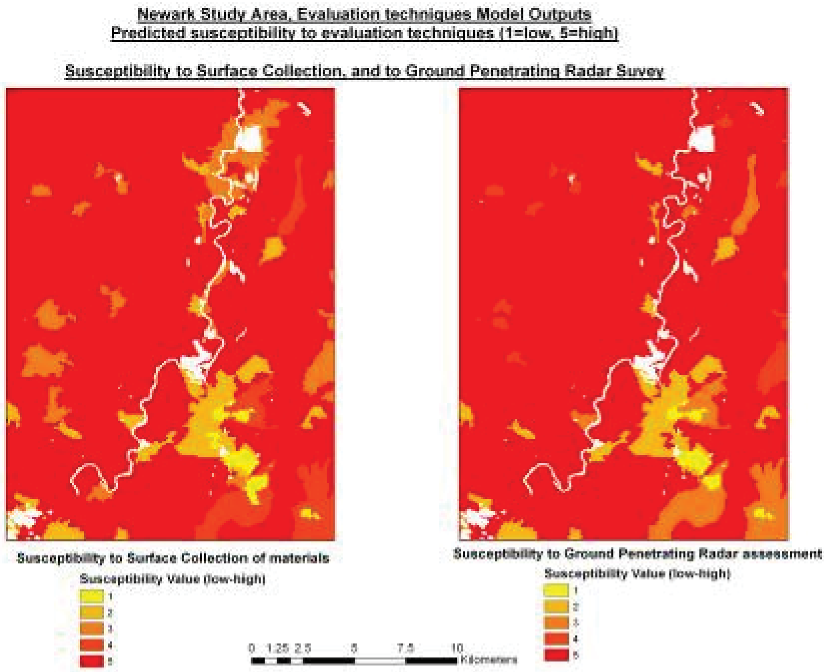


Figure 29. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) susceptibility to surface collection of artefacts and (right) susceptibility to GPR survey.

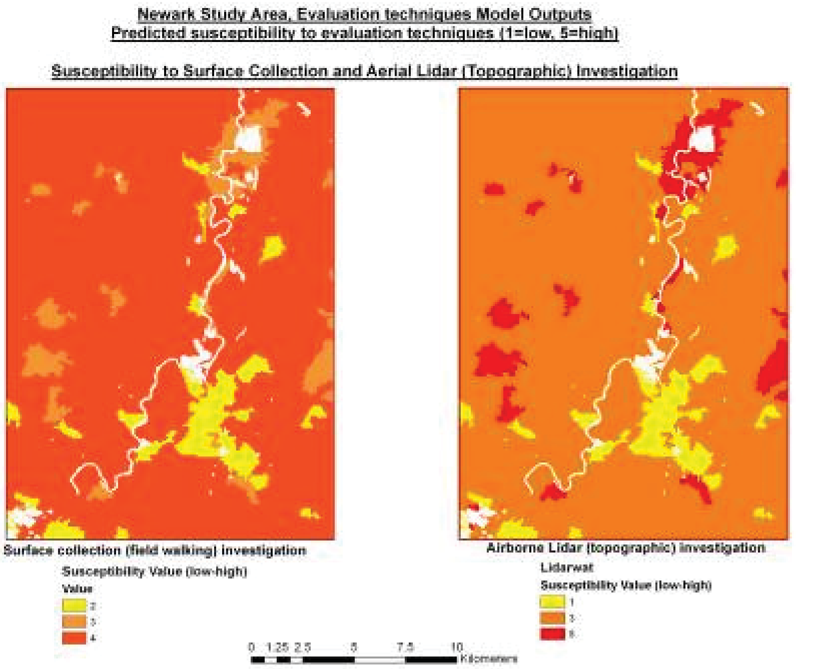


Figure 30. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) susceptibility to fieldwalking and (right) susceptibility to lidar survey.

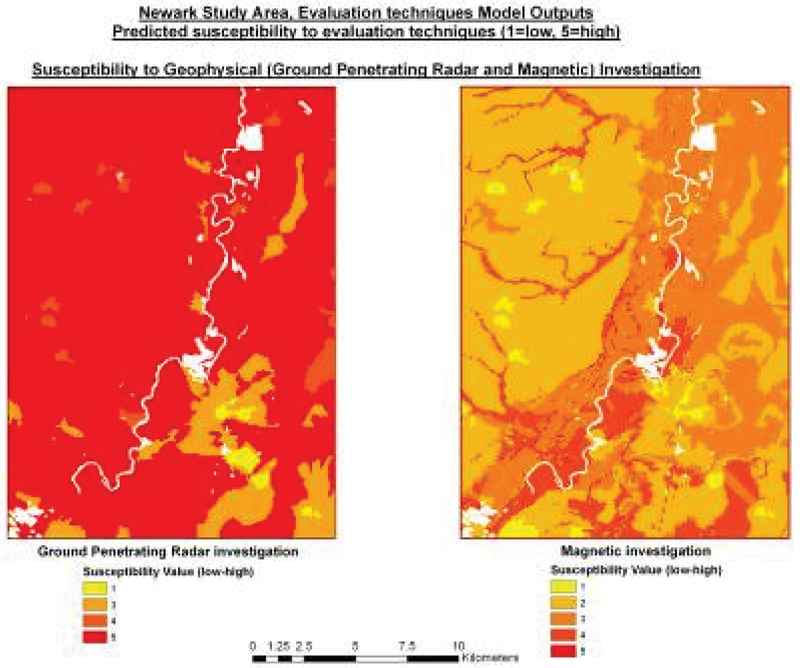


Figure 31. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) susceptibility to GPR survey and (right) susceptibility to magnetic survey.

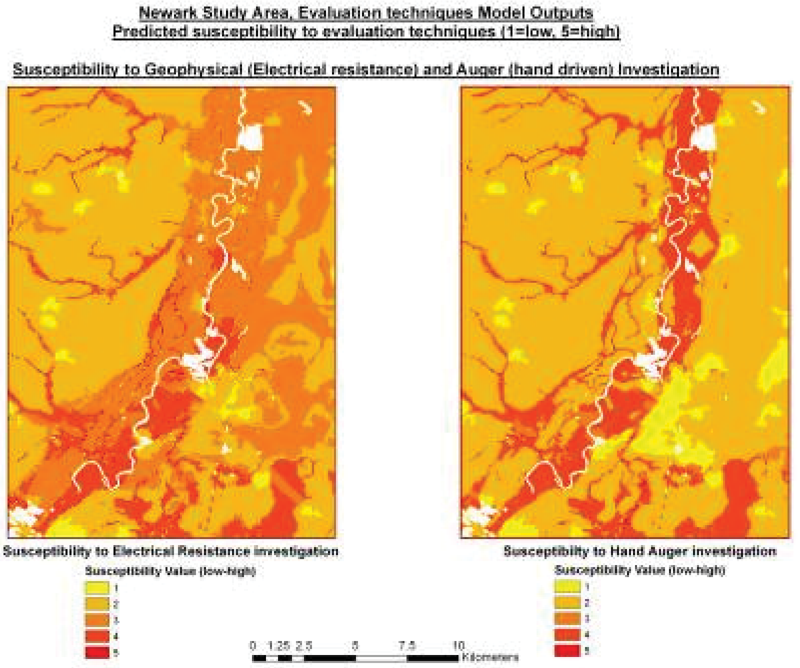


Figure 32. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) susceptibility to resistivity survey and (right) susceptibility hand auger survey.

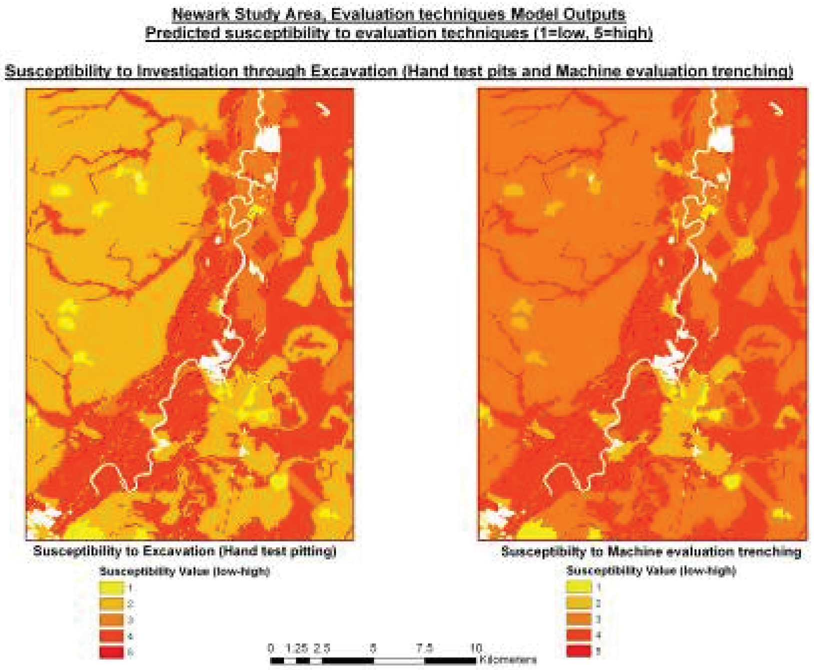


Figure 33. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) susceptibility to hand test pit excavation and (right) susceptibility to machine trial trenching.

5.5 PRESERVATION OF ANTHROPOGENIC ARCHAEOLOGICAL MATERIALS

The raster models shown here are derived directly from the data generated by Ward et al 2009 and incorporated as an "archaeology" layer in the NATMAPSoilscape digital soil mapping.

As a result variations in preservation potential are homogenous within single soil units, which is undoubtedly an oversimplification, although not unduly problematic in the UK wide mapping undertaken by Ward.

In the present study these data are provided here for completeness, and for comparison with our own more detailed models of organic preservation potential (cf Figures 37 and 38 for example).

The soilscape data is inherently more useful when values are propagated to MaterMap toids, where it is directly comparable with other modelled outputs.

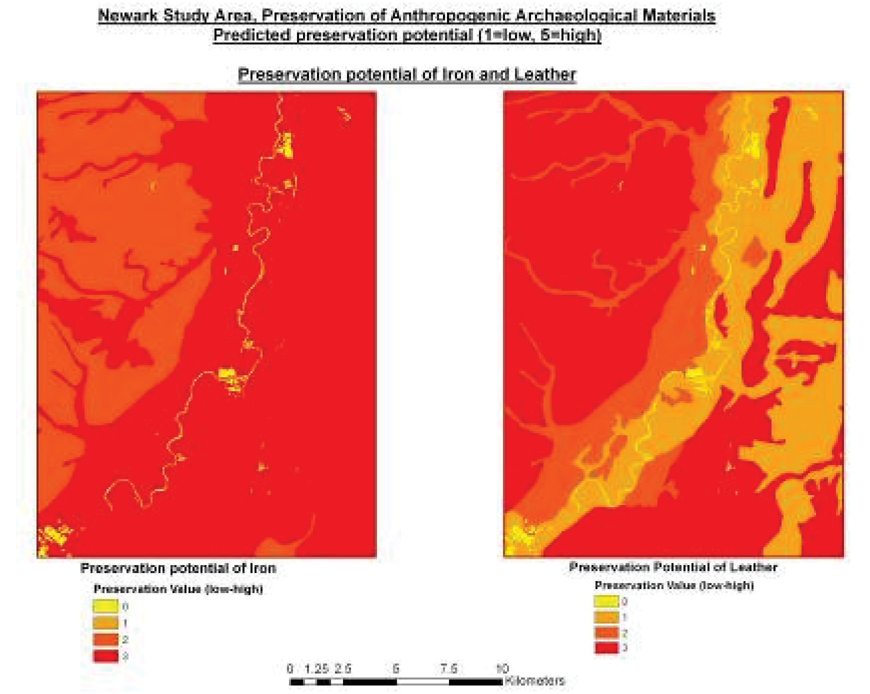


Figure 34. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) predicted preservation of iron and (right) predicted preservation of leather (after Ward 2009).

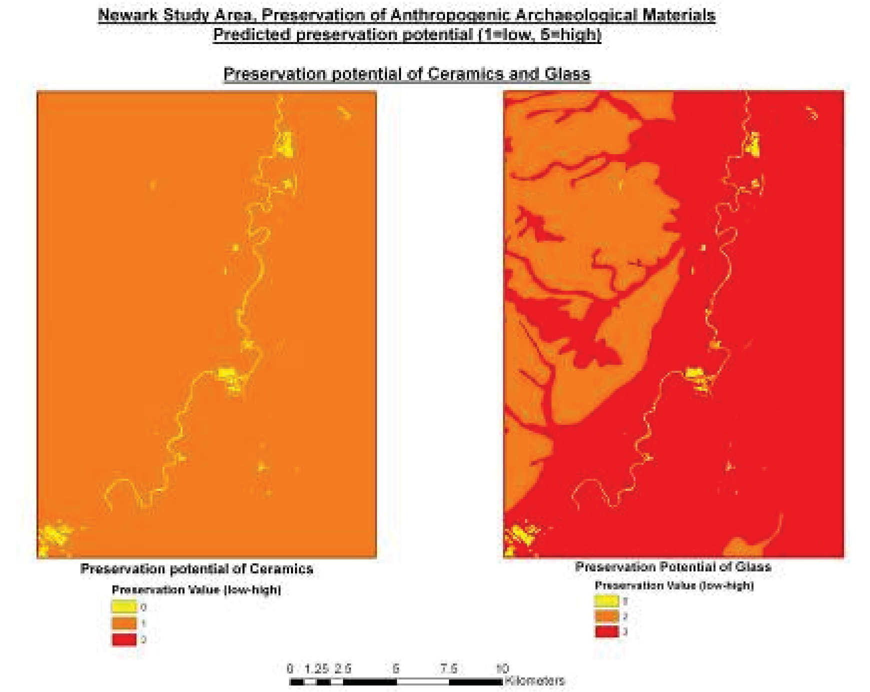


Figure 35. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) predicted preservation of ceramic material and (right) predicted preservation of glass (after Ward 2009).

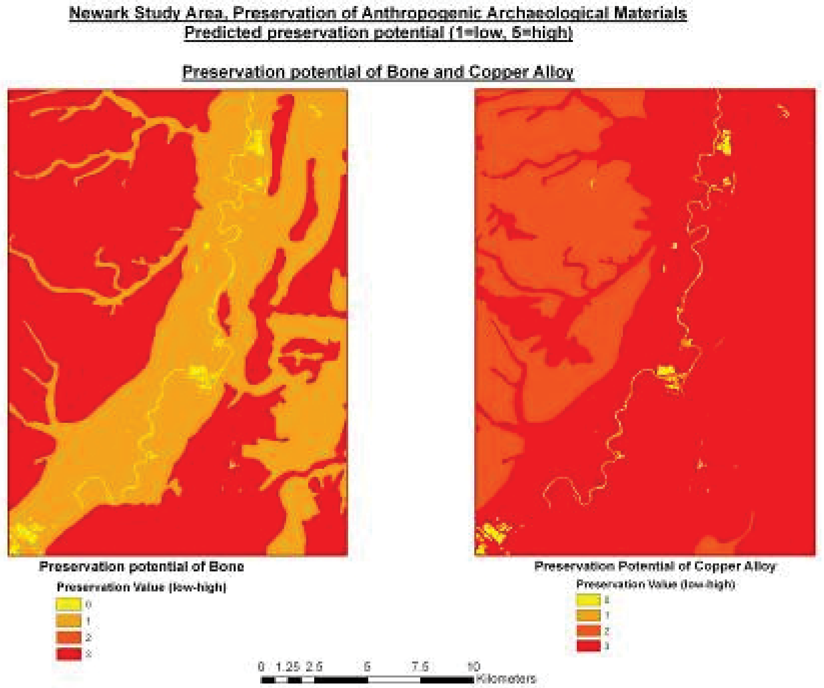


Figure 36. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) predicted preservation of bone and (right) predicted preservation of copper alloy (after Ward 2009).

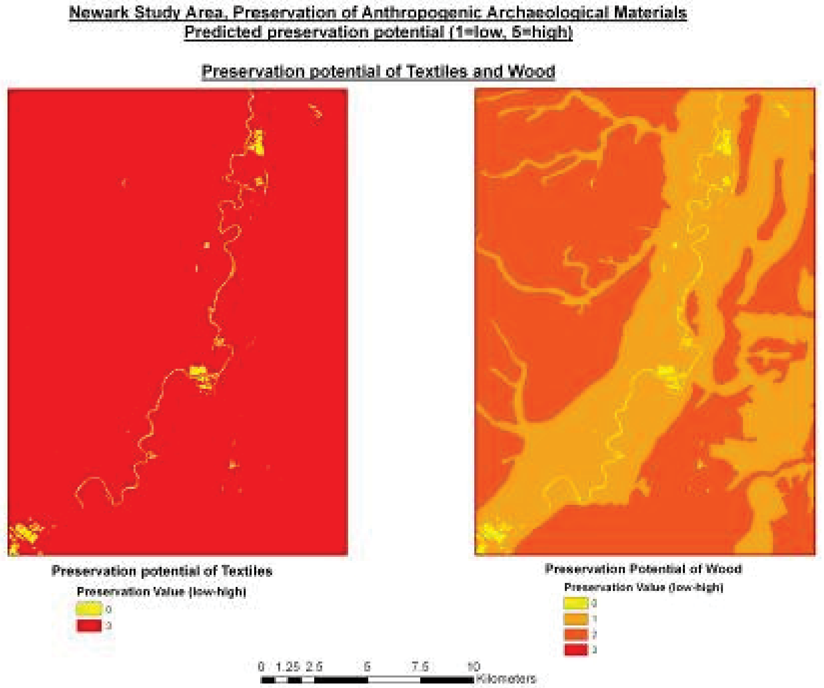


Figure 37. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) predicted preservation of textiles and (right) predicted preservation of wood (after Ward 2009).

5.6 PRESERVATION OF WATERLOGGED REMAINS

The models of the preservation potential for organic water logged remains are rooted firmly in variations in drift geology, but since this is not an unreasonable assumption, we feel that these models, fusing as they do geology, mapping of palaeochannels and observations from boreholes, produce a useful and realistic assessment of the varying preservation potential of the floodplain and terraces.

In Figures 38-43 we provide raster modelled output for each study area together with more detailed views of the raster data and model values propagated to MasterMap toid for smaller areas.

While requiring further assessment, it appears at first glance that these data provide amongst the most realistic and useful models generated by this research.

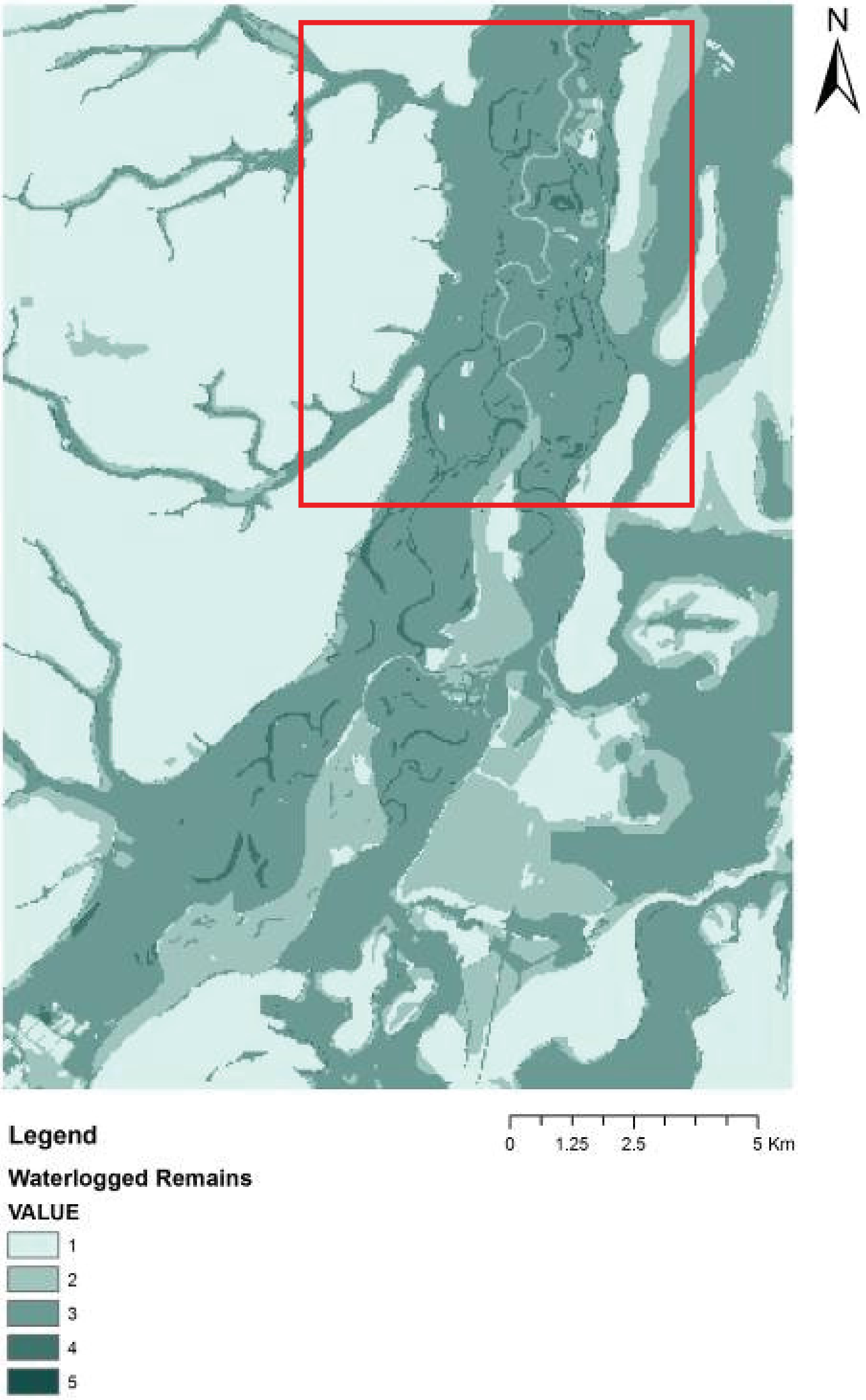


Figure 38. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) predicted preservation of organic waterlogged remains with red box indicating extent of detailed figures.

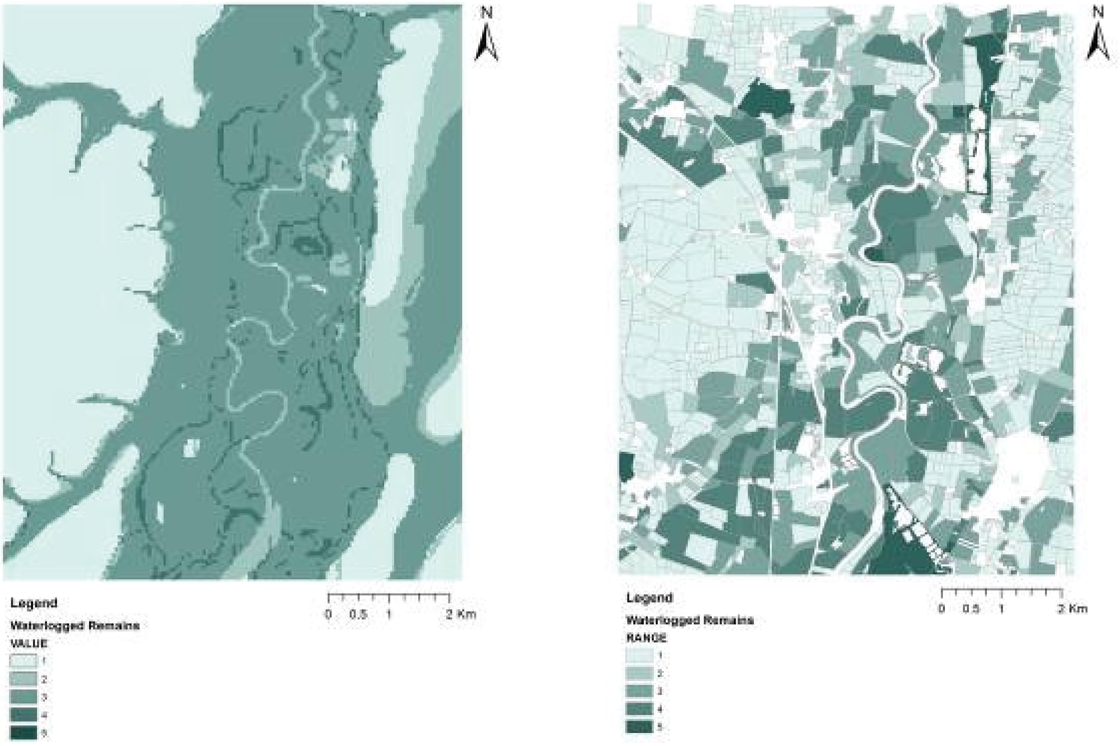


Figure 39. The Lower Trent in Nottinghamshire between Newark and Girton showing (left) in detail raster model of predicted preservation of organic waterlogged and (right) raster data propagated to MasterMap toids.

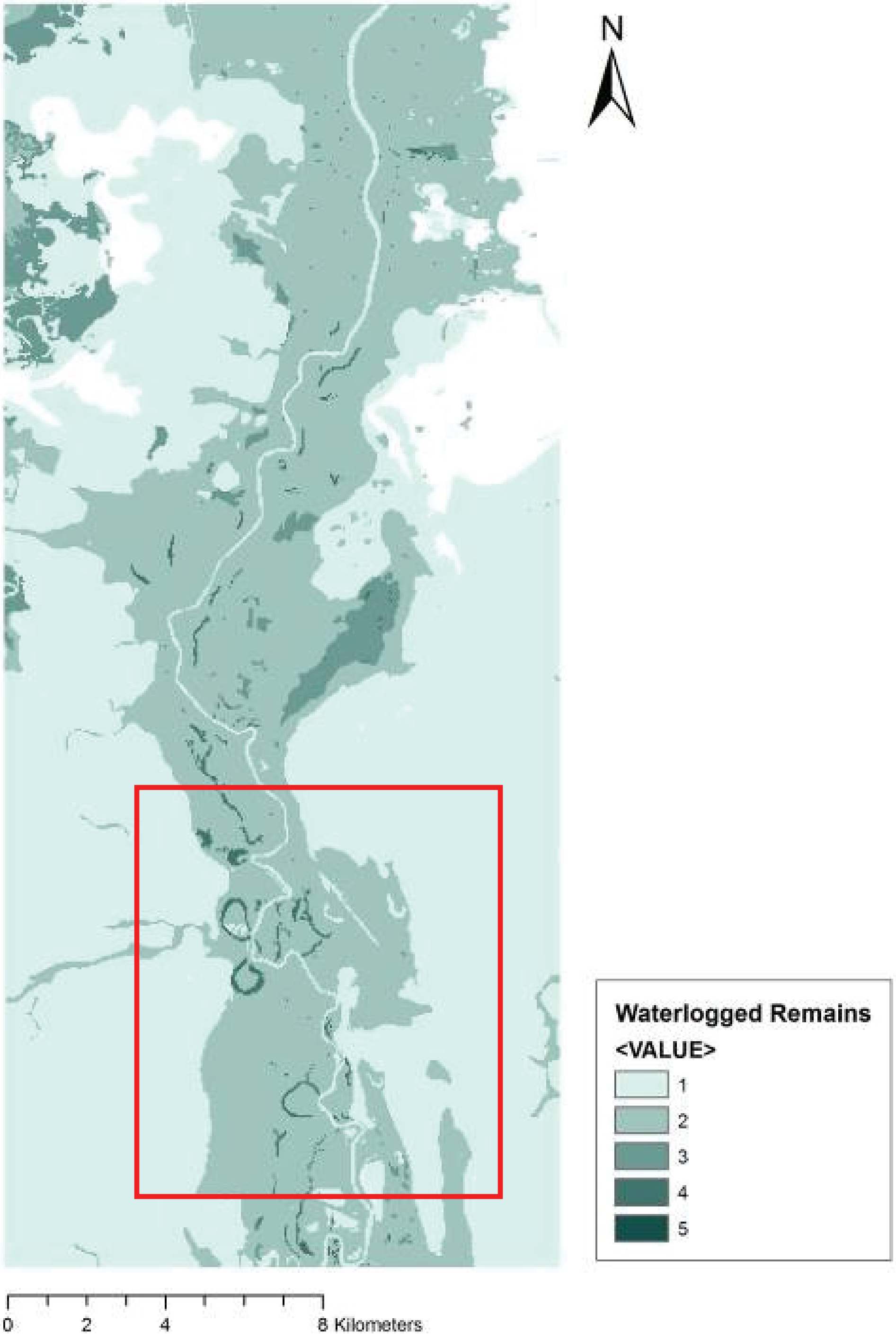


Figure 40. The Lower Trent in Lincolnshire around Gainsborough between Newark and Girton showing predicted preservation of organic waterlogged remains with red box indicating extent of detailed figures.

Figure 41. The Lower Trent in Lincolnshire around Gainsborough showing (left) in detail raster model of predicted preservation of organic waterlogged and (right) raster data propagated to MasterMap toids.

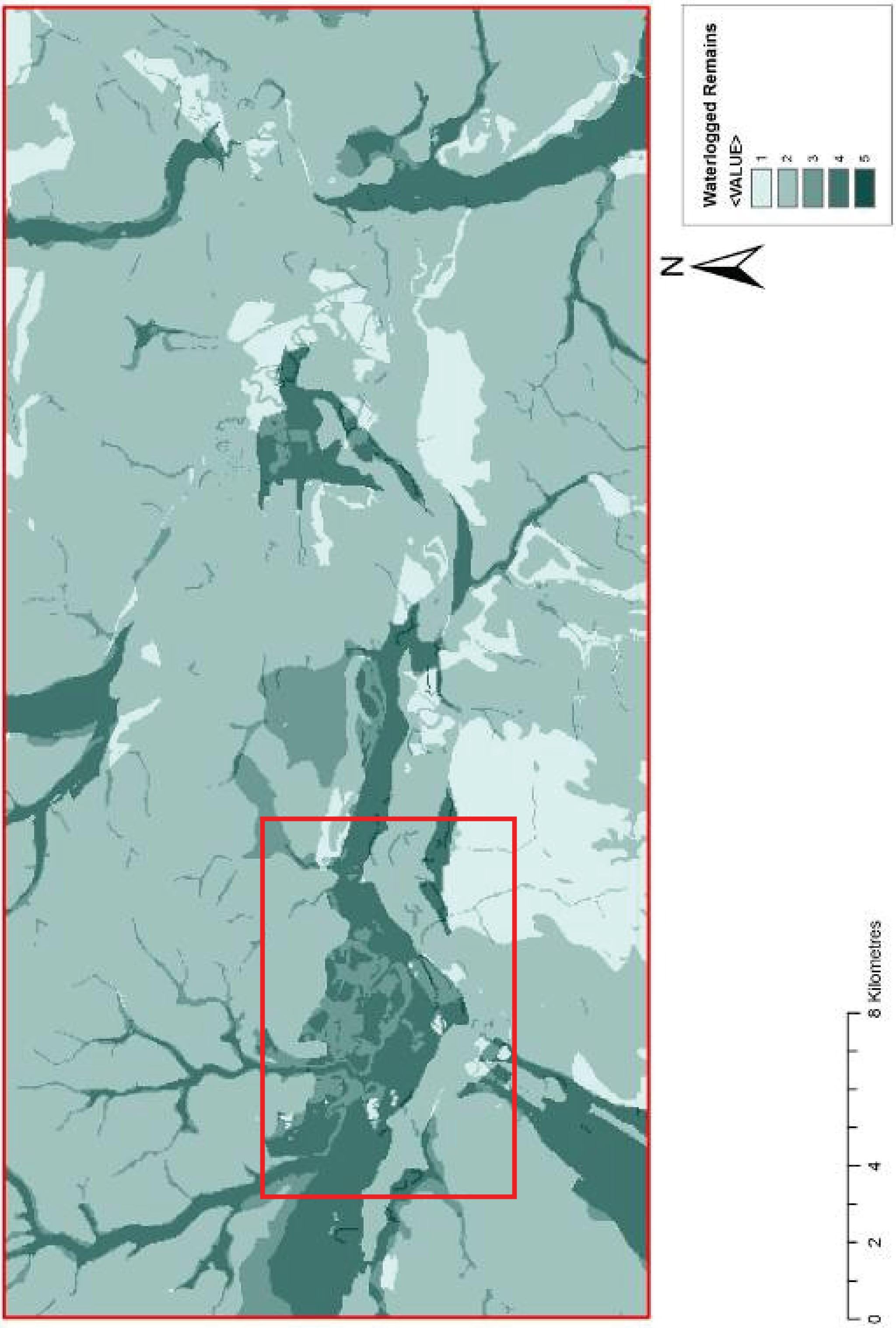


Figure 42. The Middle Trent in Derbyshire around Derby showing predicted preservation of organic waterlogged remains with red box indicating extent of detailed figures.

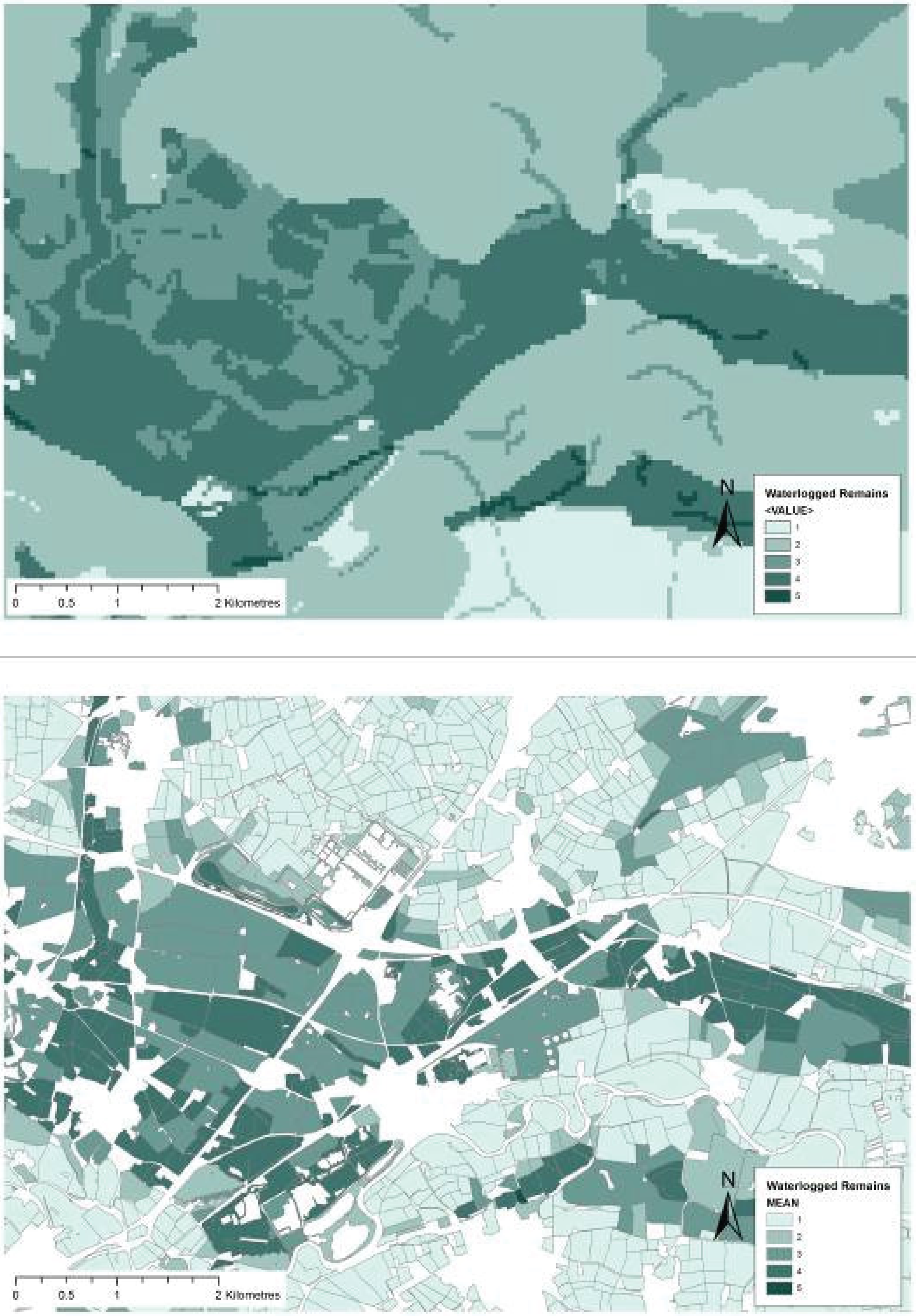


Figure 43. The Middle Trent in Derbyshire around Derby showing (lop) in detail raster model of predicted preservation of organic waterlogged and (bottom) raster data propagated to MasterMap toids.

5.7 IMPORTANCE OF ARCHAEOLOGICAL REMAINS

Modelling of the likely importance of archaeological remains is fraught with difficulties, not least those associated with the often subjective judgments about what is important.

While we have tried to root our models in objective classifications (SAMs by their very nature are nationally important) and quantification of rarity of particular classes of site, we feel that the resulting models are only useful as a methodological exercise.

In Figures 44 - 47 we show model results for the Neolithic, Iron Age and Romano-British period in the Middle Trent in Derbyshire.

Overall, we suggest that the exercise of projecting value judgements relating to particular sites, assemblages or artefacts or taphonomic processes to whole landscapes is fatally flawed in concept and not defensible in outcome.

Figure 48 attempts to show that the model outputs bear some relationship to the real world of value judgements concerning heritage by demonstrating the fact that areas around Scheduled and know sites are given elevated importance values.

Nonetheless, we feel that though in concept laudable this modelling stage is in execution too fraught with complexity and subjectivity to be of significant value.

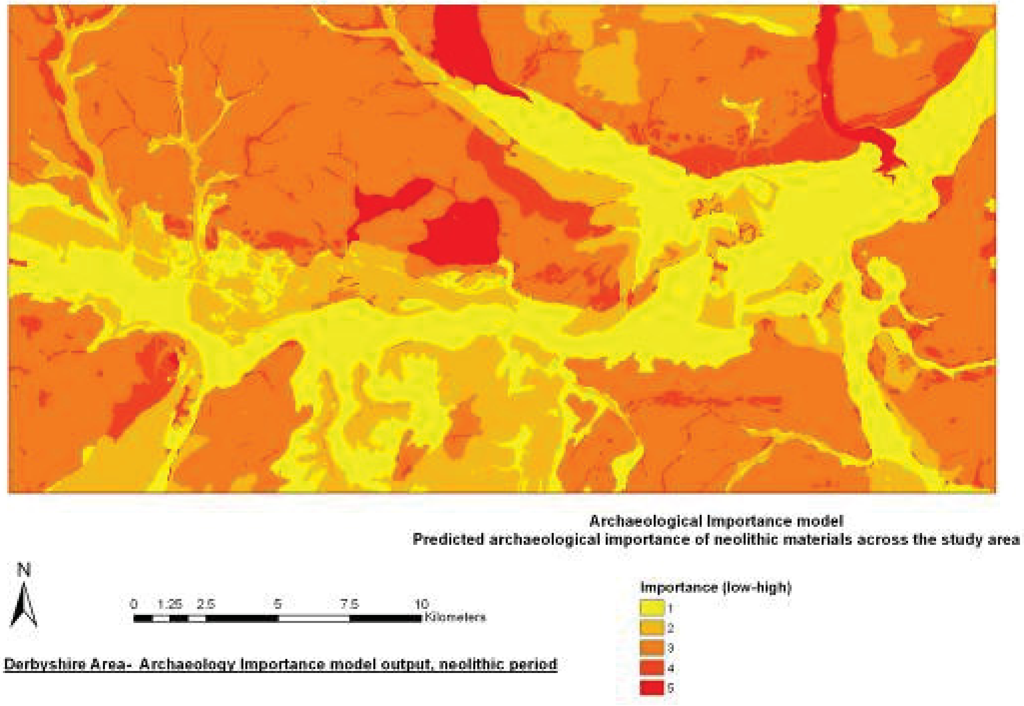


Figure 44. The Middle Trent in Derbyshire around Derby showing predicted importance of Neolithic remains.

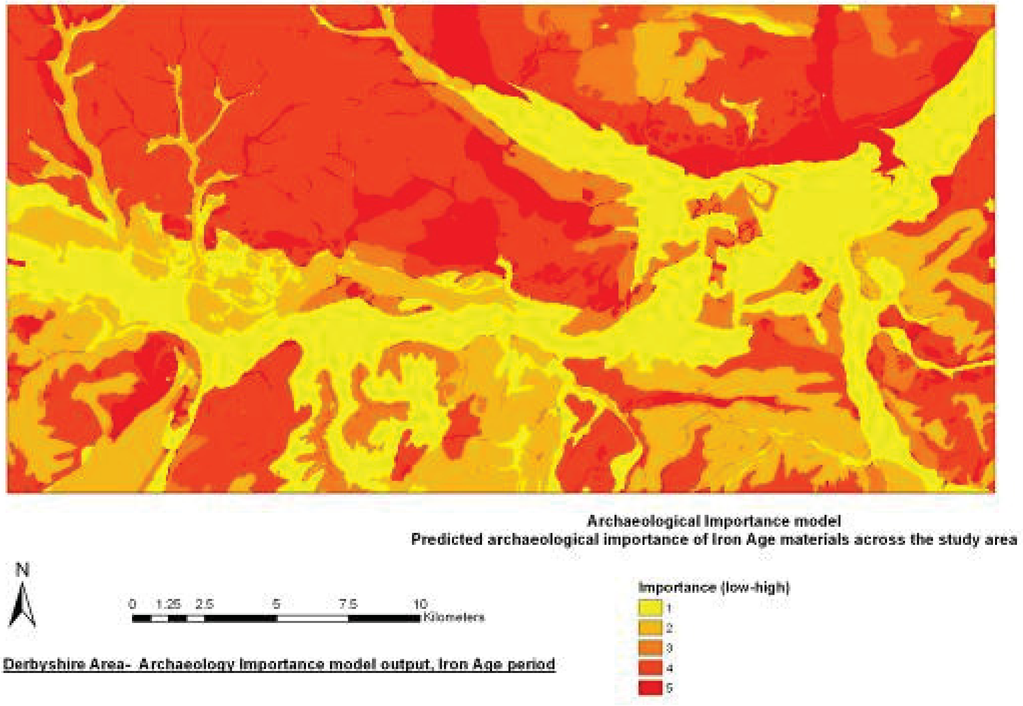


Figure 45. The Middle Trent in Derbyshire around Derby showing predicted importance of Iron Age remains.

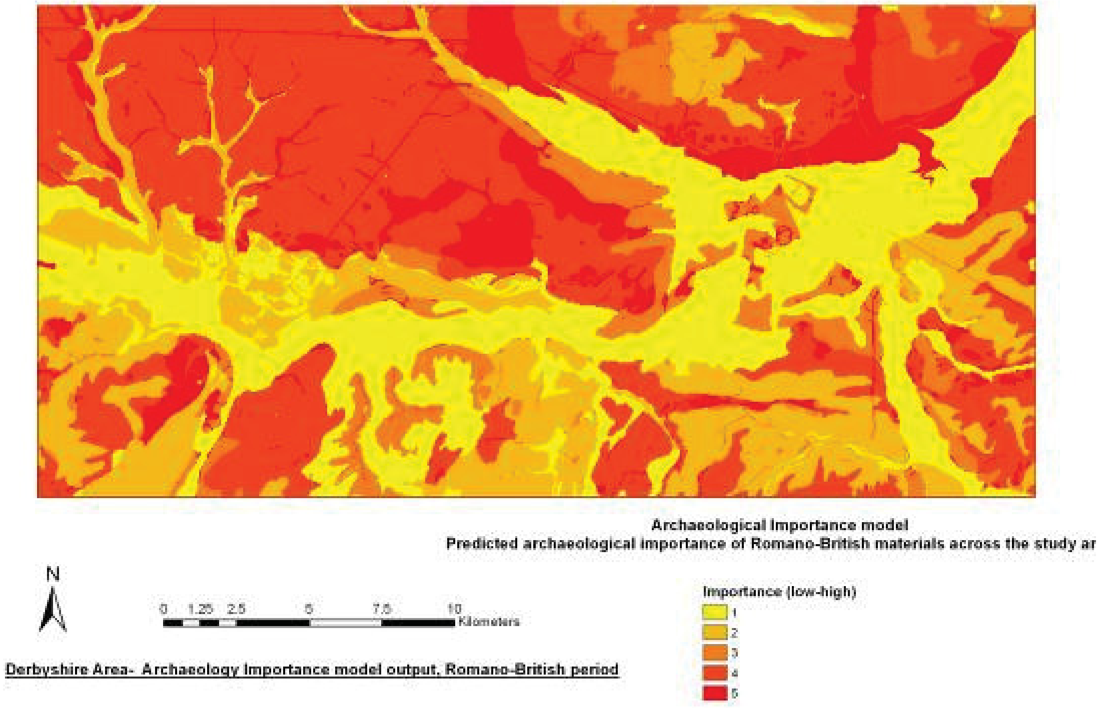


Figure 46. The Middle Trent in Derbyshire around Derby showing predicted importance of Romano-British remains.

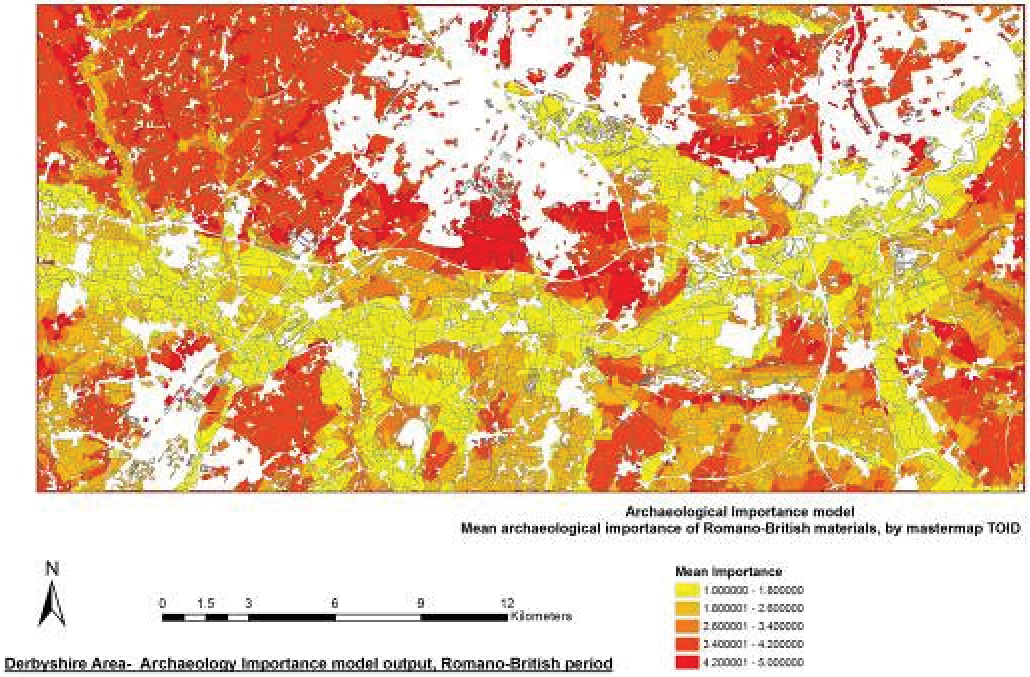


Figure 47. The Middle Trent in Derbyshire around Derby showing predicted importance of Romano-British remains with raster values propagated to MasterMap toids

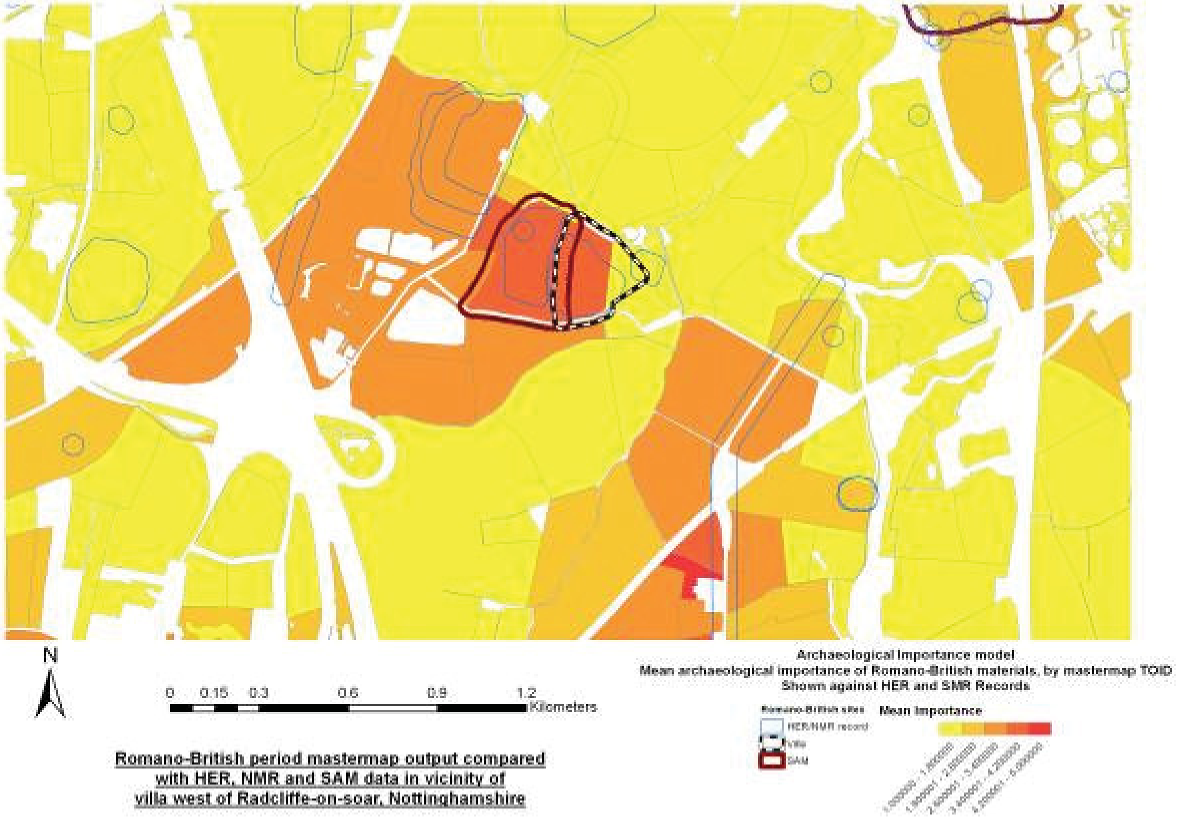


Figure 48. The Middle Trent in Derbyshire near to Willington PowerStation showing predicted importance of Romano-British remains with superimposed the outline of a Romano-British villa derived from the Derbyshire HER.

5.8 MITIGATION MEASURES

The predictive models of likely mitigation requirement are derived directly from a weighed sum of the various importance models and so reflect the flaws inherent in those models.

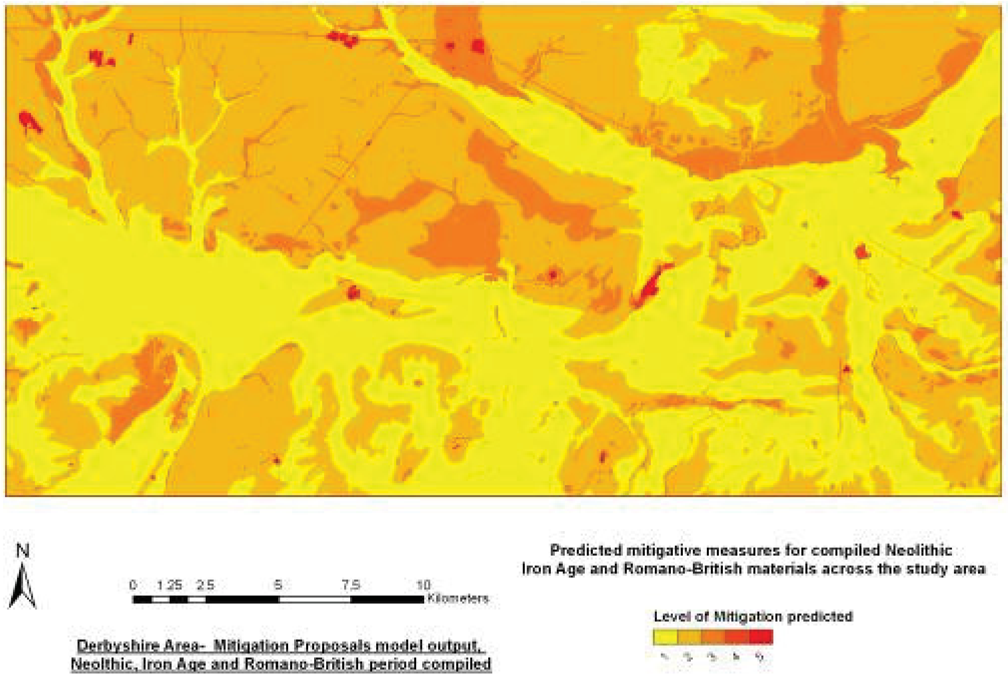
While successfully representing sites with statutory protection, the translation from summed importance to likely mitigation is too complex a process to be readily modelled, depending as it does on both the nature of the archaeology in question and the attitudes of the professionals involved in its consideration.

Our simple 5 point scale (see Figure 49):

5 - Presumption in favour of preservation in situ
4 - Pre determination evaluation followed by pre-development preservation by record
3 - Pre determination evaluation followed reservation by record
2 - Pre determination evaluation followed by watching-brief
1 - No action or watching-brief only

is both too simple and too prescriptive to be of real value.

We see these models as being of academic interest only of no durable real-world value.



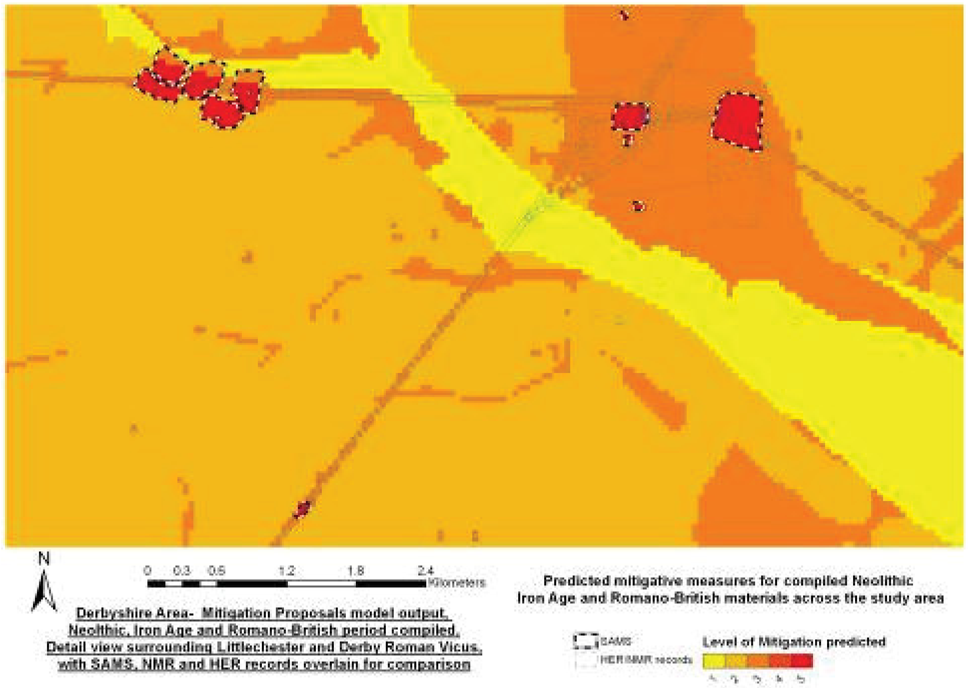


Figure 49. The Middle Trent in Derbyshire showing top predicted mitigation requirements at a landscape scale and bottom, a detailed view of the data around the Scheduled Roman site of Little Chester, showing HER data superimposed on the model for reference.

DISCUSSION

6 DISCUSSION

6.1 DISSEMINATION OF RESULTS

Presenting the results of GIS-based modelling to a non-specialist audience is always likely to be problematic.

Paper based atlas style mapping is of limited use (viz this report, where maps although faithfully representing the modelled results are difficult to interpret with any degree of confidence). We consider it likely that a modelling project of this sort will always be required to provide digital data as its prime output.

In the project design we considered tabulated model outputs appended to OS toids as being the principal digital output, suitable for reconstitution into mapped output in a suitably configured corporate GIS (Figure 51).

While this remains our view there a number of issues that require clarification, not lease the uncertain cipyright status of the toid identifiers, and the fact that to work the end user requires access to Ordnance Survey MasterMap data.

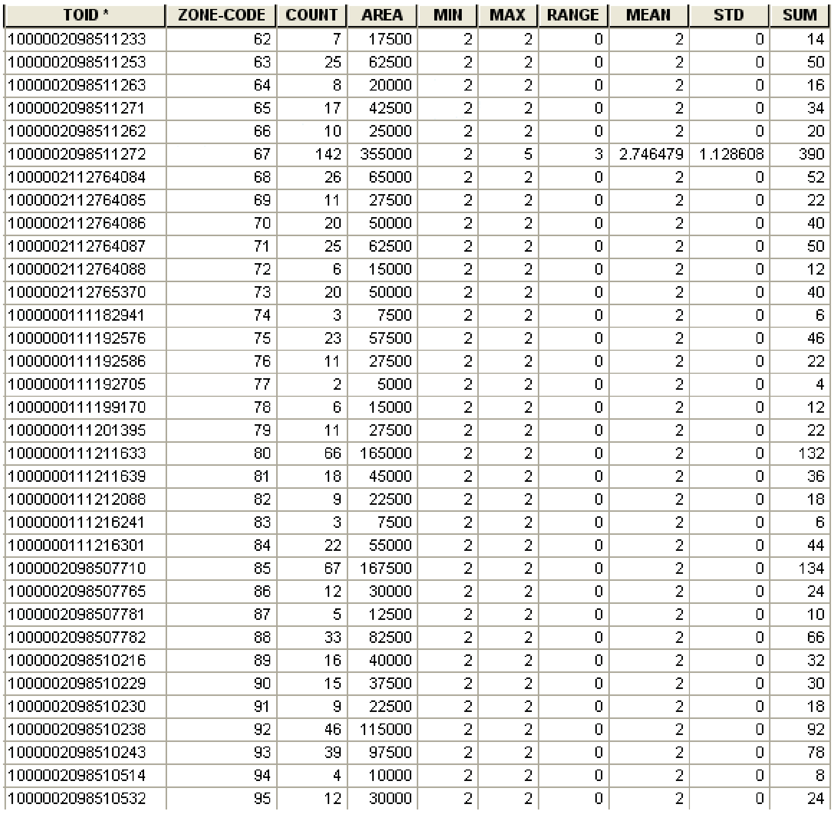
An alternative might envisage the supply of modelled raster data in appropriate generic format (rather as Environment Agency supply their lidar products) although here the utility of mapping modelled results per rea l world land parcel is lost.

A further, and attractive, possibility is the provision of output data in Keyhole Markup Language (kml) format for display in Google Earth. There are copyright issues associated with the supply of data derived from Ordnance Survey products which would need to be addressed to go down this route.

The most useful final solution would probably be a bespoke web-based service that provided access to modelled output in a web-browser based Google Earth / Maps environment and allowed users to upload and display their own data (for example, simple polygons defining a planning application area) alongside the models.

The advantages of using Google Earth / Maps lay not only in the simplicity of developing useful and robust web-based applications, but in the fact that a high-resolution, regularly updated imagery base, topographic layer and basic road and land use mapping are provided as part of the web service.

We suggest that further investigation of this dissemination route would be of benefit for both the present and other comparable research.



TOID *	ZONE-CODE	COUNT	AREA	MIN	MAX	RANGE	MEAN	STD	SUM
1000002098511233	62	7	17500	2	2	0	2	0	14
1000002098511253	63	25	62500	2	2	0	2	0	50
1000002098511263	64	8	20000	2	2	0	2	0	16
1000002098511271	65	17	42500	2	2	0	2	0	34
1000002098511262	66	10	25000	2	2	0	2	0	20
1000002098511272	67	142	355000	2	5	3	2.746479	1.128608	390
1000002112764084	68	26	65000	2	2	0	2	0	52
1000002112764085	69	11	27500	2	2	0	2	0	22
1000002112764086	70	20	50000	2	2	0	2	0	40
1000002112764087	71	25	62500	2	2	0	2	0	50
1000002112764088	72	6	15000	2	2	0	2	0	12
1000002112765370	73	20	50000	2	2	0	2	0	40
1000000111182941	74	3	7500	2	2	0	2	0	6
1000000111192576	75	23	57500	2	2	0	2	0	46
1000000111192586	76	11	27500	2	2	0	2	0	22
1000000111192705	77	2	5000	2	2	0	2	0	4
1000000111199170	78	6	15000	2	2	0	2	0	12
1000000111201395	79	11	27500	2	2	0	2	0	22
1000000111211633	80	66	165000	2	2	0	2	0	132
1000000111211639	81	18	45000	2	2	0	2	0	36
1000000111212088	82	9	22500	2	2	0	2	0	18
1000000111216241	83	3	7500	2	2	0	2	0	6
1000000111216301	84	22	55000	2	2	0	2	0	44
1000002098507710	85	67	167500	2	2	0	2	0	134
1000002098507765	86	12	30000	2	2	0	2	0	24
1000002098507781	87	5	12500	2	2	0	2	0	10
1000002098507782	88	33	82500	2	2	0	2	0	66
1000002098510216	89	16	40000	2	2	0	2	0	32
1000002098510229	90	15	37500	2	2	0	2	0	30
1000002098510230	91	9	22500	2	2	0	2	0	18
1000002098510238	92	46	115000	2	2	0	2	0	92
1000002098510243	93	39	97500	2	2	0	2	0	78
1000002098510514	94	4	10000	2	2	0	2	0	8
1000002098510532	95	12	30000	2	2	0	2	0	24

Figure 50. An example of model output provided as a simple table of MasterMap toid with relevant additional attributes.

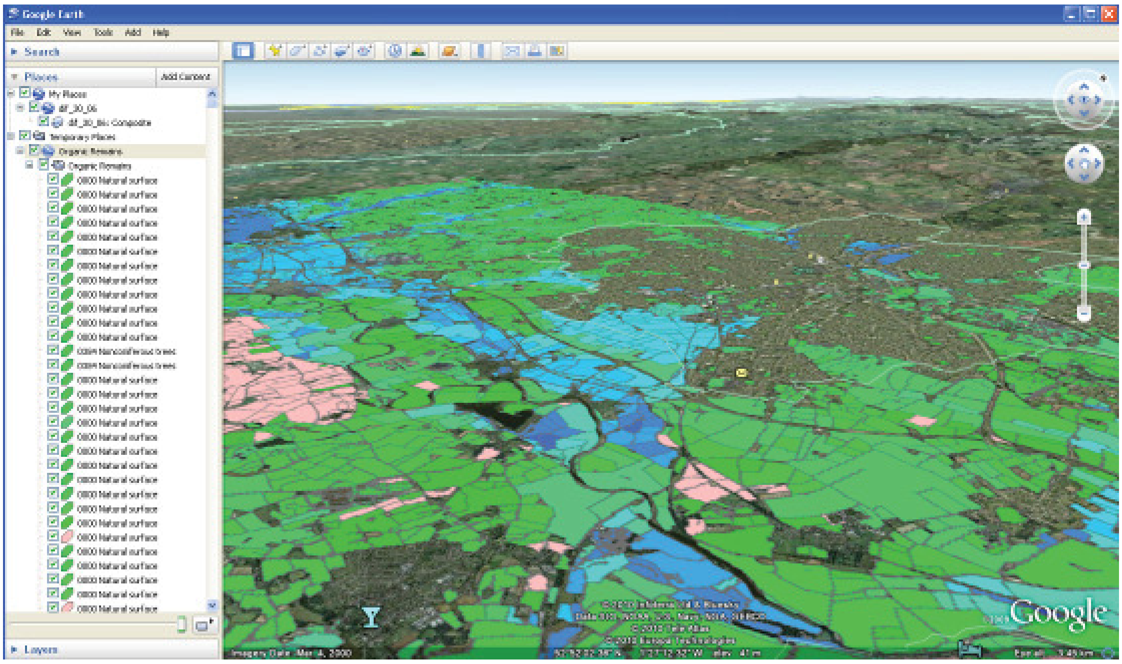


Figure 51. The Middle Trent in Derbyshire showing model data exported from ArcGIS in Keyhole Markup Language (kml) for visualisation in Google Earth.

6.2 ERROR AND ERROR CHECKING

The final analysis of error checking and quantification will be provided in the full final project report. In this summary we have sought to highlight the degree to which models of archaeological potential by period have successfully captured and retained existing knowledge regarding the presence of archaeological sites and finds.

To this end, Figures 52 provides three examples of model output for the Newark on Trent area showing model and HER data in conjunction.

Further analysis of the fidelity and accuracy of the modelled results will be included in the subsequent report.

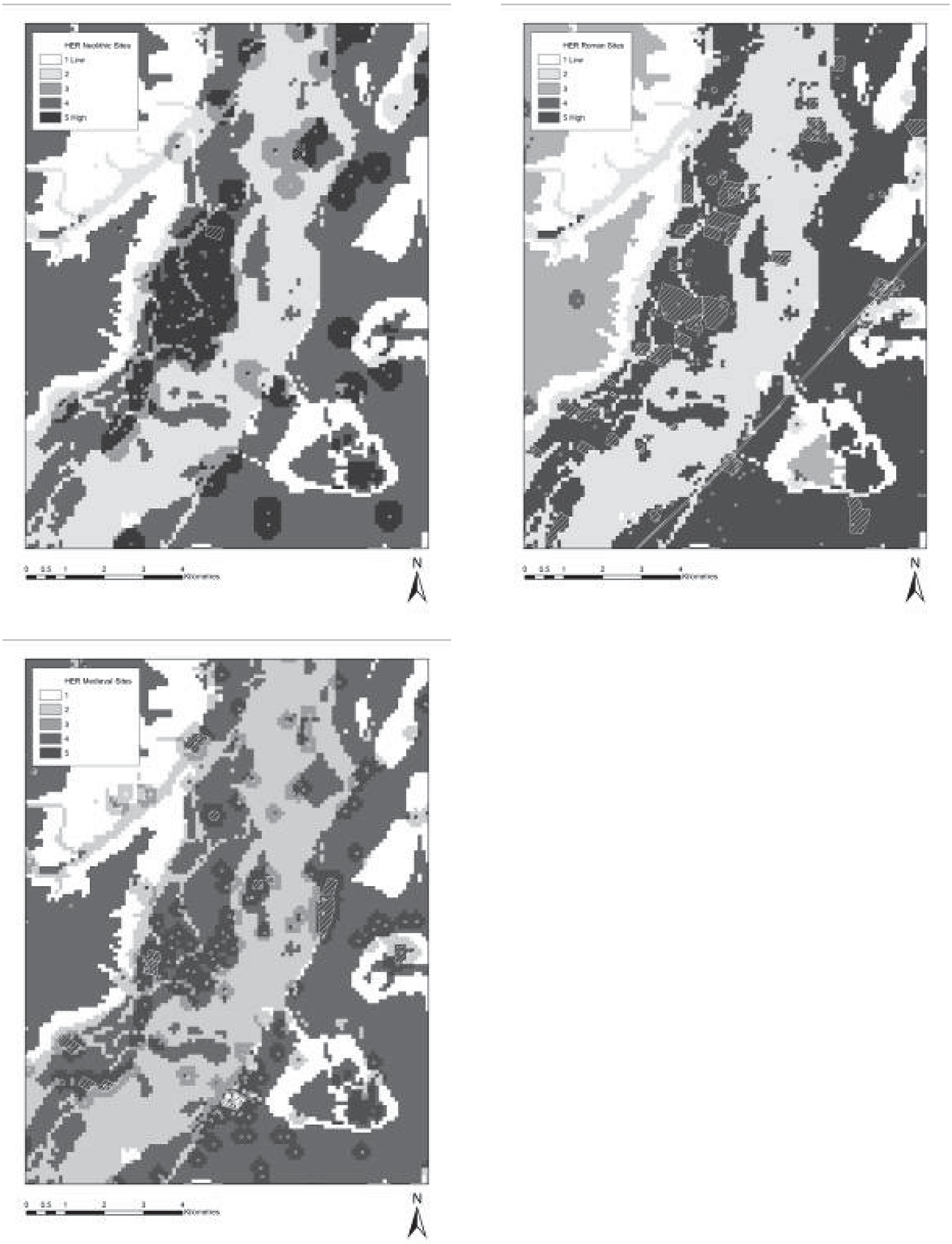


Figure 52. The Lower Trent in Nottinghamshire around Newark showing model data for Neolithic, Roman and Medieval remains with original HER data of known sites of the same period overlain for comparison.

6.3 CONCLUSIONS

The construction of the models contained in this project has proven an interesting, frustrating and in many cases ultimately questionable exercise.

It is worth reflecting on the original aim of the work o provide GIS-based spatial models which will allow a first level of understanding of the likely archaeological value of land parcels within the study area.

In these terms, and in the Topsight paradigm, the models of archaeological presence by period and organic preservation potential appear to succeed, although it should be recognised that success is about models of presentation and dissemination, not just robust modelling.

It is to be hoped that the work described herein provides a useful and thought provoking contribution to on-going debate about the role of predictive modelling in strategic management of archaeological resources.

Our own feeling is that generalised continuous landscape models derived from, but not replacing, HER data have a significant future role to play in archaeology and planning, particularly where such data are freely available to stakeholders in the spirit of Gelernter's original concept: to rapidly test multiple hypotheses, and fail softly -- without a loss of face.

REFERENCES

7 REFERENCES

Bettis III, E.A. and Hajic, E.R. 1995. Landscape development and the location of evidence of Archaic cultures in the Upper Midwest. *Geological Society of America Special Paper* **297**, 87-113.

Bettis III, E.A. and Mandel, R.D. 2002. The effects of temporal and spatial patterns of Holocene erosion and alluviation on the archaeological record of the Central and Eastern Great Plains, USA. *Geoarchaeology* **17** (**2**), 141-154.

Bishop, M. 2003. Issues and agenda in archaeological research and management: a case study from the Trent Valley, UK. In Howard, A.J., Macklin, M.G. and Passmore, D.G. (eds) *Alluvial Archaeology in Europe*. Lisse: Balkema: pp. 123-131.

Boos, S., Hornung, S. & Mueller, H., 2010. Considering Uncertainty in Archaeological Predictive Modelling: A Case Study in southern Rhineland-Palatinate (Germany). *proceedings of the 31st EARsel Symposium, Paris, France.* Available at: http://www.conferences.earsel.org/system/uploads/asset/file/54/earsel-symposium-2010_2-04.pdf [Accessed November 1, 2010].

Brandt, R., Groenewoudt, B.J. & Kvamme, K.L., 1992. Archaeological Site location: Netherlands modeling techniques. *World Archaeology*, 24(2), pp.268-282.

Bunting, M.J., Twiddle, C.L. and Middleton, R. (2008) Reconstructing past vegetation in mountain areas from pollen data: application of models of pollen dispersal and deposition. Palaeogeography, Palaeoclimology, Palaeoecology 259(1) 77-91.Canning, S., 2005. “ BELIEF ” in the past : Dempster-Shafer theory , GIS and archaeological predictive modelling. *Australian Archaeology*, (60), pp.6-15.

Catney, S. and Start, D. 2003. Time and Tide: The Archaeology of the Witham Valley. Witham Valley Archaeological Research Committee, Hertiage Trust of Lincolnshire.

Clark, J., Darlington, J. and Fairclough, G. 2004. *Using Historic Landscape Characterisation*. English Heritage.Connoly, J. & Lake, M., 2006. *Geographical Information Systems in Archaeology* Cambridge ., Cambridge: Cambridge University Press.

Coulthard, T.J., Hicks, D.M., Van De Wiel, M.J. (2007) Cellular modelling of river catchments and reaches: Advantages, limitations and prospects. Geomorphology, 90 (3-4), pp. 192-207.

Darvill, T. and Fulton, A.K. 1998. *MARS: The Monuments at Risk Survey in England 1995. Main Report*. Bournemouth and London. Bournemouth University and English Heritage.

Ebert, J., 2000. Practical Applications of GIS for Archaeologists: A predictive modelling toolkit. In K. Wescott & R. J. Brandon, eds. Taylor & Francis.

English Heritage. 2005. *English Heritage Research Agenda: An Introduction to English Heritage's Research Themes and Programmes.* Swindon, English Heritage.

English Heritage, 2008. *SHAPE 2008. A Strategic Framework for Historic Environment Activities & Programmes in English Heritage*. London, English Heritage.

French, C. 2004. Hydrological monitoring of an alluviated landscape in the Lower Great Ouse Valley at Over, Cambridgeshire. *Oxford Journal of Archaeology*, **4**, 139-156.

Gaffney, V. and van Leusen, M. 1995. Postscript – GIS, environmental determinism and archaeology: a parallel text. In Lock, G.R. and Stancic, Z. *Archaeology and geographical information systems: a European perspective*. London, Taylor and Francis.

Hill, J. b, Devitt, M. & Sergevaya, M., 2006. *Predictive Modeling and Cultural Resource Preservation in Santa Cruz County, Arizona*, Available at: https://www.cdarc.org/pdf/scnha_pred_mod.pdf.

Kamermans, H., 2008. Smashing the Crystal Ball. a Critical Evaluation of the Dutch National Archaeological Predictive Model (Ikaw). *International Journal of Humanities and Arts Computing*, 1(1), pp.71-84.

Knight, D. and Howard, A.J. 2004. *Trent Valley Landscapes*. Heritage Marketing and Publications Ltd, Kings Lynn.

Kvamme, K., 1988. Quantifying the present predicting the past; Theory Method and Application of Archaeological Predictive Modelling. In W. J. Judge & L. Sebastian, eds. Denver, Colorado. U.S. Department of the Interior, Bureasu of Land Management Service Center.

Mandel, R.D. 1995. Geomorphic controls of the Archaic record in the Central Plains of the United States. *Geological Society of America Special Paper* **297**, 37-66.

Needham, S.P. 2000. The Passage of the Thames: Holocene Environment and Settlement at Runnymede. Runnymede Bridge Research Excavations Volume 1, British Museum Press.

Needham, S. and Macklin, M.G. (Eds.) 1992. *Alluvial Archaeology in Britain*. Oxford: Oxbow Monograph **27**.

Passmore, D.G., Waddington, C. and Houghton, S.J. 2002. Geoarchaeology of the Milfield Basin, Northern England; towards an integrated archaeological prospection, research and management framework. *Archaeological Prospection* **9**, 71-91.

Passmore, D.G. and Macklin, M.G. 1997. Geoarchaeology of the Tyne Basin: Holocene river valley environments and the archaeological record. In C. Tolan-Smith (Ed.), *Landscape Archaeology in Tynedale* (Tyne Solway Ancient and Historic Landscapes Research Programme Monograph **1**). Newcastle-upon-Tyne: University of Newcastle. 11-27.

Sidell, J., Wilkinson, K., Scaife, R. & Cameron, N. 2000. The Holocene Evolution of the London Thames: Archaeological Inverstigations (1991-1998) for the London Underground Limited, Jubilee Line Extension Project. MoLAS Monograph 5, Museum of London.

Stancic & Kvamme, K, Z., 1998. Settlement patterns modelling through Boolean overlays of social and environmental variables. In J. Barceló, Briz, I & Vila. A, ed. *New Techniques for Old Times, Computer Applications and Quantitative Methods in Archaeology. Proceedings of the 26th conference, Barcelona March 1998.* Oxford: BAR International Series 757, pp. 231-237.

Stafford, C.R. and Creasman, S.D. 2002. The hidden record: Late Holocene landscapes and settlement archaeology in the Lower Ohio River Valley. *Geoarchaeology* **17** (**2**), 117-140.

Van Leusen, P.M., 2002. A review of wide-area predictive modelling using GIS. Chapter 5, in Pattern to Process. UniversityGroningen, Groningen.

Verhagen, P., 2007. Case studies in archaeological predictive modelling, Amsterdam,: Amsterdam University Press.

Walker, J. and Challis, K. 2004. *Reviewing the Effectiveness of Field Evaluation in the Trent valley: Whole Risk Reduction*. York Archaeological Trust

Ward, I., Smith, B & Lawley, R. 2009 Mapping the archaeological soil archive of sand and gravel mineral reserves in Britain. *Geoarchaeology.*

Wescott, K. & Brandon, R.J. eds., 2000. *Practical Applications of GIS for Archaeologists: A predictive modelling toolkit*, London: Taylor & Francis.

Wheatley, D., 2004. Making space for an archaeology of place. *Internet Archaeology*, (15). Available at: http://intarch.ac.uk/journal/issue15/Wheatley_index.html .

Wheatley, D. and Gillings, M. 2002. *Spatial Technology and Archaeology: The Archaeological Applications of GIS*. London, Taylor and Francis.

Whitley, T., 2003. Causality and Cross-Purposes in Archaeological Predictive Modeling *Computer Applications and Quantitative Methods in Archaeology. Proceedings of the 31st Conference, Vienna, Austria, April 2003. BAR International Series 1227*, pp.1-13.

Witcher, R., 1999. GIS and Landscapes of Perception. In J. Gillings, M. Mattingly, D.J & Van Dalen, ed. *Geographical Information Systems and Landscape Archaeology. The Archaeology of Mediterranean Landscapes 3.* Oxford: Oxbow, pp. 13-22.

Yorke, L., McManus, K. and Howard, A.J. 2004. *Fluvial Landform Risk Maps.* School of Geography, University of Leeds.

APPENDIX 1: WEIGHTS FOR ARCHAEOLOGICAL PRESENCE MODELS BY PERIOD AND STUDY AREA

Archaeological Presence Model Weights- Gainsborough Study Area

Palaeolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	5
Pal	2 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
7/10 features on terrace	Presence	9
Alluvium	no data/absence of features	1
2/10 features on alluvium	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Mesolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
meso	2 features	3
	3 features	4
note-large numbers are almost certainly due to HER data duplication	14 features	5
	28 features	6
	42 features	7
	70 features	8
	84 features	9
	98 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
232/276	Presence	9
Alluvium	no data/absence of features	1
6/276	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Neolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
Neo	2 features	2
	3 features	3
note-large numbers are almost certainly due to HER data duplication	4 features	3
	6 features	4
	7 features	5
	9 features	6
	15 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
131/320	Presence	4
Alluvium	no data/absence of features	1
78/320	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Bronze Age

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
BA	2 features	2
	3 features	3
note-large numbers are almost certainly due to HER data duplication	4 features	3
	6 features	4
	7 features	5
	9 features	6
	12 features	7
	15 features	9
	no data/absence of features	1
Terrace	no data/absence of features	1
132/302	Presence	4
Alluvium	no data/absence of features	1
81/302	Presence	3
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Iron Age

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
IA- TEST MODEL	2 features	3
	3 features	4
	5 features	5
	10 features	7
	12 features	8
	15 features	9
	no data/absence of features	1
Terrace	no data/absence of features	1
58/95 features on terrace	Presence	7
Alluvium	no data/absence of features	1
17/95 on alluvium	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance	Currently classified by distance In 10 classes- class 1-9 (distant)	1
	class 10-proximal	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Prehistoric

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1-11 feature	2
Prehistoric	12-22 features	3
	23-33 features	4
	34-44 features	5
	45-54features	6
	55-65 features	7
	66-76 features	8
	77-87features	9
	87-98 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
436/-710	Presence	6
Alluvium	no data/absence of features	1
104/-710	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Romano-British

Dataset	Potential classes	Weights
Period Differentiated Presence (for each period)	Presence Absence/no data	10 1
Gradiated Presence by period Rom	1 feature	2
	2 features	2
	3 features	2
	4 features	2
	5 features	3
	6 features	3
	7 features	3
	8 features	3
	10 features	4
	11 features	4
	12 features	4
	31 features	9
	35 features	10
	no data/absence of features	1
Terrace 177/389	no data/absence of features Presence	1 5
Alluvium 66/389	no data/absence of features Presence	1 2
Topography	Valley- Ie lowest ground for Gains Upland- ie slightly higher ground for Gains	2 5
Euclidean Distance from site	furthest classes (1-9) closest class (class 10)	1 2
Palaeochannels	Channel Proximal (within 100m) to channel no data/absence of features	2 5 1

Medieval

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
med- TEST MODEL	2 features	2
	3 features	2
(DIVIDED INTO EQUAL CLASSES DURING RECLASS)	4 features	2
	5 features	2
	6 features	3
	7 features	3
	8 features	3
	9 features	3
	10 features	4
	11 features	4
	12 features	4
	13 features	4
	14 features	5
	15 features	5
	16 features	5
	20 features	6
	22 features	7
	29 features	8
	39 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
325/758	Presence	4
Alluvium	no data/absence of features	1
75/758	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Post Medieval

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
PM- TEST MODEL	2 features	2
	3 features	2
	5 features	3
	6 features	3
	7 features	3
	8 features	4
	9 features	4
	10 features	4
	11 features	5
	24 features	9
Terrace	no data/absence of features	1
240/595	Presence	4
Alluvium	no data/absence of features	1
164/595	Presence	3
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Modern

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
mod- TEST MODEL	2 features	2
	3 features	3
note-large numbers are almost certainly due to HER data duplication	4 features	3
	5 features	3
	6 features	4
	11 features	5
	12 features	5
	13 features	6
	24 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
117/302	Presence	4
Alluvium	no data/absence of features	1
81/302	Presence	3
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Archaeological Presence Model Weights- Newark Study Area

Palaeolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	3
pal	2 features	6
	3 features	9
	no data/absence of features	1
Terrace	no data/absence of features	1
14/41	Presence	3
Alluvium	no data/absence of features	1
19/41	Presence	5
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Mesolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
mes	2 features	5
	4 features	9
	no data/absence of features	1
Terrace	no data/absence of features	1
29/39	Presence	7
Alluvium	no data/absence of features	1
4 of 39	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Neolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
neo	2 features	5
	3 features	8
	4 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
95/169	Presence	6
Alluvium	no data/absence of features	1
35/169	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Bronze Age

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
ba	2 features	3
	3 features	4
	4 features	5
	6 features	7
	7 features	8
	no data/absence of features	1
Terrace	no data/absence of features	1
98/176	Presence	6
Alluvium	no data/absence of features	1
50/176	Presence	3
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Iron Age

Dataset	Potential classes	Weights
Period Differentiated Presence (for each period)	Presence Absence/no data	10 1
Gradiated Presence by period ia	1 feature 2 features 3 features 4 features 5 features 6 features no data/absence of features	2 3 4 5 6 7 1
Terrace 120/164	no data/absence of features Presence	1 7
Alluvium 29/164	no data/absence of features Presence	1 2
Topography	Valley- Ie lowest ground for Gains Upland- ie slightly higher ground for Gains	2 5
Euclidean Distance from site	furthest classes (1-9) closest class (class 10)	1 2
Palaeochannels	Channel Proximal (within 100m) to channel no data/absence of features	2 5 1

Prehistoric

Dataset	Potential classes	Weights
Period Differentiated Presence (for each period)	Presence Absence/no data	10 1
Gradiated Presence by period pre note- high number of intersections may be due to duplications in HER dataset	1 feature 2 features 3 features 4 features 5 features 6 features 8 features no data/absence of features	2 3 4 5 6 7 9 1
Terrace 301/504	no data/absence of features Presence	1 6
Alluvium 118/504	no data/absence of features Presence	1 2
Topography	Valley- Ie lowest ground for Gains Upland- ie slightly higher ground for Gains	2 5
Euclidean Distance from site	furthest classes (1-9) closest class (class 10)	1 2
Palaeochannels	Channel Proximal (within 100m) to channel no data/absence of features	2 5 1

Romano-British

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
rom	2 features	2
	3 features	2
	4 features	2
	5 features	2
note- high number of intersections may be due to duplications in HER	6 features	3
dataset	7 features	3
	8 features	3
	9 features	3
	10 features	3
	12 features	4
	13 features	4
	14 features	4
	23 features	6
	46 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
335/554	Presence	6
Alluvium	no data/absence of features	1
94/554	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Medieval

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1-20 features	2
med	20-40 features	4
note- high number of intersections may be due to duplications in HER	40-60 features	6
dataset	180-200	10
	no data/absence of features	1
Terrace	no data/absence of features	1
562/1042	Presence	5
Alluvium	no data/absence of features	1
174/1042	Presence	2
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Post Medieval

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1-18 features	2
pm	18-36 features	3
note- high number of intersections may be due to duplications in HER	36-54 features	4
dataset	54-72 features	5
	144-162 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
588/1199	Presence	5
Alluvium	no data/absence of features	1
342/1199	Presence	3
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Modern

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1-3 features	2
mod	3-5 features	3
note- high number of intersections may be due to duplications in HER	5-7 features	4
dataset	7-10 features	5
	10-13 features	6
	13-17 features	5
	17-20 features	8
	20-30 features	9
	30-41 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
714/1404	Presence	5
Alluvium	no data/absence of features	1
347/1404	Presence	3
Topography	Valley- Ie lowest ground for Gains	2
	Upland- ie slightly higher ground for Gains	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Archaeological Presence Model Weights- Derbyshire Study Area

Palaeolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	5
Pal	2 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
20/46	Presence	5
Alluvium	no data/absence of features	1
01_46	Presence	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Mesolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	5
mes	2 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
11_/41	Presence	3
Alluvium	no data/absence of features	1
8_/41	Presence	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Neolithic

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
neo	2 features	3
	3 features	4
	4 features	5
	5 features	6
	6 features	7
	no data/absence of features	1
Terrace	no data/absence of features	1
85-/139	Presence	6
Alluvium	no data/absence of features	1
22-/139	Presence	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Bronze Age

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
ba	2 features	2
	3 features	2
	4 features	3
	5 features	3
	6 features	4
	11 features	6
	23 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
149-/236	Presence	6
Alluvium	no data/absence of features	1
12-/236	Presence	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Iron Age

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
ia	2 features	2
	3 features	3
	4 features	4
	5 features	5
	6 features	6
	7 features	7
	8 features	8
	9 features	9
	11 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
71-/137	Presence	5
Alluvium	no data/absence of features	1
9-/137	Presence	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Prehistoric

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1 feature	2
Pre	2 features	3
	3 features	4
	4 features	5
	5 features	6
	6 features	7
	no data/absence of features	1
Terrace	no data/absence of features	1
145/340	Presence	4
Alluvium	no data/absence of features	1
35/340	Presence	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Romano-British

Dataset	Potential classes	Weights
Period Differentiated Presence (for each period)	Presence Absence/no data	10 1
Gradiated Presence by period rom	1-5 feature	2
	6-10 feature	3
	11-15 feature	4
	16-19 feature	5
	20-24 features	6
	24-29 features	7
	30-33 features	8
	34-38 features	9
	39-43 features	10
	no data/absence of features	1
Terrace 148-/398	no data/absence of features Presence	1 4
Alluvium 57-/398	no data/absence of features Presence	1 2
Topography	Valley Upland	2 5
Euclidean Distance from site	furthest classes (1-9) closest class (class 10)	1 2
Palaeochannels	Channel Proximal (within 100m) to channel no data/absence of features	2 5 1

Anglo-Saxon period

Dataset	Potential classes	Weights
Period Differentiated Presence (for each period)	Presence Absence/no data	10 1
Gradiated Presence by period sax	1 feature	2
	2 feature	3
	3 feature	4
	4 feature	5
	5 feature	6
	6 feature	7
	no data/absence of features	1
Terrace 15/-51	no data/absence of features Presence	1 3
Alluvium 12/-51	no data/absence of features Presence	1 2
Topography	Valley Upland	2 5
Euclidean Distance from site	furthest classes (1-9) closest class (class 10)	1 2
Palaeochannels	Channel Proximal (within 100m) to channel no data/absence of features	2 5 1

Medieval

Dataset	Classes	Weights
Period Differentiated Presence (presence of HER/NMR records of given period)	Presence	10
	Absence/no data	1
Archaeological Intensity (incidence of intersections of HER/NMR records)	1-4 features intersecting	2
	5-7 features intersecting	3
	8-10 features intersecting	4
	11-13 features intersecting	5
	14-17 features intersecting	6
	18-20 features intersecting	7
	21-23 features intersecting	8
	24-26 features intersecting	9
	27-30 features intersecting	10
	absence of features	1
Terrace (530 NMR/HER records out of 1387 intersect terrace)	Absence of Terrace geology at location	1
	Presence of Terrace geology at location	4
Alluvium (170 NMR/HER records out of 1387 intersect alluvium)	Absence of Alluvial drift geology at location	1
	Presence of Alluvial drift geology	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	Classes 1-9- Distal from known sites	1
	Class 10- Proximal to known sites	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Post Medieval

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1-9 feature	2
PM	10-17 feature	3
	18-25 feature	4
	26-33 feature	5
	34-42 features	6
	43-50 features	7
	51-58 features	8
	59-66 features	9
	67-75 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
1245/-1380	Presence	9
Alluvium	no data/absence of features	1
487/-1380	Presence	4
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

Modern

Dataset	Potential classes	Weights
Period Differentiated Presence	Presence	10
(for each period)	Absence/no data	1
Gradiated Presence by period	1-5 feature	2
mod	6-10 feature	3
	11-15 feature	4
	16-20 feature	5
	21-24 features	6
	25-29 features	7
	30-34 features	8
	35-39 features	9
	40-44 features	10
	no data/absence of features	1
Terrace	no data/absence of features	1
624/-1666	Presence	4
Alluvium	no data/absence of features	1
376-/1666	Presence	2
Topography	Valley	2
	Upland	5
Euclidean Distance from site	furthest classes (1-9)	1
	closest class (class 10)	2
Palaeochannels	Channel	2
	Proximal (within 100m) to channel	5
	no data/absence of features	1

APPENDIX 2: WEIGHTS FOR SUSCEPTIBILITY TO EVALUATION MODELS ALL AREAS

AP- Crop and Soil weights

Dataset	Classes	Weights 1
CORINE Land Cover	Built-up	2
	Arable	5
	Pastoral	3
	Woodland	2
	Mineral	2
	Other	3
Soilscape	Clayey	1
(texture)	Loamy	7
	Sandy	7

AP- Earthwork weights

Dataset	Classes	Weights 1
Agric Land Class	Grade 1	3
	Grade 2	3
	Grade 3	3
	Grade 4	5
	Non-agricultural	1
	Urban	1
CORINE Land Cover	Built-up	2
	Arable	5
	Pastoral	7
	Woodland	2
	Mineral	2
	Other	3

Surface collection weights

Dataset	Potential classes	Weights
CORINE Land Cover	Built-up	2
	Arable	7
	Pastoral	3
	Woodland	3
	Mineral	2
	Other	3
Soilscape	Clayey	3
(texture)	Loamy	5
	Sandy	5

GPR weights

Dataset	Potential classes	Weights 1
CORINE Land Cover	Built-up	2
	Arable	5
	Pastoral	5
	Woodland	2
	Mineral	2
	Other	5
Soilscape	Clayey	1
(texture)	Loamy	5
	Sandy	5
Terrace	present	4
	absent	1

Electrical Survey

Dataset	Potential classes	Weights 1
CORINE Land Cover	Built-up	2
	Arable	5
	Pastoral	5
	Woodland	3
	Mineral	2
	Other	5
Overbuden Reclass (from aggregate model)	0m	no data
	0-1m	7
	1-2m	4
	2-3m	4
	3-4m	4
Terrace	present	4
	absent	1

Magnetic Survey

Dataset	Potential classes	Weights 1
CORINE Land Cover	Built-up	2
	Arable	5
	Pastoral	5
	Woodland	3
	Mineral	2
	Other	5
Overbuden Reclass (from aggregate model)	0m	no data
	0-1m	7
	1-2m	4
	2-3m	4
	3-4m	4
Terrace	present	4
	absent	1

Lidar weights

Dataset	Potential classes	Weights 1
Agric Land Class	Grade 1	2
	Grade 2	2
	Grade 3	2
	Grade 4	4
	Non-agricultural	1
	Urban	1
CORINE Land Cover	Built-up	2
	Arable	4
	Pastoral	7
	Woodland	7
	Mineral	2
	Other	4

Hand Augering weights

Dataset	Potential classes	Weights
CORINE Land Cover	Built-up	2
	Arable	5
	Pastoral	5
	Woodland	2
	Mineral	2
	Other	5
Terrace	present	3
	absent	1
Alluvium	Present	7
	Absent	1
Palaeochannel	present	7
	absent	1
Overburden thickness	no data	1
	1m+	4
	0-1m	3

Hand excavation (test pitting) weights

Dataset	Potential classes	Weights
CORINE Land Cover	Built-up	2
	Arable	7
	Pastoral	7
	Woodland	2
	Mineral	3
	Other	5
Terrace	present	7
	absent	1
Overburden thickness	no data	1
	1m+	2
	0-1m	5

Machine evaluation weights

Dataset	Potential classes	Weights
CORINE Land Cover	Built-up	2
	Arable	7
	Pastoral	7
	Woodland	5
	Mineral	2
	Other	7
Terrace	present	5
	absent	1
Overburden thickness	no data	1
	1m+	2
	0-1m	5

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