Master Thesis in Geographical Information Science nr 146

Implementing a multi-criteria GIS analysis and predictive modelling to locate Upper Palaeolithic decorated caves in the Périgord noir, France

Benjamin Bernard Fabien Gérard Borgeais

2022
Department of
Physical Geography and Ecosystem Science
Centre for Geographical Information Systems
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden

Benjamin Bernard Fabien Gérard Borgeais (2022). Implementing a multi-criteria GIS analysis and predictive modelling to locate Upper Palaeolithic decorated caves in the Périgord noir, France

Master degree thesis, 30 credits in Geographical Information Systems (GIS)

Department of Physical Geography and Ecosystem Science, Lund University

Implementing a multi-criteria GIS analysis and predictive modelling to locate Upper Palaeolithic decorated caves in the Périgord noir, France

---

Benjamin Bernard Fabien Gérard Borgeais
Master thesis, 30 credits, in Geographical Information Sciences

Ulrik Mårtensson
Department of Physical Geography and Ecosystems Sciences
Lund University

Acknowledgments

This research project has been fulfilling and enriching and could not have been completed without a great deal of support and assistance. I would like to thank my supervisor in the first place, Professor Ulrik Mårtensson, whose help and expertise were essential in formulating my project plan and bringing my research to completion.

I would also like to thank Stéphane Konik from the *Centre National de Préhistoire* in Périgueux who gave me precious pieces of information on the geomorphological context of the Périgord noir. I would like to thank Christophe Vigne and Claire Peyre from the *Pôle d'Interprétation de la Préhistoire* in Les Eyzies who were both very responsive and helped me access valuable pieces of data on decorated caves in the department of Dordogne.

I would particularly like to acknowledge my colleagues from Jeanne d'Arc primary school in Brive-la-Gaillarde for their valuable support. I would especially like to single out the head teacher of the school, Françoise Barbeau, who allowed me to work part-time so I could reconcile my job and my studies. Your kindness and your understanding have been essential for me to keep a healthy balance between all aspects of my life during that particularly challenging time.

In addition, I could not have completed my research project without the support of my friends, Laura Zindel, Anthony Bersanne, Alexis Crouet, Boris Vallet, and Jennifer Andrea Villamil Jiménez who provided cheerful distractions to rest my mind outside of my work.

Abstract

Geographical Information Systems are a powerful tool for the processing of geographical data and can be used to implement predictive modelling for the purpose of archaeological research. The study presented here proposes a predictive model based on multi-criteria evaluation, and aims at analysing the parameters of known Upper Palaeolithic decorated caves in the Périgord noir, in southwest France. The main objective was to show that known decorated caves have enough parameters in common to create a predictive model that would describe zones of possible decorated caves' occurrences in the area. A hybrid methodology was developed to extract significant pieces of information from the selected variables in order to design the predictive model.

Elevation, slope, aspect, and proximity to water were selected as the four variables to build the model. They were processed individually and were standardised using a numerical rating scale. Each criterion was weighted individually through the rating methodology in order to be aggregated using weighted linear combination. The model created showed that areas close to water streams were more likely to contain undiscovered decorated caves from the Upper Palaeolithic period. The validation statistic Kvamme Gain was finally used to assess the model and the value that was calculated showed that a large proportion of known caves were contained in a relatively restricted area, confirming the model's predictions.

Abstract (French)

Les Systèmes d'Information Géographique constituent un ensemble performant d'outils dans le traitement des données géographiques. Ils peuvent par exemple être utilisés pour mettre en œuvre un modèle prédictif dans le cadre de recherches archéologiques. L'étude proposée ici décrit la création d'un modèle prédictif basé sur une analyse multicritère, et vise à analyser les paramètres des grottes ornées connues datant de la période du Paléolithique supérieur dans le Périgord noir. Les principaux objectifs sont de démontrer que les grottes ornées possèdent assez de caractéristiques en commun pour le développement d'un modèle prédictif qui décrirait les zones d'intérêt archéologique. Pour se faire, une méthodologie hybride a été développée afin d'extraire des informations pertinentes à partir des critères sélectionnés.

L'altitude, la pente, l'orientation, ainsi que la proximité du réseau hydrographique sont les quatre variables utilisées pour développer le modèle. Chaque couche a été traitée individuellement, et l'ensemble des données a été standardisé par le biais d'une échelle numérique. Des poids ont été assignés à chacun des critères afin de les agréger par le biais d'une combinaison linéaire pondérée. Le modèle ainsi créé montre que les zones proches des cours d'eau semblent plus propices à la découverte de nouvelles grottes ornées datant du Paléolithique supérieur. La variable statistique de Kvamme a enfin été utilisée pour tester et valider le modèle. La valeur calculée démontre qu'une large proportion de grottes se trouve dans une zone relativement restreinte, validant ainsi la pertinence du modèle ici développé.

Table of contents

List of figures

List of tables

List of abbreviations

Abbreviation	**Meaning**
AHP	Analytical Hierarchy Process
APM	Archaeological Predictive Modelling
BC	Before Christ
BP	Before Present
CNP	Centre National de Préhistoire
CRM	Cultural Resource Management
DEM	Digital Elevation Model
DRAC	Direction Régionale des Affaires Culturelles
GCS	Geographic Coordinate System
GIS	Geographic Information System
IGN	Institut national de l'information géographique et forestière
KG	Kvamme Gain
MCA	Multi Criteria Analysis
MCE	Multi Criteria Evaluation
MCDA	Multi Criteria Decision Analysis
MCDM	Multi Criteria Decision Making
MIS	Marine Isotope Stage
PCS	Projected Coordinate System
PIP	Pôle d’Interprétation de la Préhistoire
RGF	Réseau Géodésique Français
RQ	Research Question
USA	United States of America
WLC	Weighted Linear Combination

1 Introduction

1.1 Framework

Geographical Information Systems (GIS) constitute a powerful tool for the processing of geographical data in a variety of fields. This study presents the use of GIS in the implementation of multi-criteria analysis and weights of evidence predictive modelling to locate Upper Palaeolithic decorated caves in the Périgord noir, in southwest France. Predictive modelling is a methodology that has been applied in numerous case studies in various parts of the world and for different archaeological time periods (Balla et al., 2013; Gillespie et al., 2016; Graves, 2011; Kondo et al., 2012; Parow-Souchon et al., 2021). Yet, it has never been implemented in the Périgord noir, despite the area containing a large number of prehistoric vestiges.

The design of a predictive model comprises various steps which can be combined and adapted depending on the chosen methodology and the available datasets. For instance, Balla et al. (2013) have proposed a methodology based on multi-criteria evaluation (MCE) to locate Macedonian tombs dated from the late classical and Hellenistic period (4^{th} century BC - 2^{nd} century BC) in Northern Greece. They describe the different stages of MCE as the formation of a problem, the quantification of the selected criteria, the calculation of the criteria weights, and the aggregation of the criteria in the form of probability maps, which relates to the definition given by Verhagen (2007). Moreover, Greene et al. (2011) highlight "the variety and complexity of multi-criteria decision analysis methods (MCDA)", with diverse ways of selecting the criteria, putting them on a common scale, weighting them and combining them to produce probability maps.

The selection of the different criteria in particular appears as critical in the implementation of a MCDA in the scope of predictive modelling. Malczewski (1999) states that "a set of criteria should be complete, operational, decomposable, nonredundant, and minimal" in order to be used in a multi-criteria GIS analysis. He also presents an examination of the relevant literature, analytical studies, and surveys of opinions as three fundamental techniques to perform an appropriate selection of criteria. Most models seem to incorporate similar sets of variables divided into environmental and sociocultural parameters. The behaviours of Neanderthal and *Homo sapiens* should then be studied in more details in order to select the most appropriate criteria in the building of a predictive model.

Predictive modelling aims at enriching archaeological knowledge, but also limiting the costs of field work and developing tourism and heritage-related activities. This study presents a hybrid methodology based on the review of archaeological background found in the literature for the selection of the different criteria. The numerical rating scale technique will be used for the standardisation of the selected criteria as it appears as an accurate rescaling technique. Pixels in the different GIS layers are assigned values according to their probability. A value of 1 usually represents a very low probability, while a very high probability is represented by a higher value, 5 or 10 in general. The rating methodology will be used for the weighting of the criteria. It consists in defining a value for each criterion on a common scale, all weights adding up to a defined value, usually 1, 10, or 100. Finally, the weighted criteria will be aggregated using weighted linear combination (WLC), as it constitutes a risk-neutral technique according to Greene et al. (2011). The different techniques used for processing the data are explained in more details throughout the study.

1.2 Motivation

This project was developed to highlight the potential of the Périgord noir in terms of archaeology and heritage-based tourism. The Upper Palaeolithic historical period is a very interesting period and much is still to be discovered about the behaviours of human beings who lived during that time. Decorated caves, in particular, are enthralling because researchers and scientists are still unsure about the meaning of the engravings and paintings found in the caves. Developing a model to help in the understanding of settlement patterns could then potentially help in the interpretation of cave art.

1.3 Aim and research questions

The literature and field surveys have shown that a great number of Upper Palaeolithic decorated caves are found in the Périgord noir. In that perspective, the aim of this thesis is to see if those decorated caves share similar parameters, and if it is then possible to develop a predictive model to detect areas where undiscovered decorated caves could be located. To this end, the following research question will be investigated:

RQ1: Do the values extracted from the selected criteria allow the formation of a model to predict the location of Upper Palaeolithic decorated caves in the Périgord noir?

RQ2: If so, is modelling based on a multi-criteria methodology using a numerical rating scale, the rating weighting methodology, and weighted linear combination aggregation technique efficient in the detection of Upper Palaeolithic decorated caves in the Périgord noir?

1.4 Thesis structure

This research project includes an extensive literature review showing the archaeological potential of the Périgord noir and focusing on predictive modelling and multi-criteria evaluation techniques. It presents the area of study as well as the selected procedures to extract meaningful values from the different layers and create a predictive model. It shows the application of the predictive model in the form of probability maps and explains its assessment through the Kvamme Gain validation statistic. The results of the different analyses are finally displayed and discussed in relation to the aim of the study and the research questions.

2 Study area

Due to its high archaeological potential as the literature review will show, the Périgord noir will be the study area for this analysis. The name "Périgord" is the name of a former historical region of southwest France now known as Dordogne, which is today a department located in the region of Nouvelle-Aquitaine (**Figure 1**). Bordeaux is the administrative centre of the region Nouvelle-Aquitaine and Dordogne is the third largest department in France, with a population of about 400,000. This area is an important place for tourism, especially during the summer season, with nature-based activities such as canoeing, hiking, and horse riding, but also internationally renowned cultural places such as the Lascaux Caves and the archaeological sites of the Vézère valley. There were 4.3 million tourists in Dordogne in 2020 despite the restrictions related to the Covid-19 pandemic according to the daily paper Sud Ouest (2021). The different administrative layers are presented in **Table 1**, along with their respective areas derived from the administrative layer obtained from the French government database.

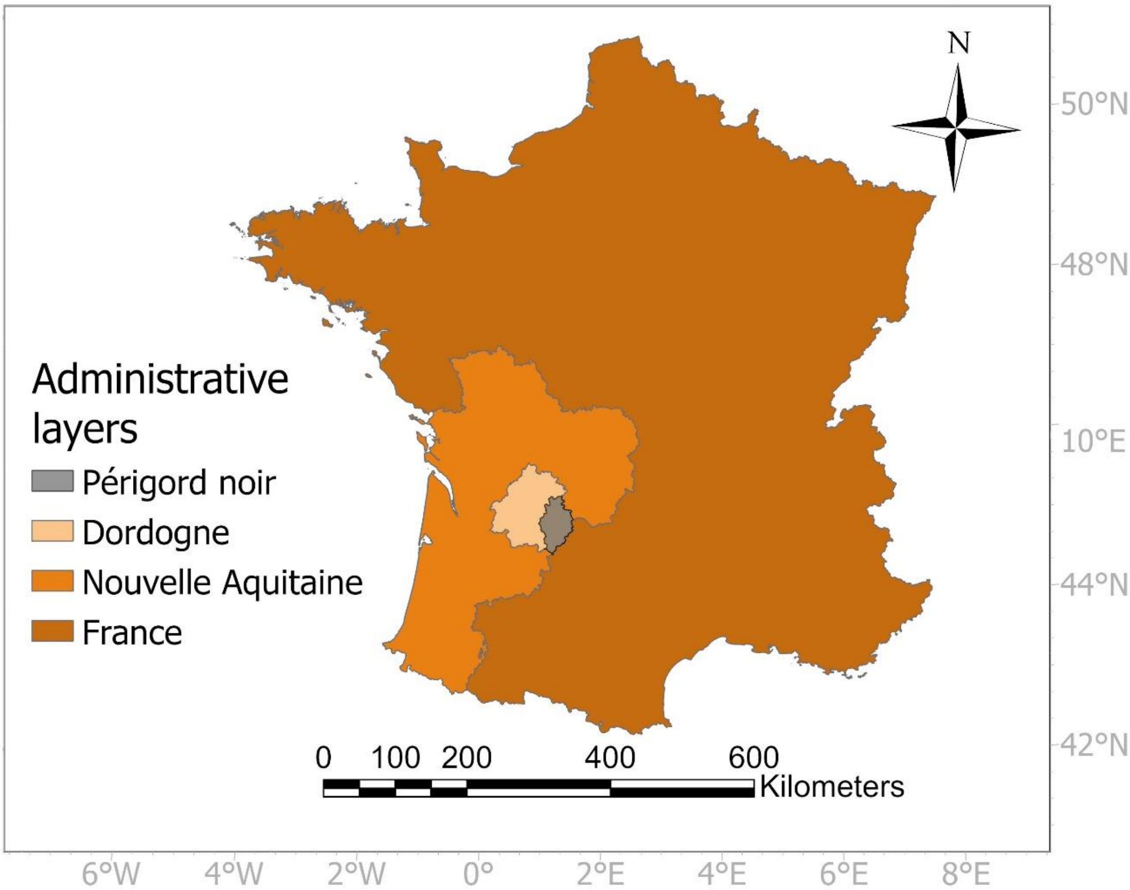

Figure 1. The location of the Périgord noir in relation to larger administrative layers

Table 1. Administrative layers within which the Périgord noir is located and their area

Administrative layer	Name	Area (km²)
Country	France	539,861
Region	Nouvelle-Aquitaine	84,748
Department	Dordogne	9,210
Subsection	Périgord noir	2,321

The Périgord noir is then an unofficial subsection of the Dordogne department but still has defined boundaries. **Figure 2** displays the four different Périgord subregions:

- The Périgord vert (green), in the north, which is named after its luxuriant vegetation. Brantôme is the largest town in this subsection and is known as "the green Venice".
- The Périgord blanc (white), in the centre, which is named after its limestone soil. Périgueux is the largest city and the administrative centre of Dordogne.
- The Périgord pourpre (purple), in the southwest, which is named after its vineyards. Bergerac is the largest city in this area and Monbazillac is renowned for its white wine.
- The Périgord noir (black), in the southeast, which is named after its holm oak trees and the truffles found in the area. Sarlat-la-Canéda is the largest city and most prehistoric sites can be found in this subsection of the department.

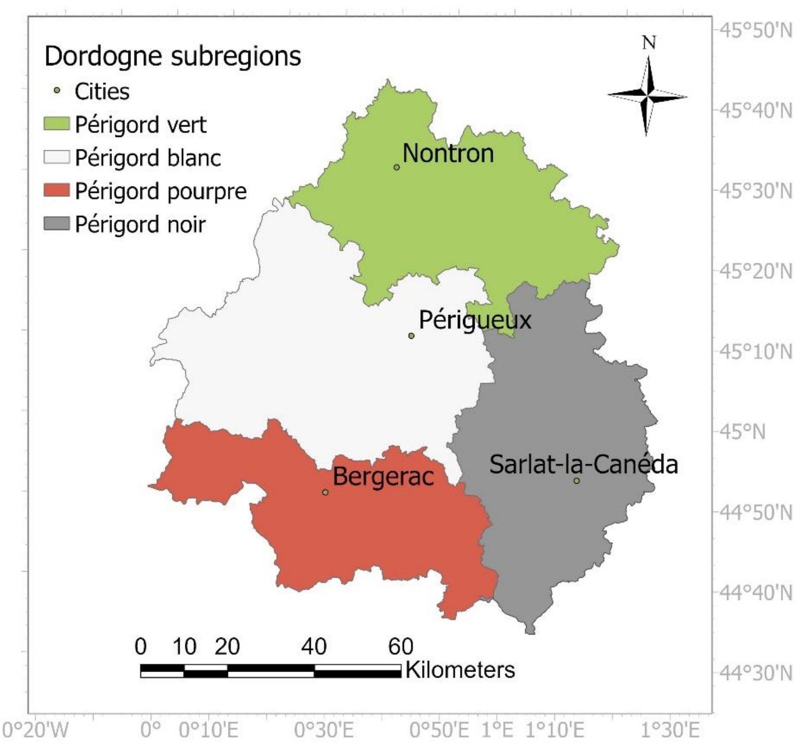

Figure 2. The four Périgord subregions

The Périgord noir (**Figure 3**) is an area with rather touristic places such as Montignac-Lascaux, Sarlat-la-Canéda, and Les Eyzies. It also has two major rivers, namely the river Vézère and the river Dordogne, the latter being named after the department. Those two rivers, along with all their tributaries, play a very important role in tourism and cultural activities nowadays. They may also have influenced the settlement of prehistoric individuals (Pôle d'Interprétation de la Préhistoire, n.d.). They shaped the area because of the friable nature of calcareous soil, and allowed the development of diverse biomes, which partly explains why the area has been inhabited for so long as described by the Interpretation Prehistory Centre, or *Pôle d'Interprétation de la Préhistoire* (PIP).

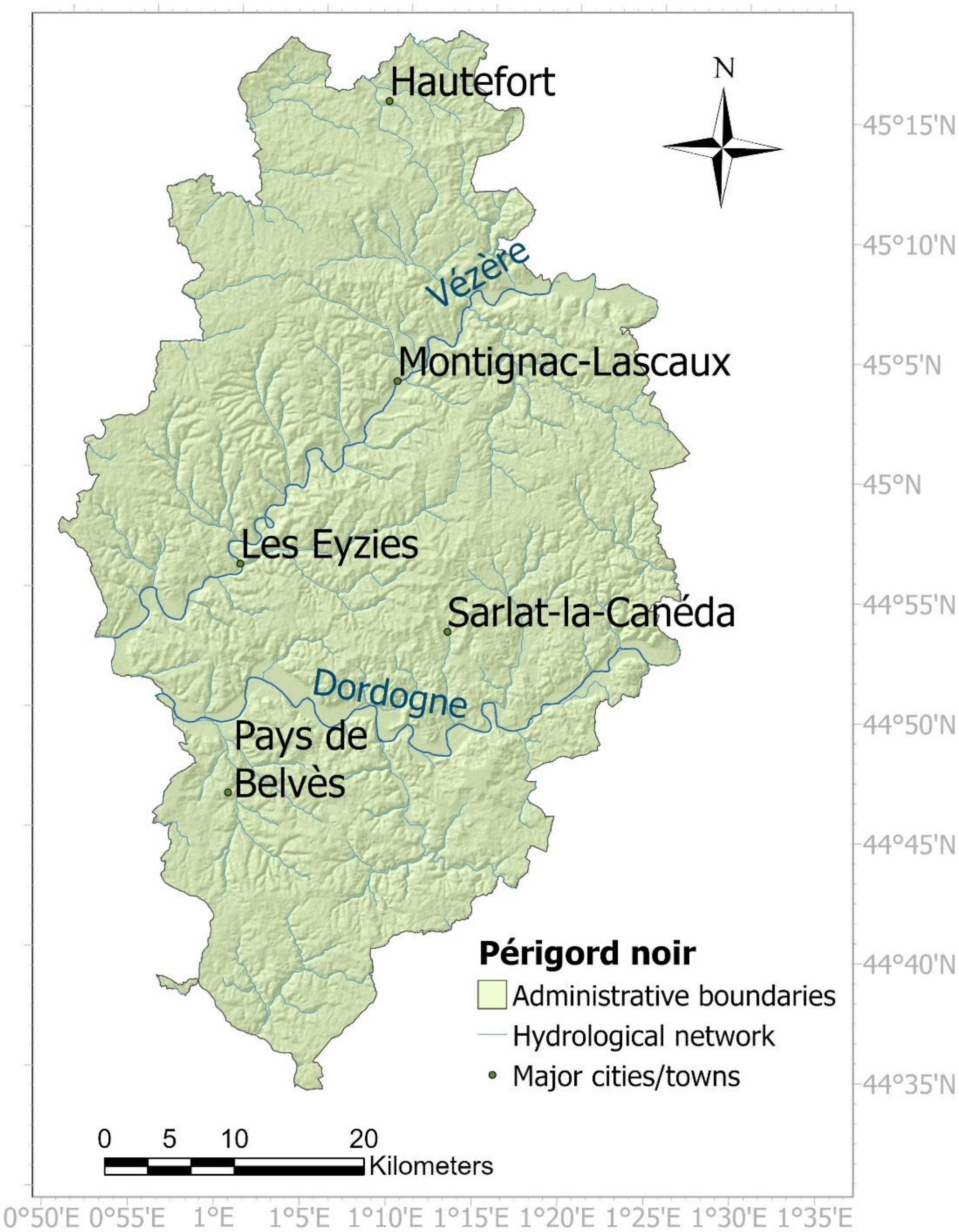

Figure 3. The Périgord noir

3 Literature review

3.1 Historical and archaeological background of the Périgord noir

3.1.1 The role of environmental and cultural parameters in the settlement of prehistoric populations in the Périgord noir

The Pôle d'Interprétation de la Préhistoire has described the state of archaeological research in the Périgord noir, especially in the Vézère Valley, in the course of the last two centuries. Several parameters make the area the capital of prehistoric archaeology according to the PIP (n.d.). First of all, the calcareous nature of soil in the region has preserved numerous remains from the prehistory, and from more recent historical periods. Indeed, according to Kibblewhite et al. (2015), some environmental factors play a major role in the preservation of cultural artefacts and buried material in the soil. When it comes to metal artefacts for instance, the authors state that "preservation in alkaline soils formed from calcareous parent materials may be augmented by protective carbonate coatings". More generally, Kibblewhite et al. (2015) indicate that soils can be a great predictor in the finding of buried infrastructures. In this way, limestone is a particularly favourable type of soil in the formation of caves as it is friable and can dissolve in water. Indeed, rainwater turns into a weak carbonic acid solution when it "absorbs some carbon dioxide as it passes through the atmosphere" (Davies and Morgan, 1991), but also when entering in contact with decaying organic material. Carbonic acid will then wear away parts of the soil and create caves under the effects of time. Karst landforms could then indicate the existence of caves on a geological point of view and raise the probabilities of decorated caves' occurrences in the area.

Another important parameter described by the PIP to explain the settlement of prehistoric individuals is the existence of an important hydrographic network, as well as a favourable climate and topography. The area of study has two main rivers, namely the river Vézère and the river Dordogne each having several tributaries, which could have played an important role in the occupation of the area throughout time. Basafa and Davari (2020) have studied the formation of prehistoric settlements of Kashfarud Basin in Iran and the role of effective factors and cultural parameters in that process. They concluded that "suitable environmental conditions including climate, important rich water resources, especially Kashfarud River, easy access to plant and animal food resources and ecological structure of the region for intra-regional and extra-regional communications, cause the formation and emergence of habitat systems to use resources". In the Périgord noir, the combination of similar factors (important hydrographic network, climate, and topography) resulted in the creation of numerous and diverse biotopes, offering a wide range of resources even during glaciations according to the PIP. The calcareous soil as well as the environmental factors presented above could then have contributed to continuous settlement in the area. Other variables such as the elevation, the aspect, the wind exposure and the sun exposure of the caves' entries could also have played a role in the selection of the sites by prehistoric individuals.

3.1.2 Neanderthal settlements in the Périgord noir: a demonstration of early cognitive capacities

The PIP describes the first occurrences of human settlements in the Périgord noir, especially in the Vézère valley, around 400,000 years Before Present (BP) with Neanderthal, who disappeared around 30,000 years BP. Soler and Soler (2016) depict Neanderthal as hominids who "were perfectly adapted to the land and its resources […] and survived all the climate and environmental changes that had occurred throughout the Pleistocene for hundreds of millennia". They also state that Neanderthal disappeared for mysterious reasons "upon the arrival of anatomically modern men, who originated in Africa". Yet, Klein (1995) suggests that "anatomically modern Africans largely or wholly replaced archaic Eurasians" due to their modern capacity for culture based on more developed cognitive and communicative abilities. Still, Neanderthal were able to produce tools as well as art using environmental features. Douka and Spinapolice (2012) for instance report that tools made of stone varieties discovered in Mousterian sites in southern Europe can be dated from 110,000 years BP to 50,000 years BP and can then be considered resulting from Neanderthal making. Aranguren et al. (2018) present "a series of wooden tools in an open-air stratified site referable to late Middle Pleistocene" which was radiometrically dated around 171,000 years BP. Moreover, uranium-thorium dating of carbonate crusts has been used by Hoffmann et al. (2018) in three sites in Spain to demonstrate that cave paintings dated from more than 64,000 years BP and were then most probably from Neanderthal origin. The authors described the paintings as using two colours, namely red and black, and representing "various animals, linear signs, geometric shapes, hand stencils, and handprints". This shows a certain reason of Neanderthal in the choice of settlements as well as a sensitivity and behaviours that go beyond primal instinct.

More importantly, intentional Neanderthal burials occurred in the Périgord noir and in surrounding areas, depicting "modern cognitive capacities and behaviours" (Balzeau et al., 2020). In that perspective, the prehistoric site of the Regourdou in Montignac, Dordogne, is depicted by Pelletier et al. (2017) as being "potentially the oldest burial in Western Europe". Furthermore, Rendu et al. (2014) studied Neanderthal burials in La-Chapelle-aux-Saints, in the neighbouring department of Corrèze, and concluded that the Neanderthal remains found on the burial site were “deposit in a pit dug by other members of its group and protected by a rapid covering from any disturbance”. As for the study by Balzeau et al. (2020), Rendu et al. (2014) described their findings as presenting the fact that Neanderthal had the cognitive capacity to produce such memorial site. The discovery of those sites gives precious pieces of information on the way Neanderthal lived and on its physical and social characteristics according to the PIP. Burial sites thus allow the study of the general state of health of buried individuals, potentially the age and the cause of death. Artefacts can also be found in or near the sites, which can help in the dating of the remains and features. Social characteristics could also be deduced from burial sites through the way sepulchres are organised.

Four main sites presenting traces of Neanderthal have been discovered in the Périgord noir. The site of La Ferrassie in Savignac-de-Miremont (Dordogne) has been excavated in the early 20th century by Denis Peyrony. It was “recently re-excavated and dated Pleistocene site in southwest France with evidence of Neanderthal activity spanning MIS 5 to MIS 3” (Pederzani et al., 2021). MIS 3, or Marine Isotope Stage 3, started 57,000 years BP, while MIS 5 started 130,000 years BP. The site of the Regourdou in Montignac was excavated in the 1950s and “a Neanderthal burial of a young adult (Regourdou 1) was found in Layer 4” (Pablos et al. 2019). Layer 4 corresponds to MIS 4 which started 71,000 years BP. The remains of at least two Neanderthal individuals were discovered in the Regourdou resulting from archaeological research. The third main site presenting traces of Neanderthal activity in the Périgord noir is Roc de Marsal in Campagne (Dordogne). Aldeias et al. (2012) have studied “a series of well-preserved fire features associated with artefact-rich Neanderthal occupations” resulting from new excavations at the prehistoric site of Roc de Marsal. The remains of one Neanderthal individual were discovered on this site in 1961 by Jean Lafille. Finally, an adolescent Neanderthal skeleton was discovered at Le Moustier (Dordogne) in 1908 by the Swiss Antiquary Otto Hauser (Daumas et al., 2021). Those numerous Neanderthal remains on such a small area show the richness of the Périgord noir in terms of archaeological potential.

3.1.3 *Homo sapiens* settlements in the Périgord noir and the development of art and artefacts

Neanderthal disappeared around 30,000 years BP and were “swiftly replaced by another new civilisation which was very different and more dynamic” (Soler and Soler, 2016). This new civilisation is called *Homo sapiens*, or more informally Cro-Magnon, and arrived from Africa to settle in Europe around 40,000 years BP. The name of Cro-Magnon originates from the name of a rock shelter in the village of Les Eyzies in Dordogne, where "human remains morphologically similar to recent humans were discovered by workers" (Thibeault and Villotte, 2018). The term comes from the Occitan language, a Romance language spoken in the south of France and in some parts of Monaco, Spain, and Italy. *Cro* means hollow, or cave, while *Magnon* could either be the name of a local hermit, or mean large.

Homo sapiens developed rather sophisticated tools using different features from his environment. Otte (2010) describes assegai made from ivory, reindeers' antlers or bones, but also flint tools used for leather working. Furthermore, Gauvrit Roux and Beyries (2018) describe hide scraping techniques using hand scrapers made from flint. They also state that "the tools were given a longer cycle of use resharpening, reshaping, reusing and adding use zones", supporting the idea that those prehistoric individuals had more advanced cognitive capacities than their predecessors. This can be confirmed when studying prehistoric cave art dating from the Upper Palaeolithic in the area.

3.2 Production and preservation of prehistoric art and its interest for cultural activities and tourism

3.2.1 Decorated caves from the Upper Palaeolithic as the result of the combination of social behaviours and favourable environmental factors

The PIP describes the Périgord noir, and the Vézère valley in particular, as a sanctuary for individuals, animals, and plants during the Palaeolithic with a virtually continuous occupation of the area throughout this time. In that context, rock shelters and caves played an important role in the development of activities of prehistoric individuals. Those geological features were used for flint cutting, meat cutting, or hide scraping but were also of major importance in a more symbolic perspective through sepulchres and cave paintings. Sites dated from the Magdalenian (17,000 years BP to 14,000 years BP) in particular, depict this combination of domestic and symbolic activities over long periods of time according to Pinçon and Fuentes (2020). Cave art through painting and engraving largely developed during the Upper Palaeolithic and show the behavioural abilities of *Homo sapiens*. For instance, the Grand Panel palimpsest in Cussac Cave (Dordogne) "constitutes a true composition whose additions were always intentional, […] and refutes the idea that any artist here intended to create a work of art for its own sake" (Feruglio et al., 2019). A 'palimpsest' is defined as "something such as a work of art that has many levels of meaning, types of style, etc. that build on each other" ('Palimpsest', n.d.). Cave art is also a representation of the world as thought by the artist and its community, and delivers pieces of information on features that surrounded them and on their ways of living according to Pinçon and Fuentes (2020).

Homo sapiens most likely took advantage of geomorphological criteria to create its art, using a rather wide range of themes and techniques. The Bernoux Cave in Bourdeilles, Dordogne, “revealed several major graphic discoveries” and seem to show “a Palaeolithic pictorial group on a larger scale” according to Petrognani et al. (2014). More generally, fingerprints, footprints, handprints and engraving are found principally on soft clay walls, while harder surfaces were used for sprayed paintings according to the PIP. Art was then adapted to the particularities and constraints of natural supports, with light and shades used to bring perspective in engraving works for instance. Jouteau et al. (2019) studied geological parameters and social behaviours in Cussac Cave, and found evidences “of a strong interaction between geological and cultural factors in the selection of the rock art panels” in the cave. More, they state that the “people that frequented Cussac Cave linked their cultural goals to what the cave had to offer in terms of geology, geomorphology and available space, [optimising] both the opportunities and constraints of the cave, thus demonstrating a strong interaction between geological and cultural parameters”.

Several variables then seem to have oriented the choice of prehistoric individuals in the selection of caves to produce their art. The PIP describes the aspect, the wind exposure, the morphology of the cave, and the proximity to resources (water, food, flint…) as the main criteria. Jègues-Wolkiewiez (2007) studied the orientation of the caves and decorated Palaeolithic rock shelters, establishing a link between the enlightening of caves and art occurrences. The study seems to show that most decorated caves in France are oriented to the south, southeast, or southwest, showing a pattern in the selection of caves by prehistoric individuals. Those criteria could thus serve as a basis for implementing a predictive model in a Geographical Information System (GIS) to describe areas of potential archaeological interest.

3.2.2 Conditions of preservation and interest of prehistoric artefacts and vestiges related to cultural management and tourism

Prehistoric artefacts and vestiges present an interest on an historical and archaeological point of view, and are important assets in the development of cultural activities and tourism in the Périgord noir. Cave paintings have been preserved due to several factors despite unfavourable conditions of temperature and humidity. Piguet (2014) describes that paintings were preserved because they were done rather deep into the caves, but also because pile of rubbles obstructed the entrance of some sites after a crumbling. This most probably preserved the paintings and the walls from damage caused by erosion and humidity, but also from human activities. Allowing tourism in those fragile sites has proved to be devastating for caves containing prehistoric art. For example, the Lascaux cave in Montignac was discovered in 1940 by Marcel Ravidat and his dog Robot and closed permanently in 1963.

Martin-Sanchez et al. (2014) describe the microbial crisis in the Lascaux cave as resulting from mass tourism and the levelling performed to facilitate visits. More particularly, the authors describe damage on the paintings as "produced by visitors' breath, lighting and algal growth" over a period of 20 years only which shows how fast vestiges can degrade. Understanding how microorganisms disperse can thus be an asset in proper cave management on a cultural point of view. For instance, the managers of the cave of Font-de-Gaume in Les Eyzies restrict the number of visitors that can enter the cave each day during the high season, and close the cave in the low season to balance carbon dioxide levels and humidity levels over the year.

In addition of being important for a better knowledge of our history, prehistoric decorated caves attract many people in the Périgord noir every year and have large positive impacts on local businesses. Helping in the prediction of occurrences of new prehistoric sites could then present several positive outcomes. First, new valuable artefacts and vestiges could be discovered, which could improve current knowledge on the Palaeolithic time. Next, this could help in the development of tourism and cultural activities in spite of prehistoric vestiges being very fragile as shown by Piguet (2014) and Martin-Sanchez et al. (2014). In that perspective and as always in cultural management and tourism, a balance should be found between the use of a site and its preservation.

3.3 Predictive modelling

3.3.1 Defining predictive modelling and its applications

Balla et al. (2013) describe the aim of predictive modelling in archaeology as "establishing a causal relationship between certain environmental parameters and known archaeological site locations, in order to create a statistical model based on that relationship that can be applied to unsurveyed areas". The aim is then the identification of patterns, assuming the populations from the studied periods did not select the sites randomly, but that this selection was instead the "result of logical decisions based on geographical considerations and factors related to human activity" (Balla et al., 2013). This idea is also described by Brandt et al. (1992) who state that, assuming patterned human behaviours, "locational behaviours should exhibit non-random tendencies". In addition, Verhagen (2007) specifies that those non-random-tendencies result from the assumption that “certain portions of the landscape were more attractive for human activities than others”.

Locational behaviours are still visible today as people tend to select places to settle related to more modern resources available nearby. For instance, Tallon and Bromley (2004) found out that British city centres were attractive in particular for the “convenience of being close to points of employment and consumption”. However, they also note that “the attractions […] are not uniform between social groups and across city centres”. Moreover, Thomas et al. (2015) conducted a survey describing the choice of a residential location in Great Britain as depending on several push and pull factors. They concluded that, for people aged 25-34, proximity to workplace, leisure and cultural facilities was determining in the choice of a residential location, being close to good schools was a main pull factor for people aged 35-54, and the proximity to green spaces was “the reason given most commonly by those aged 55 years and over”.

Furthermore, predictive modelling can be used to enrich current archaeological knowledge and develop activities related to tourism and cultural heritage. It is also a very useful tool to save prospection time as it gives an initial representation of the potential distribution of undiscovered sites over a specific area. In that perspective, it appears as a convenient methodology to compensate for lacks of funding, in limiting excavation costs for instance. Indeed, Brandt et al. (1992) describe “the process of archaeological discovery [as] a labour-intensive and expensive activity” with the need to make choices in order to find “the most suitable places to conduct the limited amount of survey it is possible to undertake given available resources”. Verhagen (2007) adds that predictive modelling is a central piece in Cultural Resource Management (CRM) and can be influenced by the academic or political contexts.

Predictive modelling using a GIS to study potential occurrences of decorated caves from the Upper Palaeolithic in the Périgord noir has not yet been done. Nonetheless, predictive modelling is a tool that has been widely used in the field of archaeological research in the past decades to explain settlement patterns and artefacts occurrences in diverse areas and for different periods of time. For instance, Graves (2011) used a predictive model based on logistic regression to identify Neolithic chambered cairns, timber halls, and pits, as well as occupation activity in mainland Scotland. Gillespie et al. (2016) applied the maximum entropy algorithm Maxent to the Indian sub-continent for the location of Ashokan edicts, while Kondo et al. (2012) developed predictive models for palaeoanthropological research using the same algorithm. Furthermore, Parow-Souchon et al. (2021) produced a model based on MCDA to locate Upper

Palaeolithic sites in the Southern Levant. A more experimental process was also tested by Mertel et al. (2018) with a predictive model based on machine learning and graph comparison to detect prehistoric sites in the Bohemian-Moravian Highlands. There is then a wide range of techniques that exist to create and apply predictive models which are mostly data-driven, as opposed to theory-driven models. As explained by Verhagen (2007), the data-driven approach is based on a set of statistical tests carried out to find relationships between known archaeological sites and the selected variables representing environmental factors. The model is then applied to a larger area to detect potential sites of interest.

3.3.2 Multi-criteria methodologies in the scope of predictive modelling

Many studies in the literature imply the use of a multi-criteria approaches for building predictive models in archaeology. Andalecio (2011) states that multi-criteria approaches "may appear in the literature as multi-criteria analysis (MCA), multiple criteria decision-making (MCDM) or multi-criteria evaluation (MCE)". Andalecio also states that, regardless of the terminology, multi-criteria approaches aim at the examination of different choice options. Greene et al. (2011) justify the development of MCDA from the 1970s as a "reaction to single-criterion optimisation techniques, most notably linear programming". In that perspective, Verhagen (2007) defines Multi Criteria Decision Making related to predictive modelling as "a set of systematic procedures for analysing complex decision problems". He specifies that MCDM can be broken down into the definition of a goal, the selection of evaluation criteria, the integration of the decision maker's preferences, the formulation of decision alternatives, and the calculation of the possible outcomes.

3.3.3 Selection of the criteria

The selection of the different criteria is fundamental in the implementation of a MCDA in the scope of predictive modelling. For instance, Balla et al. (2013) performed "an extensive archaeological literature research, followed by field survey, in order to locate the tombs in the areas indicated by the literature references", which resulted in the selection of "four environmental (altitude, slope, soil hardness, distance from rivers) and two cultural parameters (distance from settlements, distance from roads)." Their survey concluded that "the evaluation of the model demonstrated the validity of the proposed methodology". Similarly, Nicu et al. (2019) selected three factors (soil type, heat load index, and slope position classification) to model and predict areas that were likely to host Eneolithic sites after studying the archaeological background in northeast Romania. They used 20% of the sites to validate the model and came up "with a success rate of 72% [and] a prediction rate of 75%". Elevation, slope, aspect, permanent water network and modern settlements were considered as parameters by Perakis and Moysiadis (2011) in the implementation of a predictive model regarding the archaeological sites of Magnesia in Greece. They derived high probability areas of finding new sites for further on-field research. Moreover, Graves (2011) describes "elevation, slope, aspect, local relief, distance to the nearest source of water, cost-distance to the nearest source of water, and viewshed" as the most commonly used variables when implementing an archaeological predictive model. She proposes "that areas attractive for settlement and occupation activities may have been identified by modelling locations of related sites". Even though most studies cited in this paper have been mathematically validated, on-field confirmation still need to be carried out.

In order to be usable in the analysis, the data layers representing the different criteria will usually have to be pre-processed to extract valuable and exploitable pieces of information. The aspect and the slope can for instance be derived from a Digital Elevation Model (DEM) using tools included in a GIS software. Another example could be the analysis of the proximity to water through the creation of buffer zones around hydrological features. As specified by Malczewski (1999) "each criterion should be represented as a map layer in the GIS database".

3.3.4 Standardisation of the criteria

Malczewski (1999) also states that the values contained in each layer used in an MCDA should be transformed to comparable units, which is supported by Greene et al. (2011) who describe "MCDA's greatest strength [as] its ability to simultaneously consider both quantitative and qualitative criteria, as long as the latter can be represented using an ordinal or continuous scale". Criteria then have to be standardised which can be done using different techniques such as linear scale transformation, probabilities, value/utility function, or fuzzy set membership. The use of a numerical rating scale will be applied in this report because it appears as a simple but rather accurate rescaling method. It relates to the definition of linear scale transformation given by Kalmijn (2014) and is achieved by assigning a value of "0" to the least favourable situation and a value of "10" to the best possible situation on a common rating scale.

3.3.5 Weighting of the criteria

Once standardised, the selected criteria should be assigned a weight so that they are incorporated in the MCDA process. Weighting thus appears as essential in order "to express the importance of each criterion relative to other criteria" (Malczewski, 1999). Greene et al.

(2011) listed four weighting techniques which are ranking, rating, trade-off analysis, and Analytic Hierarchy Process (AHP). Ranking is described as a simple conversion of the rank of a criteria to a weight using rank sum, rank reciprocal, or rank exponent. Rating will be used in this research project and consists in assigning a value to each criterion on a common scale, all weights eventually adding up to a defined value (1 or 100 in general, even though any other value can be selected by the decision maker). Trade-off analysis and AHP both work comparing criteria pair-wise and can sometimes rely on fuzzy logic.

The literature shows diverse uses of weighting techniques and different approaches regarding the selection of a method. Balla et al. (2013) used AHP in their work and defined the process as “a structured technique for organising and analysing complex decisions”. In the same way, Nsanziyera et al. (2018) have proposed a model based on AHP-weighted criteria in the Awsard area in Morocco to identify tumuli locations. They add that there are several levels in AHP with a main objective, different criteria, possible sub-criteria, and several alternatives for each criteria or sub-criteria. Nonetheless, Ishizaka and Labib (2011) point out some limitations of the AHP technique such as the assumption of criteria independence and the arbitrary choice of a hierarchy and of a judgement scale.

Nsanziyera et al. (2018) in their study of Awsard area also assure that weights can be assigned using statistical analysis about known sites, personal knowledge, and expert opinion on the research subject. Parow-Souchon et al. (2021) convey the same idea stating that multiple datasets “can be weighted according to their perceived importance”. In addition, van Leusen and Kamermans (2005) insist on the fact that predictive models are usually partly subjective as they include expert judgement in the MCDM process. Balla et al. (2013) support a similar way of proceeding by showing that even AHP relies on the decision maker’s judgement. Finally, Stirn (2014) hypothesised on the significance of each criterion based on deductive reasoning and field observation, weighting the attributes “on a scale of observed frequency with unanimous weighted highest and occasional, lowest”. Highlighting the fact that models include a share of subjectivity is essential and shows they are imperfect by nature. Probability maps resulting from multi-criteria analyses should then be treated with care and serve as a basis for more advanced analysis.

3.3.6 Aggregation of the criteria

Weighted criteria should be combined to form the final prediction regarding the location of artefacts, vestiges, or decorated caves. Different procedures exist to aggregate criteria and Greene et al. (2011) present some of them in their study. The Weighted Linear Combination (WLC) for instance "multiplies normalised criteria scores by relative criteria weights for each alternative" and is used by Rua (2008) in the location of Roman *villae* in Portugal. This "weighted-map-layer-approach" is also used by Stirn (2014) in the location of late-prehistoric villages in the Wind River Range, Wyoming. Rua (2008) also proposes binary overlay as an aggregation technique, which is based on the attribution of 0-or-1 scores to each criterion. Greene et al. (2011) present fuzzy additive weighting and ordered weighted average as other aggregation methods.

3.3.7 Model accuracy assessment using Kvamme Gain

The model that was created and applied to the area of interest should finally be validated in order to assess its relevance and its accuracy. As for all previous steps, several methods exist to perform such validation. This report focuses on a widely used tried-and-tested validation method called Kvamme Gain (KG), named after anthropologist Kenneth Kvamme. According to Harris (2018), the KG metric "would indicate what was to be gained over random predictions". Diwan (2020) then proposes an equation of KG as:

$$G = 1 - (\%\,\mathrm{PS} / \%\,\mathrm{GS})$$

"Where G is the gain mode, PS is the percentage of the [total study] area characterized by the highest probability of hosting archaeological sites, and GS is the percentage of observed archaeological sites within this area". Kvamme Gain produces values comprised between -1 and 1. Galletti et al. (2013) affirm that a KG value approaching 1 indicates "the model performs better than random chance". They also state that "negative values mean the model is working contrary to its intended purpose". Finally, they assert that "a value of zero or near zero means the model performs no better than random chance". Nicu et al. (2019) used KG as a validation procedure for their Archaeological Predictive Modelling (APM) study in northeast Romania, considering a KG of 0.56 as a satisfactory value. Verhagen (2007) described a medium probability of locating archaeological sites with a KG of 0.13 and a high probability of doing so with a KG of 0.663.

4 Model-building process

4.1 Formation of the problem and selection of a methodology

The methodology presented in **Table 2** was developed following a thorough review of the scientific literature. The selection of the different criteria is based on existing case studies, as well as on the archaeological background of the area of interest and personal judgement. The standardisation of the different criteria will be done through the definition of a numerical rating scale using frequencies, while weighting will be done using rating. Weighted linear combination will be used to combine the parameters and Kvamme Gain will be applied to validate the model. The study of the selected variables first aims at defining if common parameters exist between decorated caves. If so, the predictive model developed in this research should specify areas of high probabilities of Upper Palaeolithic decorated caves occurrences rather than specific point-locations as caves can cover a large underground area.

Table 2. Multi-criteria methodology steps selected for the analysis and the building of the predictive model

Step number	Processing steps	Procedure
1	Selection	Literature review and archaeological background
2	Standardisation	Numerical rating scale through frequencies analysis
3	Weighting	Rating
4	Aggregation	Weighted linear combination
5	Model validation	Kvamme gain

4.2 Selection of criteria and data collection

The base of the predictive model presented in this study is then the collection of valuable data representing the criteria selected to build the predictive model. The selection of the criteria was made using the knowledge gained from the literature research and the available datasets for the area of study. The different criteria selected are elevation, slope, aspect, and proximity to water and are presented in **Table 3**, along with the datasets used to extract the variables. The metadata of the different layers are displayed in the **Appendix** section. Balla et al. (2013) used altitude, slope, and distance from rivers to build their model while elevation, slope, aspect, and permanent water network were used by Perakis and Moysiadis (2011) in a similar experiment.

Stirn (2014) only used elevation, sun exposure, and slope, showing that predictive modelling can be done using few criteria. The literature research also shows that the range of criteria used in predictive modelling for the location of prehistoric sites usually fluctuates between three and seven criteria.

Table 3. Variables and datasets used in the predictive model

Primary dataset	Class	Extracted variable
Mérimée database	Database	Decorated caves
Copernicus DEM	Raster	Elevation, slope, and aspect
Copernicus Hydrological network	Line Feature	Proximity to water

A DEM with a 25-metre resolution and a ± 7-metre RMSE vertical accuracy covering Europe, and the European hydrological network were downloaded from the Copernicus programme website (2016; 2019). The administrative boundaries of France were obtained from the database of the French government. The location of Upper Palaeolithic decorated caves in the Périgord noir was obtained through the website Monumentum (2022) and the Mérimée database of the French Ministry of Cultural Affairs (n.d.). Those organisations appear as two reliable sources of information for the listing of Upper Palaeolithic decorated caves in the area of study. Indeed, the Mérimée database lists all historical monuments in France from the prehistory to modern times and was used to gather a preliminary list of the decorated caves. The website Monumentum is linked to the Mérimée database and adds valuable pieces of information such as the precise localisation of the caves as point data. Both sources were then used concurrently to produce the list of twenty-two decorated caves presented in **Table 4**. This list serves as a basis for the development of the predictive model and for its validation. While the number of sites needed to build a predictive model is not clearly defined, the literature shows that Perakis and Moysiadis (2011) used a list of 56 known Neolithic sites in Greece, Gillespie et al. (2016) used the location of 29 Ashokan edicts in India, and Stirn (2014) only used the location of 6 prehistoric villages in Wyoming, USA, to build their model.

Table 4. The decorated caves from the Upper Palaeolithic in the Périgord noir, extracted from the Monumentum and the Mérimée database

Location	Name	Type of art
Campagne	Grotte de la Muzardie	Engravings
Domme	Grotte du Mammouth	Engravings
	Grotte du Pigeonnier	Engravings
	Grotte de la Martine	Engravings and paintings
Le Bugue	Grotte de Bara-Bahau	Engravings
Les Eyzies	Grotte de Font-de-Gaume	Engravings and paintings
	Grotte de la Croze	Not specified
	Grotte de la Mouthe	Engravings and paintings
	Grotte des Combarelles I	Engravings
	Grotte des Combarelles II	Engravings
	Grotte du château de Comarque	Engravings and sculptures
	Grotte de Nancy	Engravings
Marquay	Grotte de Puymartin	Engravings
	Grotte de la Grèze	Engravings
Meyrals	Grotte de Bernifal	Engravings
	Grotte de Sous-Grand-Lac	Engravings
Montignac	Grotte de Lascaux	Engravings and paintings
Rouffignac	Grotte du Cro de Granville	Engravings and paintings
Saint-Cirq	Grotte du Sorcier	Engravings
Tursac	Grotte de la Forêt	Engravings
Villac	Grotte de la Sudrie	Engravings
Vézac	Grotte du Roc	Not specified

Source: Monumentum.fr and French Ministry of Cultural Affairs (Mérimée database)

4.3 Data pre-processing

The various datasets presented were pre-processed in order to extract the criteria to be used in the analysis. All layers were assigned a 25-metre cell resolution and were projected to Lambert-93, which is a conformal conic projection based on RGF93 geodetic system. The reference parallels are 44°N and 49°N according to the French National Institute of Geographic and Forest Information (IGN, n.d.-b). The choice of Lambert-93 as a projected coordinate system relies on multiple motives. First, order 2006-272, which came into effect in France on March, 3rd, 2006 (Journal Officiel, 2006), defines Lambert-93 as the official projection coordinate system in France. The order states that all geographical data should be harmonised and projected to Lambert-93 in order to facilitate the production and exchange of datasets. Moreover, as a conformal conic projection, Lambert-93 map projection maintains directions, angles and shapes at infinitesimal scale (ESRI, n.d.). This is important in the processing of the aspect layer used in the analysis as it displays directions. Furthermore, ESRI states that a conformal conic projection does not preserve distances fully, with "distances [being] accurate only along the standard parallels". The study area is located along parallel 45°N which could slightly distort distances away from the 44°N standard parallel. Nonetheless, the IGN (n.d.-a) specifies that the linear alteration is in the range of 500mm/km around parallel 45°N, which seems like a reasonable alteration for the creation of 300-metre wide buffer zones. All properties cannot be maintained when using projection coordinate systems, nevertheless, Lambert-93 maintains directions, angles, and shapes, and preserves distances to a certain extent. In that perspective, it appears as a suitable projection coordinate system for the implementation of a predictive model in the field of archaeology in the Périgord noir.

The boundaries of the Périgord noir were then extracted from the administrative boundaries of France through a *Select by attribute* query. This layer is used as a mask for other layers composing the model and was presented previously in **Figure 3**. The layer containing decorated caves was created using point data from the Mérimée database. In order to produce that layer in particular, the coordinates of the different caves were compiled in an Excel file which was processed through the *Coordinate table to point* tool in ArcGIS. The resulting layer presenting the distribution of decorated caves from the Upper Palaeolithic is displayed in **Figure 4**. The Digital Elevation Model (**Figure 5**) was clipped to the study area through the *Extract by mask* geoprocessing tool. The slope (**Figure 6**) and aspect (**Figure 7**) were then derived from the DEM using *Slope* and *Aspect* geoprocessing tools respectively. The hydrological network (**Figure 8**) was also clipped to the study area using the *Extract by mask* geoprocessing tool.

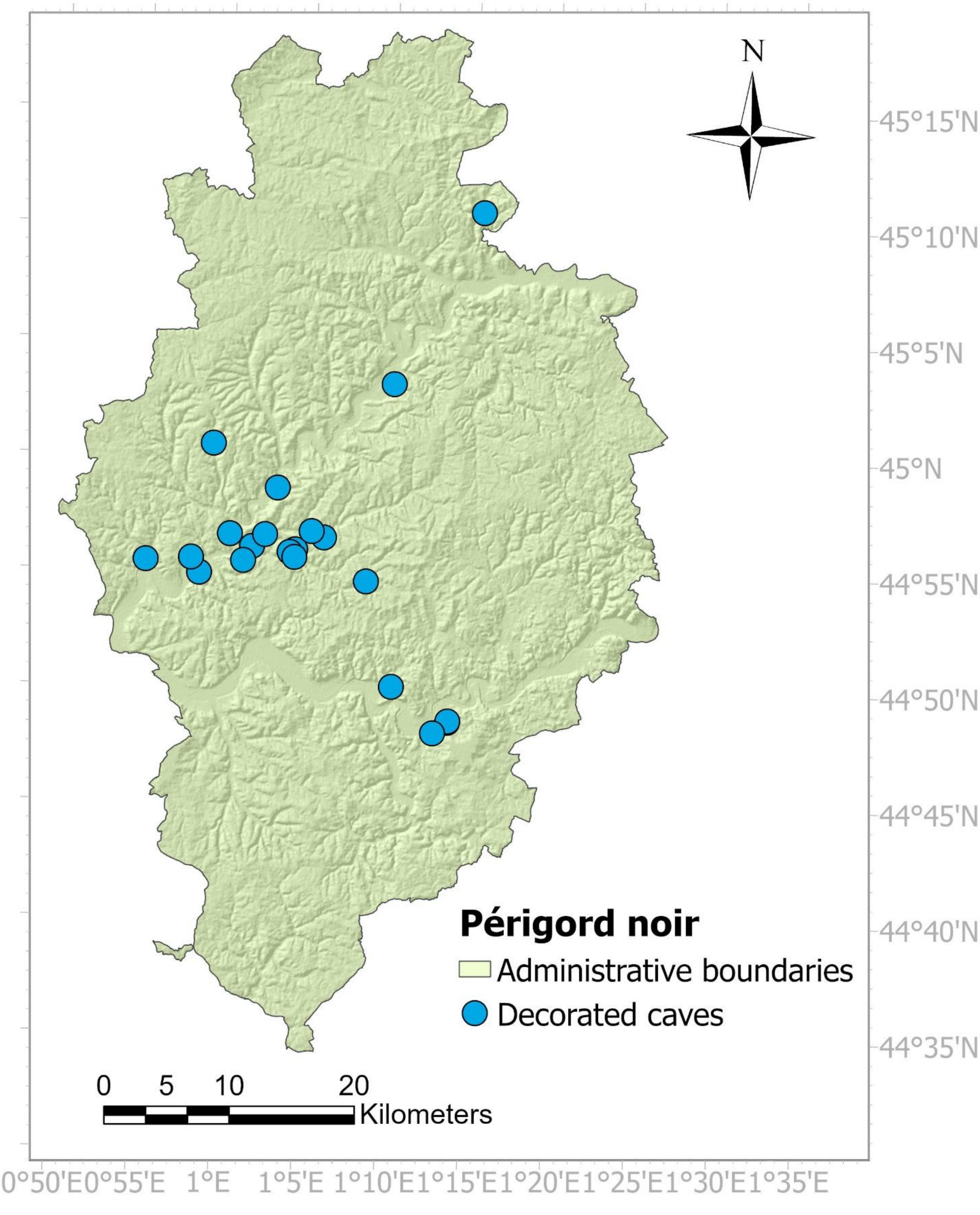

Figure 4. Distribution of decorated caves in the Périgord noir

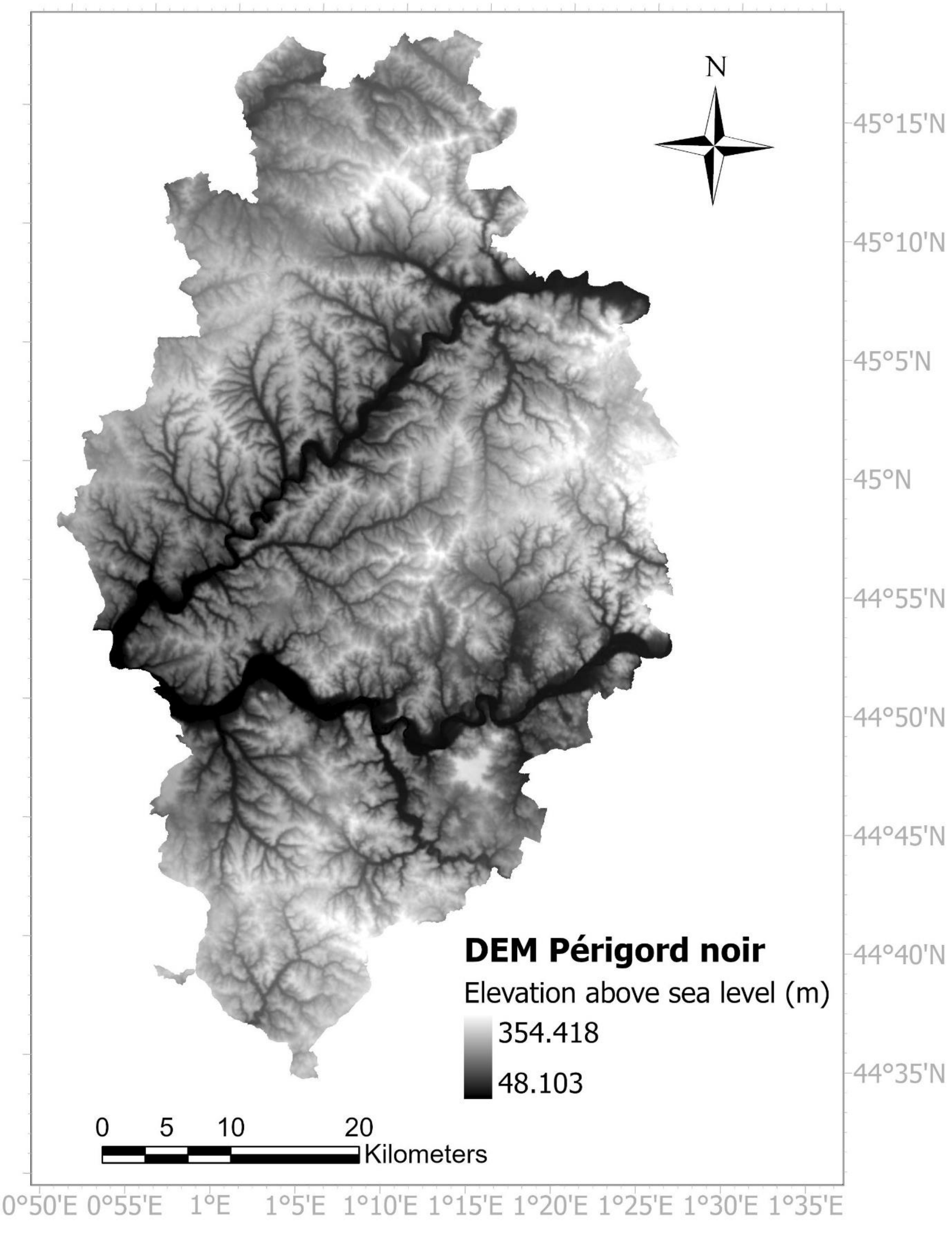

Figure 5. Digital Elevation Model (DEM) of the Périgord noir

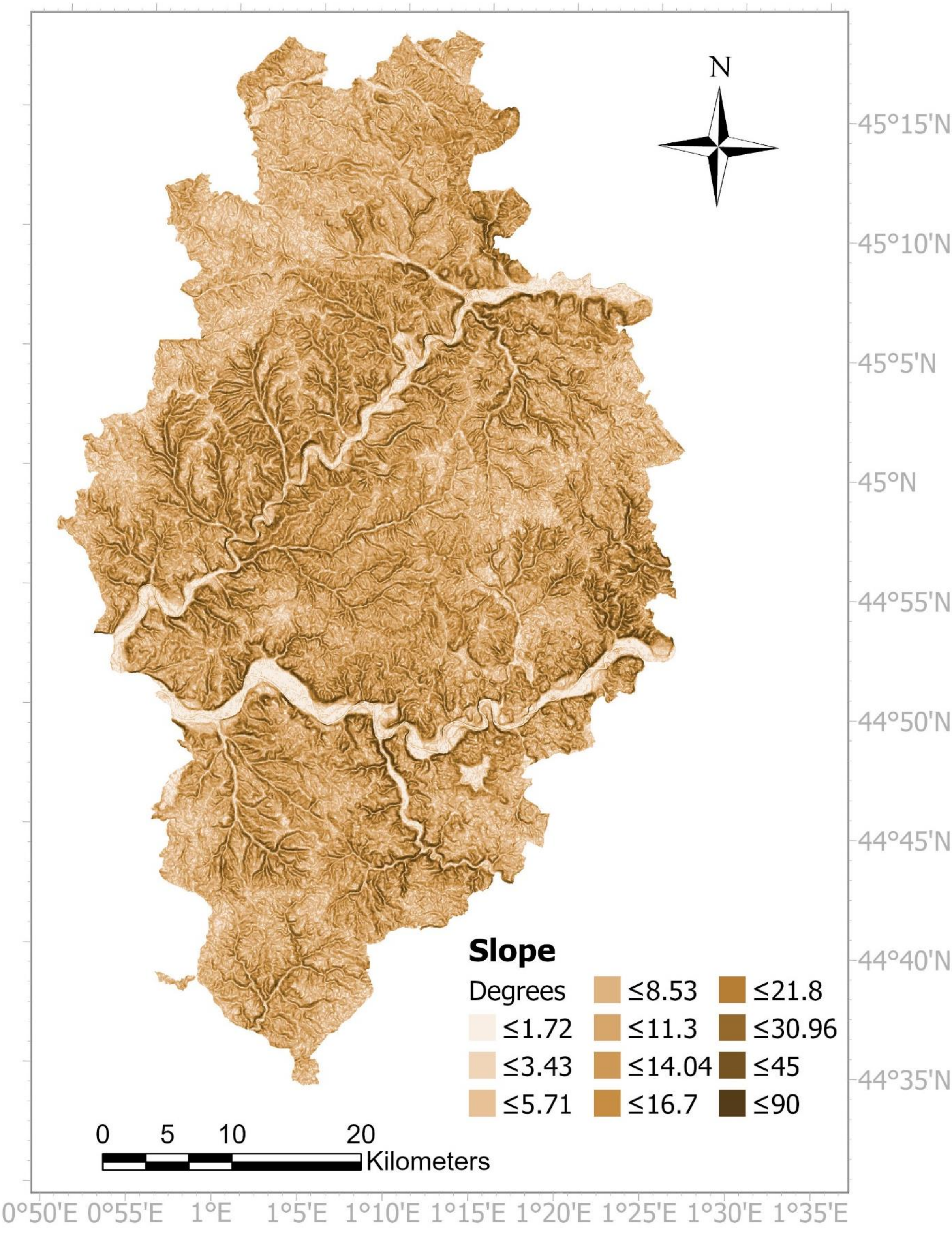

Figure 6. Slope (degrees) in the Périgord noir

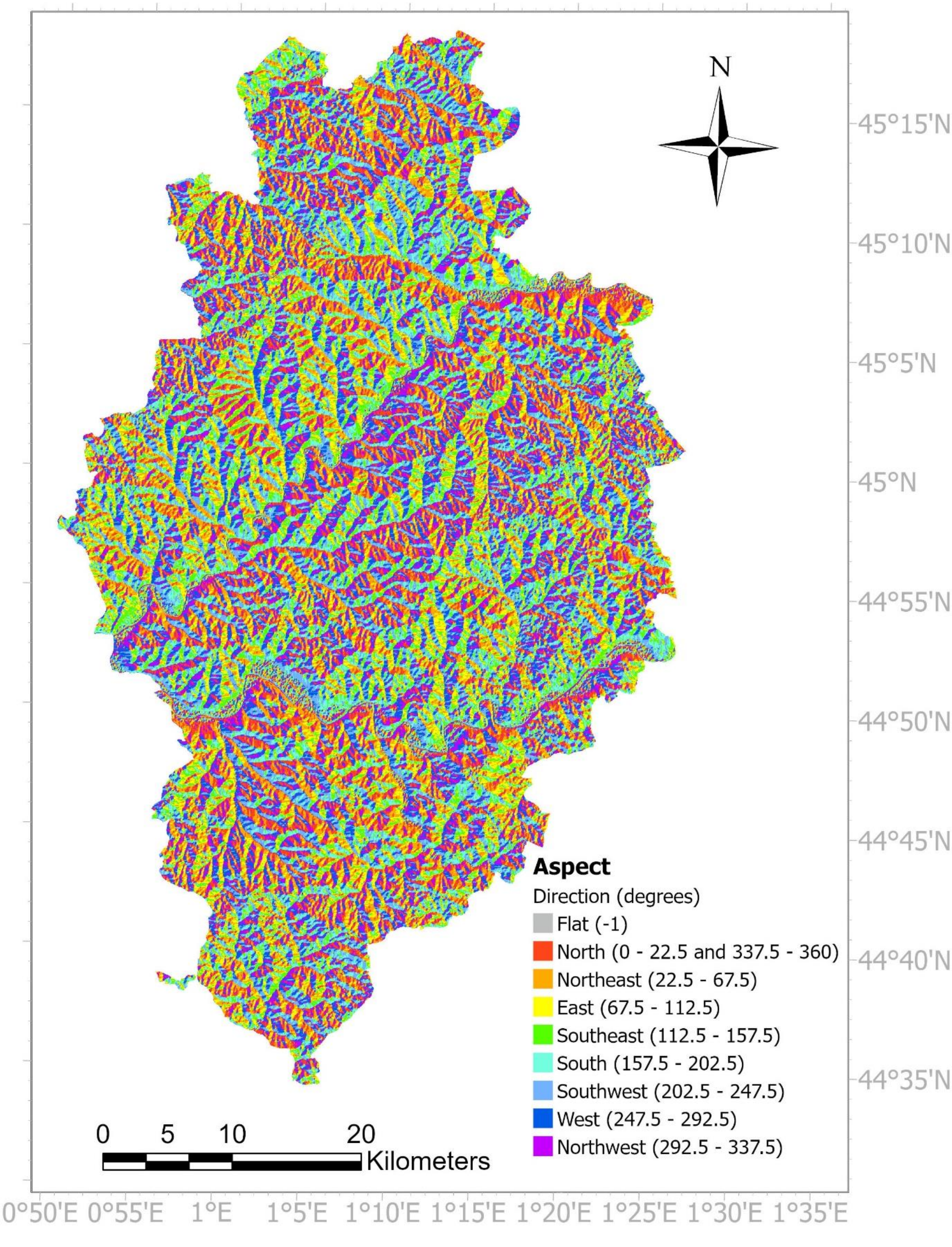

Figure 7. Aspect (direction) in the Périgord noir

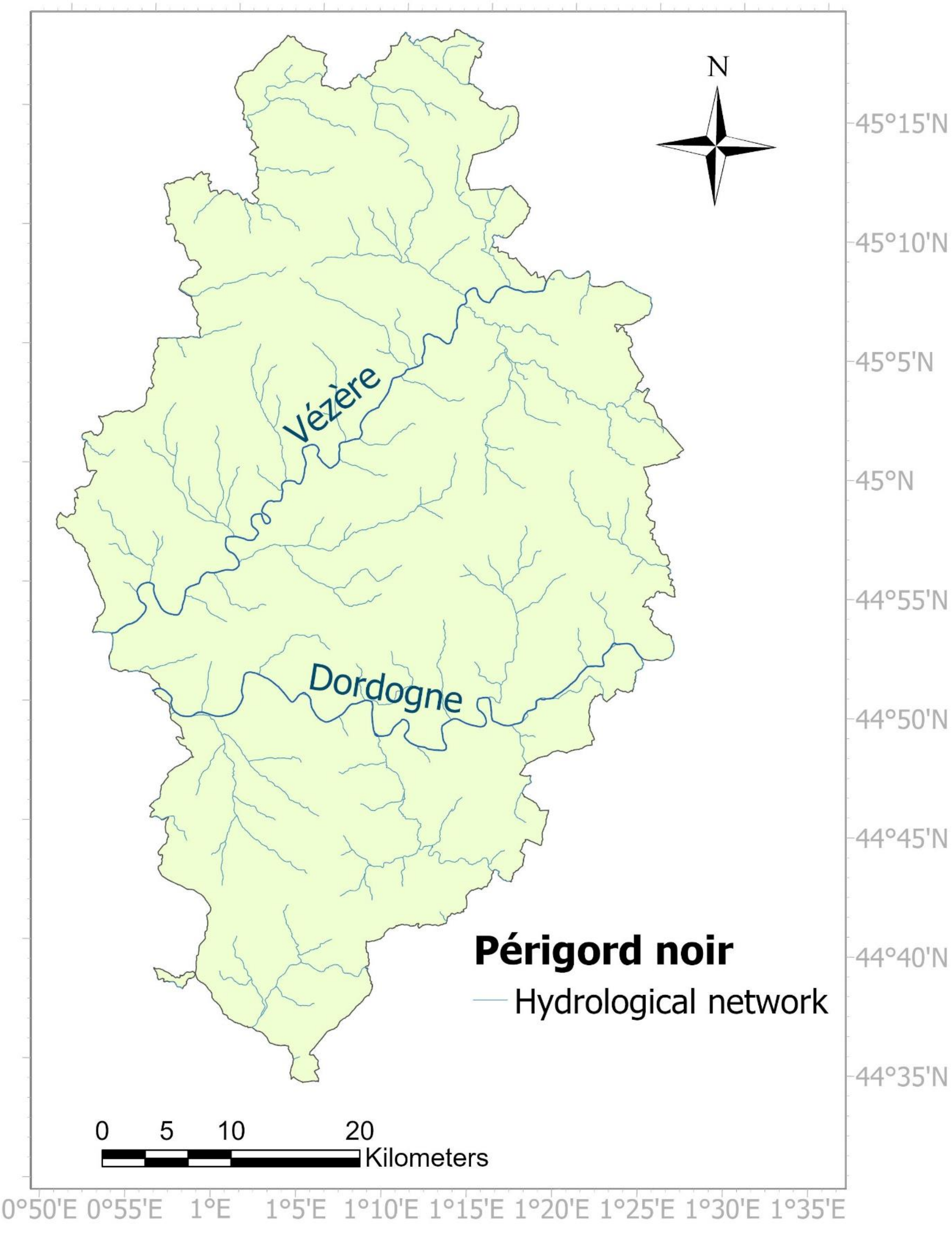

Figure 8. Hydrological network of the Périgord noir

4.4 Quantification and standardisation of the criteria

The different layers were then quantified in order to produce individual probability maps for each criterion. The four criteria were treated as factors in the multi-criteria evaluation process. Statistical analysis was carried out for the different criteria selected in order to decide on classes for each factor, similarly to Balla et al. (2013) who used the median value and its multiples for each point to define classes for their criteria. In this case study, all four factors were standardised so that they are distributed over a 1-to-5 scale, as derived from the 0-to-10 scale presented by Kalmijn (2014). The value "1" represents a very low probability while the value "5" represents a very high probability (**Table 5**). The same procedure was used by Balla et al. (2013) who used a 0-to-5 scale to assign values to their factors.

Table 5. Value-scale correspondence

Value	Probability
1	Very low
2	Low
3	Medium
4	High
5	Very high

4.4.1 Elevation

The *Zonal Statistics as Table* tool was used to determine the elevation of each decorated cave. The elevation in the study area ranges from 48 metres to 354 metres. **Table 6** shows a range of statistics calculated for the twenty-two decorated caves situated in the Périgord noir.

Table 6. Statistics on decorated caves regarding elevation

Elevation	Value (metres)
Minimum	93
Maximum	229
Mean	139
Median	130

The elevation ranges containing no decorated caves were classified in the low probability range (value 1). Classes of an equal width of 34 metres were then defined using the results of zonal statistics in the 93-to-228-metre range. The percentage of decorated caves inside the six classes were calculated and the value assigned according to the result (**Table 8**).

Table 7. Elevation classes

Class (metres)	Caves inside class (%)	Value
< 93	0	1
93 to 127	41	5
128 to 161	32	4
162 to 195	18	3
196 to 229	9	2
> 229	0	1

The DEM was then reclassified according to the values displayed in **Table 7** in order to produce a probability map for the elevation criterion (**Figure 9**).

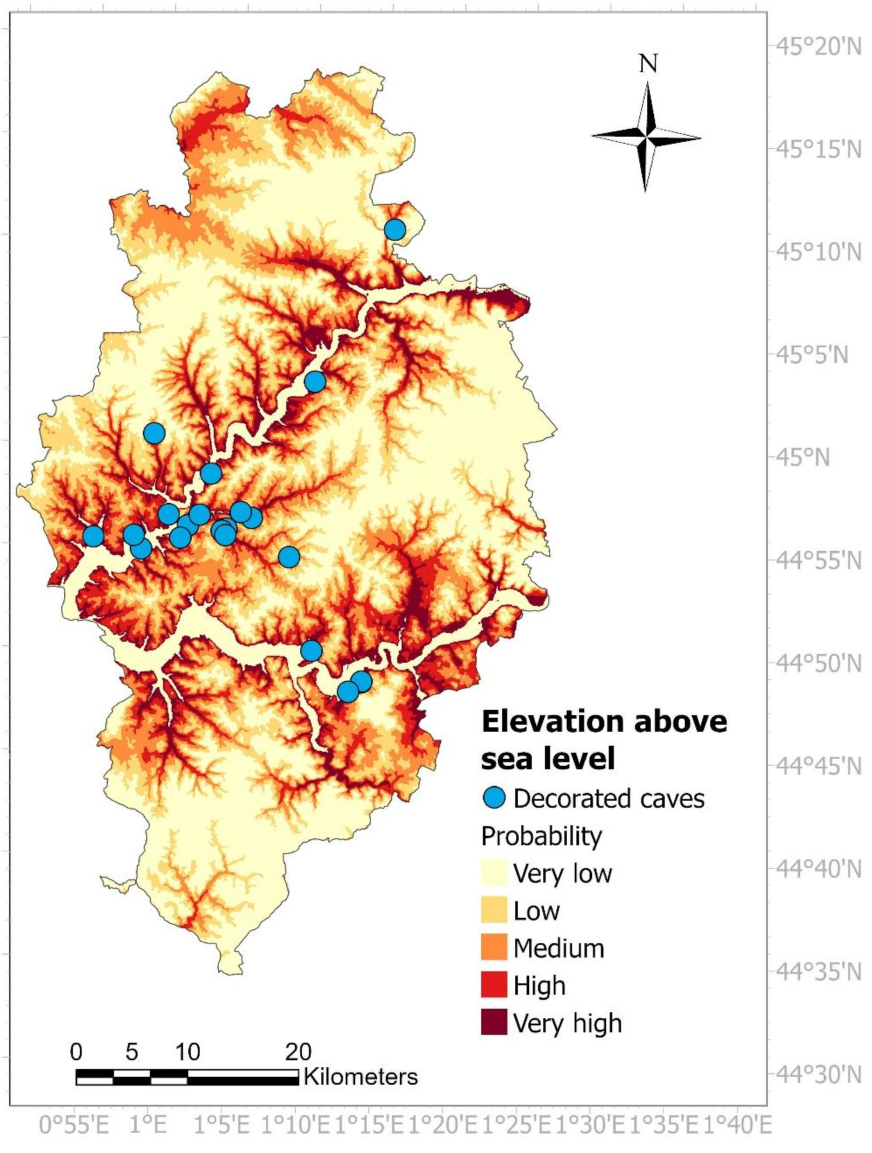

Figure 9. Probability map for the elevation criterion

4.4.2 Slope

A similar procedure was applied to the slope criterion in order to produce a probability map. Zonal statistics were first calculated to determine the slope of each decorated cave. **Table 8** shows statistics for the twenty-two decorated caves of the study area. The slope was calculated in degrees rather than in percentage.

Table 8. Statistics on decorated caves regarding slope

Slope	Value (degree)
Minimum	4
Maximum	56
Mean	26
Median	28

The slope ranges containing no decorated caves were classified in the low probability class (value 1). Classes of an equal width of 13 degrees were then defined using the results of zonal statistics in the 4-to-56-degree range. The percentage of decorated caves inside the four classes were calculated and the value assigned according to the results (**Table 9**).

Table 9. Slope classes

Class (degrees)	Caves inside class (%)	Value
< 4	0	1
4 to 17	23	3
18 to 30	41	5
31 to 43	32	4
44 to 56	4	2
> 56	0	1

The slope layer was then reclassified according to the values displayed in **Table 9** in order to produce a probability map for the slope criterion (**Figure 10**).

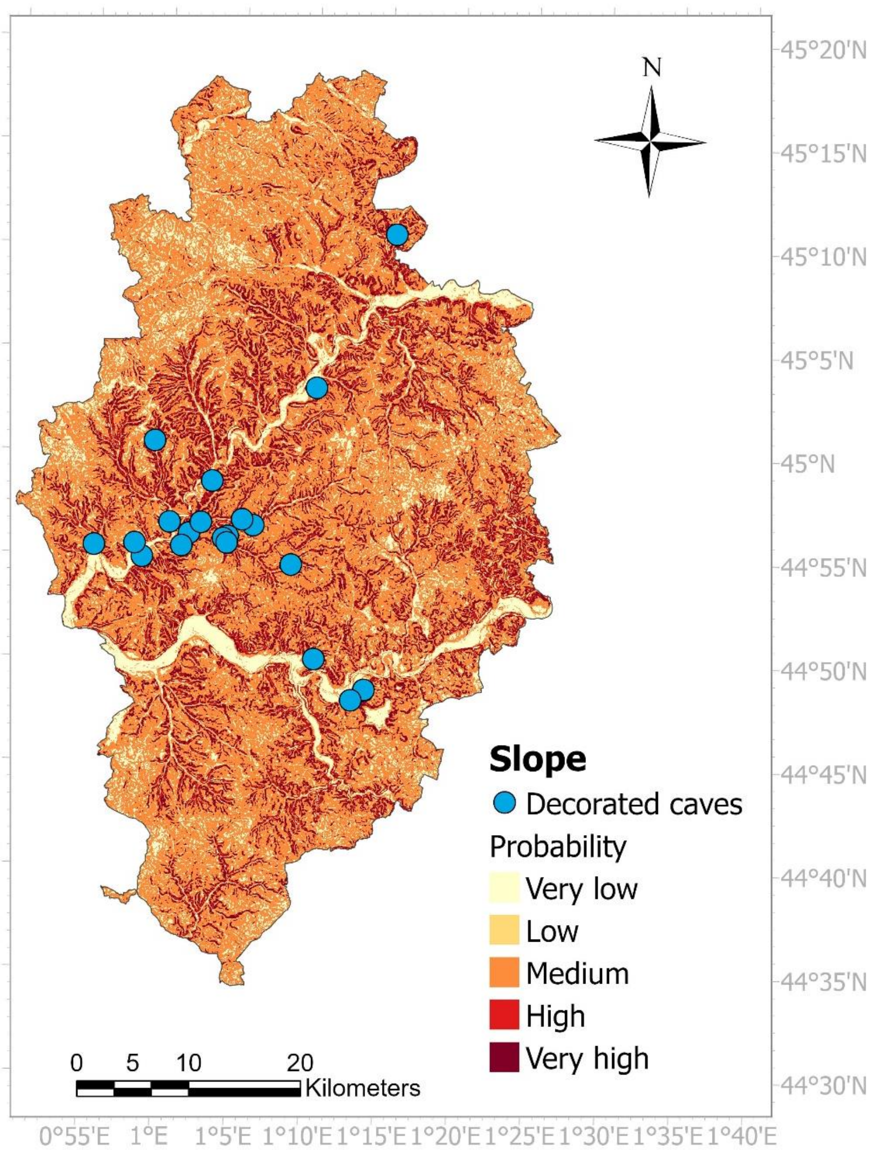

Figure 10. Probability map for the slope criterion

4.4.3 Aspect

The aspect layer was processed in a slightly different way in order to produce a probability map for that criterion. Zonal statistics were calculated once again to determine the aspect of each decorated cave. The minimum, maximum, mean, and median values do not appear as valuable elements for the processing of that layer because they only relate to directions. The different values were rather converted to directions in order to produce a probability map for the aspect variable (**Table 10**).

Table 10. Value-to-direction correspondence for aspect layer

Value	Direction
-1	Flat
0 to 22.5	North
22.5 to 67.5	Northeast
67.5 to 112.5	East
112.5 to 157.5	Southeast
157.5 to 202.5	South
202.5 to 247.5	Southwest
247.5 to 292.5	West
292.5 to 337.5	Northwest
337.5 to 360	North

The aspect ranges containing no decorated caves were classified in the low probability range (value 1). Classes were then treated individually according to the direction and the percentage of decorated caves inside each direction class (**Table 11**).

Table 11. Aspect classes

Class (direction)	Caves inside class (%)	Value
Flat	0	1
North	23	5
Northeast	0	1
East	14	3
Southeast	18	4
South	0	1
Southwest	18	4
West	18	4
Northwest	9	2

The aspect layer was then reclassified according to the values displayed in **Table 11** in order to produce a probability map for the aspect criterion (**Figure 11**).

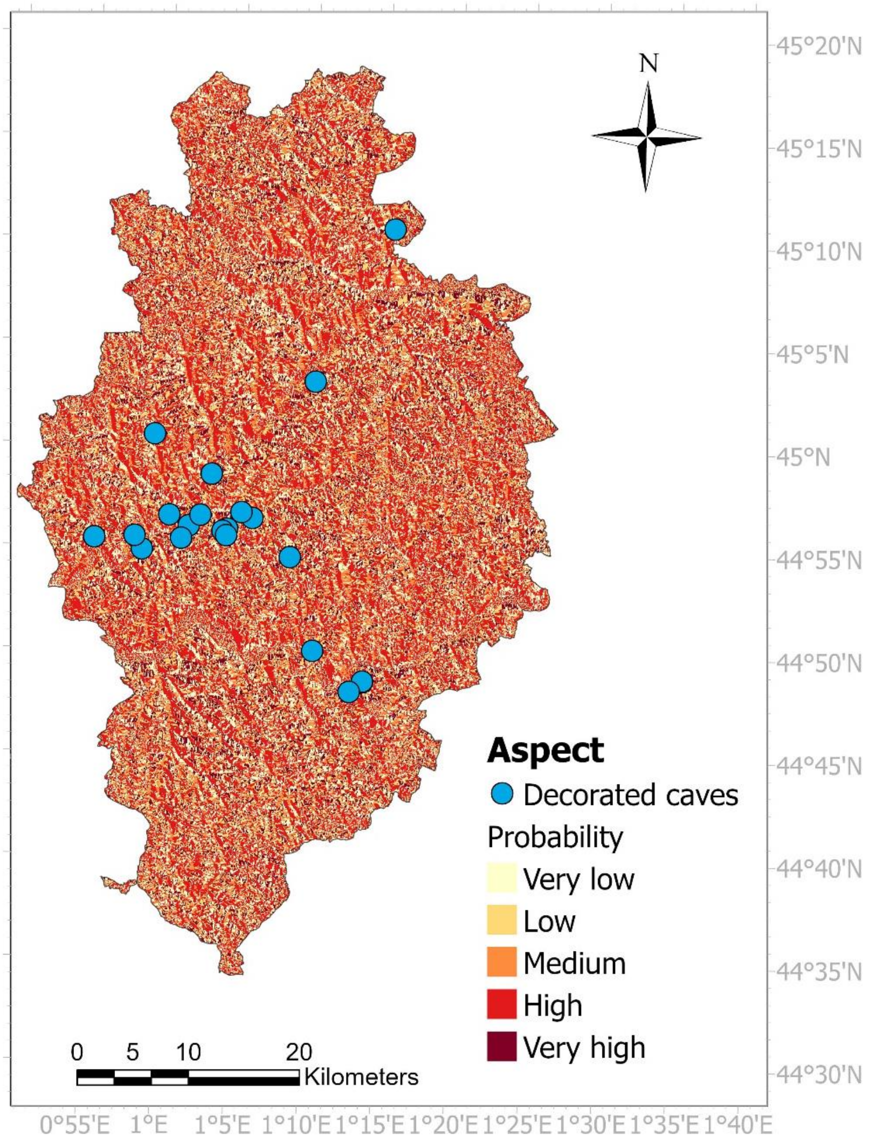

Figure 11. Probability map for the aspect criterion

4.4.4 Proximity to water

The hydrological network layer was processed in a different way. Indeed, buffer zones were created to allow the extraction of valuable data to be used in the predictive model. In order to create appropriate buffers, the geoprocessing tool *Generate Near Table* was first used to calculate distances between features that are close with one another. The decorated caves layer and the hydrological network layer were used as “input” and “near” features in that process. The result is a standalone table showing the distance between each decorated cave and the closest point on the line features from the hydrological network layer (**Table 12**).

Table 12. Results from the *Generate Near Table* process showing the shortest distance between decorated caves and water streams

Name	Closest water stream	Shortest distance (metres)
Grotte de la Muzardie	La Vézère	375
Grotte du Mammouth	La Dordogne	779
Grotte du Pigeonnier	La Dordogne	841
Grotte de la Martine	La Dordogne	283
Grotte de Bara-Bahau	Ruisseau de Ladouch	415
Grotte de Font-de-Gaume	La Beune	447
Grotte de la Croze	La Vézère	361
Grotte de la Mouthe	La Vézère	942
Grotte des Combarelles I	La Beune	163
Grotte des Combarelles II	La Beune	168
Grotte du château de Comarque	La Beune	133
Grotte de Nancy	La Petite Beune	139
Grotte de Puymartin	La Petite Beune	74
Grotte de la Grèze	La Beune	180
Grotte de Bernifal	La Petite Beune	222
Grotte de Sous-Grand-Lac	La Petite Beune	194
Grotte de Lascaux	Le Doiran	1,115
Grotte du Cro de Granville	Le Labinche	247
Grotte du Sorcier	La Vézère	759
Grotte de la Forêt	La Vézère	108
Grotte de la Sudrie	L'Elle	136
Grotte du Roc	Ruisseau de Pontou	532

The values from the standalone table were used to design the buffers for the hydrological network layer. The distribution of decorated caves according to the shortest distance from a water stream (**Figure 12**) shows that the number of caves in a range decreases as the distance from water increases. Moreover, natural breaks seem to form approximately every 300 metres, a distance that will then be used to define buffers for the analysis (**Table 13**).

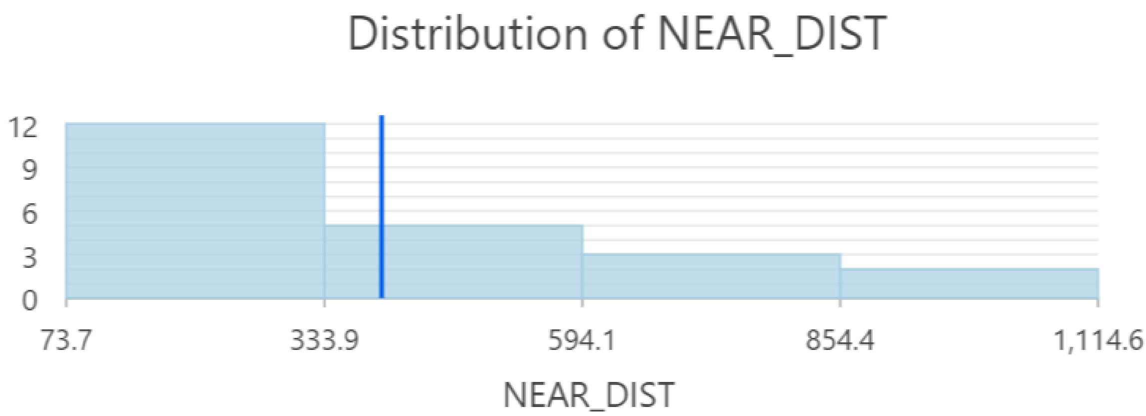

Figure 12. Distribution of the decorated caves derived from the *Generate Near Table* geoprocessing tool

Table 13. Distance to water classes

Class (metres)	Caves inside class (%)	Value
0 - 300	54	5
300 - 600	23	4
600 - 900	14	3
900 - 1200	9	2
> 1200	0	1

The buffers were created using the *Multiple Ring Buffer* geoprocessing tool and the resulting layer was converted to raster using the *Feature to Raster* geoprocessing tool. The layer showing distances were then reclassified so that each class is assigned the values presented in **Table 13**. The derived probability map presenting the proximity to water criterion is then presented in **Figure 13**.

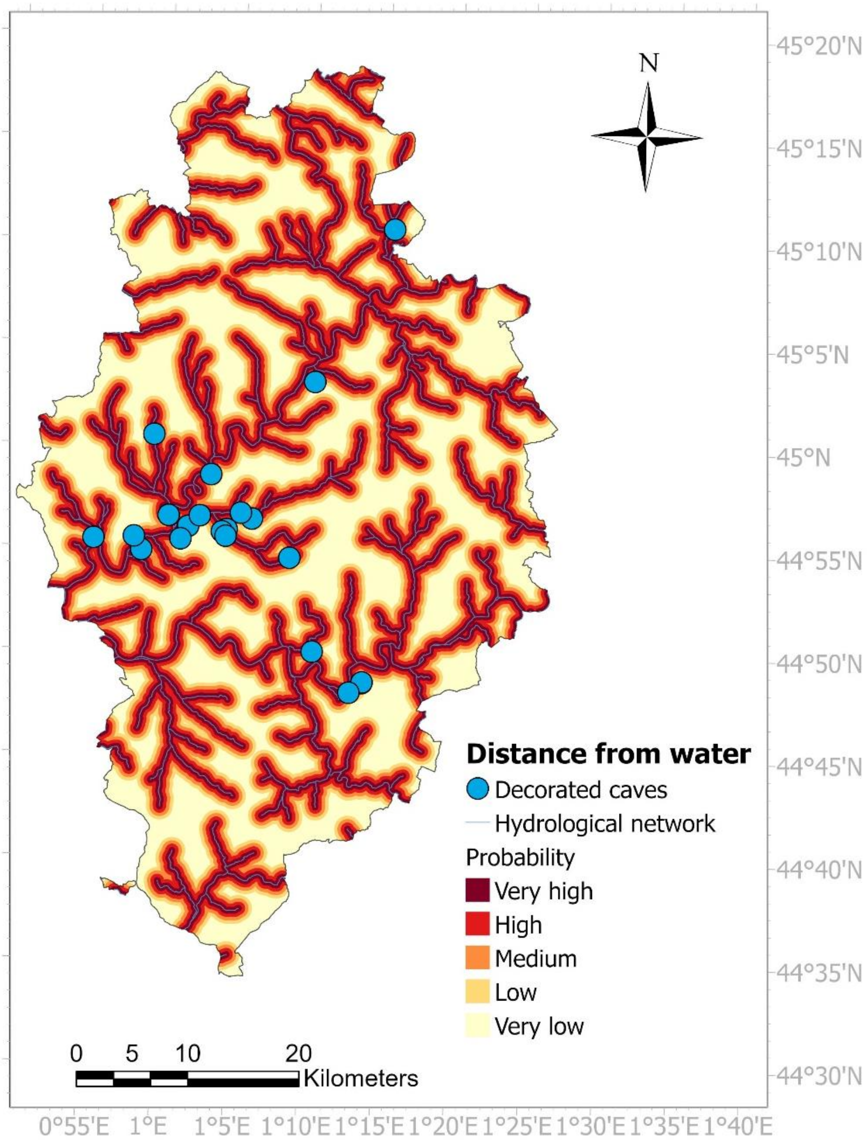

Figure 13. Probability map for the proximity to water criterion

The classes were then defined using statistical elements extracted from the different layers as described in the methodology. The criteria were then normalised on a common scale so they could be weighted and aggregated in order to produce a global probability map showing areas of high archaeological potential regarding Upper Palaeolithic decorated caves in the Périgord noir.

4.5 Weighting of the criteria

The importance of each criterion was then defined depending on their degrees of significance. Weighting can be arbitrary and often highly depends on subjectivity and expert judgement as highlighted by Verhagen (2007). Balla et al. (2013) support the same idea, stating that the weights can be assigned using the perceived meaning and importance of the different parameters. Moreover, Nsanziyera et al. (2018) depict the assignment of weights as relying on expert judgement, but also that criteria can be weighted or unweighted. Unweighted criteria are then assigned the same weight and are considered as being of equal importance. Choices were thus made during this research in order to define a weight for each of the four criteria. The rating method through the implementation of a 0-to-1 scale was first decided on as it appears as a relatively straightforward technique to assign weights to the selected parameters. All weights will then be comprised between 0 and 1, eventually adding up to 1. The literature shows that Stirn (2014) assigned a 0.5 weight to elevation, a 0.3 weight to slope, and a 0.2 weight to aspect. Parow-Souchon et al. (2021) weighted all datasets equally in their assessment of site expectancy in the Southern Levant. Mertel et al. (2018) described the access to water variable as highly significant compared to elevation and slope. It was decided to assign the same weight to all criteria as the literature does not state clearly if some criteria should be considered more important than others, even though some criteria are weighted higher than others in some case studies. The different references also show different treatment of the weights for identical criteria. **Table 14** then presents a summary of the criteria and their characteristics to be used in the final step of the multi-criteria analysis.

Table 14. Selected criteria, standardised classes and criteria weights

Factor	Description	Classes	Value	Weight
Elevation	Altitude in metres	< 93 and > 229	1	
		196 to 229	2	
		162 to 195	3	0.25
		128 to 161	4	
		93 to 127	5	
Slope	Slope in degrees	< 4 and > 56	1	
		44 to 56	2	
		4 to 17	3	0.25
		31 to 43	4	
		18 to 30	5	
Aspect	Aspect in directions	Flat, northeast, and south	1	
		Northwest	2	
		East	3	0.25
		Southeast, southwest, and west	4	
		North	5	
Proximity to water	Buffer zones in metres	> 1200	1	
		900 - 1200	2	
		600 - 900	3	0.25
		300 - 600	4	
		0 - 300	5	

5 Results and model validation

5.1 Aggregation of the criteria and predicted zones

The aggregation of the different criteria and probability maps is done using Weighted Linear Combination (WLC). The WLC methodology is used by Balla et al. (2013) who describe it as a method “whereby each criterion’s value is multiplied with the value of its weight and the results are summed”. The WLC methodology is also expressed mathematically through the equation:

$$S = \Sigma w_i x_i$$

Where:

- S is the probability of Upper Palaeolithic decorated caves occurrence
- w_i the weight of a criterion
- x_i the value of a criterion.

The *Raster Calculator* in ArcGIS appeared as the most convenient tool to aggregate the different variables in order to produce a map of the different probability classes. The weights of each criterion were multiplied for each cell in the different rasters and added as described in a mathematical way by the following operation:

$$Probability\ class = \ Elevation * 0.25 + Slope * 0.25 + Aspect * 0.25 + Proximity\ to\ water * 0.25$$

The final probability map (**Figure 14**) resulting from the operation was reclassified according to **Table 15** in order to design five distinct probability classes.

Table 15. Reclassification parameters for the final probability map of Upper Palaeolithic decorated caves occurrences in the Périgord noir

Range	Reclassification value	Probability
1 - 1.8	1	Very low
1.8 - 2.6	2	Low
2.6 - 3.4	3	Medium
3.4 - 4.2	4	High
4.2 - 5	5	Very high

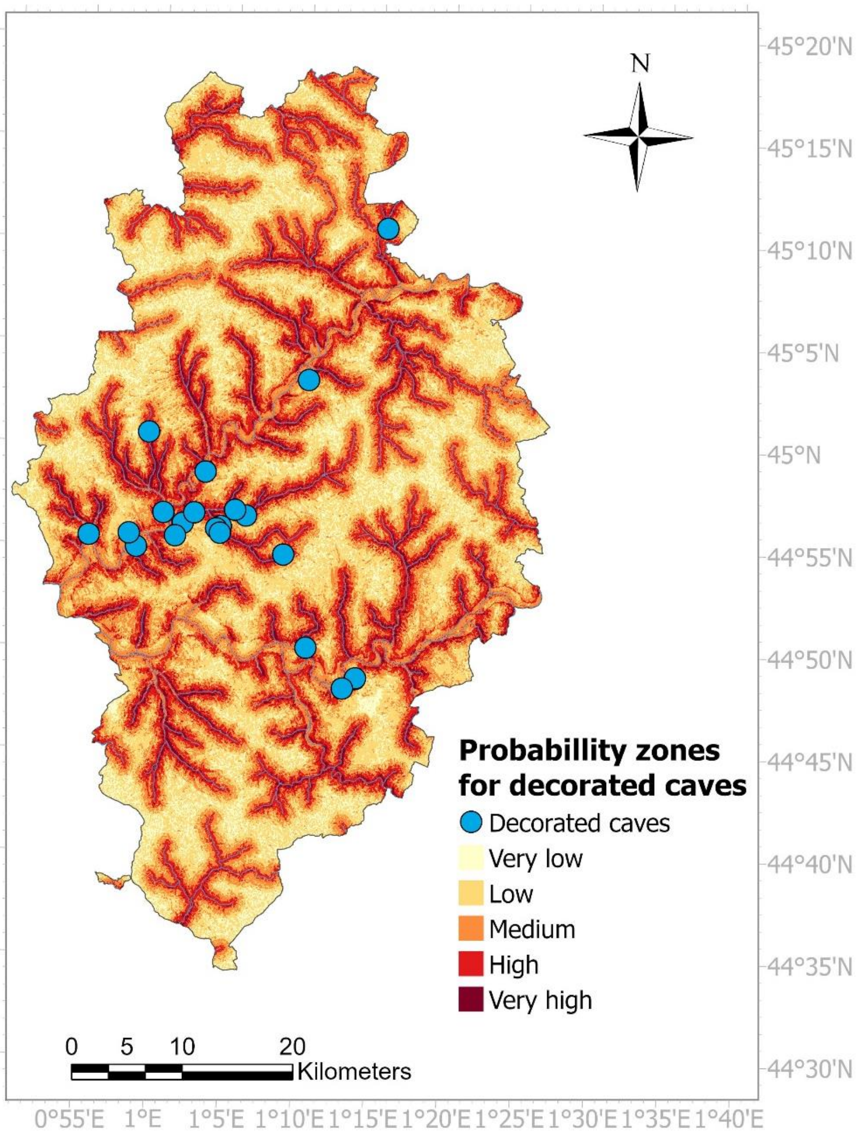

Figure 14. Map results showing probability zones and distribution of known Upper Palaeolithic decorated caves in the Périgord noir

The map displaying probability zones and distribution of known Upper Palaeolithic decorated caves in the Périgord noir shows that zones of very high probability seem to be close to water streams, especially the Vézère River and the Dordogne River. It also shows that known decorated caves seem to be distributed in areas of relatively high probability of finding undiscovered decorated caved. Areas farther away from water streams do not seem to have great archaeological interest as they seem mostly classified in the low-to-medium probability classes. In order to be valuable and quantifiable, those preliminary observations of the results need to be processed in some way and the model validated.

5.2 Model validation using Kvamme Gain

The results presented in this report shows that it seems possible to design a model from the values extracted from the selected criteria. However, according to Balla et al. (2013), "the fact that it has been possible to construct a predictive model does not in itself guarantee the accuracy of its predictions" and "the validation of the model must be examined with reference to the areas". Thus, Kvamme Gain is described by Harris (2018) as presenting "what was to be gained over random prediction". It then seems an appropriate method of measurement for assessing the accuracy of the predictive model and showing its relevance in the case of detecting areas of high archaeological potential for Upper Palaeolithic decorated caves in the Périgord noir. Kvamme Gain requires two main parameters, namely "the percentage of the area characterised by the highest probability of hosting archaeological sites (PS) and the percentage of observed archaeological sites within this area (GS)" (Diwan, 2020). The equation to be used as presented in the literature review then is:

$$G = 1 - (\%\,PS / \%\,GS)$$

The attribute table corresponding to the map presented in **Figure 14** was first analysed to get the number of pixels for each probability class (**Table 16**). The percentage of each area over the total area was also calculated to derive PS (**Table 17**).

Table 16. Attribute table of the map showing probability zones and distribution of known Upper Palaeolithic decorated caves in the Périgord noir

Probability value	Count (number of pixels)
1	350,829
2	1,191,911
3	1,123,795
4	852,723
5	181,861
Total	3,701,119

Table 17. Share of each probability class in the map showing probability zones and distribution of known Upper Palaeolithic decorated caves in the Périgord noir

Probability value	Count (number of pixels)	Share (%)
1	350,829	9.49
2	1,191,911	32.20
3	1,123,795	30.36
4	852,723	23.04
5	181,861	4.91
Total	3,701,119	100.00

The value of PS is then 4.91%, meaning that 4.91% of the total area of the Périgord noir has a very high probability of containing undiscovered Upper Palaeolithic decorated caves. GS then needs to be determined as well in order to define the share of existing decorated caves inside PS. **Table 18** displays the number of decorated caves inside each probability class as well as their corresponding percentage.

Table 18. Distribution of decorated caves within each probability class of the map of probability zones for Upper Palaeolithic decorated caves in the Périgord noir

Probability value	Number of decorated caves	Share (%)
1	0	0.00
2	0	0.00
3	4	18.18
4	7	31.82
5	11	50.00
Total	22	100.00

With a PS of 4.91% and a GS of 50%, KG can now be calculated using the mathematical formula:

$$G = 1 - (4.91 / 50)$$

The result of the calculation of Kvamme Gain is 0.9018, meaning that 50% of the known decorated caves in the Périgord noir fall in the very high probability area of 4.91% of the total study area.

5.3 Application of the model to the rest of the department of Dordogne

The model was applied to the rest of the department of Dordogne in order to check for its relevance on a wider scale. A list of seven caves containing Upper Palaeolithic decorated caves was compiled using the website Monumentum and the Mérimée database of the French Ministry of Cultural Affairs (**Table 19**). All four variables were processed in the same way as in the predictive model derived from the Périgord noir datasets, in order to produce a probability map for the whole department of Dordogne (**Figure 24**).

Table 19. Additional list of known Upper Palaeolithic decorated caves found in the Dordogne department

Location	Name	Type of art
Bourdeilles	Grotte des Bernoux	Engravings
Champeaux-et-la-Chapelle-Pommier	Grotte de la Font-Bargeix	Paintings and engravings
Couze-et-Saint-Front	Grotte de la Cavaille	Paintings
La-Tour-Blanche	Grotte de Jovelle	Engravings
Le Buisson-de-Cadouin	Grotte de Cussac	Engravings
Saint-Martin-de-Fressengeas	Grotte des Fraux	Not specified
Vieux-Mareuil	Grotte de Fronsac	Engravings

Source: Monumentum.fr and French Ministry of Cultural Affairs (Mérimée database)

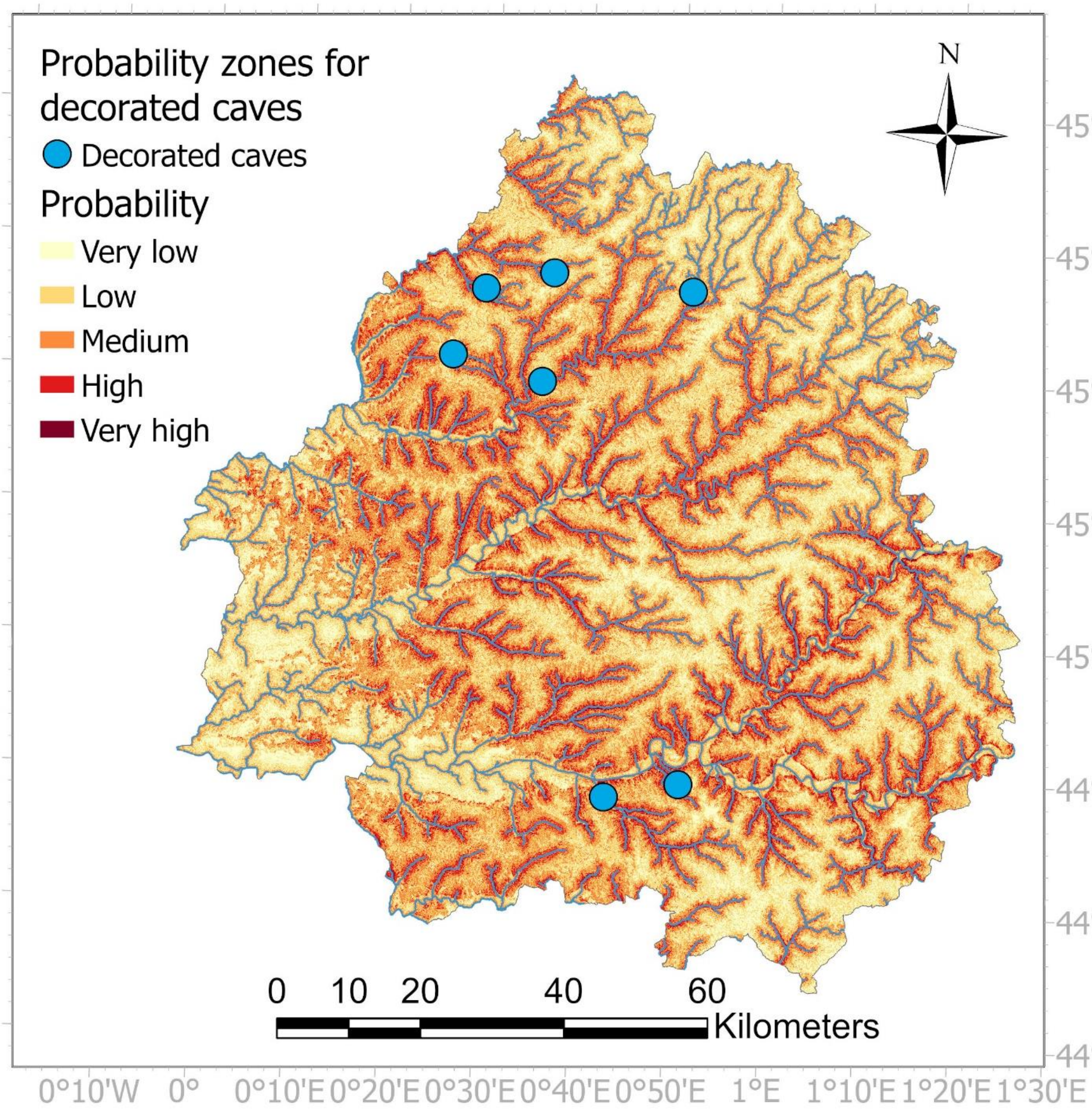

Figure 15. Map results showing probability zones and distribution of known Upper Palaeolithic decorated caves in the department of Dordogne

The map presented in **Figure 15** shows greater variability in the pixels values than the map focusing on the Périgord noir (**Figure 14**). Indeed, some areas close to water streams in the west and in the northeast of the Dordogne department seem to have very low to low probability of containing undiscovered decorated caves. This demonstrates that the model is not dependent on the proximity to water variable as the map of the Périgord noir could have suggested. The map of the Dordogne department also shows that the validation set of seven decorated caves seem to belong to medium to very high probability zones. The attribute table of the newly created raster file was thus analysed to confirm those observations. **Table 20** shows that no additional cave was to be found in the very low probability zone while four of them are in the medium probability class. Two decorated caves are found in either high or very high probability zones which denotes the model produces reasonable results when applied to the rest of the department.

Table 20. Affiliation of additional decorated caves in the different probability classes from the Périgord noir predictive model

Probability value	Number of decorated caves within the probability class
1	0
2	1
3	4
4	1
5	1

Producing a validation dataset of seven decorated caves allows the calculation of a new KG value. **Table 21** shows the number of pixel per probability class that was first analysed using the attribute table corresponding to **Figure 15**. The share of each probability class in the map showing probability zones and distribution of known Upper Palaeolithic decorated caves in Dordogne could then be defined (**Table 22**) as well as the distribution of decorated caves within each probability class (**Table 23**).

Table 21. Attribute table of the map showing probability zones and distribution of known Upper Palaeolithic decorated caves in the department of Dordogne

Probability value	Count (number of pixels)
1	2,175,209
2	5,258,635
3	4,978,621
4	2,020,925
5	279,023
Total	14,712,413

Table 22. **Share of each probability class in the map showing probability zones and decorated caves occurrences in the department of Dordogne**

Probability value	Count (number of pixels)	Share (%)
1	2,175,209	14.78
2	5,258,635	35.74
3	4,978,621	33.84
4	2,020,925	13.74
5	279,023	1.90
Total	14,712,413	100.00

Table 23. **Distribution of decorated caves within each probability class in the map showing probability zones and decorated caves in the department of Dordogne**

Probability value	Number of decorated caves	Share (%)
1	0	0.00
2	1	14.29
3	4	57.13
4	1	14.29
5	1	14.29
Total	7	100.00

For the department of Dordogne, the value of PS is then 1.90%, meaning that 1.90% of the total area of the department of Dordogne has a very high probability of containing undiscovered Upper Palaeolithic decorated caves. GS was determined as having a value of 14.29% allowing the calculation of KG as:

$$G = 1 - (1.90 / 14.29)$$

The result of the calculation of Kvamme Gain is 0.8670, meaning that 14.29% of the known decorated caves in the department of Dordogne fall in the very high probability area of 1.90% of the total study area. Despite KG value decreasing slightly compared to the value calculated for the Périgord noir, the model seems to show reasonable performance when applied to the whole department of Dordogne, using a set of seven independent caves.

6 Discussion

6.1 Main findings of the study

The multi-criteria analysis based on the use of GIS and predictive modelling used in this report was founded on a hybrid methodology using a range of techniques extracted from existing studies. The scientific literature showed that no predictive models have been applied to the Périgord noir before, presenting a knowledge gap which tried to be addressed in this study. The work carried out by Balla et al. (2013) was largely referred to throughout the report as it presented predictive modelling in a clear and organised way. Nonetheless, their model was adapted, especially with the use of a different methodology for the weighting of the criteria, using rating rather than the AHP technique. The criteria that were selected also differed slightly from their study as their work focused on the Hellenistic period. In that perspective, criteria related to roads and settlements could not be used for the Upper Palaeolithic period, and elevation, slope, aspect, and proximity to water appeared as the four main criteria selected to design the archaeological predictive model.

The study by Parow-Souchon et al. (2021) was also determining in the choice of a methodology. Indeed, they presented clear and meticulous processes in their assessment of site expectancy in the Southern Levant. The processing of the data in the present report then largely referred to their work and revealed that the values contained in each of the four layers representing each variable allowed the building of a predictive model (**RQ1**). Indeed, the analysis of the different attribute tables showed that similarities existed between the known Upper Palaeolithic decorated caves regarding the four selected variables. An analysis of the frequencies was also carried out to design probability classes in the predictive model in regard to the parameters of the twenty-two decorated caves that were selected.

The predictive model when applied to the Périgord noir also put to light that areas close to water streams were more likely to contain undiscovered decorated caves from the Upper Palaeolithic period. Areas close to the Vézère River and the Dordogne River in particular, as well as areas close to their respective tributaries, seem to have higher archaeological potential than areas farther inland. Basafa and Davari (2020) showed that important rich water resources were essential conditions to form habitat systems and provide resources, which supports the accuracy of the parameters of the model designed in this study. The fact that the four variables used in the model presented here were weighted equally also tends to demonstrate that the proximity to water criterion could be the main criterion for the selection of caves by prehistoric individuals for the production of their art. It was also found that 36% of the known decorated caves were oriented to the south, southeast, or southwest, supporting the observations made by Jègues-Wolkiewiez (2007).

The validation of the model finally appeared as essential to make the study presented here as reliable. In that perspective, Kvamme Gain was used as a validation metric to test the predictability and the performance of the model. The results of the different analyses showed that the model designed performed rather well in the area it was designed for. Indeed, the area of very high probability of containing undiscovered Upper Palaeolithic decorated caves defined by the model is rather small (4.91%), while the number of known decorated caves found inside that area is quite consequent (50%). According to KG values from other case studies found in the literature, the model presented here seems fairly reliable with a good predictive capacity. Indeed, "a random model would place 50% of known sites in 50% of the study area" according to van Leusen and Kamermans (2005). More, Graves (2011) describes "gains above 0.50 [as being] within expectations for archaeological predictive models" meaning that the gain achieved in this study shows good predictability. In that perspective, Balla et al. (2013) describe the highest KG value they were able to reach as 0.812. Moreover, Nicu et al. (2019) described an APM with a KG with a value of 0.56 as reliable. Nsanziyera et al. (2018) found a gain of 92.87% with a PS of 4.04% and a GS of 56.87%, closely relating to the results found in this study. They then qualified the high probability zone defined in their model as "a high potential zone for archaeological sites".

The KG values described in the references found on the subject of predictive modelling seem to indicate that the hybrid model built in this study through archaeological research, frequencies analysis, rating, and weighted linear combination is an appropriate way of working. The resulting KG value also shows the reliability of the model and the techniques used to design it. This supports the fact that the methodology chosen for predictive modelling in the Périgord noir seems reasonable (**RQ2**). The application of the model to the rest of the department of Dordogne also showed that the model developed performed rather well when applied to the department, as shown by the Kvamme Gain value calculated for that area (0.8670). This application revealed that some areas close to water streams were not in the very high or high probability classes of the model, highlighting the fact that the model is not too dependent on the proximity to water variable, or any other of the four variables.

6.2 Limitations and shortcomings of the methodology

The archaeological predictive model designed in this report was inspired from different studies found in the scientific literature and depended on available datasets for the area of interest. Even though the existing studies used between three and seven criteria, using four variables in this multi-criteria evaluation could appear as too few. Nonetheless, many studies that were referred to did use the same set of criteria which proves that the methodology is still appropriate. Another question that arose is the interdependency of the criteria. Indeed, it could be possible that the DEM and the hydrological network layers are too dependent on one another on a topographical point of view. This could have introduced biases in the analysis and that interdependency could probably be investigated further in future research.

The soil layer was not included in the model despite calcareous soils favouring the formation of caves on a geological point of view as demonstrated by Davies and Morgan (1991). If the potential for geological caves is higher, then the existence of decorated caves should be higher in zones with calcareous soil. Nonetheless, very few studies did include the soil type in the predictive model which influenced the choice not to include it here either. An updated model containing the soil variable could be designed and compared to the model presented here in order to check for similarities and differences.

The number of points used in the analysis could also be a source of error in the efficiency of the model as twenty-two decorated caves is a rather small sample. Nonetheless, some literature studies presented in the references present cases using even fewer points (Stirn, 2014). The weights assigned also could be refined to give more or less importance to the selected criteria. This would necessitate the gathering of data in various fields and should also be investigated further. Other weighting methods could also be applied and the results compared with the results presented here.

6.3 Further research

In any event, the model created here is only a preliminary work to define areas of potential archaeological interest. The main interest of predictive modelling is then to avoid excessive excavation costs when doing on-field work and it should be crossed with other datasets (geology, speleology, etc.) and studies from other fields in order to be useful. The model could also be completed with other variables that could present a particular interest. On-field work could also help to reclassify areas in other probability zones as it adds an invaluable dimension to computer work. Finally, the landcover could be analysed in relation to the distribution of decorated caves in the areas. Even though the time span is wide between the Upper Palaeolithic time and nowadays, there could be a correlation between the present landcover and past behaviours as suggested by some scientific articles.

7 Conclusion

This report described a multi-criteria methodology to design an archaeological predictive model that can be applied to identify probability areas of Upper Palaeolithic decorated caves' occurrences. The model is based on a hybrid methodology, presenting and testing four variables, namely elevation, slope, aspect, and proximity to water. A set of twenty-two known decorated caves was used and the values extracted for each criterion allowed the creation of a model to predict the location of Upper Palaeolithic decorated caves in the Périgord noir (**RQ1**). The prediction maps designed for each criterion appeared as satisfactory and presented valuable pieces of information to design the final model. The proximity to water streams seems to be a major variable in the selection of caves by prehistoric individuals for the purpose of art. Indeed, the final probability map shows patterned results with the highest probability areas along the Vézère and the Dordogne Rivers and their tributaries despite all criteria having the same weight.

The methodology selected relying on a numerical rating scale for the standardisation of the variables, rating for the weighting of the criteria, and weighted linear combination for the aggregation of the different datasets then appeared as satisfactory (**RQ2**). Indeed, the validation of the model through the calculation of Kvamme Gain demonstrated the ability of the model to predict areas of great archaeological interest. A large percentage of known decorated caves was identified into a rather restricted area showing the predictability of the model. In that perspective, on-field costs should be limited to the confined areas that were defined as having very high archaeological potential.

The predictive model presented in this study could also be extended to other areas as it showed good predictability when applied to the whole department of Dordogne. Other criteria could be included in the model in order to refine it or extend it to other archaeological artefacts or vestiges. The model should also be treated as a preliminary study and should be crossed with other data and on-field studies in order to be fully valuable, which could constitute the subject of further research on the matter. Finally, other techniques used in predictive modelling presented in the literature review, such as graph comparison or the Maxent algorithm, could be used to predict areas of high archaeological potential in the Périgord noir. The results should be compared to the present model and the similarities and differences explored.

8 References

Aldeias, V. et al. (2012) 'Evidence for Neanderthal use of fire at Roc de Marsal (France)', *Journal of Archaeological Science*, 39(7), pp. 2414–2423. doi: https://doi.org/10.1016/j.jas.2012.01.039

Andalecio, M.N. (2011) 'Multi-Criteria Decision Models for Management of Tropical Coastal Fisheries. In: Lichtfouse, E., Hamelin, M., Navarrete, M., Debaeke, P. (eds) *Sustainable Agriculture Volume 2*. Springer, Dordrecht. doi : https://doi-org.ludwig.lub.lu.se/10.1007/978-94-007-0394-0_14

Aranguren, B. et al. (2018) 'Wooden tools and fire technology in the early Neanderthal site of Poggetti Vecchi (Italy)', Proc*eedings of the National Academy of Sciences of the United States of America*, 115(9), pp. 2054–2059. Available at: https://www.jstor.org/stable/26507940 (Accessed: 27 February 2022)

Balla, A. et al. (2013) 'Locating Macedonian tombs using predictive modelling', *Journal of Cultural Heritage*, 14(5), pp. 403–410. doi: https://doi.org/10.1016/j.culher.2012.10.011

Balzeau, A. et al. (2020) 'Pluridisciplinary evidence for burial for the La Ferrassie 8 Neanderthal child', *Scientific Reports*, 10(1), p. 21230. doi: https://doi.org/10.1038/s41598-020-77611-z

Basafa, H. and Davari, M.S. (2020) 'Landscape archaeological approach to explain the settlement and cultural pattern of Kashfarud Basin (Mashhad Plain) from Neolithic to Middle Bronze', *Journal of Research on Archaeometry*, 6(2), pp. 141–155. doi: https://doi.org/10.52547/jra.6.2.141

Brandt, R., Groenewoudt, B.J. and Kvamme, K.L. (1992) 'An experiment in archaeological site location: modeling in the Netherlands using GIS techniques', *World Archaeology*, 24(2), pp. 268–282. Available at: http://www.jstor.org.ludwig.lub.lu.se/stable/124828 (Accessed: 18 February 2022).

Copernicus (2016) EU-DEM v1.1. Available at: https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1?tab=mapview (Accessed: 12 June 2022).

Copernicus (2019) EU-Hydro - River Network Database. Available at: https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database?tab=mapview (Accessed: 12 June 2022).

Daumas, M., Chapman, T. and Louryan, S. (2021) ‘Le Moustier 1 Neandertal – The discovery of two new sets of casts, 3D reconstruction and comparison with original fossils’, *Digital Applications in Archaeology and Cultural Heritage*, 23, p. e00204. doi: https://doi.org/10.1016/j.daach.2021.e00204

Davies, W. E and Morgan, I. M (1991) *Geology of caves*. Reston, VA.: U.S. Dept. of the Interior, U.S. Geological Survey.

Diwan, G. (2020) ‘GIS-based comparative archaeological predictive models: a first application to Iron Age sites in the Bekaa (Lebanon)’, *Mediterranean Archaeology and Archaeometry*, 20(2), pp. 143-158. doi: https://doi.org/10.5281/ZENODO.3819601

Douka, K. and Spinapolice, E.E. (2012) ‘Neanderthal Shell Tool Production: Evidence from Middle Palaeolithic Italy and Greece’, *Journal of World Prehistory*, 25(2), pp. 45–79. Available at: https://www.jstor.org/stable/23324620 (Accessed: 27 February 2022).

ESRI (n.d.), *Lambert conformal conic*. Available at: https://pro.arcgis.com/en/pro-app/2.8/help/mapping/properties/lambert-conformal-conic.htm (Accessed: 14 June 2022).

Feruglio, V. et al. (2019) ‘Rock art, performance and Palaeolithic cognitive systems. The example of the Grand Panel palimpsest of Cussac Cave, Dordogne, France’, *Journal of Anthropological Archaeology*, 56, p. 101104. doi: https://doi.org/10.1016/j.jaa.2019.101104

Galletti, C.S. et al. (2013) ‘Maxent modeling of ancient and modern agricultural terraces in the Troodos foothills, Cyprus’, *Applied Geography*, 39, pp. 46–56. doi: https://doi.org/10.1016/j.apgeog.2012.11.020

Gauvrit Roux, E. and Beyries, S. (2018) ‘Le travail de la peau au Magdalénien moyen ancien : analyse fonctionnelle de l’industrie lithique de la Marche (Lussac-les-Châteaux, Vienne)’, *Bulletin de la Société préhistorique française*, 115(4), pp. 647–675. doi: https://doi.org/10.3406/bspf.2018.14943

Gillespie, T. et al. (2016) ‘Predictive modelling for archaeological sites: Ashokan edicts from the Indian subcontinent’, *Current Science*, 110(10), pp. 1916–1921. Available at: http://www.jstor.org.ludwig.lub.lu.se/stable/24908179 (Accessed: 18 February 2022).

Graves, D. (2011) ‘The use of predictive modelling to target Neolithic settlement and occupation activity in mainland Scotland’, *Journal of Archaeological Science*, 38(3), pp. 633–656. doi: https://doi.org/10.1016/j.jas.2010.10.016

Greene, R. et al. (2011) ‘GIS-Based Multiple-Criteria Decision Analysis: GIS-based MCDA’, *Geography Compass*, 5(6), pp. 412–432. doi: https://doi.org/10.1111/j.1749-8198.2011.00431.x.

Hoffmann, D.L. et al. (2018) ‘U-Th dating of carbonate crusts reveals Neanderthal origin of Iberian cave art’, *Science*, 359(6378), pp. 912–915. doi: https://doi.org/10.1126/science.aap7778

Institut national de l'information géographique et forestière (n.d.-a), *Projection associée au système géodésique RGF93.* Available at: https://geodesie.ign.fr/contenu/fichiers/documentation/rgf93/Lambert-93.pdf (Accessed: 14 June 2022).

Institut national de l'information géographique et forestière (n.d.-b), *Que sont les projections Lambert-93 et Coniques Conformes 9 zones?.* Available at: https://geodesie.ign.fr/contenu/fichiers/Lambert93_ConiquesConformes.pdf (Accessed: 14 June 2022).

Ishizaka, A. and Labib, A. (2011) ‘Review of the main developments in the analytic hierarchy process’, *Expert Systems with Applications*, p. S0957417411006701. doi: https://doi.org/10.1016/j.eswa.2011.04.143

Jouteau, A. et al. (2019) ‘Choosing rock art locations: geological parameters and social behaviours. The example of Cussac Cave (Dordogne, France)’, *Journal of Archaeological Science*, 105, pp. 81–96. doi: https://doi.org/10.1016/j.jas.2019.03.008

Jègues-Wolkiewiez, C. (2007) ‘Chronologie de l’orientation des grottes et abris ornés Paléolithiques français’, *Valcamonica Symposium*. Darfo Boario Terme, Italy: 18-24 May. Available at: https://www.ccsp.it/web/INFOCCSP/VCS%20storico/vcs2007pdf/J%C3%A8gues-Wolkiewiez.pdf (Accessed: 10 March 2022).

Kalmijn, W. (2014) ‘Linear Scale Transformation’, in Michalos, A.C. (ed.) *Encyclopedia of Quality of Life and Well-Being Research*. Dordrecht: Springer Netherlands, pp. 3627–3629. doi: https://doi.org/10.1007/978-94-007-0753-5_3659

Kibblewhite, M., Tóth, G. and Hermann, T. (2015) 'Predicting the preservation of cultural artefacts and buried materials in soil', *Science of The Total Environment,* 529, pp. 249–263. https://doi.org/doi:10.1016/j.scitotenv.2015.04.036

Klein, R.G. (1995) 'Anatomy, behaviour, and modern human origins', *Journal of World Prehistory,* 9(2), pp. 167–198. doi: https://doi.org/10.1007/BF02221838

Kondo, Y., Omori, T. and Verhagen, P. (2012) '*Developing predictive models for palaeoanthropological research: a preliminary discussion*'. Technical Report. Tokyo Institute of Technology, Department of Computer Science, Tokyo, 11 pp.

Malczewski, J. (1999) *GIS and Multi-criteria Decision Analysis*. John Wiley & Sons, Inc.

Martin-Sanchez, P. et al. (2014) 'Airborne microorganisms in Lascaux Cave (France)', *International Journal of Speleology,* 43(3), pp. 295–303. doi: https://doi.org/10.5038/1827-806X.43.3.6

Mertel, A., Ondrejka, P. and Šabatová, K. (2018) 'Spatial predictive modeling of prehistoric sites in the Bohemian-Moravian Highlands based on graph similarity analysis', *Open Geosciences*, 10(1), pp. 261–274. doi: https://doi.org/10.1515/geo-2018-0020

Ministère de la culture (n.d.), POP : la plateforme ouverte du patrimoine. Available at: https://www.pop.culture.gouv.fr/search/list?base=%5B%22Patrimoine%20architectural%20%28M%C3%A9rim%C3%A9e%29%22%5D (Accessed: 14 June 2022).

Ministère des transports, de l'équipement, du tourisme et de la mer. Décret n°2006-272 du 3 mars 2006 modifiant le décret n°2000-1276 du 26 décembre 2000 portant application de l'article 89 de la loi n°95-115 du 4 février 1995 modifiée d'orientation pour l'aménagement et le développement du territoire relatif aux conditions d'exécution et de publication des levés de plans entrepris par les services publics, *Journal officiel*, n°59 du 10 mars 2006. Available at: https://www.legifrance.gouv.fr/loda/id/JORFTEXT000000813996 (Accessed: 14 June 2022).

Monumentum (2022), *Carte des Monuments Historiques français*. Available at: https://monumentum.fr/dordogne-d-24-carte.html (Accessed: 14 June 2022).

Nicu, I., Mihu-Pintilie, A. and Williamson, J. (2019) 'GIS-based and statistical approaches in archaeological predictive modelling (NE Romania)', *Sustainability*, 11(21), p. 5969. doi: https://doi.org/10.3390/su11215969

Nsanziyera, A. et al. (2018) ‘GIS and Remote-Sensing Application in Archaeological Site Mapping in the Awsard Area (Morocco)’, *Geosciences*, 8(6), p. 207. doi: https://doi.org/10.3390/geosciences8060207

Otte, M. (2010) *Cro-Magnon: aux origines de notre humanité*. Paris: Perrin (Collection Tempus, 315).

Pablos, A. et al. (2019) ‘Neanderthal foot remains from Regourdou 1 (Montignac-sur-Vézère, Dordogne, France)’, *Journal of Human Evolution*, 128, pp. 17–44. doi: https://doi.org/10.1016/j.jhevol.2018.11.003

‘Palimpsest’ (n.d.) Cambridge Dictionary. Available at: https://dictionary.cambridge.org/dictionary/english/palimpsest (Accessed 10 June 2022).

Parow-Souchon, H., Zickel, M. and Manner, H. (2021) ‘Upper Palaeolithic sites and where to find them: a predictive modelling approach to assess site expectancy in the Southern Levant’, *Quaternary International*, pp. 1-20. doi: https://doi.org/10.1016/j.quaint.2021.05.020

Pederzani, S. et al. (2021) ‘Reconstructing Late Pleistocene paleoclimate at the scale of human behaviour: an example from the Neanderthal occupation of La Ferrassie (France)’, *Scientific Reports*, 11(1), p. 1419. doi: https://doi.org/10.1038/s41598-020-80777-1

Pelletier, M. et al. (2017) ‘Rabbits in the grave! Consequences of bioturbation on the Neanderthal “burial” at Regourdou (Montignac, Dordogne)’, *Journal of Human Evolution*, 110, pp. 1–17. doi: https://doi.org/10.1016/j.jhevol.2017.04.001

Perakis, K. and Moysiadis, A. (2011) ‘Geospatial predictive modelling of the Neolithic archaeological sites of Magnesia in Greece’, *International Journal of Digital Earth*, 4(5), pp. 421-433. doi: https://doi.org/10.1080/17538947.2011.576778

Petrognani, S. et al. (2014) ‘Au cœur des premières manifestations graphiques du Paléolithique supérieur : Nouvelles découvertes dans la grotte des Bernoux (Dordogne)’, *Bulletin de la Société préhistorique française*, 111(3), pp. 413–432. doi: https://doi.org/10.3406/bspf.2014.14430

Piguet, M. (2014) Les grottes ornées préhistoriques : de la conservation préventive à la valorisation d’un patrimoine. MA Dissertation. ICOM Suisse.

Pinçon, G. and Fuentes, O. (2020) 'L'art rupestre en abri sous-roche du Paléolithique supérieur', *L'Anthropologie*, 124(3), p. 102782. doi: https://doi.org/10.1016/j.anthro.2020.102782

Pôle d'Interprétation de la Préhistoire (n.d.) *La vallée de la Vézère, capitale de l'archéologie préhistorique*. Available at: https://www.pole-prehistoire.com/fr/decouvrir/les-ressources-en-ligne/expositions-virtuelles/76-vallee-de-la-vezere/92-la-vallee-de-la-vezere-capitale-de-l-archeologie-prehistorique?showall=1 (Accessed 25 February 2022).

Rendu, W. et al. (2014) 'Evidence supporting an intentional Neanderthal burial at La Chapelle-aux-Saints', *Proceedings of the National Academy of Sciences*, 111(1), p. 81. doi: https://doi.org/10.1073/pnas.1316780110

Rua, H. (2009) 'Geographic information systems in archaeological analysis: a predictive model in the detection of rural Roman *villae', Journal of Archaeological Science*, 36(2), pp. 224–235. doi: https://doi.org/10.1016/j.jas.2008.09.003

Soler, N. and Soler, J. (2016) 'The First *Homo sapiens* in Catalonia, hunters and gatherers from the old Upper Palaeolithic', *Catalan Historical Review*, (9), pp. 9–23. doi: https://doi.org/10.2436/20.1000.01.119

Stirn, M. (2014) 'Modelling site location patterns amongst late-prehistoric villages in the Wind River Range, Wyoming', *Journal of Archaeological Science*, 41, pp. 523–532. doi: https://doi.org/10.1016/j.jas.2013.09.018

SudOuest.fr (2021) 'Dordogne : 4,3 millions de touristes accueillis en 2020', Sud Ouest, 23 February. Available at: https://www.sudouest.fr/dordogne/bergerac/dordogne-4-3-millions-de-touristes-accueillis-en-2020-1412444.php (Accessed: 29 March 2022).

Tallon, A.R. and Bromley, R.D.F. (2004) 'Exploring the attractions of city centre living: evidence and policy implications in British cities', Geoforum, 35(6), pp. 771–787. doi: https://doi.org/10.1016/j.geoforum.2004.05.004

Thibeault, A. and Villotte, S. (2018) 'Disentangling Cro-Magnon: a multiproxy approach to reassociate lower limb skeletal remains and to determine the biological profiles of the adult individuals', *Journal of Archaeological Science*: Reports, 21, pp. 76–86. doi: https://doi.org/10.1016/j.jasrep.2018.06.038

Thomas, E et al. (2015) ‘Urban demographics: Why people live where they do’. doi: https://doi.org/10.13140/RG.2.1.1053.8965

van Leusen, M. and Kamermans, H. (eds.) (2005) *Predictive modelling for archaeological heritage management: a research agenda*. Amersfoort: Rijksdienst voor het Oudheidkundig Bodemonderzoek.

Verhagen, P. (2007) *Case studies in archaeological predictive modelling*. PhD thesis. Leiden University. Available at: https://hdl.handle.net/1887/11863 (Accessed: 18 February 2022).

Appendix

Decorated caves metadata (list of Mérimée database reference numbers)

Panier de notices

22 notices

Grotte préhistorique de la Muzardie
Nouvelle-Aquitaine ; Dordogne (24) ; Campagne
Préhistoire
propriété privée ; 2013/07/03 : inscrit MH

Mérimée

PA24000080

Grotte ornée dite du Mammouth
Nouvelle-Aquitaine ; Dordogne (24) ; Domme
Paléolithique supérieur
propriété privée ; 1983/06/26 : classé MH ; 1983/06/27 :

Mérimée

PA00082516

Grotte ornée dite du Pigeonnier
Nouvelle-Aquitaine ; Dordogne (24) ; Domme
Paléolithique supérieur
propriété privée ; propriété d'un établissement public ;

Mérimée

PA00082517

Grotte préhistorique dite Grotte de la Martine
Nouvelle-Aquitaine ; Dordogne (24) ; Domme
Préhistoire, Paléolithique supérieur, Age du bronze
propriété de l'Etat ; 1978/03/15 : classé MH

Mérimée

PA00082515

Grotte de Bara-Bahau
Nouvelle-Aquitaine ; Dordogne (24) ; Le Bugue
Paléolithique supérieur
propriété privée ; propriété d'une société privée ;

Mérimée

PA00082413

Grotte de Font-de-Gaume (grotte du Sourd)
Nouvelle-Aquitaine ; Dordogne (24) ; Les Eyzies-de-Tay-
Paléolithique moyen, Paléolithique supérieur
propriété de l'Etat ; 1902/07/03 : classé MH

Mérimée

PA00082550

1 / 4

Grotte de la Croze
Nouvelle-Aquitaine ; Dordogne (24) ; Les Eyzies-de-Tay-
Paléolithique supérieur
propriété privée ; 1914/05/09 : classé MH

Mérimée

PA00082549

Grotte de la Mouthe contenant des peintures préhistoriques
Nouvelle-Aquitaine ; Dordogne (24) ; Les Eyzies-de-Tay-
Préhistoire, Paléolithique moyen, Paléolithique
propriété privée ; 1953/06/11 : classé MH

Mérimée

PA00082551

Grotte des Combarelles I
Nouvelle-Aquitaine ; Dordogne (24) ; Les Eyzies-de-Tay-
Paléolithique supérieur
propriété de l'Etat ; 1902/12/12 : classé MH

Mérimée

PA00082546

Grotte des Combarelles II
Nouvelle-Aquitaine ; Dordogne (24) ; Les Eyzies-de-Tay-
Paléolithique supérieur
propriété de l'Etat ; 1943/09/24 : inscrit MH

Mérimée

PA00082547

Grotte du château de Comarque
Nouvelle-Aquitaine ; Dordogne (24) ; Les Eyzies-de-Tay-
Préhistoire, Paléolithique supérieur
propriété privée ; 1924/02/12 : classé MH

Mérimée

PA00082548

Grotte préhistorique de Nancy
Nouvelle-Aquitaine ; Dordogne (24) ; Les Eyzies-de-Tay-
Paléolithique
propriété privée ; 2005/12/20 : inscrit MH

Mérimée

PA24000048

2 / 4

Grotte de Puymartin

Nouvelle-Aquitaine ; Dordogne (24) ; Marquay
Paléolithique
propriété privée ; 1995/10/24 : inscrit MH

Mérimée

PA00135166

Grotte préhistorique de la Grèze

Nouvelle-Aquitaine ; Dordogne (24) ; Marquay
Paléolithique
propriété privée ; 2009/10/09 : inscrit MH

Mérimée

PA24000072

Grotte de Bernifal

Nouvelle-Aquitaine ; Dordogne (24) ; Meyrals
Paléolithique supérieur
propriété privée ; 1904/05/27 : classé MH

Mérimée

PA00082644

Grotte dite Sous le Grand Lac

Nouvelle-Aquitaine ; Dordogne (24) ; Meyrals
Paléolithique supérieur
1981/02/26 : inscrit MH

Mérimée

PA00082645

Grotte de Lascaux

Nouvelle-Aquitaine ; Dordogne (24) ; Montignac
Paléolithique supérieur
propriété de l'Etat ; propriété privée ; 1940/12/27 : classé

Mérimée

PA00082696

Grotte du Cro de Granville ornée de peintures et de gravures pariétales

Nouvelle-Aquitaine ; Dordogne (24) ; Rouffi-
Age du bronze
propriété privée ; 1957/08/20 : classé MH

Mérimée

PA00082788

Grotte ornée de gravures prehistoriques, dite aussi Grotte du Sorcier
Nouvelle-Aquitaine ; Dordogne (24) ; Saint-Cirq
Paléolithique supérieur
propriété privée ; 1958/11/19 : classé MH

Mérimée

PA00082813

Grotte de La Forêt
Nouvelle-Aquitaine ; Dordogne (24) ; Tursac
Paléolithique supérieur
propriété privée ; 1981/07/03 : classé MH

Mérimée

PA00083041

Grotte préhistorique de la Sudrie
Nouvelle-Aquitaine ; Dordogne (24) ; Villac
Paléolithique
propriété privée ; 2005/12/20 : inscrit MH

Mérimée

PA24000050

Grotte du Roc
Nouvelle-Aquitaine ; Dordogne (24) ; Vézac
Paléolithique supérieur
propriété privée ; 1927/05/16 : classé MH

Mérimée

PA00083060

4 / 4

Digital Elevation Model metadata

EU-DEM v1.1

Map View (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1?tab=mapview)
Metadata (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1?tab=metadata)
Download (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1?tab=download)

DATA IDENTIFICATION

Resource title: European Digital Elevation Model (EU-DEM), version 1.1

Resource abstract: The EU-DEM v1.1 is a resulting dataset of the EU-DEM v1.0 upgrade which enhances the correction of geo-positioning issues, reducing the number of artefacts, improving the vertical accuracy of EU-DEM using ICESat as reference and ensuring consistency with EU-Hydro public beta.

EU-DEM v1.1 is available in Geotiff 32 bits format. It is a contiguous dataset divided into 1000 x 1000 km tiles, at 25m resolution with vertical accuracy: +/- 7 meters RMSE. The tiles have been grouped in big regions:

- EUDEM2_ASIA (Turkey)
- EUDEM2_ATLAN (Hondo and Fr_Islands)
- EUDEM2_BRITAIN (Thames, Shannon and Tweed)
- EUDEM2_EUROPE_1 (Duero, Ebro, Tajo, Guadalquivir and Jucar)
- EUDEM2_EUROPE_2 (Tirso, Mesima, Tevere and Po)
- EUDEM2_EUROPE_3 (Garonne, Rhone, Loire, Seine and western Rhine)
- EUDEM2_EUROPE_4 (Danube)
- EUDEM2_EUROPE_5 (Skjern, Nemunas, Vistula, Oder, Elbe and Eastern Rhine)
- EUDEM2_EUROPE_6 (Bulgaria and Pinios)
- EUDEM2_ICELAND (Iceland)
- EUDEM2_SCAND (Vorma, Gota, Angerman, Tana, Kemi and Neva)
- EUDEM2_SOUTH_AMERICA (Fr_Guiana)

EU-DEM v1.1 upgrade was coordinated by the European Environment Agency (EEA) in the frame of the EU Copernicus programme.

Resource type: Dataset

Resource Locator: http://land.copernicus.eu/pan-european/satellite-derived-products/eu-dem/eu-dem-v1.1/view (http://land.copernicus.eu/pan-european/satellite-derived-products/eu-dem/eu-dem-v1.1/view)

CLASSIFICATION OF SPATIAL DATA

Topic of category: Climatology/Meteorology/Atmosphere, Environment

Keyword:
Copernicus (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1/dataset_tag_search?tag=Cope
Elevation (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1/dataset_tag_search?tag=Elevati
Digital Elevation Model (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1/dataset_tag_sea
DSM (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1/dataset_tag_search?tag=DSM)
Copernicus Land (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1/dataset_tag_search?tag
hydrography (https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1/dataset_tag_search?tag=hy

GEOGRAPHIC REFERENCE

Bounding Box:
West = -54.925613
East = 93.178583
North = 71.899220
South = -21.567515

Coverage:	Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom
Geotags:	Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, North Macedonia, Malta, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom
Coordinate Reference System:	EPSG:3035 (ETRS89, LAEA)

TEMPORAL REFERENCE

Temporal extent:	2011
Date of publication:	Apr 20, 2016

QUALITY AND VALIDITY

Lineage:

- Correction of geo-positioning issues in EU-DEM v1.0 as reference also using SPOT 2011 imagery
- Bias adjustment with ICESat points
- Screening and removal of artefacts in the EU-DEM v1.0, including the presence of blunders (i.e. negative or positive anomalies)
- Ensuring consistency with EU-Hydro to produce a better river network topology:
  - Consistency of the coastline with the EU-HYDRO coastline, including the removal of DEM values outside the EU-HYDRO coastline
  - Use of the EU-HYDRO coastline to smooth the gradient to the coast in flat regions
  - Burning of EU-HYDRO water bodies to set EU-DEM to the minimum height inside the water body, smoothing the boundaries

Spatial resolution: 25 m

CONFORMITY

Specification:	Commission Regulation (EU) No 1089/2010 of 23 November 2010 implementing Directive 2007/2/EC of the European Parliament and of the Council as regards interoperability of spatial data sets and services, Date of publication: 2010-12-08
Degree:	Null

CONSTRAINTS RELATED TO ACCESS AND USE

Conditions applying to access and use:

Access to data is based on a principle of full, open and free access as established by the Copernicus data and information policy Regulation (EU) No 1159/2013 of 12 July 2013. This regulation establishes registration and licensing conditions for GMES/Copernicus users and can be found here (http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32013R1159)
. Free, full and open access to this data set is made on the conditions that:

1. When distributing or communicating Copernicus dedicated data and Copernicus service information to the public, users shall inform the public of the source of that data and information.
2. Users shall make sure not to convey the impression to the public that the user's activities are officially endorsed by the Union.
3. Where that data or information has been adapted or modified, the user shall clearly state this.

4. The data remain the sole property of the European Union. Any information and data produced in the framework of the action shall be the sole property of the European Union. Any communication and publication by the beneficiary shall acknowledge that the data were produced "with funding by the European Union".

Limitation of public access:	No Limitation
	RESPONSIBLE ORGANISATION
Responsible party:	European Environment Agency (EEA) under the framework of the Copernicus programme - copernicus@eea.europa.eu (mailto:copernicus@eea.europa.eu)
Responsible party role:	Resource Provider

Hydrological network metadata

EU-Hydro - River Network Database

Map View (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database?tab=mapview)
Metadata (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database?tab=metadata)
Download (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database?tab=download)

DATA IDENTIFICATION

Resource title: EU-Hydro – River Network Database, Version 1.3

Resource abstract: EU-Hydro is a dataset for all EEA39 countries providing photo-interpreted river network, consistent of surface interpretation of water bodies (lakes and wide rivers), and a drainage model (also called Drainage Network), derived from EU-DEM, with catchments and drainage lines and nodes.
The EU-Hydro dataset is distributed in separate files (river network and drainage network) for each of the 35 major basins of the EEA39 area.
The production of EU-Hydro and the derived layers was coordinated by the European Environment Agency in the frame of the EU Copernicus programme.

Resource type: Dataset

Resource Locator: https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database)

CLASSIFICATION OF SPATIAL DATA

Topic of category: Environment, Geoscientific Information, Inland Water, Oceans

Keyword:
Copernicus (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_ta
EU-Hydro (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_
Hydrology (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag
River Network (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset
EU-DEM (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_s
CLMS (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_sear
Catchments (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_t
Land (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_sear
Coastline (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_
EEA39 (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_se
Drainage (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_
Canals (https://land.copernicus.eu/imagery-in-situ/eu-hydro/eu-hydro-river-network-database/dataset_tag_se

GEOGRAPHIC REFERENCE

Bounding Box:
West = -31.561261
East = 44.820775
North = 71.409109
South = 27.405827

Bounding Box:
West = -61.906047
East = -60.905616
North = 16.607552
South = 15.736333

Bounding Box:
West = -55.660672
East = -51.075939
North = 7.005530
South = 1.167271

Bounding Box:	West = -61.326095 East = -60.711516 North = 14.970484 South = 14.29692
Bounding Box:	West = 55.114983 East = 55.935919 North = -20.77811 South = -21.482245
Coverage:	Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom
Geotags:	Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom
Coordinate Reference System:	EPSG:3035 (ETRS89, LAEA)
	TEMPORAL REFERENCE
Temporal extent:	2006-2012
Date of publication:	Nov 19, 2019
Revision date:	Nov 25, 2020
	QUALITY AND VALIDITY
Lineage:	Space imagery SP05 (resolution 2.5 m) and SP06 (resolution 2.5 m), space imagery IMAGE2009 (resolution 20 m), EEA member countries WFD reporting data on water bodies: for Turkey (EEA member), Albania, Bosnia-Herzegovina, North Macedonia, Montenegro, Kosovo and Serbia (all EEA cooperating countries) no spatial data for any category of water bodies was available, European Catchments and Rivers Network System (ECRINS); ancillary data: European Lakes and Reservoirs database (Eldred), Russian topographic maps. The upgrade of the EU-Hydro beta version includes improvements of the usability of the dataset, of its topological and logical consistency and the River network characteristics. Catchments layers were also modified to fit the River networks. Topological overlapping and gaps between River Basin Districts were corrected. The EU-Hydro **V1.1** upgrade includes the reclassification of polygons between InlandWater, Coastal-p, Transit_p and River_Net_p classes, the upgrade of the WFD codes using the WISE geospatial dataset for these feature classes, the improvement of logical consistency of attribute tables (deletion of irrelevant fields, recalculation of OBJECT_ID field, recalculation of geometry properties field). In Version **1.2** the Drainage network derived from EUDEM was incorporated to the river network of EU hydro: four feature classes were generated: River_Net_l_DN, Canals_l_DN, Ditches_l_DN and Nodes_DN. River names were updated using WISE geospatial database, except for Thames, Tweed and Turkey where ECRINS was used instead. In version **1.3**, "River_Net_l" topology was adjusted to fit Coastal_p and Transit_p: polylines were deleted for Gota, Skjern, Shannon, Tweed. Polylines were added in Skjern, Mesima and Tajo on areas overlapping Transit_p. Nodes were modified accordingly. CUM_LEN, LONGPATH, LENGTH GEO fields were recalculated.
Spatial resolution:	Minimum Mapping Unit (MMU): 1 ha
	CONFORMITY

Specification:	Commission Regulation (EU) No 1089/2010 of 23 November 2010 implementing Directive 2007/2/EC of the European Parliament and of the Council as regards interoperability of spatial data sets and services.
Degree:	Null
	CONSTRAINTS RELATED TO ACCESS AND USE
Conditions applying to access and use:	Access to data is based on a principle of full, open and free access as established by the Copernicus data and information policy Regulation (EU) No 1159/2013 of 12 July 2013. This regulation establishes registration and licensing conditions for GMES/Copernicus users and can be found here (http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32013R1159) . Free, full and open access to this data set is made on the conditions that: 1. When distributing or communicating Copernicus dedicated data and Copernicus service information to the public, users shall inform the public of the source of that data and information. 2. Users shall make sure not to convey the impression to the public that the user's activities are officially endorsed by the Union. 3. Where that data or information has been adapted or modified, the user shall clearly state this. 4. The data remain the sole property of the European Union. Any information and data produced in the framework of the action shall be the sole property of the European Union. Any communication and publication by the beneficiary shall acknowledge that the data were produced "with funding by the European Union".
Limitation of public access:	No Limitation
	RESPONSIBLE ORGANISATION
Responsible party:	European Environment Agency (EEA) under the framework of the Copernicus programme - copernicus@eea.europa.eu
Responsible party role:	Resource Provider

Administrative boundaries metadata

RÉPUBLIQUE
FRANÇAISE

data.gouv.fr

Accueil   Jeux de données   Découpage administratif communal ...

Découpage administratif communal français issu d'OpenStreetMap

54 favoris

Mis à jour le 6 janvier 2022 — Open Data Commons Open Database License (ODbL)

administratif   administration-locale   administratives   communes   contours

crowdsourcing   decoupage   frontiere   geo   geographie   geographique

geolocalisation   geolocalise   limite   limites-administratives   openstreetmap

osm

INFORMATIONS

Licence

Open Data Commons Open Database License (ODbL)

ID

53699233a3a729239d203e69

TEMPORALITÉ

Fréquence

Annuelle

Date de création

17 novembre 2013

Dernière mise à jour de ressource

1 janvier 2022

Description

Exports du découpage administratif français au niveau communal (contours des communes) issu d'OpenStreetMap produit dans sa grande majorité à partir du cadastre.

Ces données sont issues du crowdsourcing effectué par les contributeurs au projet OpenStreetMap et sont sous licence ODbL qui impose un partage à l'identique et la mention obligatoire d'attribution doit être "© les contributeurs d'OpenStreetMap sous licence ODbL" conformément à http://osm.org/copyright

Un export automatique quotidien au format shapefile est disponible, ainsi qu'un second export avec des géométries allégées et vérifiées topologiquement (pas de chevauchement).

Descriptif du contenu des fichiers "communes"

Origine

Les données proviennent de la base de données cartographiques OpenStreetMap.
Celles-ci ont été constituées à partir du cadastre mis à disposition par la DGFiP sur cadastre.gouv.fr.
En complément sur Mayotte où le cadastre n'est pas disponible sur cadastre.gouv.fr, ce sont les limites du GEOFLA de l'IGN qui ont été utilisées ainsi que le tracé des côtes à partir des images aériennes de Bing.

Plus d'infos: http://prev.openstreetmap.fr/36680-communes

Format

Ces fichiers sont proposés au format shapefile, en projection WGS84 avec plusieurs niveaux de détails:

- simplification à 5m
- simplification à 50m
- simplification à 100m

La topologie est conservée lors du processus de simplification (cf: http://prev.openstreetmap.fr/blogs/cquest/limites-administratives-simplifiees)

Contenu

Ces fichiers contiennent l'ensemble des communes françaises, y compris les DOM, Mayotte et Saint-Pierre-et-Miquelon. Pour Paris, Lyon, Marseille, ce sont les limites d'arrondissements qui sont fournies à la place des limites de communes.

Pour chaque commune ou arrondissement, les attributs suivants sont ajoutés:

- insee: code INSEE à 5 caractères de la commune
- nom: nom de la commune (tel que figurant dans OpenStreetMap, si possible conforme aux règles de toponymie)
- wikipedia: entrée wikipédia (code langue suivi du nom de l'article)
- surf_ha : surface en hectares de la commune

Pour les communes de Bois-Guillaume et Bihorel, les données du GEOFLA ont été corrigées manuellement suite à l'annulation de la fusion le 1er Janvier 2014.

Historique

- 19-12-2013 : première génération du fichier, basé sur le découpage communal OSM au 19-12-2013
- 20-12-2013 : correction de 2 erreurs (un cimetière militaire était exclu du territoire par erreur, la géométrie de la commune de Landerneau manquait)
- 06-03-2014 : troisième génération du fichier, basé sur le découpage communal OSM au 06-03-2014
- 29-06-2014 : remplacement des limites de Paris, Lyon, Marseille par les limites de leurs arrondissements municipaux.
- 30-06-2014 : ajout de la version "enrichie"
- 10-10-2014 : ajout d'un export CSV de la version "enrichie"
- 01-01-2015 : quatrième version du fichier, prenant en compte les fusions de communes au 1/1/2015 ainsi que les communes ayant changé de nom le 3/12/2014. Pour les communes fusionnées et à titre temporaire (attente de publication du COG 2015) le code INSEE conservé est celui de la commune où le chef-lieu est fixé par le JORF.
- **19-01-2016** : cinquième version du fichier, prenant en compte les **fusions de communes au 19/1/2016 ainsi que les changements intervenus en 2015** (nouveaux noms, etc). Voir ce jeu de données pour plus de détail sur les fusions et communes nouvelles. Les arrondissements municipaux (Paris, Lyon, Marseille) sont disponibles dans un fichier séparé avec les communes déléguées issues de la création des communes nouvelles.
- **11-01-2017** : version prenant en compte les **181 fusions de communes au 1/1/2017 ainsi que les changements intervenus en 2016** (nouveaux noms, fusions, etc). Voir ce jeu de données pour plus de détail sur les fusions et communes nouvelles.
- **01-01-2018** : version comprenant les 33 fusions de communes au 1/1/2018 et la fusion au 1/7/2017, ainsi que les changements de noms intervenus en 2017. St-Pierre et Miquelon sont dans le fichier des communes des Collectivités d'Outre-Mer.
- **26-02-2018** : version au 1/1/2018 complétée par 3 communes nouvelles (Aubessagne, Blancs-Coteaux, Geiswiller-Zœbersdorf) soit au total 36 fusions.
- **01-01-2019** : version au 1/1/2019 comprenant 232 communes nouvelles répertoriées sur wikipédia au 01/01/2019
- **11-02-2019** : intégration des communes nouvelles répertoriées par l'INSEE
- **07-03-2019** : correction du code INSEE de La Léchère (73187)
- **01-01-2021** : Fusion des communes au 1/1/2021

Versions précédentes disponibles sur: http://osm13.openstreetmap.fr/~cquest/openfla/export/

Pour toute question concernant ces exports, vous pouvez contacter exports@openstreetmap.fr

Series from Lund University

Department of Physical Geography and Ecosystem Science

Master Thesis in Geographical Information Science

1. *Anthony Lawther*: The application of GIS-based binary logistic regression for slope failure susceptibility mapping in the Western Grampian Mountains, Scotland (2008).
2. *Rickard Hansen*: Daily mobility in Grenoble Metropolitan Region, France. Applied GIS methods in time geographical research (2008).
3. *Emil Bayramov*: Environmental monitoring of bio-restoration activities using GIS and Remote Sensing (2009).
4. *Rafael Villarreal Pacheco*: Applications of Geographic Information Systems as an analytical and visualization tool for mass real estate valuation: a case study of Fontibon District, Bogota, Columbia (2009).
5. *Siri Oestreich Waage*: a case study of route solving for oversized transport: The use of GIS functionalities in transport of transformers, as part of maintaining a reliable power infrastructure (2010).
6. *Edgar Pimiento*: Shallow landslide susceptibility – Modelling and validation (2010).
7. *Martina Schäfer*: Near real-time mapping of floodwater mosquito breeding sites using aerial photographs (2010).
8. *August Pieter van Waarden-Nagel*: Land use evaluation to assess the outcome of the programme of rehabilitation measures for the river Rhine in the Netherlands (2010).
9. *Samira Muhammad*: Development and implementation of air quality data mart for Ontario, Canada: A case study of air quality in Ontario using OLAP tool. (2010).
10. *Fredros Oketch Okumu*: Using remotely sensed data to explore spatial and temporal relationships between photosynthetic productivity of vegetation and malaria transmission intensities in selected parts of Africa (2011).
11. *Svajunas Plunge*: Advanced decision support methods for solving diffuse water pollution problems (2011).
12. *Jonathan Higgins*: Monitoring urban growth in greater Lagos: A case study using GIS to monitor the urban growth of Lagos 1990 - 2008 and produce future growth prospects for the city (2011).

13. *Mårten Karlberg*: Mobile Map Client API: Design and Implementation for Android (2011).
14. *Jeanette McBride*: Mapping Chicago area urban tree canopy using color infrared imagery (2011).
15. *Andrew Farina*: Exploring the relationship between land surface temperature and vegetation abundance for urban heat island mitigation in Seville, Spain (2011).
16. *David Kanyari*: Nairobi City Journey Planner: An online and a Mobile Application (2011).
17. *Laura V. Drews*: Multi-criteria GIS analysis for siting of small wind power plants - A case study from Berlin (2012).
18. *Qaisar Nadeem*: Best living neighbourhood in the city - A GIS based multi criteria evaluation of ArRiyadh City (2012).
19. *Ahmed Mohamed El Saeid Mustafa*: Development of a photo voltaic building rooftop integration analysis tool for GIS for Dokki District, Cairo, Egypt (2012).
20. *Daniel Patrick Taylor*: Eastern Oyster Aquaculture: Estuarine Remediation via Site Suitability and Spatially Explicit Carrying Capacity Modeling in Virginia's Chesapeake Bay (2013).
21. *Angeleta Oveta Wilson*: A Participatory GIS approach to unearthing Manchester's Cultural Heritage '*gold mine*' (2013).
22. *Ola Svensson*: Visibility and Tholos Tombs in the Messenian Landscape: A Comparative Case Study of the Pylian Hinterlands and the Soulima Valley (2013).
23. *Monika Ogden*: Land use impact on water quality in two river systems in South Africa (2013).
24. *Stefan Rova*: A GIS based approach assessing phosphorus load impact on Lake Flaten in Salem, Sweden (2013).
25. *Yann Buhot*: Analysis of the history of landscape changes over a period of 200 years. How can we predict past landscape pattern scenario and the impact on habitat diversity? (2013).
26. *Christina Fotiou*: Evaluating habitat suitability and spectral heterogeneity models to predict weed species presence (2014).
27. *Inese Linuza*: Accuracy Assessment in Glacier Change Analysis (2014).
28. *Agnieszka Griffin*: Domestic energy consumption and social living standards: a GIS analysis within the Greater London Authority area (2014).

29. *Brynja Guðmundsdóttir*: Detection of potential arable land with remote sensing and GIS - A Case Study for Kjósarhreppur (2014).
30. *Oleksandr Nekrasov*: Processing of MODIS Vegetation Indices for analysis of agricultural droughts in the southern Ukraine between the years 2000-2012 (2014).
31. *Sarah Tressel*: Recommendations for a polar Earth science portal in the context of Arctic Spatial Data Infrastructure (2014).
32. *Caroline Gevaert*: Combining Hyperspectral UAV and Multispectral Formosat-2 Imagery for Precision Agriculture Applications (2014).
33. *Salem Jamal-Uddeen*: Using GeoTools to implement the multi-criteria evaluation analysis - weighted linear combination model (2014).
34. *Samanah Seyedi-Shandiz*: Schematic representation of geographical railway network at the Swedish Transport Administration (2014).
35. *Kazi Masel Ullah*: Urban Land-use planning using Geographical Information System and analytical hierarchy process: case study Dhaka City (2014).
36. *Alexia Chang-Wailing Spitteler*: Development of a web application based on MCDA and GIS for the decision support of river and floodplain rehabilitation projects (2014).
37. *Alessandro De Martino*: Geographic accessibility analysis and evaluation of potential changes to the public transportation system in the City of Milan (2014).
38. *Alireza Mollasalehi*: GIS Based Modelling for Fuel Reduction Using Controlled Burn in Australia. Case Study: Logan City, QLD (2015).
39. *Negin A. Sanati*: Chronic Kidney Disease Mortality in Costa Rica; Geographical Distribution, Spatial Analysis and Non-traditional Risk Factors (2015).
40. *Karen McIntyre*: Benthic mapping of the Bluefields Bay fish sanctuary, Jamaica (2015).
41. *Kees van Duijvendijk*: Feasibility of a low-cost weather sensor network for agricultural purposes: A preliminary assessment (2015).
42. *Sebastian Andersson Hylander*: Evaluation of cultural ecosystem services using GIS (2015).
43. *Deborah Bowyer*: Measuring Urban Growth, Urban Form and Accessibility as Indicators of Urban Sprawl in Hamilton, New Zealand (2015).
44. *Stefan Arvidsson*: Relationship between tree species composition and phenology extracted from satellite data in Swedish forests (2015).

45. *Damián Giménez Cruz*: GIS-based optimal localisation of beekeeping in rural Kenya (2016).
46. *Alejandra Narváez Vallejo*: Can the introduction of the topographic indices in LPJ-GUESS improve the spatial representation of environmental variables? (2016).
47. *Anna Lundgren*: Development of a method for mapping the highest coastline in Sweden using breaklines extracted from high resolution digital elevation models (2016).
48. *Oluwatomi Esther Adejoro*: Does location also matter? A spatial analysis of social achievements of young South Australians (2016).
49. *Hristo Dobrev Tomov*: Automated temporal NDVI analysis over the Middle East for the period 1982 - 2010 (2016).
50. *Vincent Muller*: Impact of Security Context on Mobile Clinic Activities - A GIS Multi Criteria Evaluation based on an MSF Humanitarian Mission in Cameroon (2016).
51. *Gezahagn Negash Seboka*: Spatial Assessment of NDVI as an Indicator of Desertification in Ethiopia using Remote Sensing and GIS (2016).
52. *Holly Buhler*: Evaluation of Interfacility Medical Transport Journey Times in Southeastern British Columbia. (2016).
53. *Lars Ole Grottenberg*: Assessing the ability to share spatial data between emergency management organisations in the High North (2016).
54. *Sean Grant*: The Right Tree in the Right Place: Using GIS to Maximize the Net Benefits from Urban Forests (2016).
55. *Irshad Jamal*: Multi-Criteria GIS Analysis for School Site Selection in Gorno-Badakhshan Autonomous Oblast, Tajikistan (2016).
56. *Fulgencio Sanmartín*: Wisdom-volkano: A novel tool based on open GIS and time-series visualization to analyse and share volcanic data (2016).
57. *Nezha Acil*: Remote sensing-based monitoring of snow cover dynamics and its influence on vegetation growth in the Middle Atlas Mountains (2016).
58. *Julia Hjalmarsson*: A Weighty Issue: Estimation of Fire Size with Geographically Weighted Logistic Regression (2016).
59. *Mathewos Tamiru Amato*: Using multi-criteria evaluation and GIS for chronic food and nutrition insecurity indicators analysis in Ethiopia (2016).
60. *Karim Alaa El Din Mohamed Soliman El Attar*: Bicycling Suitability in Downtown, Cairo, Egypt (2016).

61. *Gilbert Akol Echelai*: Asset Management: Integrating GIS as a Decision Support Tool in Meter Management in National Water and Sewerage Corporation (2016).
62. *Terje Slinning*: Analytic comparison of multibeam echo soundings (2016).
63. *Gréta Hlín Sveinsdóttir*: GIS-based MCDA for decision support: A framework for wind farm siting in Iceland (2017).
64. *Jonas Sjögren*: Consequences of a flood in Kristianstad, Sweden: A GIS based analysis of impacts on important societal functions (2017).
65. *Nadine Raska:* 3D geologic subsurface modelling within the Mackenzie Plain, Northwest Territories, Canada (2017).
66. *Panagiotis Symeonidis*: Study of spatial and temporal variation of atmospheric optical parameters and their relation with PM 2.5 concentration over Europe using GIS technologies (2017).
67. *Michaela Bobeck:* A GIS-based Multi-Criteria Decision Analysis of Wind Farm Site Suitability in New South Wales, Australia, from a Sustainable Development Perspective (2017).
68. *Raghdaa Eissa*: Developing a GIS Model for the Assessment of Outdoor Recreational Facilities in New Cities Case Study: Tenth of Ramadan City, Egypt (2017).
69. *Zahra Khais Shahid*: Biofuel plantations and isoprene emissions in Svea and Götaland (2017).
70. *Mirza Amir Liaquat Baig*: Using geographical information systems in epidemiology: Mapping and analysing occurrence of diarrhoea in urban-residential area of Islamabad, Pakistan (2017).
71. *Joakim Jorwall*: Quantitative model of Present and Future well-being in the EU-28: A spatial Multi-Criteria Evaluation of socioeconomic and climatic comfort factors (2017).
72. *Elin Haettner*: Energy Poverty in the Dublin Region: Modelling Geographies of Risk (2017).
73. *Harry Eriksson*: Geochemistry of stream plants and its statistical relations to soil- and bedrock geology, slope directions and till geochemistry. A GIS-analysis of small catchments in northern Sweden (2017).
74. *Daniel Gardevarn:* PPGIS and Public meetings – An evaluation of public participation methods for urban planning (2017).

75. *Kim Friberg:* Sensitivity Analysis and Calibration of Multi Energy Balance Land Surface Model Parameters (2017).
76. *Viktor Svanerud:* Taking the bus to the park? A study of accessibility to green areas in Gothenburg through different modes of transport (2017).
77. *Lisa-Gaye Greene*: Deadly Designs: The Impact of Road Design on Road Crash Patterns along Jamaica's North Coast Highway (2017).
78. *Katarina Jemec Parker*: Spatial and temporal analysis of faecal indicator bacteria concentrations in beach water in San Diego, California (2017).
79. *Angela Kabiru*: An Exploratory Study of Middle Stone Age and Later Stone Age Site Locations in Kenya's Central Rift Valley Using Landscape Analysis: A GIS Approach (2017).
80. *Kristean Björkmann*: Subjective Well-Being and Environment: A GIS-Based Analysis (2018).
81. *Williams Erhunmonmen Ojo*: Measuring spatial accessibility to healthcare for people living with HIV-AIDS in southern Nigeria (2018).
82. *Daniel Assefa*: Developing Data Extraction and Dynamic Data Visualization (Styling) Modules for Web GIS Risk Assessment System (WGRAS). (2018).
83. *Adela Nistora*: Inundation scenarios in a changing climate: assessing potential impacts of sea-level rise on the coast of South-East England (2018).
84. *Marc Seliger*: Thirsty landscapes - Investigating growing irrigation water consumption and potential conservation measures within Utah's largest master-planned community: Daybreak (2018).
85. *Luka Jovičić*: Spatial Data Harmonisation in Regional Context in Accordance with INSPIRE Implementing Rules (2018).
86. *Christina Kourdounouli*: Analysis of Urban Ecosystem Condition Indicators for the Large Urban Zones and City Cores in EU (2018).
87. *Jeremy Azzopardi*: Effect of distance measures and feature representations on distance-based accessibility measures (2018).
88. *Patrick Kabatha*: An open source web GIS tool for analysis and visualization of elephant GPS telemetry data, alongside environmental and anthropogenic variables (2018).
89. *Richard Alphonce Giliba*: Effects of Climate Change on Potential Geographical Distribution of Prunus Africana (African cherry) in the Eastern Arc Mountain Forests of Tanzania (2018).

90. *Eidur Kristinn Eidsson*: Transformation and linking of authoritative multiscale geodata for the Semantic Web: A case study of Swedish national building data sets (2018).
91. *Niamh Harty*: HOP!: a PGIS and citizen science approach to monitoring the condition of upland paths (2018).
92. *Jose Estuardo Jara Alvear*: Solar photovoltaic potential to complement hydropower in Ecuador: A GIS-based framework of analysis (2018).
93. *Brendan O'Neill*: Multi criteria Site Suitability for Algal Biofuel Production Facilities (2018).
94. *Roman Spataru*: Spatial-temporal GIS analysis in public health – a case study of polio disease (2018).
95. *Alicja Miodońska*: Assessing evolution of ice caps in Suðurland, Iceland, in years 1986 - 2014, using multispectral satellite imagery (2019).
96. *Dennis Lindell Schettini*: A Spatial Analysis of Homicide Crime's Distribution and Association with Deprivation in Stockholm Between 2010-2017 (2019).
97. *Damiano Vesentini*: The Po Delta Biosphere Reserve: Management challenges and priorities deriving from anthropogenic pressure and sea level rise (2019).
98. *Emilie Arnesten*: Impacts of future sea level rise and high water on roads, railways and environmental objects: a GIS analysis of the potential effects of increasing sea levels and highest projected high water in Scania, Sweden (2019).
99. *Syed Muhammad Amir Raza*: Comparison of geospatial support in RDF stores: Evaluation for ICOS Carbon Portal metadata (2019).
100. *Hemin Tofiq*: Investigating the accuracy of Digital Elevation Models from UAV images in areas with low contrast: A sandy beach as a case study (2019).
101. *Evangelos Vafeiadis*: Exploring the distribution of accessibility by public transport using spatial analysis. A case study for retail concentrations and public hospitals in Athens (2019).
102. *Milan Sekulic*: Multi-Criteria GIS modelling for optimal alignment of roadway by-passes in the Tlokweng Planning Area, Botswana (2019).
103. *Ingrid Piirisaar*: A multi-criteria GIS analysis for siting of utility-scale photovoltaic solar plants in county Kilkenny, Ireland (2019).
104. *Nigel Fox*: Plant phenology and climate change: possible effect on the onset of various wild plant species' first flowering day in the UK (2019).

105. *Gunnar Hesch*: Linking conflict events and cropland development in Afghanistan, 2001 to 2011, using MODIS land cover data and Uppsala Conflict Data Programme (2019).
106. *Elijah Njoku*: Analysis of spatial-temporal pattern of Land Surface Temperature (LST) due to NDVI and elevation in Ilorin, Nigeria (2019).
107. *Katalin Bunyevacz*: Development of a GIS methodology to evaluate informal urban green areas for inclusion in a community governance program (2019).
108. *Paul dos Santos*: Automating synthetic trip data generation for an agent based simulation of urban mobility (2019).
109. *Robert O' Dwyer*: Land cover changes in Southern Sweden from the mid-Holocene to present day: Insights for ecosystem service assessments (2019).
110. *Daniel Klingmyr*: Global scale patterns and trends in tropospheric NO2 concentrations (2019).
111. *Marwa Farouk Elkabbany*: Sea Level Rise Vulnerability Assessment for Abu Dhabi, United Arab Emirates (2019).
112. *Jip Jan van Zoonen*: Aspects of Error Quantification and Evaluation in Digital Elevation Models for Glacier Surfaces (2020).
113. *Georgios Efthymiou*: The use of bicycles in a mid-sized city – benefits and obstacles identified using a questionnaire and GIS (2020).
114. *Haruna Olayiwola Jimoh*: Assessment of Urban Sprawl in MOWE/IBAFO Axis of Ogun State using GIS Capabilities (2020).
115. *Nikolaos Barmpas Zachariadis*: Development of an iOS, Augmented Reality for disaster management (2020).
116. *Ida Storm*: ICOS Atmospheric Stations: Spatial Characterization of CO2 Footprint Areas and Evaluating the Uncertainties of Modelled CO2 Concentrations (2020).
117. *Alon Zuta*: Evaluation of water stress mapping methods in vineyards using airborne thermal imaging (2020).
118. *Marcus Eriksson*: Evaluating structural landscape development in the municipality Upplands-Bro, using landscape metrics indices (2020).
119. *Ane Rahbek Viero*: Connectivity for Cyclists? A Network Analysis of Copenhagen's Bike Lanes (2020).
120. *Cecilia Baggini*: Changes in habitat suitability for three declining Anatidae species in saltmarshes on the Mersey estuary, North-West England (2020).
121. *Bakrad Balabanian*: Transportation and Its Effect on Student Performance (2020).

122. *Ali Al Farid*: Knowledge and Data Driven Approaches for Hydrocarbon Microseepage Characterizations: An Application of Satellite Remote Sensing (2020).
123. *Bartlomiej Kolodziejczyk*: Distribution Modelling of Gene Drive-Modified Mosquitoes and Their Effects on Wild Populations (2020).
124. *Alexis Cazorla*: Decreasing organic nitrogen concentrations in European water bodies - links to organic carbon trends and land cover (2020).
125. *Kharid Mwakoba*: Remote sensing analysis of land cover/use conditions of community-based wildlife conservation areas in Tanzania (2021).
126. *Chinatsu Endo*: Remote Sensing Based Pre-Season Yellow Rust Early Warning in Oromia, Ethiopia (2021).
127. *Berit Mohr*: Using remote sensing and land abandonment as a proxy for long-term human out-migration. A Case Study: Al-Hassakeh Governorate, Syria (2021).
128. *Kanchana Nirmali Bandaranayake*: Considering future precipitation in delineation locations for water storage systems - Case study Sri Lanka (2021).
129. *Emma Bylund*: Dynamics of net primary production and food availability in the aftermath of the 2004 and 2007 desert locust outbreaks in Niger and Yemen (2021).
130. *Shawn Pace*: Urban infrastructure inundation risk from permanent sea-level rise scenarios in London (UK), Bangkok (Thailand) and Mumbai (India): A comparative analysis (2021).
131. *Oskar Evert Johansson*: The hydrodynamic impacts of Estuarine Oyster reefs, and the application of drone technology to this study (2021).
132. *Pritam Kumarsingh*: A Case Study to develop and test GIS/SDSS methods to assess the production capacity of a Cocoa Site in Trinidad and Tobago (2021).
133. *Muhammad Imran Khan*: Property Tax Mapping and Assessment using GIS (2021).
134. *Domna Kanari*: Mining geosocial data from Flickr to explore tourism patterns: The case study of Athens (2021).
135. *Mona Tykesson Klubien*: Livestock-MRSA in Danish pig farms (2021).
136. *Ove Njoten*: Comparing radar satellites. Use of Sentinel-1 leads to an increase in oil spill alerts in Norwegian waters (2021).
137. *Panagiotis Patrinos*: Change of heating fuel consumption patterns produced by the economic crisis in Greece (2021).

138. *Lukasz Langowski*: Assessing the suitability of using Sentinel-1A SAR multi-temporal imagery to detect fallow periods between rice crops (2021).
139. *Jonas Tillman*: Perception accuracy and user acceptance of legend designs for opacity data mapping in GIS (2022).
140. *Gabriela Olekszyk*: ALS (Airborne LIDAR) accuracy: Can potential low data quality of ground points be modelled/detected? Case study of 2016 LIDAR capture over Auckland, New Zealand (2022).
141. *Luke Aspland:* Weights of Evidence Predictive Modelling in Archaeology (2022).
142. *Luís Fareleira Gomes*: The influence of climate, population density, tree species and land cover on fire pattern in mainland Portugal (2022).
143. *Andreas Eriksson*: Mapping Fire Salamander (Salamandra salamandra) Habitat Suitability in Baden-Württemberg with Multi-Temporal Sentinel-1 and Sentinel-2 Imagery (2022).
144. *Lisbet Hougaard Baklid*: Geographical expansion rate of a brown bear population in Fennoscandia and the factors explaining the directional variations (2022).
145. *Victoria Persson*: Mussels in deep water with climate change: Spatial distribution of mussel (Mytilus galloprovincialis) growth offshore in the French Mediterranean with respect to climate change scenario RCP 8.5 Long Term and Integrated Multi-Trophic Aquaculture (IMTA) using Dynamic Energy Budget (DEB) modelling (2022).
146. *Benjamin Bernard Fabien Gérard Borgeais*: Implementing a multi-criteria GIS analysis and predictive modelling to locate Upper Palaeolithic decorated caves in the Périgord noir, France (2022).