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Optimal resolution of soil properties maps varies according to their geographical extent and location

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Highlights

- Large-scale model or map performance significantly decreases above 1 km resolution
- Fine resolution is more accurate for heterogeneous landscapes and for reduced extents
- Aggregation of the cell values of predictive maps can improve their precision
- Different spatial resolution levels should be compared before soil mapping

Abstract

The important development of digital soil mapping (DSM) these last decades has led to a large number of maps of soil properties with increasingly finer raster size. Map resolution is mostly determined by expert knowledge or by matching with the resolution of existing data, while scale is recognized as a major issue. Using the pH and the C/N ratio describing the surface horizon of forest soils and estimated by bioindication, we evaluated the effect of resolution changes on model and map performance for different geographical extents. Using 40,663 plots from the national forest inventory and 25 environmental variables calculated at eight different spatial resolution levels (50, 100, 250, 500, 1,000, 8,000, 16,000, and 50,000 m), we modeled and mapped pH and C/N over a vast and diversified area of 91,000 km² in the north-east of France. The models highlighted the importance of geology in pH and C/N spatial variations, and to a lesser extent the importance of stand type, climate and topography, with a slight influence of data resolution on predictor selection. On the contrary, the accuracy of model or map performance decreased significantly above 1,000 m resolution. Significant performance differences were observed according to the location and the size of the geographical extent. Globally, the more heterogeneous environmental characteristics and the smaller the geographical extent, the better fine spatial resolution performed. In addition, the aggregation of fine-resolution pH or C/N maps at a coarser cell size improved map performance as compared to the direct use of the coarse-resolution predictors. The impact of resolution changes on map accuracy varies according to the mapping procedure, the local environment, and the geographical extent, and should be evaluated in DSM studies to optimize map accuracy.

Keywords

Resolution, scale, soil properties, digital soil mapping, environmental predictors, map accuracy.

1 Introduction

Soils provide important services including water, carbon, nutrient storage or water filtering, and represent ecological support for vegetation, with implications on biodiversity, food and biomass production. Accurate knowledge of the soil chemical, physical and biological properties is important to improve research and practices in environmental management. The challenge is to understand their horizontal and vertical spatial variations, that can be substantial even on short distances (Wilding and Drees, 1987). For example, surface pH variation ranged between 7.2 and 10.1 across a 41,000-ha area in Iran (Pahlavan-Rad et al., 2018). At a more local scale, significant changes in texture and soil thickness were observed in an experimental 567 m² plot in Italy by Buttafuoco et al. (2005). Different pedogenic factors and landscape processes linked to lithology, topography, hydrology and weathering operate at varying intensities according to the location, leading to possible multi-scale variation across a same area (Stolt et al., 1993). Liu et al. (2013) observed short-range variation driven by topography and long-range changes driven by parent materials in eastern China. In a context of increased demand for spatial data, identifying these sources of spatial variability and representing their variation at the relevant scale is crucial for agricultural and forest management, land use planning, and natural resource conservation.

Digital soil mapping (DSM) has considerably developed since the 1990s following increased spatial data availability and the development of data processing techniques and tools (Lagacherie, 2007;

McBratney et al., 2003). It employs empirical correlations between field observations and digital environmental data often available through geographic information systems (GIS) layers (i.e. the environmental covariates) to create digital maps (McBratney et al., 2003). DSM techniques are based on the factors of soil formation (climate, organisms, relief, parent material and time – clorpt, Jenny, 1941). They provide a comprehensive digital framework describing the empirical relationships between maps of environmental covariates related to the soil class or properties, that represent proxies of the signatures left on the landscape by the factors and processes of soil formation. The most commonly used are topographic information based on digital elevation models (DEM), existing soil maps, climate parameters, sometimes complemented by remote sensing images or other existing soil maps according to data availability (Nussbaum et al., 2018). The accuracy of these digital soil maps varies according to the number, the distribution and the accuracy of the observations used for calibration, the nature and the quality of the environmental covariates used for prediction, the model structure, and the mapping procedure (Scull et al., 2003).

Numerous studies have demonstrated the importance of scale in DSM (Roecker and Thompson, 2010), and the need to further investigate it (Cavazzi et al., 2013; Moore et al., 1993). The notion of scale includes the measurement scale and the modelling scale, and is characterized by three concepts: i) the extent is represented by the area covered by the dataset or the map, ii) spacing is the distance between samples, which corresponds to the resolution or cell size for gridded datasets, and iii) the spatial support refers to the area covered by each sample (Western and Bloschl, 1999; Wiens, 1989). A change of scale means a change in extent, spacing, or spatial support (Dungan et al., 2002). For a given geographical extent, the resolution of digital soil maps is usually determined by the resolution of available environmental covariates, not according to the spatial variation of soil properties. The increasing availability of high-resolution DEM and remote sensing images have made much finer resolution possible, even across large areas. For example, the GlobalSoilMaps consortium has made fine-resolution maps available (nearly from 100 m.) for many countries (Mulder et al., 2016). It is commonly believed that fine spatial resolution provides more accurate information, because calculating maps at too large resolution can mask fine-scale variation and alter their performance. Calculating maps at too fine resolution can also be inefficient to improve accuracy if the raw dataset and the methods do not capture local-scale variability (Cavazzi et al., 2013), and can generate noise that impairs data accuracy (Roecker and Thompson, 2010). The optimal cell size should correspond to an area with little variation of the studied property value (Florinsky and Kuryakova, 2000; Hengl, 2006). These questions of resolution and geographical extent are strongly linked, and refer to the geographers' "modifiable areal unit problem" (MAUP) (Openshaw and Taylor, 1981). The MAUP states that for the same area, a change in the shape or the size of the units often leads to different results. The MAUP includes two components: the "scale problem", which relates to the change in spatial resolution through the level of aggregation of pixels, and the "zoning problem", concerning the changes in the boundaries. It was demonstrated that MAUP effects can lead to meaningless results (Jelinski and Wu, 1996).

Different spatial resolution levels can be compared in many ways, including directly recording data at different resolutions (for remote sensing mainly), transforming raw data from plots or polygons into raster data at different resolutions, or upscaling raster datasets by coarsening spatial resolution (Gottschalk et al., 2011). Existing studies mainly concern the effect of environmental factors calculated for a same extent at different spatial resolutions, to predict species distribution (Guisan et al., 2007), to elaborate hydrological models (Dixon and Earls, 2009), or relevant remote sensing data (Stow, 1999). Most of them focus on the DEM resolution effect (Chow and Hodgson, 2009; Gao, 1997), but also sometimes on the mapping of soil properties (Guo et al., 2019; Florinsky and Kuryakova, 2000; Maynard and Johnson, 2014; Sena et al., 2020; Thompson et al., 2001). They show a significant effect of cell size on predictions (Usery et al., 2004; Wu et al., 2005), and globally an increase of performance with decreasing resolution (Guo et al., 2019; Lassueur et al., 2006; Zhang and Montgomery, 1994). Other

studies also suggest no effect of resolution, or better performance of coarser resolution (Costa et al., 2018; Kim et al., 2014; Roecker and Thompson, 2010). An effect of pixel aggregation from small size to coarse resolution showed both improved and decreased digital map accuracy (Carmel, 2005; McCloy and Bocher, 2007). These different results illustrate that decreasing cell size does not always describe more detailed information (Samuel-Rosa et al., 2015). They suggest that fine spatial resolution could be more accurate only if the fine-scale variables can better describe the drivers of soil forming processes.

This research work aims to evaluate how spatial resolution can impact the accuracy of soil properties maps, by studying a large range of ecological conditions and different geographical extents. We focused on two soil properties among those most commonly used in ecological studies – the pH and the C/N ratio – recognized for their interest in explaining plant distribution and growth (Beauregard and de Blois, 2014; Seynave et al., 2005). Using a large number of plots with pH and C/N values estimated from bioindication from field observations collected in forests, and a dataset of environmental variables mapped at eight spatial resolution levels, we addressed the following four questions:

- Question 1: how does the resolution of the candidate environmental predictors influence the model calibration? We compared the composition and performances of models elaborated with predictors calculated at different resolutions;
- Question 2: how the predictor's spatial resolution influence map accuracy? We compared the performance of the same model mapped with predictors at increasing spatial resolution;
- Question 3: does aggregation of the fine-resolution maps of soil properties at different coarser resolution levels improve accuracy? The pH and C/N maps calculated at the finest spatial resolution were aggregated at coarser resolution, and their performances were compared with those of the maps directly built from the environmental predictors calculated at different cell sizes (Question 2);
- Question 4: do the performances of the maps calculated at different spatial resolution vary according to their location and extent? We compared the performances of the maps calculated for questions 2 and 3 for different geographical extents.

2 Methods

To evaluate the optimal resolution of maps, defined as the resolution leading to the highest accuracy for a fixed geographical extent, pH and C/N bioindicator values were modeled with candidate variables describing topography, geology, climate and stand type calculated for eight different spatial resolution levels (Figure 1). The models were first compared (Question 1). Then, the model calibrated with the most local information was directly mapped at the eight resolution levels, and the performances of the maps were compared (Question 2). Finally, these maps were compared with those elaborated by aggregating the 50-m pH and C/N maps at coarser resolution (Question 3). All the calculations were validated with an independent dataset. Because we hypothesized that results could differ according to the studied area, map performances were compared for different geographical extents of four different sizes (the whole studied area, divided in 100*100 km, 50*50 km, and 25*25 km squares).

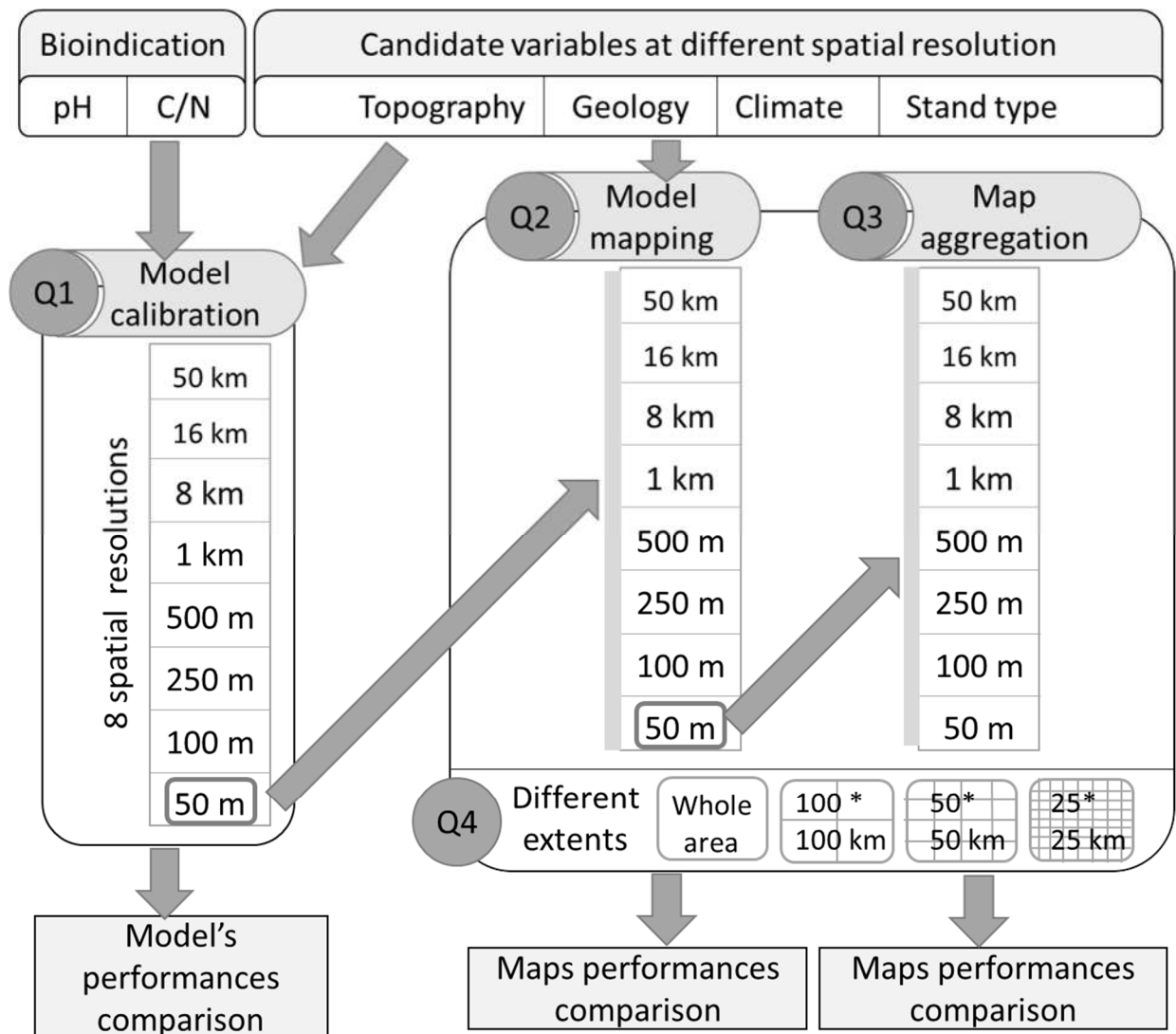


Figure 1: Synthetic presentation of the methods used to answer the four questions addressed in the paper (Q1, Q2, Q3, and Q4).

2.1 Study site

The study area encompassed a 91,364 km² area in the north-east of France where plains are dominant, surrounded by four mountain ranges (Jura, Massif Central, Ardennes and Vosges), and crossed by one calcareous plateau (Figure 2A). The average elevation is close to 300 meters; it reaches 1,493 m in the Jura mountains and 1,424 m in the Vosges mountains (Figure 2B). The Vosges mountains, the Ardennes and the Massif Central are composed of a wide variety of Paleozoic rocks like granites, gneiss, schists, or volcanic – mainly acidic – rocks (Figure 2C). The calcareous plateau and the Jura Mountains are mainly made of limestone, with rich soils. The sedimentary basins contain limestones, marls, clays or sandstones (Champagne, central plain), or alluvial sediment made of sand or gravel (Alsace).

Topography combined with oceanic and semi-continental influences lead to a wide gradient of climates, and occasional abrupt changes at short distances. Annual rainfall ranges from 500 mm in Alsace to 2,000 mm in the Vosges and Jura mountains, while mean annual temperatures range between 9°C and 11°C (Cachan, 1974; Canellas et al., 2014). The driest areas are found in Champagne, the south

of the central plain, and Alsace (Figure 2D). Soil and climate variability lead to a gradient of vegetation, with mainly broadleaved species (oak, beech) in plains and coniferous species (silver fir, spruce) in the mountains, often in a mixture with beech (Figure 2E).

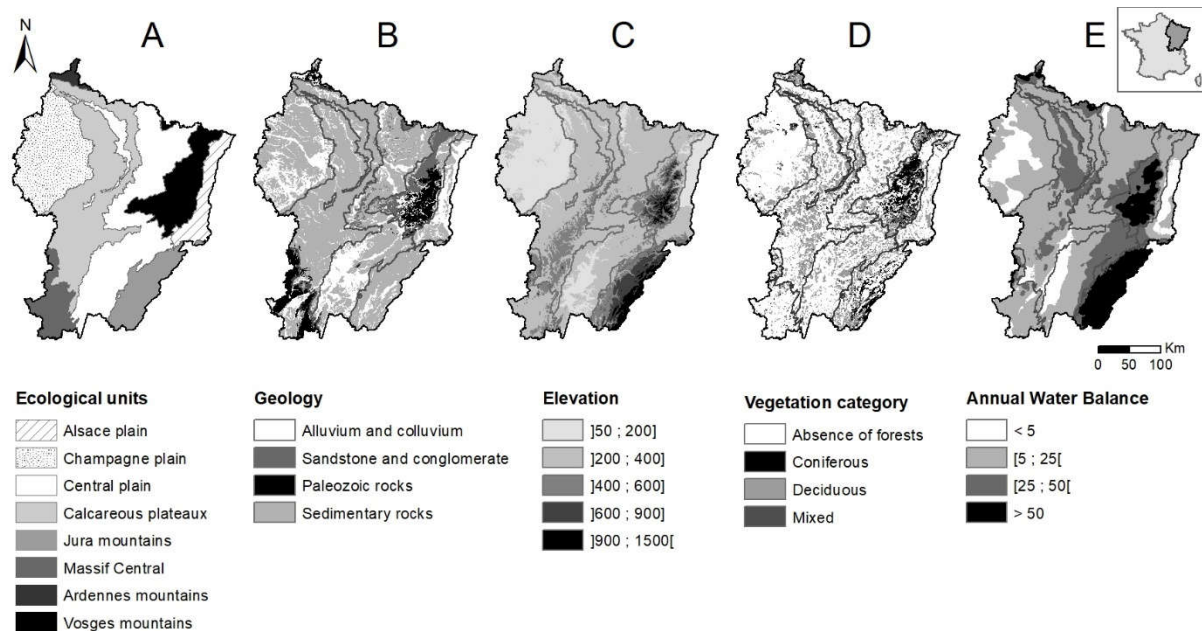


Figure 2: Simplified maps of the studied area: A, ecological units (based on *Sylvoecoregions*¹); B, geology; C, elevation (m.); D, vegetation category; E, annual average 1961-1990 climatic water balance (the difference between rainfall and potential evapotranspiration, in mm.). The climatic water balance (Piedallu et al., 2013) summarizes climate conditions, with low values in dry areas vs. high values in wet ones.

2.2 Bioindication of pH and C/N on NFI plots

We used floristic surveys from 40,663 temporary plots recorded between 1984 and 2017 by the **French National Institute of Geographic and Forest Information (IGN)** and stored in the National Forest Inventory (NFI) database (Drapier and Cluzeau, 2001) to predict pH and C/N values using bioindication (Ellenberg et al., 1992). This inventory was realized with a similar sampling density for all the forested areas, by administrative units between 1984 and 2005, and on a regular mesh shift each year encompassing the whole of France since 2005 (about 7000 plots per year). The floristic survey was realized on a circular plot on a 700 m² area. Indicator values (IVs) were calibrated for the most common forest plant species in France using the *Ecoplant* database (Gegout et al., 2005), which contains both floristic surveys and soil analyses for the same locations. For each of the most common forest species, IVs provide the highest probability to observe the species along different ecological gradients (Gegout et al., 2003). For each of the 40,663 plots, we obtained bioindicated pH and C/N values for the soil surface layer by averaging the IV values of the plants present in the floristic survey. At large scales, the validation of these values with independent datasets yielded R² values of 0.45 and 0.41, and RMSEs of 0.47 and 3.8 for pH and C/N, respectively (Gegout et al., 2003). Because prediction is less accurate when few species are present, pH and C/N were not estimated when less than five species with IVs were surveyed. We obtained 37,958 plots with pH estimations and 37,737 with C/N estimations, collected

¹ https://inventaire-forestier.ign.fr/IMG/pdf/IF_SER_web.pdf

with a density near of 1.10 plot *per* km² in forested areas. pH values ranged between 3 and 8, and C/N values between 10 and 35 (See Appendix A for plot location, Appendix B for the observed spatial distribution of pH and C/N, and Appendix C for the range of pH and C/N values). Values from the plots were autocorrelated up to 110 km for pH and 96 km for C/N (Appendix D).

2.3 Explanatory environmental variables

A set of 25 potential explanatory environmental variables was identified from the literature (McBratney et al., 2003; Scull et al., 2003), describing topography, geology, climate and stand type (Table 1). Because gravity plays a role in water and nutrient transport, topography is described as an important driver of the redistribution of soil properties along slopes. For the whole studied area, we used the 50-m resolution digital elevation model (DEM) from the IGN to calculate topographic indices². Elevation (DEM), slope, shape of the soil surface (concave, convex, curved), sine and cosine of aspect (sinaspect and cosaspect), and relative distance or elevation between ridges and talwegs (reldist/relalt) characterized the position in the landscape (Table 1). Flow accumulation (flac) and topographic wetness index (TWI) quantified the topographic drivers of hydrological processes.

Because parent materials provide *nutrients to the soil*, a simplified geological map based on the 1:50000 vector maps of the Bureau de Recherches Géologiques et Minières (BRGM) was calculated over the whole study area (Geol). The original maps, which contain data about bedrocks and most of the time superficial units, were homogenized by the BRGM for each French “département” (administrative unit). We concatenated the sixteen departmental maps describing the study area. The 130,164 polygons and 2,841 different units were homogenized and simplified according to the chemical characteristics of the units to obtain 16 simplified units (Appendix E).

Monthly mean temperature (TM) and rainfall (R) were modeled and mapped for the whole of France at 50 m resolution for the 1961-1990 period (Table 1), using variables describing distances to the sea, vegetation, and topography (Piedallu et al., 2013). Two hundred and thirty-seven Météo France weather stations were used for temperature calibration and 432 for rainfall calibration. The data were validated using annual values from independent weather stations. Ninety-three percent of the variance was explained for temperature, and 78% for rainfall. Climatic water balance (CWB) was calculated as the difference between rainfall and potential evapotranspiration (Piedallu et al., 2013). Monthly mean data were averaged for temperature and cumulated for rainfall and CWB for each season: winter (wi, December to February), spring (sp, March to May), summer (su, June to August) and autumn (au, September to November). Finally, an IGN vector map representing stand composition (BD Forêt³) for units greater than 0.5ha was used to characterize the stand types of the forested areas (Stand). The 22 initial units were simplified into five stand types: coniferous, broadleaved, mixed, tree-less forest, and others.

The 25 predictors were calculated and mapped for the whole area at eight spatial resolution levels: 50, 100, 250, 500, 1,000, 8,000, 16,000 and 50,000 m. We studied a large range of resolutions to detect if predictive ability could decrease beyond a specific threshold. All the variables initially existed in 50 m resolution grids, except Geol and Stand that were in vector format and were rasterized. For

²

https://geoservices.ign.fr/ressources_documentaires/Espace_documentaire/MODELES_3D/BDALTIV2/SE_BDAL_T1.pdf

³ <https://inventaire-forestier.ign.fr/spip.php?article646>

these last two predictors, the pixel value was attributed for each of the eight spatial resolution levels according to the polygon unit with the greatest area in the cell. The raster layers were calculated at the coarser resolution by averaging the cells from the 50-m resolution maps.

Category	Variable name	Definition	Units	Input Data set	References/Algorithm
Topography	DEM	Elevation	Meter	BD Alti® V2-IGN	
	Slope	Change in altitude for a defined distance	Degree		Neighborhood Slope Algorithm
	Concav/Convex/Curv	Relief form index: convexity, concavity, or linear, of the soil surface	Unitless		Fit 2.Degree polynomial
	Sinaspect/Cosaspect	Sine and cosine of aspect			compass direction of the maximum rate of change (3*3 cells window)
	RELdist/RELalt	Topographic position: relative distance/elevation between ridges and talwegs			Gégout et al., 2008
	Flac	Flow accumulation: potential contributing runoff of upslope catchment	Log scale		D8, Multiple Flow Direction (MFD) and D-infinity flow methods
	TWI	Topographic Wetness Index (TWI): potential accumulation of water	Unitless		Moore et al., 1991
Geology	Geol	Simplified geological units (16 units)	Unitless	Adapted from BRGM	BRGM
Climate	TM _{wi/sp/su/au}	Mean seasonal temperature for the 1961-1990 period	°C	Digitalis V2	Piedallu et al., 2013
	R _{wi/sp/su/au}	Cumulated seasonal rainfall for the 1961-1990 period	mm		Thorntwaite, 1948
	CWB _{wi/sp/su/au}	Thorthwaite's seasonal climatic water balance for the 1961-1990 period	mm		
Stand type	Stand	Stand types: coniferous, broadleaved, mixed, tree-less forest, other	Unitless	BD Foret® V2- IGN	IGN 2016

Table 1: Ecological variables used to model pH and C/N, units and references. wi= winter, sp= spring, su= summer, au= autumn.

2.4 Effect of the resolution of variables on model calibration

To evaluate the influence of the resolution of the candidate variables on model calibration (Question 1), we calibrated the pH and C/N models with the set of the 25 environmental variables (Table 1) calculated for the eight resolution levels. Each model was calibrated independently using multiple linear regression. The explanatory variables were selected one by one. At each step, the variable best explaining the variance was selected, provided that it was statistically significant (P value < 0.001). To ensure a selection of relevant responses according to current knowledge, we allowed a pH decrease or a C/N increase with altitude or slope increase, on convex areas or near the ridges with low Flac and TWI values, on northern or eastern slopes, in cold areas, and with high R or CWB values. At each step, variables were discarded if they were correlated with another previously selected variable (Pearson's $r > 0.7$). The model ended if the R^2 increase was less than 0.001. For each model, the relative importance of each variable contribution was calculated with the relaimpo package (Gromping, 2006). We used the averaging over ordering method (lmg) that provides the R^2 contribution averaged over orderings among regressors, identified as one of the most relevant ones (Lindeman et al., 1980). Then, the model compositions and performances were compared at the eight resolution levels.

2.5 Effect of spatial resolution on model mapping

Once the models were calibrated, we evaluated how the resolution of the maps describing the selected variables influenced the accuracy of the maps of soil properties (Question 2). To only consider the effect of the predictor's resolution on accuracy, we used the same model (those previously calibrated with the most local information, 50 m) to map pH and C/N with the predictors calculated at the eight spatial resolution levels. Because pixel aggregation can improve map performance (Carmel, 2004), we also used the finest-resolution pH and C/N maps (50 m) and averaged their cell values to the coarser resolution levels (Question 3). For different coarser resolutions, we compared the performances of the maps obtained by aggregation with those of the maps directly built from the environmental predictors with the same validation dataset.

Because map performance can vary according to the geographical extent (Openshaw and Taylor, 1981), we compared the performance of all the pH and C/N maps elaborated at the eight spatial resolution levels at different geographical extents: the whole studied area, and 100*100 km, 50*50 km, and 25*25 km squares (Question 4). For these last three extents, the study area was split into squares that contained a subset of plots. For the whole area and each square that contain more than 100 plots, maps values (Appendix A and B) were compared to an independent subset of plot estimations and the differences in performances were mapped. For the eight resolution levels and the four geographical extents, global performances were compared, by averaging the performances of all the 100*100 km, 50*50 km, and 25*25 km squares.

2.6 Comparison of model and map performances

Four metrics were used to evaluate model performance following calibration at different resolution levels: R^2 , root mean squared error (RMSE), mean absolute error (MAE), and mean bias error (MBE). R^2 assesses the proportion of explained variance, but does not inform about the difference between predicted and estimated values. RMSE and MAE are two of the most common metrics used to evaluate model prediction error in units of the variable of interest; RMSE gives a more important weight to large errors (Willmott & Matsuura, 2005):

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^n [(y_j - \hat{y}_j)]^2}$$

$$MAE = \frac{1}{n} \sum_{j=1}^n [|y_j - \hat{y}_j|]$$

$$MBE = \frac{1}{n} \sum_{j=1}^n [(y_j - \hat{y}_j)]$$

Where n is the number of recordings, y_j is the observed value, and \hat{y}_j is the predicted value.

Due to a large number of calculations and the difficulties in representing all the results, we only used R^2 and MAE to evaluate map performance (Questions 2, 3 and 4) for the whole area and for each 100*100 km, 50*50 km and 25*25 km square. The metrics were estimated with an independent dataset both for model calibration and map accuracy evaluation. The model and maps were set up with 80% of the randomly selected plots, and predictions were validated with the remaining 20%. Performances were calculated by averaging values from 100 iterations.

3 Results

3.1 Similar variables but decreasing performances when calibrating models with data at increasing spatial resolution

Two to 6 variables were selected to calibrate each model for the eight resolution levels, with responses in line with current knowledge (*Appendix F*). Although 25 candidate variables were evaluated, most of the selected ones were similar for the different resolution levels (Table 2). The maximum R^2 values were about 0.65 and 0.54 for pH and C/N, and the minimum MAEs were 0.48 and 2.25, respectively. A large part of the variance (> 60%) was explained by geology for both pH and C/N. Climate also explained the variance of pH (except when the models were calibrated with the variables at coarse resolution), with stand type and topography to a lesser extent. For C/N, stand type performed better than topography and climate (Table 2-B). We showed a slight decrease of the variance explained by geology at resolution levels < 1km, compensated by an increase of the variance explained by stand type (for pH) and topography (for C/N) (*Appendix G*). At coarser resolution, the importance of stand type and climate decreased while the importance of topography increased. R^2 , RMSE and MAE were comparable

when the resolution of the input variables ranged between 50 m and 1 km, and strongly decreased at coarser resolution. The best performances were reached for input variables at 250 m resolution for pH. For C/N, they were reached at 250 m resolution according to R^2 and 50 m according to RMSE and MAE (Table 2).

A) PH		CATEGORY	VARIABLE	50 M	100 M	250 M	500 M	1 KM	8 KM	16 KM	50 KM	
VARIABLES	Geology	Geol		74	74	72	70	69	72	73	75	
	Stand type	Stand		9	8	15	16	17	1	6		
	Climate	TM _{wi}		13	13	8						
		CWB _{su}					7	6	20	12		
	Topography	Slope		3	4	4	6	7				25
		Flac		1	1	1	1	1	7			
		TWI									8	
		Sinaspect									1	
PERFORMANCES	R ²		0.64	0.64	0.65	0.65	0.64	0.56	0.52	0.40		
	RMSE		0.65	0.64	0.64	0.64	0.64	0.71	0.74	0.83		
	MAE		0.48	0.48	0.48	0.48	0.48	0.53	0.56	0.64		
	MBE						0.00					

B) C/N		CATEGORY	VARIABLE	50 M	100 M	250 M	500 M	1 KM	8 KM	16 KM	50 KM	
VARIABLES	Geology	Geol		70	70	69	67	66	63	66	76	
	Stand type	Stand		18	18	18	18	18	8	9		
	Climate	TM _{su}		6	6	5	5	4				
		CWB _{su}							14			
	Topography	Curv		1	1							
		Slope		4	5	7	9	11	15	22	24	
		RELalt		1		1	1	1				
		Convex									3	

PERFORMANCES	R ²	0.54	0.53	0.54	0.53	0.53	0.45	0.42	0.31
	RMSE	3.2	3.2	3.2	3.2	3.2	3.5	3.6	3.9
	MAE	2.2	2.3	2.3	2.3	2.3	2.4	2.5	2.8
	MBE	0.00							

Table 2: Selected variables and performances of the models for eight spatial resolution levels A) for pH and B) for C/N (Question 1). The numbers provided for each selected variable indicate the part of explained variance they added to the model (in %). RMSE, MAE and MBE were expressed in pH or C/N units. The highest performances are highlighted in grey. See Table 1 for explanations about the names of the variables.

3.2 Lower accuracy when digital maps larger than 1 km resolution

We used the equation calibrated with the most local data (i.e. at 50 m resolution, *Appendix F*), to map pH and C/N with the sets of variables calculated at the eight spatial resolution levels (Figure 3). Logically, both for pH and C/N, the more reduced the geographical extent, the lower the R^2 value (Figure 4). MAE decreased with geographical extent, except for predictions taking the whole area into account. Performances varied according to location, with both for pH and C/N globally better R^2 but higher MAE on the Vosges mountains, and lower R^2 but also lower MAE in calcareous plateaux and Jura mountains (*Appendix H* and Figure 1 for the location of ecological units).

Using variables with different spatial resolution levels had a limited impact on map accuracy, whatever the extent up to 1 km cell size, and then map performance dropped significantly at coarser resolution levels (Figure 4). The highest R^2 and lowest MAE were consistently obtained in 250 m resolution maps for pH. For C/N, the highest R^2 were obtained at 50 or 100 m resolution, and the lowest MAEs were found between 250 m and 1 km resolution (Figure 4). Beyond these mean performances, significant spatial variability was highlighted (Figure 5). Fine-resolution maps globally performed better in the Vosges mountains, in the north of the Jura mountains and the south of the central plain (see Figure 1 for the location of ecological units). Great discrepancies were found for C/N, whether R^2 or MAE was used (Figure 5). When we compared the performances of the 50 m and 1 km spatial resolution maps, fine resolution mainly improved map performances in the Vosges mountains, with a greater effect on R^2 than on MAE and on C/N than on pH (*Appendix I*). The maximum increase of R^2 at 50 m resolution comparatively to 1 km resolution was + 0.15 for pH and + 0.21 for C/N at the 25km*25km scale.

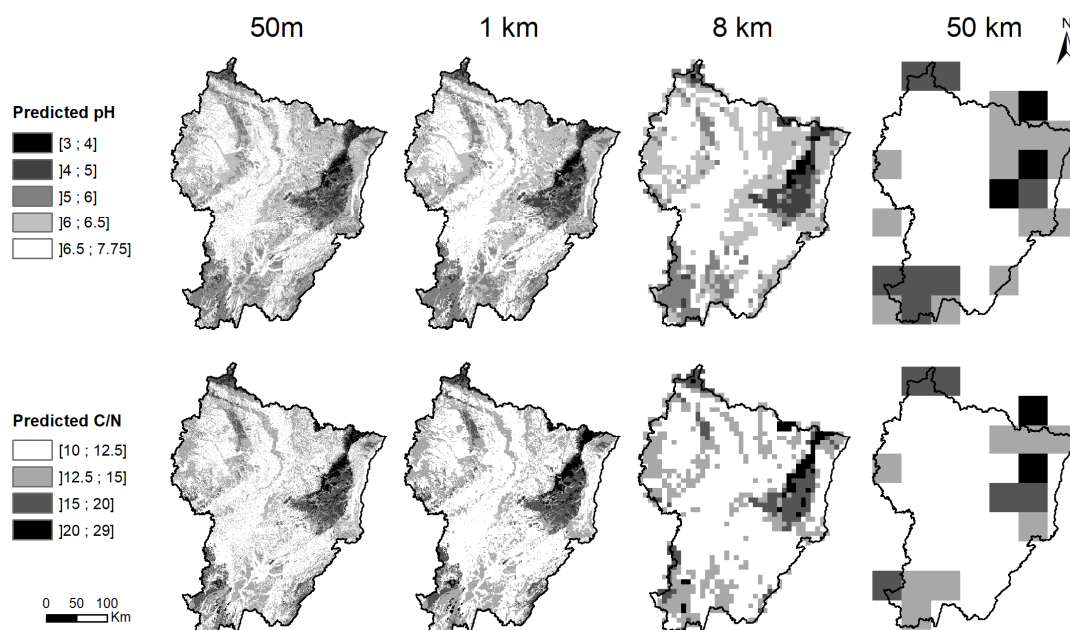


Figure 3: Examples of pH and C/N maps calibrated using the model with the most local data and mapped with explanatory variables at 50-m, 1-km, 8-km and 50-km spatial resolution levels.

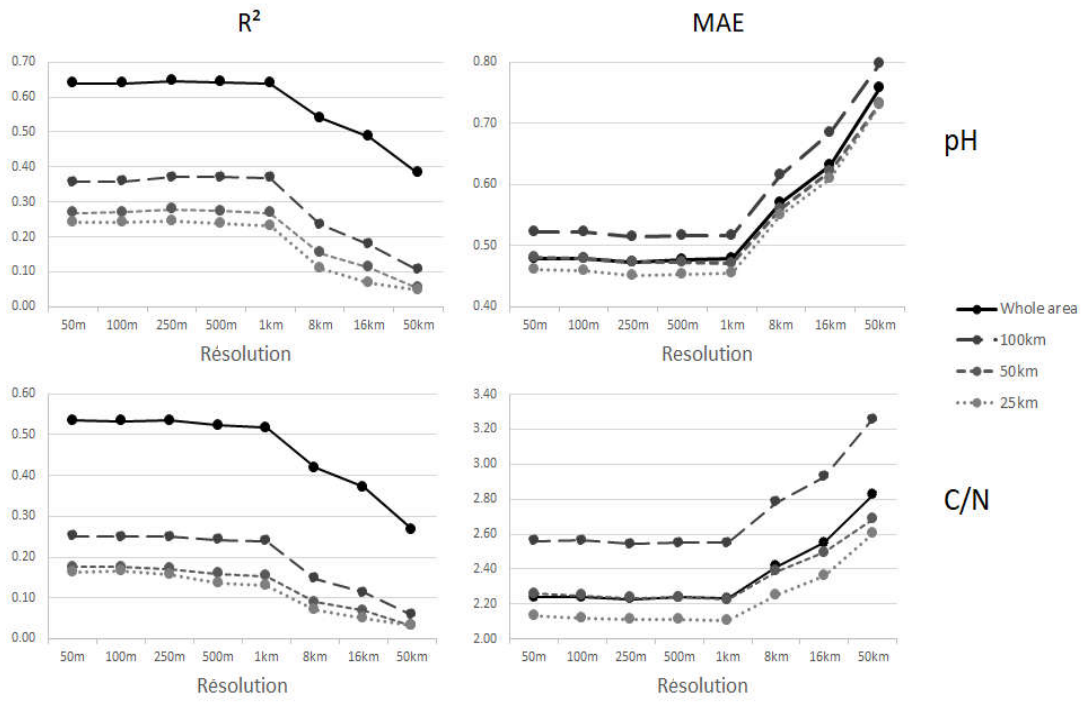


Figure 4: Performance (R^2 and MAE) of pH and C/N maps calculated at the eight different spatial resolution levels (50 m to 50 km) for different geographical extents (Question 2). For the 100, 50, and 25 km extents, values were averaged from the different squares.

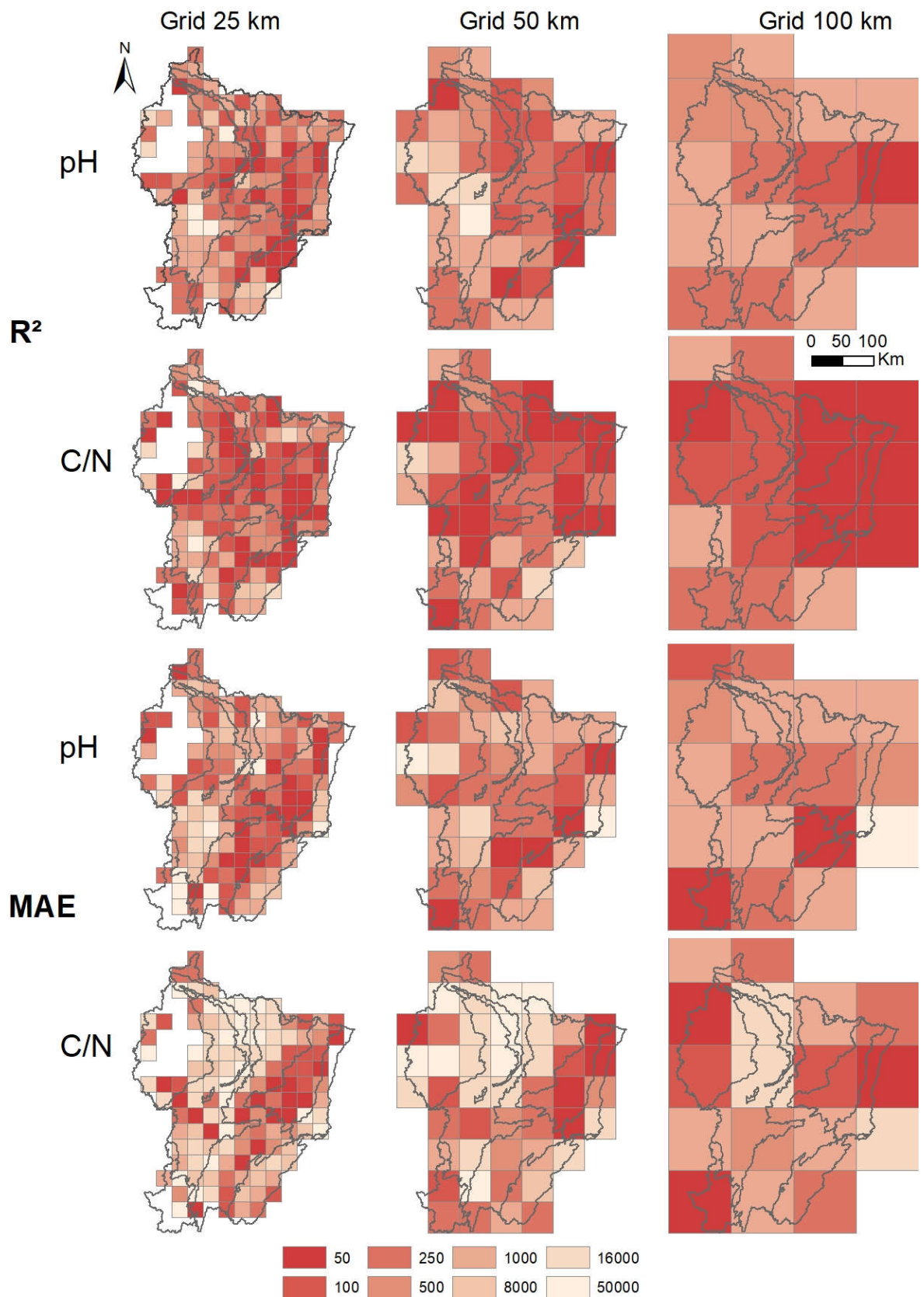
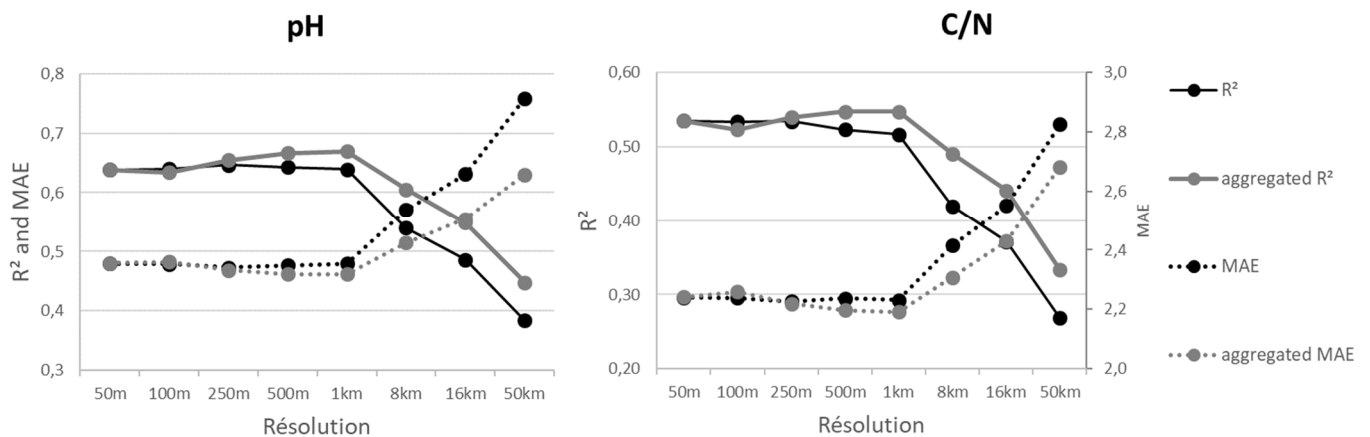


Figure 5: Resolution with the best performance (R^2 and MAE) for pH and C/N and for different geographical extents (100*100km, 50*50 km and 25*25 km, Question 2 and 4). For each square, performances were calculated between the maps calculated at different spatial resolution and an independent subset of plots. White areas, no performance calculated because the number of plots was lower than 100.

3.3 Spatial aggregation improves map quality

We compared the performances of the maps calculated by directly using the variables at different spatial resolution levels with the maps calculated by aggregating the 50-m pH or C/N maps at coarser resolution (Figure 6). For large resolution ($\geq 500\text{m}$), the maps consistently performed better when they were calculated by aggregation. The highest R^2 and lowest MAE were reached at 1 km resolution, whatever the geographical extent (*Appendix J*). Although aggregation improved the performance of the 1 km maps, some of the maps at smaller resolution levels remained more accurate locally, mainly when considering R^2 and C/N, and in the Vosges mountains (*Appendix K and L*).



and C/N maps at coarser resolution levels (Question 3).

3.4 Fine-resolution maps better describe local variability when geographical extents are smaller

Because optimal resolution can vary according to the size of the geographical extent (Figure 5), we compared the performance of the maps calculated at different resolution levels for the studied geographical extents (table 3). We compared the 50 m and 1 km resolution maps because the previous analysis had shown that performance significantly decreased above 1 km cell size. For the maps directly calculated at different resolutions, 50 m resolution maps showed on average a higher R^2 and lower MAE than 1 km resolution maps for the 25*25 km extent compared to the whole area (*Appendix M for average performances, Appendices I, and L for the maps*). The efficiency of the 50 m resolutions maps increased compared to the coarser resolution maps as the extent decreased. The better performance of the 50 m maps was mainly observed when focusing on R^2 rather than on MAE, and was better for C/N than for pH (Table 3). The 50 m resolution maps had higher R^2 than the 1 km resolution maps for 59 and 80 % of the squares in the 25*25 km extent for pH and C/N, respectively. The percentage of the squares for which the 50 m resolution maps performed better than the 1 km resolution maps decreased when they were calculated with aggregation: 48 and 41 % of the squares had a higher R^2 than at 1 km resolution for pH and C/N, respectively, for the 25*25 km extent.

Extent		25*25 km	50*50 km	100*100 km
	n	132	46	17
R ²	pH	59	57	35
	CN	80	76	71
	pH aggregated	37	17	0
	CN aggregated	61	48	35
MAE	pH	48	41	35
	C/N	41	41	35
	pH aggregated	23	17	24
	C/N aggregated	26	22	24

Table 3: Percentage of the squares where the 50 m resolution maps performed better than the 1 km resolution maps, for the 25*25, 50*50 and 100*100 km extents, for pH and C/N calculated directly using the variables at different resolution or by aggregating the 50 m maps (Question 4, see Appendices G and J for the maps).

4 Discussion

4.1 Using bioindication to optimize the calibration dataset

Although the question of resolution has been extensively studied for terrain attributes (Deng et al., 2007), and despite the increasing number of digital maps of soil properties calculated at finer and finer spatial resolution (Dai et al., 2019), the question remains about the impact of scale on DSM performance. Using bioindication allowed to calibrate and validate models and maps with a large dataset based on floristic surveys carried out at high sampling density. Bioindication has long been used in ecology (Ellenberg et al., 1992) and has proved efficient to represent local variation of soil properties (Coudun et al., 2006; Simon et al., 2020). Its main weaknesses are linked to greater uncertainty compared to measurements, whose intensity can vary along the gradient of variables (Gegout et al., 2003). For example, bioindicated pH does not discriminate values from acidic soils as precisely as it discriminates values from neutral or alkaline soils (Riofrio-Dillon et al., 2012). A comparison with measurements should allow to quantify if these differences could have an impact on the map's performances calculated at different scales. Thanks to the large dataset used, various ecological conditions have been investigated. A large amount of pH and C/N variance was explained by our models, allowing us to study how resolution influences model and map performances for a large range of environmental conditions and different geographical extents.

4.2 Resolution had a limited influence on predictor selection

In our models, the resolution had little influence on variable selection but influenced the proportion of variance they explain. Whatever the resolution, simplified geology was the most efficient predictor, and represented 63 to 75% of explained pH and C/N variances, respectively. It was complemented by stand type, climate and topography. Different studies reported the most commonly used predictors are terrain attributes, while the parent material was used in only less than 10% and 25 % of DSM studies according to the reviews by Grunwald (2009) and McBratney (2003), respectively. The importance of the parent material has been highlighted in different studies carried out in Europe (Simon et al., 2020) or in China (Wiesmeier et al., 2011). We demonstrated geology can be a good surrogate in the absence of soil maps. Its efficiency in our models can be explained by the large variety of units of different

chemical characteristics. The absence of quaternary deposits on some maps and the difficulty in summarizing a great variety of substrates, mainly in mountainous areas, constitute the main obstacles to the use of geology. Stand type and climate also contributed significantly to our models, and showed relevant responses according to current knowledge. The negative effect of coniferous species on the pH reflected the soil acidification by coniferous tree species already observed in experimental studies (Augusto et al., 1998). The pH increase and C/N decrease with temperature and water stress are in agreement with experimental studies showing better N mineralization under warm temperature and a low water content (Cassman and Munns, 1980). In a context where topography is often showed to be the most efficient predictor, we highlighted the important role of parent material, stand type and climate variables in DSM studies. This comparison was based on explanatory variables all calculated at the same resolution, but some authors found better results when considering predictors at different resolution levels (Miller et al., 2015). Therefore, further investigations should be carried out to evaluate the optimal resolution of each soil property predictor taken independently.

4.3 Resolution strongly influences map accuracy

The optimal resolution of maps of soil properties is complex to determine because different categories of factors interplay (McBratney et al., 2003), while biophysical processes can operate at different spatial scales (Deng et al., 2007; Phillips, 1988). Map cell size is often determined subjectively to match with the finest data available, or by expert knowledge (Deng et al., 2007). Florinsky and Kuryakova (2000) proposed a framework to identify optimal map cell size by correlating topographic variables derived from a DEM calculated at different resolution levels with landscape properties. We adapted this approach to compare the performances of models and maps of soil properties. Although average performances can mask great discrepancies, we determined that the average optimal resolution, i.e., the largest cell size before performance decreases, was 1 km cell size. Performances for pH and C/N were on average comparable at resolution levels ranging between 50 m and 1 km, and strongly decreased at coarser resolution. We expected a global improvement of accuracy with decreasing cell size because important variations in soil pH can be observed on short distances (Laslett et al., 1987), and smoothed variables can mask fine-scale variations (Chow and Hodgson, 2009; Gao, 1997). Our result can reflect the local spatial relationships between soil properties and the underlying pedogenic factors that operate at a specific range of spatial scales (Maynard and Johnson, 2014; Samuel-Rosa et al., 2015). A value below which increased resolution does not seem to impact performance has already been reported for terrain parameters (Zhang and Montgomery, 1994). The scale invariance that we globally observed below 1 km resolution, already observed with fine-resolution predictors (Pradervand et al., 2014), can also suggest that the study design failed to completely capture the spatial variability of soil properties when variations were low. This result can be influenced by the bioindication of pH and C/N values, that increased uncertainty compared to laboratory analyses, and probably smoothed out spatial variability in areas with little changes. Better performance of the fine-resolution maps can be expected using measured pH and C/N values.

Different spatial supports were used in this study: point support collected on a 700 m² plot for soil data, used for model and map calibration and validation, and cells of different surfaces from the digital maps. The support size should be relevant to describe the natural variability of the soil properties: if the support of the soil data is too large compared to the process scale, variability can be averaged (Western and Bloschl, 1999). The use of bioindication increases the support size comparatively to soil analysis classically collected from a single point at the plot center. Complementary studies should investigate the small-scale variability of pH and C/N in heterogeneous areas to evaluate the optimal support size. The difference in support size between digital maps and the validation dataset probably underestimates the map performances, and the validation of digital maps at the point support probably performs worse than larger spatial units (Bishop et al., 2015).

Optimal resolution matched point density – around one plot *per* km² in our calibration dataset, potentially contributing to the scale invariance below 1 km resolution. Sampling density is known to have a strong influence (Loiseau et al., 2021): increasing it globally improves the accuracy of prediction (Guo et al., 2018). On the other hand, the 1 km threshold beyond which accuracy decreases is an average value that hides important local differences. This does not advocate for a global effect of the sampling density on our results. For example, in some heterogeneous areas, map accuracy strongly decreased both for pH and C/N above 50 m resolution (R^2 was up to 0.15 and 0.11 higher for the 50 m resolution maps than for the 1 km resolution maps for pH and C/N maps, respectively; see appendix I), while sampling density remained the same. We suggest further studies to better understand how the sampling scheme can influence the results, by comparing optimal resolution with models calibrated at various sampling densities. We recommend such comparisons of maps with different cell sizes with an independent dataset of field observations to reach an optimal resolution.

4.4 Using cell aggregation improves the performances of predictive maps

We observed better performances when upscaling finer pH or C/N resolution maps rather than calibrating them at coarser resolution. Data aggregation results are controversial across studies. In some cases, coarsening spatial resolution by aggregating cell size causes a loss of information that increases uncertainties. For example, Maharjan et al. (2019) showed that aggregating climatic and soil data led to a greater error when simulating crop yields, in agreement with other studies and despite the use of diverse models, crops, production conditions, and variables (Zhao et al., 2015). On the other hand, several studies demonstrated the interest of cell aggregation, mainly for the classification of remote sensing images (Carmel, 2004; Townshend et al., 1992). As in our study, they showed better accuracy when aggregating pixels up to the object size, followed by a decrease when the pixel was bigger (McCloy and Bocher, 2007; Woodcock and Strahler, 1987).

The gain in performance we observed with aggregation can be attributed to the qualitative predictors available through vector maps. When a vector map was rasterized at different cell sizes, the pixel value was attributed according to the polygon unit that occupied the greatest area in the cell, and information about minority units was lost. On the contrary, cell aggregation after pH or C/N mapping at fine spatial resolution allowed for unbiased calculations that considered all the existing units proportionally to their geographical extent. The two vector datasets we used (Geol and Stand type) explained a large part of the variance in our models, so that performance was improved by aggregation. On the contrary, the quantitative predictors initially available through raster maps at 50 m resolution were calculated at coarser resolution using aggregation. This method probably contributes to improve the performance of the maps directly calculated at a coarser resolution than 50 m, and could contribute to explain the global scale invariance observed below 1 km resolution. Aggregation efficiency can vary according to the upscaling method (Dai et al., 2019), and this effect could be evaluated in further studies. Therefore, data aggregation can be an efficient tool to improve map accuracy, and its use should be evaluated in DSM studies.

4.5 Environmental characteristics and geographical extent have a strong impact on optimal map resolution

Beyond the average performances showing a scale invariance below 1 km resolution, important differences were recorded according to the location and the size of the geographical extent. Fine-resolution maps performed better in heterogeneous areas, while the coarse resolution was more efficient in homogeneous ones. As already reported by other studies (Liu et al., 2013), multi-scale variation can be observed depending on the different environmental characteristics. In our case, geology and climate varied at a regional scale, but also more locally in mountainous areas. Acidic units were mainly grouped in a few specific regions (see paleozoic rocks in Figure 2-C), but significant short-distance variation can occur locally. Climate gradients also operated at a large scale (Figure 2-D), but

were influenced locally by topographic gradients (Piedallu and Gegout, 2008). This probably explains why fine-resolution maps performed better in the Vosges mountains because they better described these strong local changes in an area showing highly diverse chemical characteristics among parent materials (Nedeltcheva et al., 2006) and a great diversity of climates, topographies, and stand types (Cachan, 1974). On the contrary, in homogeneous areas, coarse cells probably improve the prediction by smoothing out local uncertainties. Similar findings have been reported for topographic variables calculated with DEMs, with a better performance at coarse resolution in flat areas and at fine resolution in morphologically varied areas (Cavazzi et al., 2013; Thompson et al., 2001). Our results suggest that different spatial resolution could be used according to the environmental characteristics of the areas to be studied.

The size of the studied geographic space influences the results because the range of soil properties globally decreases with decreasing extents (Grunwald et al., 2011). The performance of the fine-resolution maps was clearly improved compared to coarser resolution when the size of the study area decreased. For reduced extents, the 50 m maps were most of the time more efficient than the 1 km maps to explain pH or C/N variations because they exhibited a higher variance that better described local spatial variability than coarser resolution did. Their ability to describe local variability is an important advantage for managers or policymakers, who often need to extract data about a specific extent from maps calibrated and validated over broad areas. Further investigations should be carried out to evaluate if the performance of fine-resolution maps keeps increasing relatively to coarse-resolution maps when geographical extents are further decreased. These results argue for the calculation of fine-resolution maps in heterogeneous landscapes and for local use. On the other hand, coarse data do not dramatically degrade map quality and could be used when they are the sole data available, particularly for homogeneous areas or regional studies. Multi-scale validation of the map performances should provide a more comprehensive evaluation of their quality according to the intended use.

5 Conclusion

The need for relevant digital data about soil properties has increased in recent years in link with the need to manage the consequences of human actions on environmental changes. Two pitfalls have to be avoided: too coarse resolution that leads to less precision, and too fine resolution that makes users believe in false precision. We observed that optimal map resolution varied according to soil properties, local environmental characteristics, and geographical extent. In a context where digital maps of soil properties are calculated at finer and finer resolution, we did not show an altogether linear improvement of accuracy as resolution grew finer. However, we did observe a significant effect of cell size on performances, with a range of suitable resolution levels before an abrupt loss of performance at coarser resolution. The finest spatial resolution proved to be of interest as it significantly improved accuracy in heterogeneous areas, with rising performances as the geographical extent decreased. Moreover, fine-resolution maps allowed for cell aggregation, which showed promising results. In a context where the benefits of digital maps are highly dependent on their accuracy, we highlighted the importance of identifying the best resolution to provide land managers and policymakers with relevant maps available for a broad range of geographical extents.

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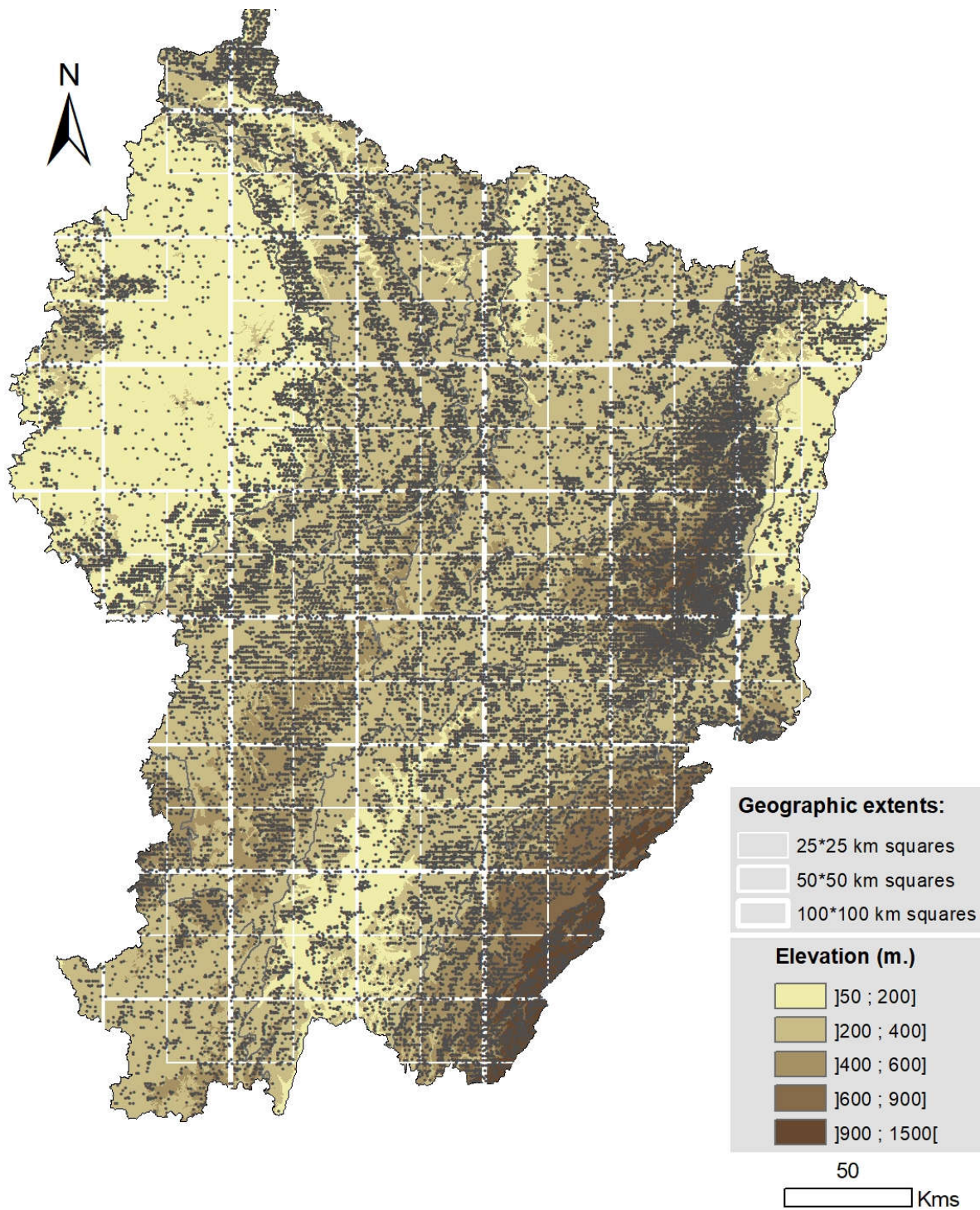
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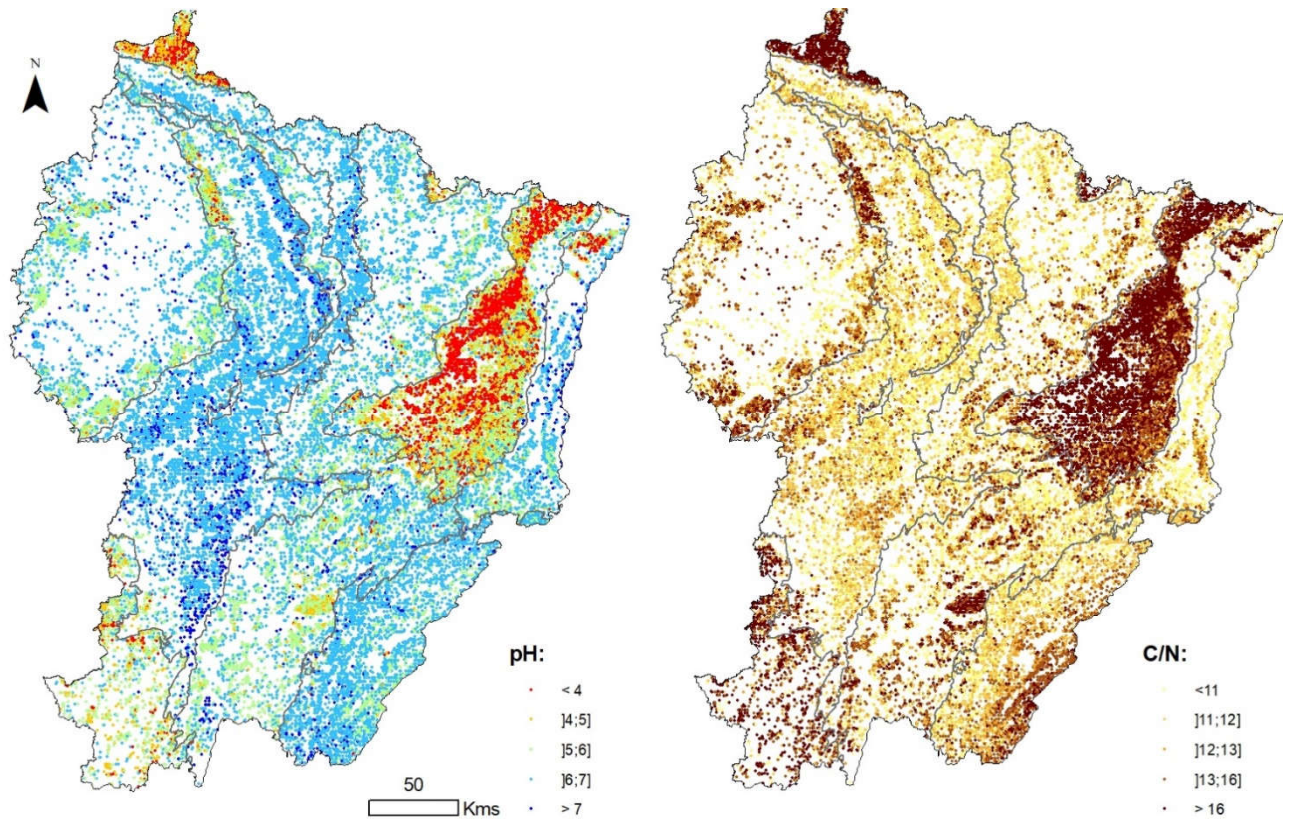
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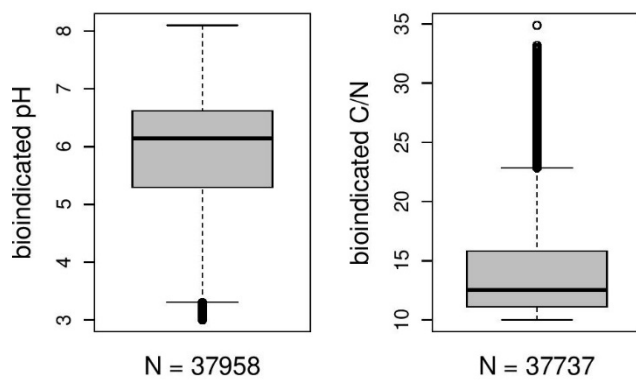
Appendices



Appendix A: Location of the 37,958 plots from the National Forest Inventory used for model calibration (black dots), and delineation of the four geographical extents: the whole studied area, 100*100 km, 50*50 km, and 25*25 km squares (squares with less than 100 plots does not appear and were not used in the analysis).



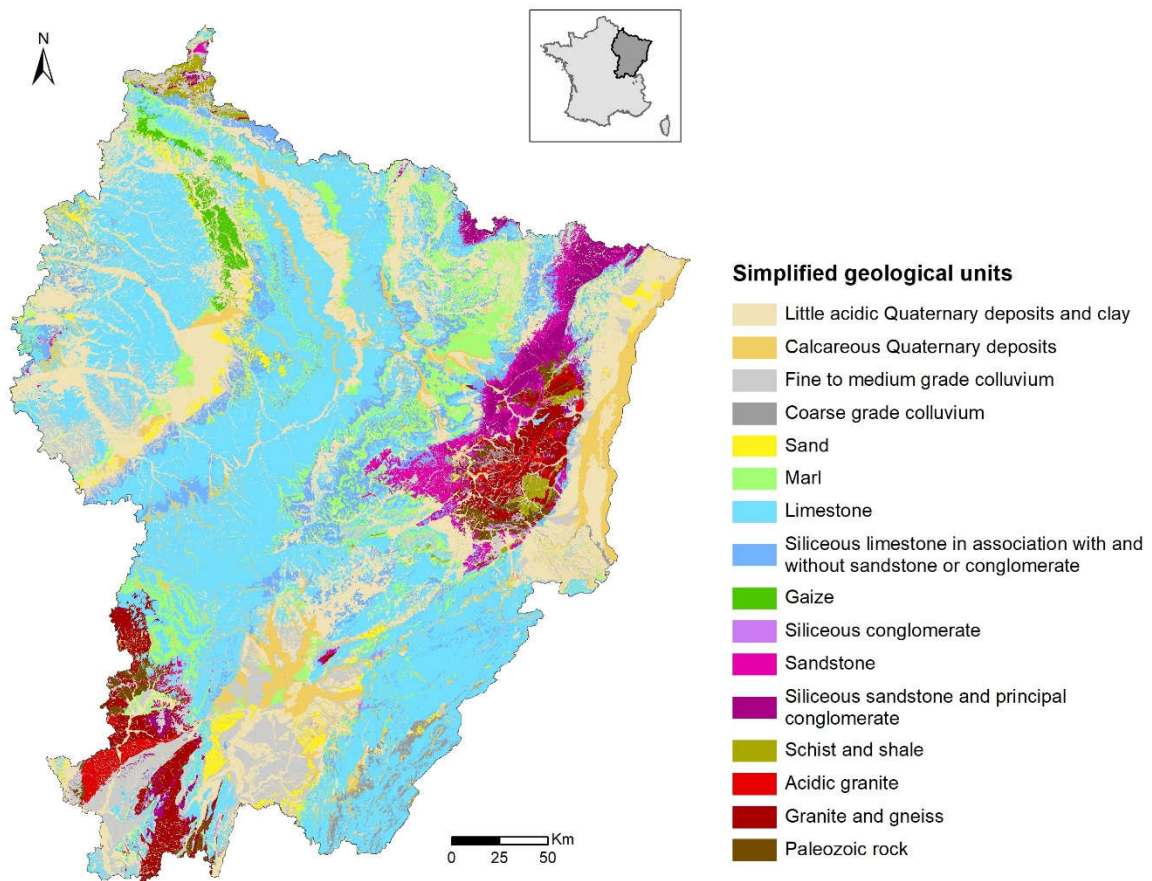
Appendix B: Spatial distribution of pH values (left, $n = 37,958$) and C/N (right, $n = 37,737$) bioindicated with floristic inventories collected on temporary plots.



Appendix C: Ranges of pH (left) and C/N (right) values throughout the dataset.

	<i>pH</i>	<i>C/N</i>
<i>n</i>	37958	37737
<i>Sill</i>	1.15	14.7
<i>Range</i>	110 km	96 km
<i>Nugget</i>	0.19	7.29

Appendix D: parameters of exponential semivariograms for *pH* and *C/N* values bioindicated on temporary plots.



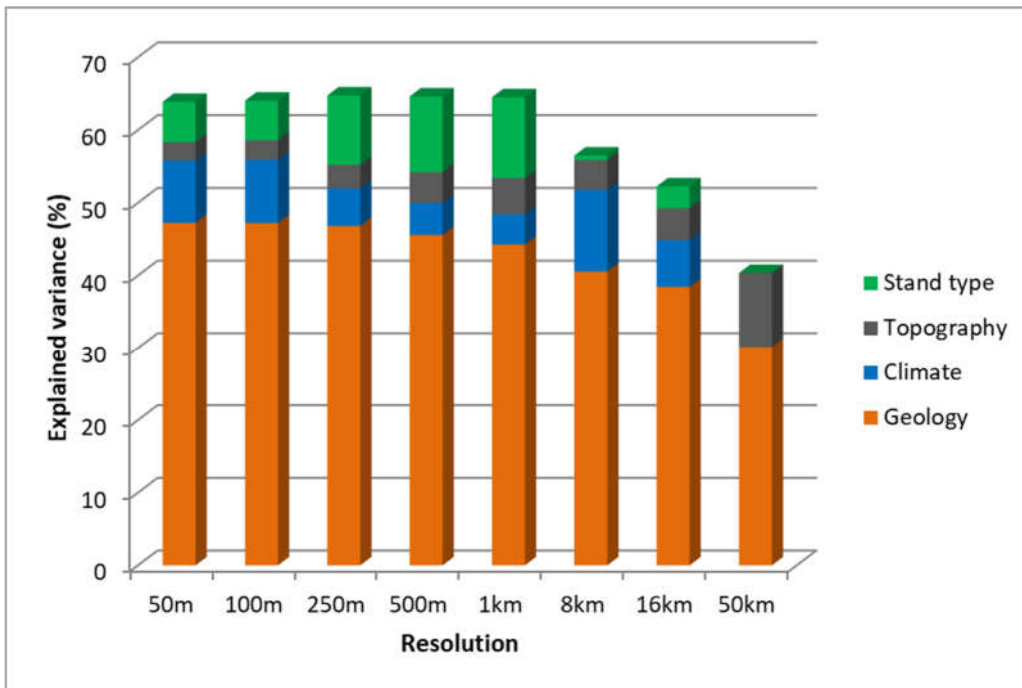
Appendix E: The 16 geological units from the simplified geological map

0

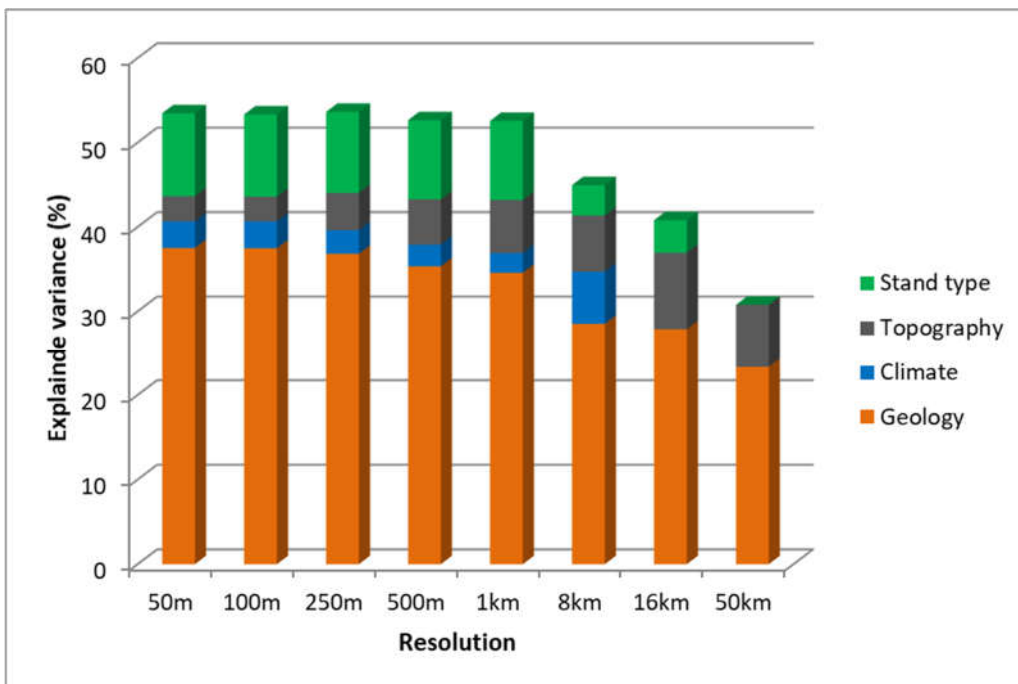
pH		C/N	
Variable	Coefficient	Variable	Coefficient
(Intercept)	5.6369	(Intercept)	21.5651
geology - Siliceous sandstone and Principal Conglomerate	-1.9001	geology - Siliceous sandstone and Conglomerate Principal	9.0011
geology - Sandstone	-1.2852	geology - Sandstone	5.3393
geology - Acidic granite	-1.1678	geology - Schist and shale	4.3154
geology - Schist and shale	-1.0318	geology - Acidic granite	4.3072
geology - Siliceous conglomerate	-0.9242	geology - Siliceous conglomerate	3.6765
geology - Granite and gneiss	-0.8440	geology - Granite and gneiss	2.9312
geology - Gaize	-0.6779	geology - Gaize	2.6781
geology - Paleozoic rock	-0.6770	geology - Fine to medium grade colluvium	2.5974
geology - Fine to medium grade colluvium	-0.6062	geology - Paleozoic rock	2.3061
geology - Sand	-0.4564	geology - Coarse grade colluvium	2.0758
geology - Coarse grade colluvium	-0.4145	geology - Sand	1.4229
geology - Little acidic quaternary deposits and clay	-0.1821	geology - Little acidic quaternary deposits and clay	0.3845
geology - Marl	0.1953	geology - Calcareous quaternary deposits	-0.5376
geology - Calcareous quaternary deposits	0.2953	geology - Marl	-0.9792
geology - Limestone	0.6423	geology - Limestone	-1.5933
TM _{wi}	0.2019	stand type- Coniferous	2.7162
stand type- Coniferous	-0.6478	stand type- Tree-less forest	1.6703
stand type- Tree-less forest	-0.5197	stand type- Mixed	1.5508
stand type- Mixed	-0.3767	stand type- Broadleaved	0.2893
stand type- Broadleaved	-0.2261	TM _{su}	-0.5642
slope	0.0125	curv	1.0620
Flac	0.0887	slope	-0.0307
		relalt	0.5493

1 Appendix F: coefficients and variables for the 50-m resolution pH and C/N models. See Table 1 for variable description

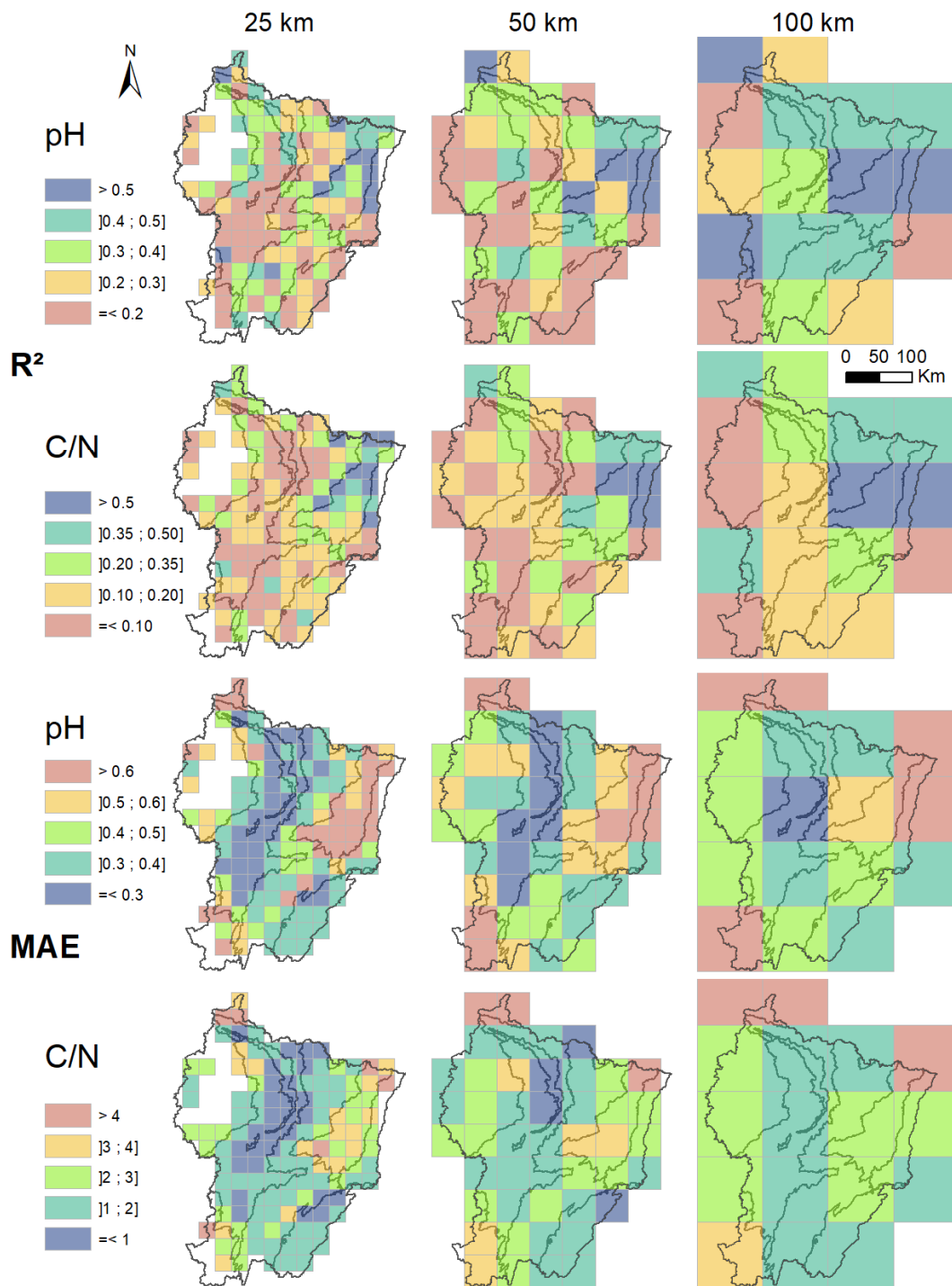
pH



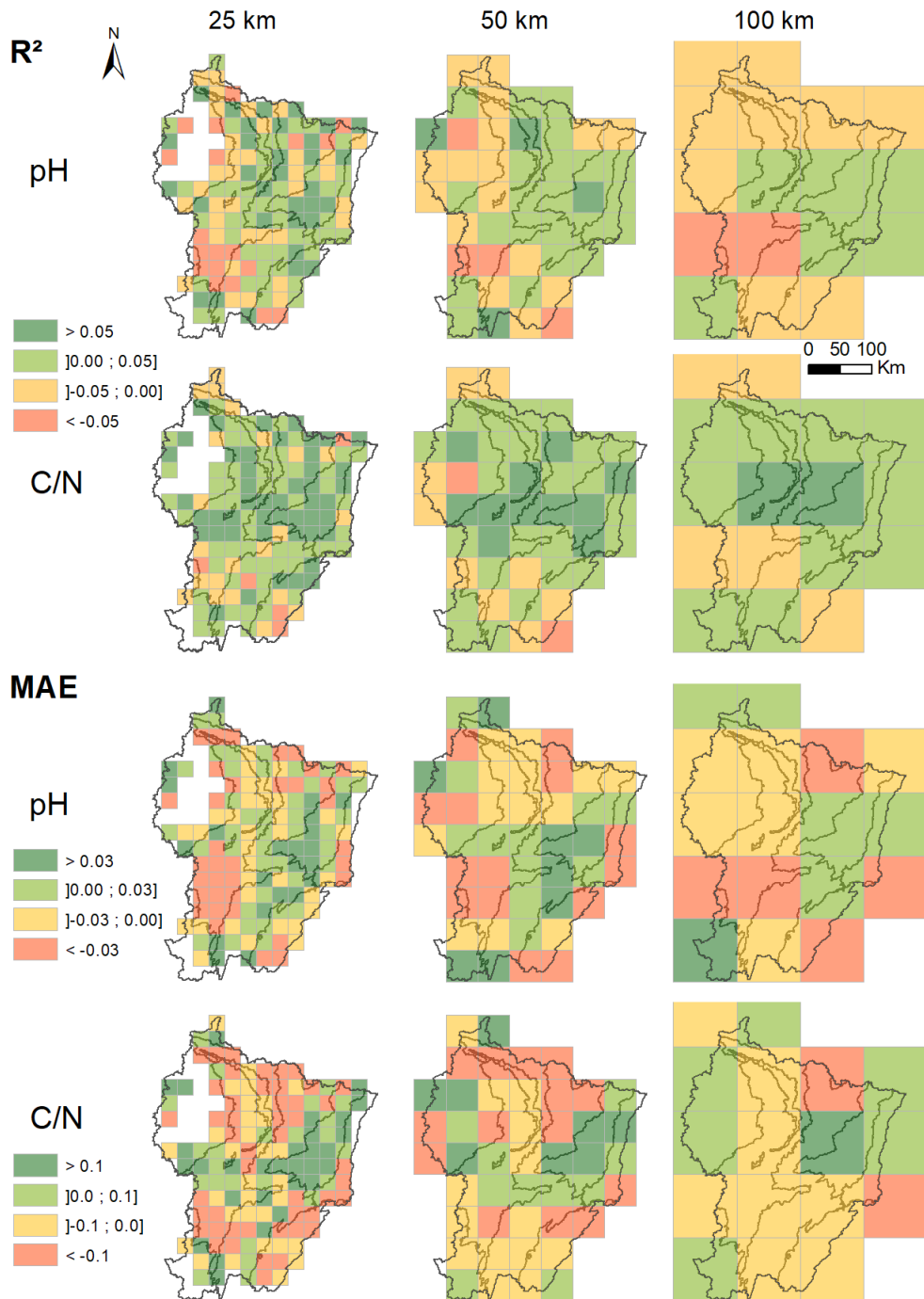
C/N



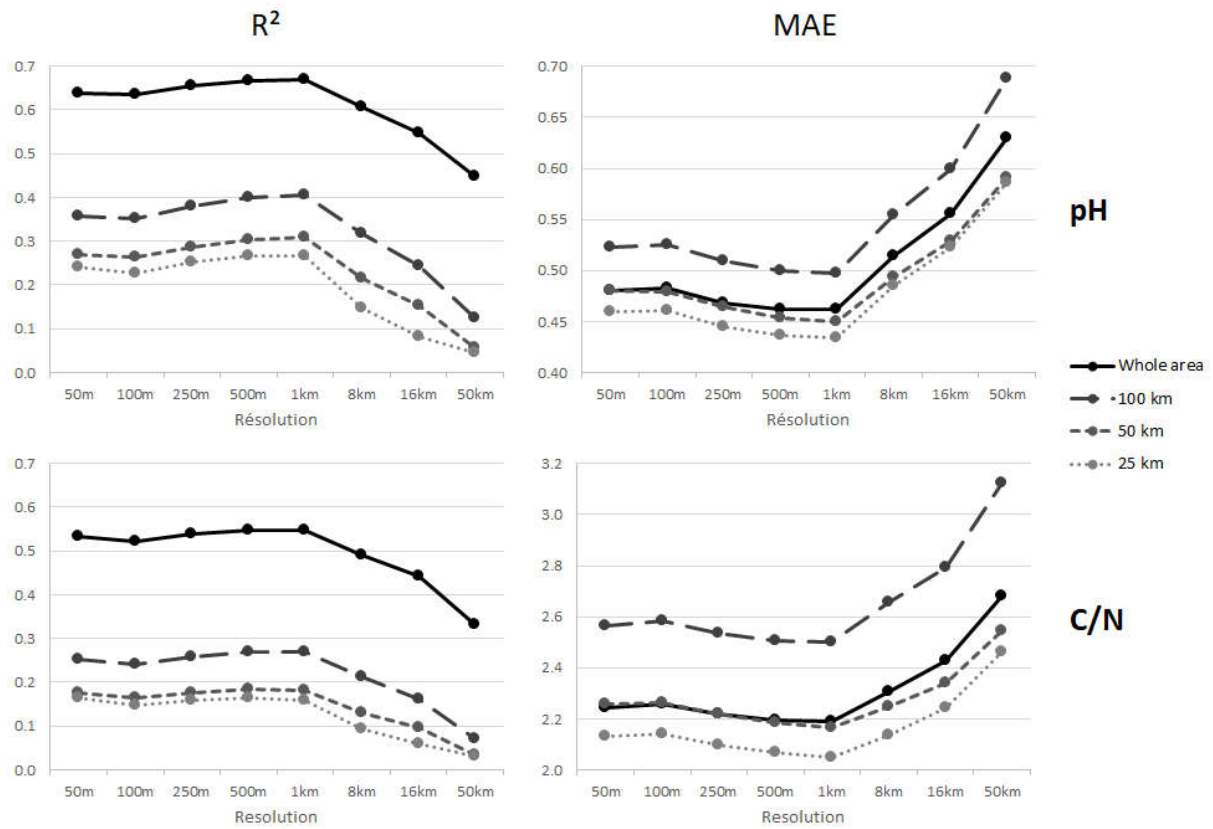
Appendix G: Explained variance per variable category for the pH and C/N models calculated at eight resolution levels (Question 1).



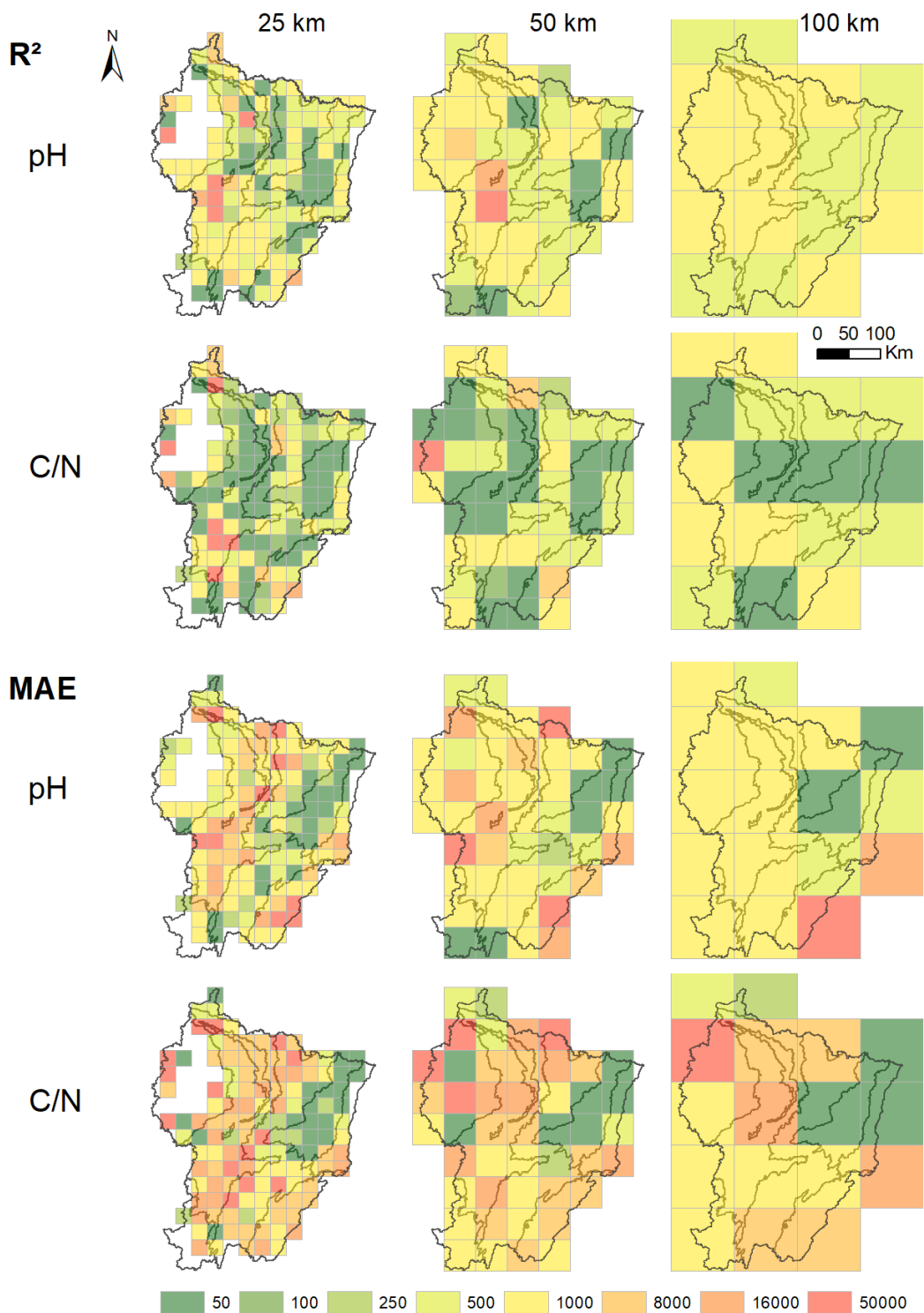
*Appendix H: Best R² and MAEs for the pH and C/N models whatever the resolution level, for three extents (100*100 km, 50*50 km, 25*25 km) (Questions 2 and 4). No performance was calculated when the number of plots in a cell was lower than 100. For each square, performances were calculated between the maps calculated at different spatial resolution and an independent subset of plots.*



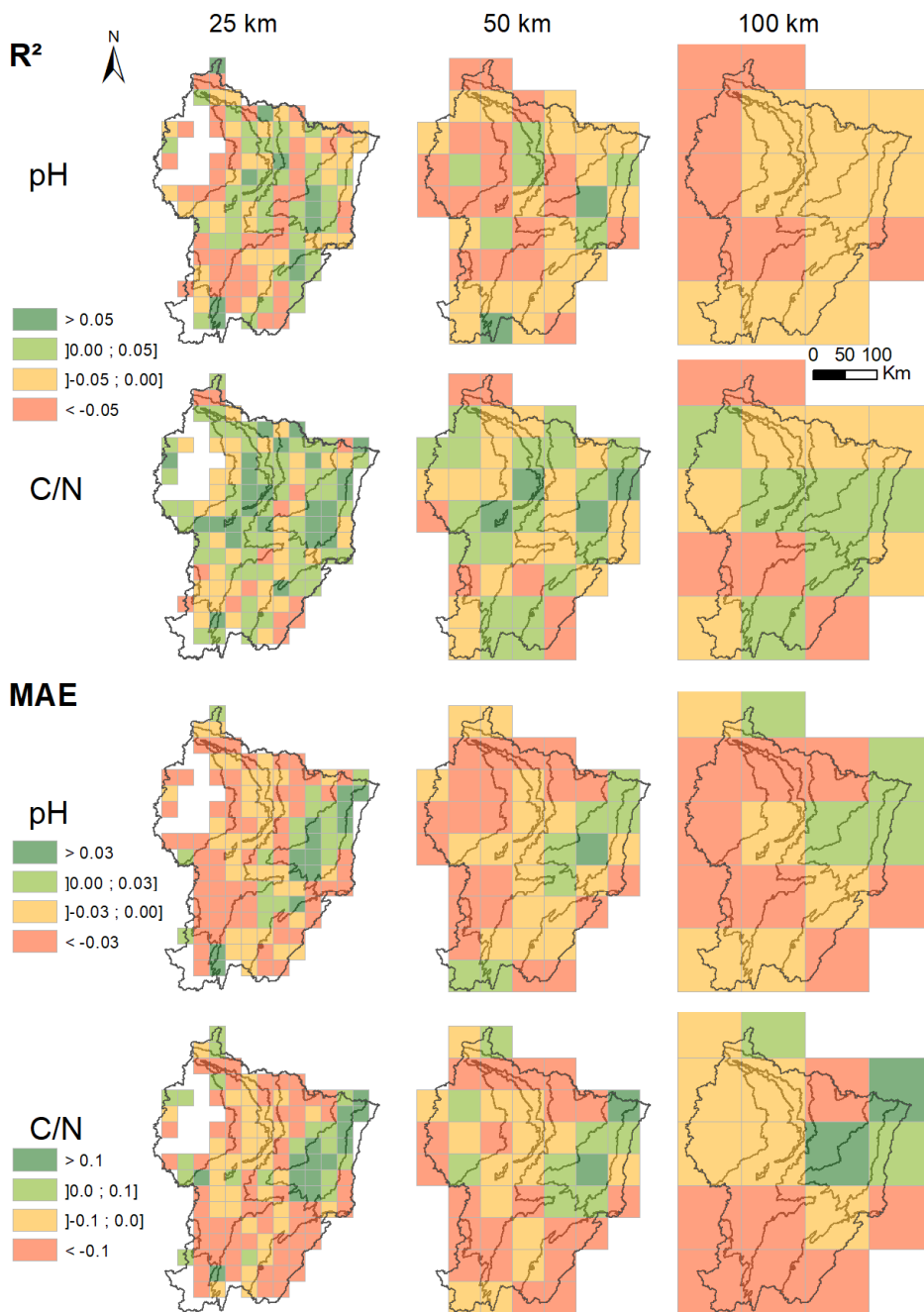
Appendix I: Differences in performance between the 50-m and 1-km resolution maps of pH and C/N (R^2 and MAEs) for the different extents (Questions 2 and 4). Positive values highlight better performance of 50-m resolution maps, while negative values highlight better performance of 1-km resolution maps. No performance was calculated when the number of plots in a cell was lower than 100. For each square, performances were calculated between the maps calculated at different spatial resolution and an independent subset of plots.



Appendix J: Average performance (R^2 and MAE) of aggregated pH and C/N maps for 100*100km, 50*50 km and 25*25 km geographical extents at eight spatial resolution levels (Questions 3 and 4). Values were averaged from the different squares for the geographical extents.



Appendix K: Resolution with the best performance (R^2 and MAEs) for the aggregated pH and C/N maps, at the 100*100km, 50*50 km and 25*25 km geographical extents (Questions 3 and 4). No performance was calculated when the number of plots in a cell was lower than 100. For each square, performances were calculated between the maps calculated at different spatial resolution and an independent subset of plots.



Appendix L: Difference of performance (R^2 and MAEs) between the aggregated maps of pH and C/N at 50 m and 1 km resolution for the different geographical extents (Questions 3 and 4). Positive values highlight better performance of 50 m maps while negative values highlight better performance of 1 km maps. No performance was calculated when the number of plots in a cell was lower than 100. For each square, performances were calculated between the maps calculated at different spatial resolution and an independent subset of plots.

Extent		25*25 km	50*50 km	100*100 km	Whole area
	n	132	46	17	1
R ²	pH	0.01	0.00	-0.01	0.00
	CN	0.04	0.02	0.01	0.02
	pH aggregated	-0.03	-0.04	-0.05	-0.03
	CN aggregated	0.01	-0.01	-0.02	-0.01
MAE	pH	-0.01	-0.01	-0.01	0.00
	C/N	-0.03	-0.04	-0.01	0.00
	pH aggregated	0.03	0.03	0.03	0.02
	C/N aggregated	0.08	0.09	0.07	0.05

*Appendix M: Averaged differences in pH and C/N R² and MAE values between i) the 50 m and 1 km resolution maps following direct calculations and ii) pH and C/N calculated by aggregation, for the 25*25, 50*50 and 100*100 km extents (Question 4). For each extent, values were calculated by averaging the performances of the different squares. Positive R² and negative MAE values highlight better performance of 50 m maps than 1 km maps. n= number of geographical units used for averaging performances.*