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## Abstract

Grasslands offer many environmental and economic advantages that put them at the heart of future sustainable ruminant production systems. This study aimed to quantify and map the dry matter yield (DMY) and nitrogen yield (NY) of French grasslands resulting from cutting and grazing practices, based on the existing diversity of grassland vegetation, management, soil and climate conditions, using a research version of the STICS crop model called PâturSTICS. This model simulates daily dry matter (DM), nitrogen (N) and water fluxes involved in the functioning of grasslands and crops in response to management and environmental conditions. It was improved to represent deposition of animal waste on grassland soils during grazing and to simulate DM production and N content of grasses and legumes more accurately. Simulations were performed for locations across France on a high-resolution grid composed of pedoclimatic units (PCU) obtained by combining the spatial resolutions of climate and soil. The main grassland types and associated management types were determined for each PCU and then simulated over 30 years (1984-2013). Using the simulated values, predictive metamodels of annual grassland DMY and NY were developed from easily accessible explanatory variables using a random forest approach. Annual model predictions were aggregated and averaged at the PCU scale, then compared to regional observations. Predicted DMY agreed with available observations, except in semi-mountainous and mountainous regions, where PâturSTICS tended to overpredict DMY, probably because it ignores effects of snow, frost and slope, and due to how it represents effects of temperature and water stress on plant growth. According to results, three-quarters of French grasslands produce and export at least 7.6 t DM $ha^{-1}$ $yr^{-1}$ and 172 kg N $ha^{-1}$ $yr^{-1}$, respectively. One-quarter of French grasslands produce and export at least 10.7 t DM $ha^{-1}$ $yr^{-1}$ and 254 kg N $ha^{-1}$ $yr^{-1}$, respectively. The latter are located mainly in north-western France, the north-western Massif Central, the French Alps and the western Pyrénées, all of which have environmental conditions favourable for grass growth. The metamodels developed are interesting proxies for PâturSTICS' predictions of grassland DMY and NY. Our results provided valuable knowledge that promotes better use of the potential forage production of French and European grasslands to improve protein self-sufficiency and N fertilisation management in ruminant livestock systems.

**Keywords**: grassland, modelling, STICS, dry matter yield, nitrogen yield, France

## 1. Introduction

Ecosystem services of grasslands are increasingly promoted, in particular their ability to reduce water pollution by nitrates (Cameron et al., 2013; Di and Cameron, 2002) and mitigate climate change by storing carbon in their soils (Paustian et al., 2016; Soussana et al., 2010). Grasslands are also of interest because of their fundamental provisioning service of producing high-quality and protein-rich food products *via* ruminants, which can produce these products from this protein resource that humans cannot digest directly. Grasslands are also able to extract and export more nitrogen (N) from the environment than other crops (Delaby and Lucbert, 1999), which makes them an interesting land use to manage N fertilisation and decrease N emissions to the environment. Despite the advantages they provide, grasslands may be undervalued in some French regions. Mapping French herbage dry matter (DM) and N yields could therefore help assess the value of local grasslands and promote better use of these areas, with positive consequences for the environment and for the self-sufficiency of ruminant farms in supplying DM and protein to their animals (Brocard et al., 2016; Capitain et al., 2003).

A process-based modelling approach is required to simulate grassland DM yield (DMY) and N yield (NY) at a national scale. Several process-based models for temperate grasslands have been developed since the 1990s in countries in north-western Europe. These models are used mainly to address grassland productivity and greenhouse gas emissions, using either a multi-model ensemble (Ehrhardt et al., 2017; Sándor et al., 2017) or a single-model approach (e.g. Graux et al., 2013). Few of them are able to simulate accurately both herbage growth and N and water fluxes in response to soil, climate and management drivers, including grazing. Previous modelling studies have predicted current grassland productivity at European or French scales, although they simplified representation of grassland processes and management and/or provided model predictions at a low spatial resolution (Chang et al., 2015; Huyghe et al., 2014; Ruget et al., 2006), sometimes without representing soil processes. The process-based crop model STICS (Brisson et al., 2003) was chosen for this study as it was found a valuable tool for studying effects of changes in agro-ecosystems on DMY over a wide range of agropedoclimatic conditions in France (Coucheney et al., 2015). STICS also represents soil and plant processes robustly for a range of crops including temporary and permanent grasslands (Ruget et al., 2006), although it does not consider animal urine and faeces deposition (i.e. “returns”) or fate.

The objective of this study was to provide a spatially explicit view of grassland DMY and NY in France, using a mechanistic modelling approach and considering as much as possible the existing variety of pedoclimatic, vegetation and management situations, and to derive metamodels from annual STICS predictions that could be transferable to stakeholders. Metamodels are able to simplify process-based models and predict the same outputs accurately using fewer input data, provided they make predictions within the boundaries of their validity domain (Luo et al., 2013). The first step was to improve STICS’ ability to simulate DM and N fluxes in grasslands, in particular by representing animal returns during grazing, and by comparing its predictions to a database of observed grassland yields.

## 2. Materials and methods

### 2.1. Description of the PâturSTICS soil-crop model

STICS is a deterministic process-based and generic soil-crop model. STICS simulates consequences of changes in pedoclimatic conditions and management on crops and grassland production (amount and quality) and the environment (water and air quality) (Brisson et al. 2003, 2009). It simulates, in a daily time step, the main soil-plant processes associated with plant phenology, shoot and root growth, yield formation, microclimate, water and N balances and, if desired, agricultural practices. Crop development is based calculating a daily thermal index from daily mean crop temperature and basal, optimum and maximum temperature thresholds for crop development. This thermal index can be decreased by sub-optimal photoperiods, unattained vernalisation requirements or effects of water and nitrogen stresses. The sum of the daily thermal index (expressed in degree days) is used to define crop phenological stage. Potential crop production is simulated by converting the radiation intercepted by photosynthetic parts of the plant into biomass using Beer's law for grasslands (Varley Grancher et al., 1989) and the concept of radiation use efficiency (Monteith, 1972; 1977). This potential is modulated by effects of crop temperature, water and N stresses, atmospheric carbon dioxide ($CO_2$) concentration, and potential remobilisation of crop reserves. Crop N content depends on shoot biomass accumulation, root system development, soil N availability and, for legumes only, biological $N_2$ fixation (BNF). Crop N demand is derived from the maximum N dilution curve (Justes et al., 1997; Lemaire and Gastal, 1997), and crop N uptake is calculated daily as the minimum of crop N demand or soil N availability. N inputs to the soil-plant system include N fertilisation, BNF and precipitation. N outputs include N exports associated with plant defoliations and N emissions to air and water. STICS also simulates internal N fluxes (e.g. litter fall, soil organic matter mineralisation and immobilisation). STICS represents the most common agricultural practices (e.g. ploughing, sowing, fertilisation, harvest) and some grassland-specific practices (cutting). For the present study, a research version of STICS (derived from the trunk version 8.3.1, release 1276), called PâturSTICS, was developed to represent animal returns to the soil in grazed grasslands, following the concepts of Faverdin and Vérité (1998). Appendix A provides PâturSTICS' new equations.

## 2.2. Data collection and processing

### 2.2.1. Weather and soil conditions: definition of the spatial resolution of simulations

The weather information required to run STICS was provided by the mesoscale atmospheric analysis system (SAFRAN) (Durand et al. 1993). Soil information from the 1:1,000,000-scale soil geographic database of France (Jamagne et al., 1995) was used to parameterise STICS' soil parameters. In this database, soil information is available in soil mapping units (SMU), which are areas which consist of 1-6 soil types whose percentage within the SMU is known. STICS soil parameters were provided by the INRA InfoSol lab. Soil organic N content in the topsoil (0-30 cm) was estimated according to Mulder et al. (2015) for both temporary and permanent grasslands. Soil types with an organic texture such as histosols were excluded from the simulation plan (i.e. 1% of soils, 0.3% of simulations), as they lay outside STICS' validity domain. Similarly, according to STICS' limits, soil organic N content in the topsoil was limited to 0.4% (i.e. soil organic matter content < 7.6%; Graux et al., 2017).

Corsica and overseas French regions were excluded from simulations as they were not included in the databases used. Combining weather and soil information at the SMU level led to definition of 30,966 pedoclimatic units (PCU), each of which was no larger than 6400 ha (Figure 1). Only PCU with utilised agricultural area (UAA) greater than 100 ha and with grassland area greater than 10% of UAA were considered in the simulation plan. This led to the definition of 15,032 PCU (i.e. half of the total number of PCU), thus excluding four highly urbanised departments (Hauts-de-Seine (department code 92), Paris (75), Seine-Saint-Denis (93) and Val-de-Marne (94)). Overall, 21 of 27 former (pre-2016) French administrative regions and 90 of 101 French departments were simulated, with coverage varying by region and department (Table 2).

Simulations were performed for a 30-year period (1984-2013) across France on this high-resolution grid. Since slope was not available, its influence on surface water run-off was ignored. Atmospheric $CO_2$ concentration was kept constant at its default value of 350 ppm, as changing it to its mean value from 1984-2013 (i.e. 413 ppm) would have had little influence on model DMY and NY predictions (due to the equations used in STICS).

**2.2.2. Grassland types and duration**

A typology of four grassland types was defined according to their level of N input self-sufficiency (Table 1). Types 1 and 4 referred to permanent grasslands (never sown and at least 5 years old), managed extensively (e.g. most mountain grasslands) or intensively, respectively. Type 2 referred to temporary grasslands sown with pure legumes (e.g. lucerne (*Medicago sativa*)). Type 3 referred to temporary grasslands sown with pure grass or grass-legume mixtures. As the current version of STICS cannot simulate grass-legume mixtures, each species was simulated independently, and their results were aggregated later, assuming a constant legume percentage of 30%. One single parameterisation each was used to represent grasses and legumes in permanent or temporary grasslands, including grass-legume mixtures. The grass species was parametrised similar to species such as tall fescue (*Festuca arundinacea*) and orchard grass (*Dactylis glomerata*), while the legume species was parametrised as lucerne (as clover parameterisation was not available in the STICS version used).

The percentage of each grassland type within each PCU and the duration of temporary grasslands were estimated by combining information about the use of agricultural fields from the Graphical Register of Fields, derived from farmers' Common Agricultural Policy declarations (available since 2004), and information from the last agricultural census (2010). According to this information, the mean duration of temporary grasslands was ca. 3 years (standard deviation = 1 year). Permanent grassland duration was arbitrarily set to 5 years.

### 2.2.3. Planned management

Grassland management for each grassland type in a given PCU was defined according to the French ISOP system (Ruget et al., 2006), which provides this information at the scale of small agricultural regions (i.e. areas with homogeneous grassland management and production level; Hentgen, 1982). The diversity of grassland management in the ISOP system was summarised into 30 management types (M, Figure B.1 in Appendix B) derived from a survey about French grassland-specific agricultural practices (SCEES, 2000) and the expertise of INRA scientists working on grasslands. Management descriptions included grassland use (cutting for hay or silage, grazing, number and timing of grassland uses per year) and N fertilisation practices (timing and amount of N applications). N fertiliser can be applied at the end of winter and again after plant defoliation(s). To represent regional and inter-annual diversity in management, the timing of operations is expressed in degree days and compared to the sum of the daily thermal index for crop development (as defined in section 2.1). Agricultural practices range from extensive (one cut per year) to intensive practices (up to 10 grazing periods per year).

The severity of grazing and cutting management is modelled using parameter values of residual plant biomass and leaf area index after plant defoliations. To trigger planned cutting and grazing events, the model checks that the degree days defined by the user have been reached and that the corresponding standing biomass is greater than or equal to a minimum harvestable biomass also defined by the user (Table B.2 in Appendix B). These decision rules determine whether the planned cutting, grazing and associated fertilisation events are performed or not. When practices in the ISOP system were considered less frequent than current practices, their frequency was increased, thus improving representation of consequences on the quality of ingested herbage and animal N returns to the soil.

Observed annual fertilisation was 0-200 kg N $ha^{-1}$ $yr^{-1}$ of ammonium nitrate; however, the simulated amounts of mineral N applied represented both mineral and organic N fertilisation practices. Extensive permanent grasslands (Table 1, type 1) were assumed to be only grazed and not fertilised (M15, Figure B.1 in Appendix B). Pure legume swards (Table 1, type 2) were associated with only five management types (M8, M12, M19, M21 and M24, Figure B.1 in Appendix B).

### 2.3. Design and running of simulations

The simulation design was built in collaboration with the EFESE study (Thérond et al., 2017). To decrease the number of simulations, only the main soil types and grassland types within each PCU were considered: the smallest number of soil types (from one to three) that covered at least 90% of each SMU were kept in the simulation plan. Similarly, only one type of grassland was selected if it covered more than 50% of a PCU. When necessary, two grassland types were chosen if each covered at least 10% of a PCU. Simulations performed within each PCU were therefore a combination of one climate over 30 years, 1-3 soil types and 1-2 grassland types, each with 1-18 management types (Figure 1). Combining all information about weather and soil conditions, grassland types and associated management types led to a maximum of 1,262,575 simulations, each combining one PCU, one grassland type, one management type and one sequence of several years, corresponding to the grassland duration. When grouping the successive grassland sequences that would occur during the 1984-2013 period, the number of simulations fell to 173,260. This huge number of simulations was launched on the GenoToul Bioinformatics hardware infrastructure, using the STICS crop model embedded in the INRA modelling platform (Bergez et al., 2013). To decrease the volume of outputs and calculation time, model predictions were generated at an annual scale.

## 2.4. Analysis of model predictions

R software (v. 3.4.4) (R Core Team, 2019) was used to process and analyse data (main R packages: *caret, data.table, dplyr, plyr, ranger* and *tidyr*), and generate figures (main R packages: *ggplot2*, *maptools* and *rgdal*).

### 2.4.1. Analysis of aggregated results per pedoclimatic unit

Model predictions from the establishment period of grasslands (i.e. first year of the grassland sequence) were excluded from analysis, as the low predicted DMY these years did not represent established grasslands. Mapping mean predictions at the national scale first required aggregating predictions to one mean value per PCU. Predictions were aggregated by calculating weighted averages of DMY and NY, using the percentage of each input factor addressed in this study: soil type, management type, grassland type and climate year. When a PCU contained a grass-legume mixture (Table 1, type 3), a weighted average of model predictions for grasses and legumes was first calculated. We then calculated, in this order, a weighted average of soil types, management types, grassland types and finally, climate years. Aggregated results per PCU were then mapped to provide an average picture of model predictions at national, regional and departmental scales. Much information about simulated grassland DM and N fluxes was available from model predictions. In this article, we focus on predicted DMY and NY potentials.

### 2.4.2. Evaluation of accuracy of results

To assess the accuracy of PâturSTICS' developments, its predictions of grazing features were compared to literature data and expertise. These features include the proportion of DMY that is grazed vs. cut, the number of grazing days, expressed in livestock unit (LSU) grazing days per ha of grassland per year (Peyraud and Delaby, 2008), and animal N returns. An LSU grazing day (hereafter referred to as "grazing day") equals one day's grazing by a standard dairy cow. Grazing days were calculated by dividing the total herbage removed by animals by daily animal intake, which was set to 17 kg DM LSU$^{-1}$ grazing day$^{-1}$. We also analysed other annual management variables (N fertilisation, number of grass defoliations) that were influenced by the model's decision rules.

To assess the accuracy of model DMY predictions, mean predictions were calculated per department and region and compared to 12,739 field-growth estimates per 10-day period from a French network covering four administrative regions (Auvergne, Bretagne, Franche-Comté and Pays de la Loire, Graux et al., 2017). In each region of this network, herbage growth is measured every 10 days in at least 20 grazed paddocks of commercial farms by technicians from several livestock advisory services. Herbage biomass is estimated from herbage height measured with a rising-plate meter and from herbage density, equal to either a constant annual value (250 kg DM ha$^{-1}$ cm$^{-1}$) or seasonal values (source: Defrance et al., 2004). Herbage N content is not usually measured in this network. The quality of such observations thus depends on assumptions about herbage density. However, this network represents the diversity of grassland situations within a given region better than other observations available from local and sometimes short-term experimental sites. In each region, several thousand validated data points from 6-11 years during the 1997-2014 period (680, 3397, 5161 and 3501 data points in Auvergne, Bretagne, Franche-Comté and Pays de la Loire, respectively) were averaged per 10-day period to build regional herbage growth profiles. Several regional herbage growth profiles were defined according to discriminating factors: elevation in Auvergne, weather conditions in Bretagne, soil depth in Franche-Comté and latitude in Pays de la Loire. From these profiles, it was possible to calculate mean observed regional DMY.

### 2.4.3. Development of metamodels

Metamodels of annual grassland DMY and NY were developed from annual non-aggregated PâturSTICS predictions. The latter were supplemented by summary information about the textural class of the topsoil and the water holding capacity of the main soil type in each PCU.

To develop metamodels, we used a random forest (RF) approach that was found to be more accurate in predicting the annual yields predicted by process-based models than the usual use of multiple linear regressions (e.g. Jeong et al., 2016). RF is a binary-tree-based machine-learning method that can be used for both classification and non-linear regression (Breiman, 2001). To train RF regression models, a forest of decision trees is grown. Each tree is built using a random subset of *mtry* explanatory variables and a sample of source data that is obtained by a random two-thirds sampling with replacement of source data. The remaining one-third, called *out-of-bag* data, is set aside by the RF algorithm to internally validate prediction quality of the tree. For each tree, the data are recursively split into the two most homogeneous subsamples based on a threshold value of one explanatory variable identified to best split the data. The split points are commonly called *nodes*. The source data are bootstrapped to randomly generate a large number of random trees that are averaged and then used to predict the continuous variable. The importance of explanatory variables in the prediction is assessed by how often they were selected for the splits and how much they increase the prediction error of the average tree after permutation of their values.

Ten continuous variables were selected to be both *a priori* explanatory of grassland DMY and NY and easily accessible to stakeholders, while avoiding correlations between variables. They related to climate, soil, vegetation and grassland management (Table 3). “Age” refers to grassland age during the simulation of a grassland sequence and varied from one year to the maximum grassland duration). These variables were used for training RF models to predict DMY and NY, using the R *ranger* package (Wright and Ziegler, 2017), which is particularly suited for high-dimensional data. We used default algorithm values for the number of trees (*num.trees* = 500), set the number of explanatory variables to one-third of all available explanatory variables (*mtry* = 3), and restricted the minimum size of nodes to its default value for regression models (*min.node.size* = 5). The variable importance available from the *ranger* R package and calculated by permutation was used to rank the explanatory variables.

To ensure fair comparison of RF metamodels to PâturSTICS predictions, we used a random two-thirds of the dataset to train RF models and the remaining one-third to evaluate performances of RF metamodels. How well the metamodel predicted PâturSTICS predictions was assessed by combining a graphical and statistical approach, using common indicators for validation of biophysical models (Bellocchi et al., 2010 ; Wallach et al., 2018). The indicators were i) root mean square error (RMSE, Eq. 1), which is a quantitative measure of distance between observed and simulated values; ii) its relative value (RRMSE, Eq. 2), which expresses error as a percentage of the mean measured value; iii) Nash-Sutcliffe model efficiency (EF), interpreted as the proportion of variance explained by the model; and iv) graphs of observed vs. predicted DMY and NY.

$$RMSE = \sqrt{\left(\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}\right)} \quad (1)$$

$$RRMSE = \frac{RMSE}{\bar{y}} \times 100 \quad (2)$$

$$EF = 1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \quad (3)$$

where $y_i$ is the measured value, $\hat{y}_i$ is the corresponding predicted value, n the number of measurements and $\bar{y}$ is the mean of measured values. Metamodel performance was interpreted from the following RRMSE thresholds: RRMSE ≤ 10%: excellent, 10% < RRMSE ≤ 20%: good, 20% < RRMSE ≤ 30%: fair, RRMSE > 30%: poor.

# 3. Results

## 3.1 Simulated grassland management and N inputs

Mean grassland management from 1984-2013 varied by region (Figures 2 and 3). The mean frequency of herbage use was 3-4 grazing and/or cutting events per year, sometimes reaching 9 events in rare situations (Figure 3A). Herbage use appeared to be higher in northern and far western Bretagne (Bre), western Pays de la Loire (PdL) and Limousin (Lim) regions (Figure 2A) and in the Manche (50) and Pyrénées-Atlantiques (64) departments (Figure 2B). In the Bretagne, Basse-Normandie (BaN) and Haute-Normandie (HaN) regions, western Massif Central, Alps and Pyrénées, grasslands were mainly grazed (Figure 3B). These areas had the largest numbers of grazing days and amounts of animal N returns to the soil (Figures 3C and 3D). By construction, these predictions were highly correlated as they were both calculated from herbage ingestion. Grasslands were used mostly for hay and silage production in the Champagne-Ardenne (ChA), Lorraine (Lor), part of Pays de la Loire, Haute-Normandie and Centre (Cen) regions and the south-western and eastern Massif Central (Figure 3B). Total N application from mineral fertilisers, animal returns and BNF had a mean (± standard deviation) of 108 ± 63 kg N $ha^{-1}$ $yr^{-1}$ (Figure 3F) and reached more than 200 kg N $ha^{-1}$ $yr^{-1}$ in some departments, such as Finistère (29) and Manche (50). French grasslands received a mean of ca. 40 ± 25 kg N ha$^{-1}$ yr$^{-1}$ as mineral N fertiliser (Figure 3E), 73 ± 41 kg N ha$^{-1}$ yr$^{-1}$ as animal N returns and, for PCU with grasslands containing legumes 38 ± 25 and 329 ± 44 N ha$^{-1}$ yr$^{-1}$ from BNF for grass-legume mixtures and temporary sown swards of pure legumes, respectively. Fertilisation was higher in northern and north-western France, with the largest values predicted in the Nord-Pas-de-Calais (NPC), Picardie (Pic), Haute-Normandie, Basse-Normandie, Bretagne and southern Pays de la Loire regions. Maximum N fertilisation reached 115 kg N ha$^{-1}$ yr$^{-1}$. Mean N returns from animal faeces and urine were 30 and 38 kg N ha$^{-1}$ yr$^{-1}$, respectively, with maximum values reaching 115 and 133 kg N ha$^{-1}$ yr$^{-1}$, respectively. BNF by legumes was related to the geographic location of grass-legume mixtures and pure legume swards. It was highest in the production area of lucerne (i.e. Champagne-Ardenne), reaching nearly 250 kg N ha$^{-1}$ yr$^{-1}$.

**3.2. Mean grassland DM and N yields in France**

Mean predicted DMY agreed relatively well with observed data in Pays de la Loire and part of Bretagne (Figure 4), though it was overpredicted in Bretagne under dry summer conditions. Mean predicted DMY were 9.7 ± 2.2 and 7.6 ± 2.3 t DM ha$^{-1}$ yr$^{-1}$ in Bretagne and Pays de la Loire, respectively (Table 2, Figure 4), while observed DMY were 8.3-10.6 and 6.9-9.1 t DM ha$^{-1}$ yr$^{-1}$, respectively. Nevertheless, the model tended to overpredict observed DMY in mountainous regions. For instance, in Franche-Comté, mean predicted DMY was 10.3 ± 1.0 t DM ha$^{-1}$ yr$^{-1}$, while observations were 7.2-9.9 t DM ha$^{-1}$ yr$^{-1}$. Observations on shallow soils were particularly overpredicted (Figure 4). Likewise, in Auvergne, mean predicted DMY (9.0 ± 2.7 t DM ha$^{-1}$ yr$^{-1}$) was notably higher than observed DMY (6.5-7.2 t DM ha$^{-1}$ yr$^{-1}$).

More generally, the map of mean predicted DMY (Figure 5B left) was consistent with existing grassland productivity gradients, associated with specific soil-climate conditions identified within some regions. For instance, the model partly reproduced the expected north-south DMY gradient in the Pays de la Loire and the east-west DMY gradient in Bretagne (Figures 4 and 5B). The mean N content of cut and grazed herbage varied from 13.1-31.6 g N kg DM$^{-1}$ according to location and management, with distribution differing among regions (results not shown). Nevertheless, maps of DMY and NY looked similar, as the two variables were directly correlated.

Comparison of mean predicted DMY and NY highlighted regional and departmental differences in grass forage production (Table 2, Figure 5 B and 5C). Three-quarters of French grasslands produced and exported at least 7.6 t DM ha$^{-1}$ yr$^{-1}$ and 172 kg N ha$^{-1}$ yr$^{-1}$, respectively. One-quarter of French grasslands produced and exported at least 10.7 t DM ha$^{-1}$

yr$^{-1}$ and 254 kg N ha$^{-1}$ yr$^{-1}$, respectively (Figure 5A, Table 2). These grasslands benefit from environmental conditions favourable for grass growth, with the oceanic climate in north-western regions of France: Bretagne (mainly Finistère (29), western Morbihan (56) and Côtes d'Armor (22) departments), Basse-Normandie (mainly Manche (50) and Calvados (14) departments), Haute-Normandie, Picardie and Nord-Pas-de-Calais. These productive grasslands were also located in eastern regions: Franche-Comté, Champagne-Ardennes (Ardennes (08) and Marne (51) departments, where most lucerne production is concentrated) and Lorraine (Vosges (88) department). They were also predicted in the north-western Massif Central (Limousin and Auvergne regions), the northern Alps and western Pyrénées. In contrast, production of less than 5 t DM ha$^{-1}$ yr$^{-1}$ and 115 kg N ha$^{-1}$ yr$^{-1}$ was predicted in the southern Pays de la Loire region (mainly Loire-Atlantique (44), Maine-et-Loire (49) and Vendée (85) departments), the eastern Massif Central (mainly Haute-Loire (43) and Puy-de-Dôme (63) departments), where weather was drier and/or with soils with low water holding capacity, as well as in the Provence-Alpes-Côte d'Azur (PACA) region.

**3.3. PâturSTICS metamodelling**

RF metamodels successfully predicted grassland DMY and NY in the test datasets that were not used to train the model, explaining 95% and 97% of variance, respectively, with good agreement between predictions of RF metamodels and PâturSTICS (Table 4; Figure 6). For predicted DMY, RF metamodels had RMSE of 0.77 t DM ha$^{-1}$ yr$^{-1}$ and RRMSE of 21.8% compared to PâturSTICS predictions ("fair" performance). For predicted NY, RF metamodels had RMSE of 16.5 kg N ha$^{-1}$ yr$^{-1}$ and RRMSE of 18.3% compared to PâturSTICS predictions ("good" performance). Slopes of the regression between PâturSTICS and RF metamodel predictions were 0.92 and 0.94 for DMY and NY, respectively (Pearson correlation coefficient = 0.98 for both).

The validity domain of these metamodels encompasses a large number of soil and climate situations in which French grasslands are established, with annual values of mean temperatures, global radiation and precipitation ranging, respectively, from ca. -2.5 to 17°C, 2850-6500 MJ m$^{-2}$ yr$^{-1}$ and 270-3300 mm (Table 3). This corresponds to 8 climate types (e.g. oceanic, semi-continental, mountainous, Mediterranean) as defined by Joly et al. (2010) that are common to other European regions. The soils include shallow and sandy soils with low water holding capacity (ca. 10 mm) up to deep soils with medium texture and water holding capacity up to ca. 170 mm. Soil organic matter content in the topsoil ranges from 1.3-7.6%, thus excluding richer soils. The duration of grasslands was limited to 5 years, which excluded older permanent grasslands. Agricultural practices are representative of the 1984-2013 period in France. N fertilisation did not exceed 200 kg N ha$^{-1}$ yr$^{-1}$ and thus did not represent more intensive N application rates that can be observed in other European countries. The intensity and frequency of herbage defoliations range from extensive to intensive practices.

Variable importance measures of the RF models revealed that grassland age was the most influential variable for predicting grassland DMY, followed by annual global radiation and mean temperature, which had similar influence, and then by soil water holding capacity, annual precipitation, annual N fertilisation and soil organic N content in topsoil (Table 4). Grazing days, number of cutting events and legume percentage in the vegetation had the least influence on predicting grassland DMY.

The ranking of variables according to their influence on predicted NY was somewhat similar to that on DMY, with the three most and least influential variables being the same for DMY and NY. Of the top three, however, annual global radiation was the most influential variable for predicting NY, closely followed by annual mean temperature and grassland age, which had similar influence, and then by soil organic N content in topsoil, annual N fertilisation, water holding capacity and annual precipitation.

## 4. Discussion

The main objective of this study was to predict French grassland DMY and NY at a high spatial resolution while considering the existing diversity of soil and climate conditions, grassland types and associated management types. The study achieved this objective despite making certain assumptions because of the information available and model limitations, which do not alter the value of the results.

### 4.1. Implementation of simulations

The simulation plan was designed to consider the diversity of existing soil and climate conditions, grasslands and management situations in France. It could be built due to the existence of other studies (i.e. French Evaluation of Ecosystems and Ecosystem Services (EFESE); Thérond et al., 2017) and several detailed French databases for the definition of soils (1:1,000,000-scale soil geographic database of France, Jamagne et al., 1995), climates (SAFRAN system, Durand et al. 1993), management types (statistical agronomic surveys on grasslands and the ISOP system, Ruget et al., 2006) and grassland types and ages (Graphical Register of Fields, last agricultural census). The present study seems difficult to transfer to other European countries, where equivalent databases are often not available. The need to have a high spatial resolution of outputs and a reasonable time to build the simulation plan and calculate results led us to reuse these databases while avoiding updating management information, which would have been time-consuming.

Some limits concern the simplifications made to reduce the number of simulations. The existing diversity of grassland vegetation and agricultural practices was limited to four grassland types and 30 management types, respectively, with fixed conditions for triggering planned cut and grazing events. Information about agricultural practices was available at the scale of small agricultural regions and was assumed to remain the same at smaller scales, thus ignoring variability in agricultural practices in a given small agricultural region. Definitions of grassland types and associated management types within a PCU were fixed for the simulation period, thus overlooking possible local changes in the presence and percentage of grassland types and associated management types. This study benefitted, however, from simulated adaptation of the planned number and timing of herbage defoliations and fertilisation events within a given year according to herbage availability, conditions for triggering management events and climatic conditions. In addition, these assumptions helped in analysis of results as they reduced the number of explicative factors and interactions involved. They also provided the ability to compare similar conditions of grassland types and management types under different climate and soil conditions. Finally, the simulation plan provided a coherent picture of the annual frequency and timing of grass defoliations and N applications, and of the local balance between grazing and cutting.

Other limits were related to the validity domain of STICS (v. 8.3.1, release 1276). First, simulation of grass-legume mixtures did not consider changes in the legume percentage in response to N fertilisation, animal N returns and defoliation, as STICS cannot simulate vegetation dynamics. This is a common limit of process-based models simulating grasslands at the field scale, and explains why the legume percentage was the input factor with the least influence on DMY and NY predictions by RF metamodels. Second, PâturSTICS cannot represent the diversity of grassland functional types in permanent grasslands (Cruz et al., 2010), and parameterising the model for only one grass and legume species (tall fescue/orchard grass and lucerne, respectively) may have biased predicted DMY and NY in western France (Bretagne, Pays de la Loire, Poitou-Charentes), where perennial ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*) are the most commonly sown species. Third, predictions of DMY and NY may have been biased by the current version of STICS' poor representation of grassland roots and their role in soil N availability for plant growth and soil carbon immobilisation. STICS was recently improved to better represent perennial organs and their relationship with non-perennial organs in a Miscanthus (*Miscanthus* × *giganteus*) case study (Strullu et al., 2014). Such improvements are intended to be generic for perennial plants, supported by the functional approach of STICS, and could be adapted to the simulation of grasslands and used in future simulations.

### 4.2. Consistency of grazing simulation

The grazing module we developed (Appendix A) is a simplified but useful representation of animal returns during grazing in which animals are assumed to be fed with grazed grass with no concentrate supply. Grassland intake was simulated as a cutting event, with all of the herbage removed being assumed to feed a fluctuating number of animals that have a uniform and fixed DM intake (17 kg DM day$^{-1}$). Animal stocking density and the length of each grazing period are thus model outputs instead of inputs, but it is possible to calculate grazing days. This simplification makes it difficult to compare predictions to observations, as simulated herbage growth may differ from reality, and simulated grazing days may not reflect the stocking density or grazing period length observed.

This module is based on known relationships between animal N returns during grazing, animal herbage DM intake and herbage N content (Delaby and Lucbert, 1999), all of which respond to N availability (including fertilisation) (Delaby et al., 1997; Delaby, 2000). Predicted faecal and urinary N returns lay in the expected range of observations from the literature (i.e. 30-120 and 60-350 kg N ha$^{-1}$ yr$^{-1}$ for 400-1000 grazing days, respectively) (Delaby et al., 1997, Vertès et al., 2018).

Like most grassland simulation models, PâturSTICS assumes uniform spatial return of faecal and urinary N to the soil, as representing their spatial and temporal distribution in models remains a challenge (Hutchings et al., 2007; Selbie et al., 2015; Snow et al., 2009). Applying animal N returns on a single day and not considering the spatial heterogeneity of dung and urine patches within the paddock could have distorted predictions of grassland production and N fluxes associated with animal N returns (Leterme et al., 2003). For the range of N fertilisation simulated (0-200 kg N ha$^{-1}$ yr$^{-1}$), assuming a uniform spatial return of dung and urine to the soil can lead models to overpredict plant N uptake and thus grassland DMY and NY, as well as to overpredict ammonia emissions and underpredict nitrous oxide emissions and nitrate leaching (Hutchings et al., 2007).

### 4.3. Evaluation of grassland DM and N yields

This study is the first high-resolution assessment of current DMY and NY of French grasslands based on sound representation of environmental conditions, grassland types and management types and on a process-based representation of soil, plant and grazing animal processes.

Predictions of annual DMY and NY of French grassland lay in the same order of magnitude as those of previous simulation studies under European (specifically, French) conditions. In particular, predicted NY was consistent with that of Herrmann et al. (2005) for similar levels of N fertilisation and plant defoliation regimes. Similarly, the amount and regional distribution of predicted DMY in France appeared consistent with those of Huyghe et al., (2014) and Chang et al. (2015). Predicted herbage N content (13.1-31.6 g N $kg^{-1}$ DM) lay in the same range as crude protein (CP) contents of green grass forages according to INRA feed tables (INRA, 2018) (75-290 g CP $kg^{-1}$ DM, i.e. ca. 12.0-46.5 g N $kg^{-1}$ DM). Our predictions of French grassland DMY were also consistent with available regional observations, giving a realistic view of the diversity of French grassland productivity, especially in areas where they are intensively managed.

Our predictions of French grassland DMY and NY support the idea that French grasslands can produce large amounts of good-quality forage in regions with favourable conditions for grass growth. Such predictions could be locally compared to current annual DMY and NY to encourage farmers to further exploit the production potential of their grasslands and to gain in feeding and protein self-sufficiency. Our results also reinforce the view that grasslands can export large amounts of N through cutting and grazing, usually ca. 170 kg N $ha^{-1}$ $yr^{-1}$, which is more than other crops (Lassaletta et al., 2014). This N export, due to grasslands' permanent cover and ability to grow during drainage periods, may help decrease water pollution.

Particular situations may have limited the model's accuracy. PâturSTICS tended to overpredict DMY observed in semi-mountainous and mountainous regions, perhaps because it ignores effects of snow and frost, which stop and delay grass growth for several days, even when favourable environmental conditions return. It could also be due to ignoring effects of slope on water run-off and availability for plant growth. PâturSTICS also overpredicted DMY observed in lowlands with shallow soils and/or under dry summer conditions, probably due to how it represents effects of temperature and water stress on plant growth, as it tends to simulate soil water content accurately (Coucheney et al., 2015; Sándor et al. 2017). However, we compared PâturSTICS' predictions to observations that did not cover the entire soil, climate and management conditions that had been simulated.

This study benefited from existing grassland monitoring networks, which are essential for evaluating grassland models. However, it highlighted the lack of observations of herbage N or CP content of French grasslands, which made it impossible to compare predicted herbage N content or grassland NY to regional observations. This advocates for continuation and expansion of existing grassland monitoring networks.

### 4.4 Usefulness of the random forest metamodels

Process-based crop models are helpful and valuable tools for predicting crop yields, as they simulate crop functioning in response to environmental conditions and agricultural practices. Metamodelling is an alternative to process-based models that significantly reduces the requirement for input data (e.g. Luo et al., 2013; Qi et al., 2017). Metamodels are developed using a statistical approach usually based on multiple linear regressions but more recently based on machine-learning algorithms such as RF as a complementary or alternative approach. Like Jeong et al. (2016) found for crops, we found that RF was effective in predicting annual grassland DMY and NY predicted by PâturSTICS. This kind of data-mining method is especially useful for developing metamodels trained by extensive simulation scenarios. As a complementary approach to sensitivity analysis, RF can also identify the model inputs that explain predictions the most. The metamodels we developed from PâturSTICS predictions are promising as they provide immediate information from a smaller number of available input information about soil, climate and grassland management. As long as predictions are made within the boundaries of metamodels' validity domain, they can be used to make predictions under similar European climate and management conditions, and could be embedded in decision support tools dedicated to ruminant livestock systems.

## 5. Conclusions

This study provided a detailed view of French grassland dry matter and protein yield potentials, considering the diversity of climates, soils, grassland types and management types. In many French regions, grasslands can provide large amounts of herbage rich in protein. With the expected fluctuation and increase in input prices, taking better advantage of this potential could help farmers increase feed and protein self-sufficiency. Nevertheless, this study made certain assumptions due to the quality of input data and to limits of the current model. Future research is required to improve grassland models' representation of soil processes involved in dynamics of soil organic matter. Doing so will help address environmental issues related to the ability of grasslands to mitigate air pollution by greenhouse gases and water pollution by nitrates.

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Figure 1. Diagram of grassland simulations performed at the resolution of pedoclimatic units (PCU) in France.

Figure 2. Boundaries of A) administrative regions (pre-2016) and B) departments (current) of metropolitan France, showing elevation and the main mountain ranges. See Appendix C for meanings of region abbreviations and department number codes.

Figure 3. Mean annual simulated management of French grasslands over the 1984-2013 period: A) Number of cutting and grazing events per year (CGE), B) Grazed percentage of dry matter yield (GP), C) Grazing days (GD), D) Animal nitrogen (N) returns (AN), E) N fertilisation (FN), and F) Total N (TN) inputs from fertilisation, animal returns and biological fixation.

Figure 4. Comparison of mean predicted grassland dry matter yield (DMY) (boxplots) to mean observations (symbols) in four French regions: Auvergne (Auv), Bretagne (Bre), Franche-Comté (FrC) and Pays de la Loire (PdL). Solid lines in the boxplot are medians. Blue symbols are means. Whiskers represent 1.5 times the interquartile range. Predictions were aggregated at the pedoclimatic unit scale over the 1984-2013 period. Observations were estimated from herbage height measurements in grazed paddocks of several commercial farms for 6-11 years during the 1997-2014 period, each for specific conditions of observations.

Figure 5. A) Distribution, B) map and C) regional values of (left) mean predicted grassland dry matter yield (DMY) and (right) nitrogen yield (NY) over the 1984-2013 period associated with cutting and grazing activities. In (A), the solid vertical line refers to the median and the dashed vertical lines to the first and third quartiles. Corresponding values are indicated to the right of each vertical line. Whiskers represent 1.5 times the interquartile range. See Appendix C for meanings of region abbreviations.

Figure 6. Random forest (RF) model performance for test datasets assessed by comparing RF metamodel and PâturSTICS predictions of dry matter yield (DMY) and nitrogen yield (NY). Dashed lines are 1:1 lines, while solid blue lines are linear regressions between RF metamodelled and PâturSTICS predictions.

## Appendix A. Simulation of animal returns in grazed grasslands

In the research version of STICS called PâturSTICS, animal grazing is simulated as a cutting event. The amount of biomass removed by the cut (*msrecfou*, t DM ha$^{-1}$) is assumed to represent herbage dry matter intake (*DMI*, t DM.ha$^{-1}$) by the animals during their presence on the field. Animal faeces and urine are represented by an application of cattle liquid manure and urea, respectively, to the soil surface on the day of herbage defoliation. Some parameters describing animal faeces are assumed constant and are parametrised using data for animals receiving a grass-based diet: carbon (*Crespc*), mineral N (*Nminres*) and water contents (*eaures*) are set to 7.4%, 0.045% and 87% of faeces fresh matter (FM), respectively.

Animal faeces N ($N_{faeces}$, kg N ha$^{-1}$) is estimated as a linear function of animal *DMI* (t DM ha$^{-1}$) after Cutullic et al. (2013) (Eq. A.1), with a proportionality coefficient $\alpha$ of 7.53 g N kg$^{-1}$ DM for a grass-only diet and assuming that 20% of the faeces is returned elsewhere than on grazing areas (e.g. resting areas, milking parlour, housing, paths/roads) ($p_{faeces}$ = 0.2, dimensionless). Animal faeces ($Q_{faeces}$, t FM ha$^{-1}$) are calculated from $N_{faeces}$ assuming a mean N content in fresh faeces ($C_{N,faeces}$) of 2.87% (Eq. A.2).

$$N_{faeces} = \alpha\left(1 - p_{faeces}\right) DMI \tag{A.1}$$

$$Q_{faeces} = \frac{10}{\left((100 - eaures) \times C_{N,faeces}\right)} N_{faeces} \tag{A.2}$$

The faeces C:N ratio ($C{:}N_{faeces}$) is derived from plant N concentration ($C_{N,plant}$, kg N kg DM$^{-1}$) the day before herbage defoliation, as follows (Eq. A.3):

$$C{:}N_{faeces} = \beta - \gamma\, C_{N,plant} \tag{A.3}$$

where $\beta$ is the maximum C:N ratio in faeces of animals receiving a grass-based diet (32.201) and $\gamma$ is the slope of the linear regression line between $C{:}N_{faeces}$ and $C_{N,plant}$ (505.29)."

Decomposition of animal faeces uses existing STICS equations for simulating mineralisation of organic residues, with grazing-related parameter values (Table A.1). Urea return is represented as an application of mineral fertiliser, of which up to 15% can be volatilised (*voleng*), taken up by plants, nitrified, leached, denitrified and immobilised in soil organic matter.

Following the concepts of Faverdin and Vérité (1998), N in urine ($N_{urine}$, kg N ha$^{-1}$) is calculated as animal N intake minus N losses in milk and faeces. We assumed a daily N balance of 20.6 g N per animal (Spanghero and Kowalski, 1997) and that a dairy cow ingests a mean of 17 kg of herbage DM per day and produces 25 kg of milk per day containing 31 g of protein per kg of milk. Under these assumptions, the $\delta$ coefficient is set to 16.25 g N kg DM$^{-1}$, and $N_{urine}$ is derived from both plant N concentration ($C_{N,plant}$, kg N kg DM$^{-1}$) the day before cutting and from herbage *DMI* (t DM ha$^{-1}$) by animals, as follows (Eq. A.4 and A.5):

$$N_{urine} = \left(10\ C_{N,plant} - \delta\right)\left(1 - p_{faeces}\right) DMI \quad \text{(A.4)}$$

$$\text{With } N_{urine} = 0\ if\ C_{N,plant} \leq \frac{\delta}{10} \quad \text{(A.5)}$$

Animal stocking density and length of the grazing period are thus not model inputs but rather model outputs. The number of livestock unit (LSU) grazing days per ha of grassland per year can be calculated by dividing the total herbage removed by animals (*DMI*, t DM ha$^{-1}$) by daily animal intake (17 kg DM (LSU.grazing day)$^{-1}$).

Table A.1. Parameter values used to represent mineralisation of animal faeces during grazing

| Parameter | Definition | Unit | Value |
|---|---|---|---|
| akres | parameter of organic residue decomposition | $d^{-1}$ | 0.064 |
| bkres | potential rate of decomposition of organic residues | $g.g^{-1}$ | -0.552 |
| awb | parameter determining the C:N ratio of biomass during organic residue decomposition | dimensionless | 28.8 |
| bwb | parameter determining the C:N ratio of biomass during organic residue decomposition | $g.g^{-1}$ | -325.7 |
| cwb | minimum C:N ratio of the microbial biomass decomposing organic residues | $g.g^{-1}$ | 13.0 |
| ahres | parameter of organic residue humification | $g.g^{-1}$ | 36.5 |
| bhres | parameter of organic residue humification | $g.g^{-1}$ | 1354.7 |
| kbio | potential decay rate of microbial biomass decomposing organic residues | $d^{-1}$ | 0.00213 |
| yres | carbon assimilation yield by microbial biomass during crop residue decomposition | $g.g^{-1}$ | 0.62 |

## Appendix B. Description of grassland management types

Each of the 30 management types is defined by a sequence of cutting and/or grazing events (Figure B.1). Events are planned using degree days (°C), equal to the sum of the positive values of daily mean temperature minus a basal temperature. Triggering of each planned cutting and grazing event requires a minimum harvestable biomass above a target residual biomass, both defined by the model user (Table B.2). Each event can therefore be delayed and sometimes not occur depending on the availability of herbage biomass. Each event can be associated with an application of ammonium nitrate (kg N ha$^{-1}$). Grasslands can also receive additional winter mineral N application around 1 February. Figure B.1 shows amounts of N (kg N ha$^{-1}$) applied to grasslands for each management type.

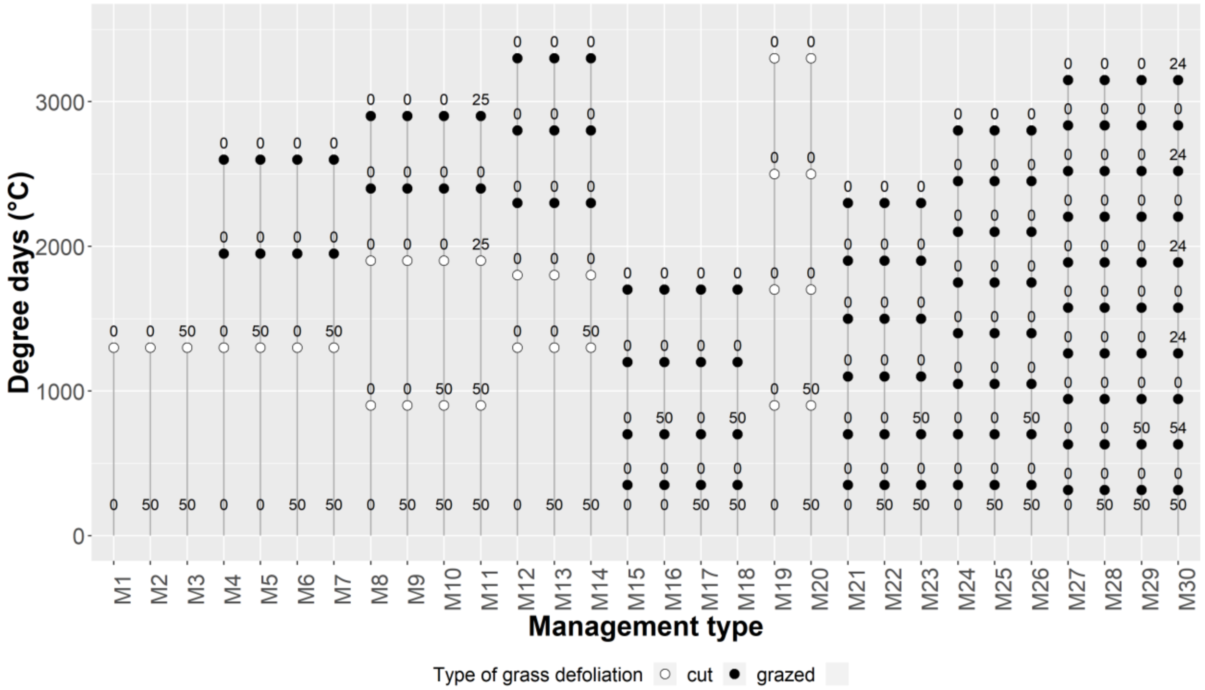


Figure B.1. Definition of planned cutting or grazing events and N fertiliser applications (kg N ha$^{-1}$) for each management type simulated

Table B.2. Conditions for triggering planned cutting and grazing events

| Event | Residual biomass (t DM ha$^{-1}$) | Residual leaf area index ($m^2$ $m^{-2}$) | Minimum harvestable biomass (t DM ha$^{-1}$) |
|---|---|---|---|
| Cutting | 2.0 | 0.5 | 1.0 |
| Grazing | 1.5 | 1.0 | 0.5 |

**Appendix C. Description of French metropolitan regions and departments**

Table C.1. Names and abbreviations of former (pre-2016) French regions, the names of the departments they contain and the departments' identification codes

| Former region name | Former region abbreviation | Department name | Department identification code |
|---|---|---|---|
| Alsace | Als | Bas-Rhin | 67 |
| | | Haut-Rhin | 68 |
| Aquitaine | Aqu | Dordogne | 24 |
| | | Gironde | 33 |
| | | Landes | 40 |
| | | Lot-et-Garonne | 47 |
| | | Pyrénées-Atlantiques | 64 |
| Auvergne | Auv | Allier | 03 |
| | | Cantal | 15 |
| | | Haute-Loire | 43 |
| | | Puy-de-Dôme | 63 |
| Basse-Normandie | BaN | Calvados | 14 |
| | | Manche | 50 |
| | | Orne | 61 |
| Bourgogne | Bou | Côte-d'Or | 21 |
| | | Nièvre | 58 |
| | | Saône-et-Loire | 71 |
| | | Yonne | 89 |
| Bretagne | Bre | Côtes d'Armor | 22 |
| | | Finistère | 29 |
| | | Ille-et-Vilaine | 35 |
| | | Morbihan | 56 |
| Centre | Cen | Cher | 18 |
| | | Eure-et-Loir | 28 |
| | | Indre | 36 |
| | | Indre-et-Loire | 37 |
| | | Loir-et-Cher | 41 |
| | | Loiret | 45 |
| Champagne-Ardennes | ChA | Ardennes | 08 |
| | | Aube | 10 |
| | | Haute-Marne | 52 |
| | | Marne | 51 |
| Corse | Co | Corse-du-sud | 2A |
| | | Haute-Corse | 2B |
| Franche-Comté | FrC | Doubs | 25 |
| | | Haute-Saône | 70 |
| | | Jura | 39 |
| | | Terr. de Belfort | 90 |
| Haute-Normandie | HaN | Eure | 27 |
| | | Seine-Maritime | 76 |
| Ile-de-France | IdF | Essonne | 91 |
| | | Paris | 75 |
| | | Seine-et-Marne | 77 |

| | | | |
|---|---|---|---|
| | | Hauts-de-Seine | 92 |
| | | Seine-Saint-Denis | 93 |
| | | Val-de-Marne | 94 |
| | | Val-D'Oise | 95 |
| | | Yvelines | 78 |
| Languedoc-Roussillon | LaR | Aude | 11 |
| | | Gard | 30 |
| | | Hérault | 34 |
| | | Lozère | 48 |
| | | Pyrénées-Orientales | 66 |
| Limousin | Lim | Corrèze | 19 |
| | | Creuse | 23 |
| | | Haute-Vienne | 87 |
| Lorraine | LoR | Meurthe-et-Moselle | 54 |
| | | Meuse | 55 |
| | | Moselle | 57 |
| | | Vosges | 88 |
| Midi-Pyrénées | MiP | Ariège | 09 |
| | | Aveyron | 12 |
| | | Gers | 32 |
| | | Haute-Garonne | 31 |
| | | Hautes-Pyrénées | 65 |
| | | Lot | 46 |
| | | Tarn | 81 |
| | | Tarn-et-Garonne | 82 |
| Nord-Pas-de-Calais | NPC | Nord | 59 |
| | | Pas-de-Calais | 62 |
| Pays de la Loire | PdL | Loire-Atlantique | 44 |
| | | Maine-et-Loire | 49 |
| | | Mayenne | 53 |
| | | Sarthe | 72 |
| | | Vendée | 85 |
| Picardie | Pic | Aisne | 02 |
| | | Oise | 60 |
| | | Somme | 80 |
| Poitou-Charentes | PoC | Charente | 16 |
| | | Charente-Maritime | 17 |
| | | Deux-Sèvres | 79 |
| | | Vienne | 86 |
| Provence-Alpes-Côte d'Azur | PACA | Alpes-de-Haute-Provence | 04 |
| | | Alpes-Maritimes | 06 |
| | | Bouches-du-Rhône | 13 |
| | | Hautes-Alpes | 05 |
| | | Var | 83 |
| | | Vaucluse | 84 |
| Rhône-Alpes | RhA | Ain | 01 |
| | | Ardèche | 07 |
| | | Drôme | 26 |
| | | Haute-Savoie | 74 |
| | | Isère | 38 |
| | | Loire | 42 |

| | |
|---|---|
| Rhône | 69 |
| Savoie | 73 |

Figure1
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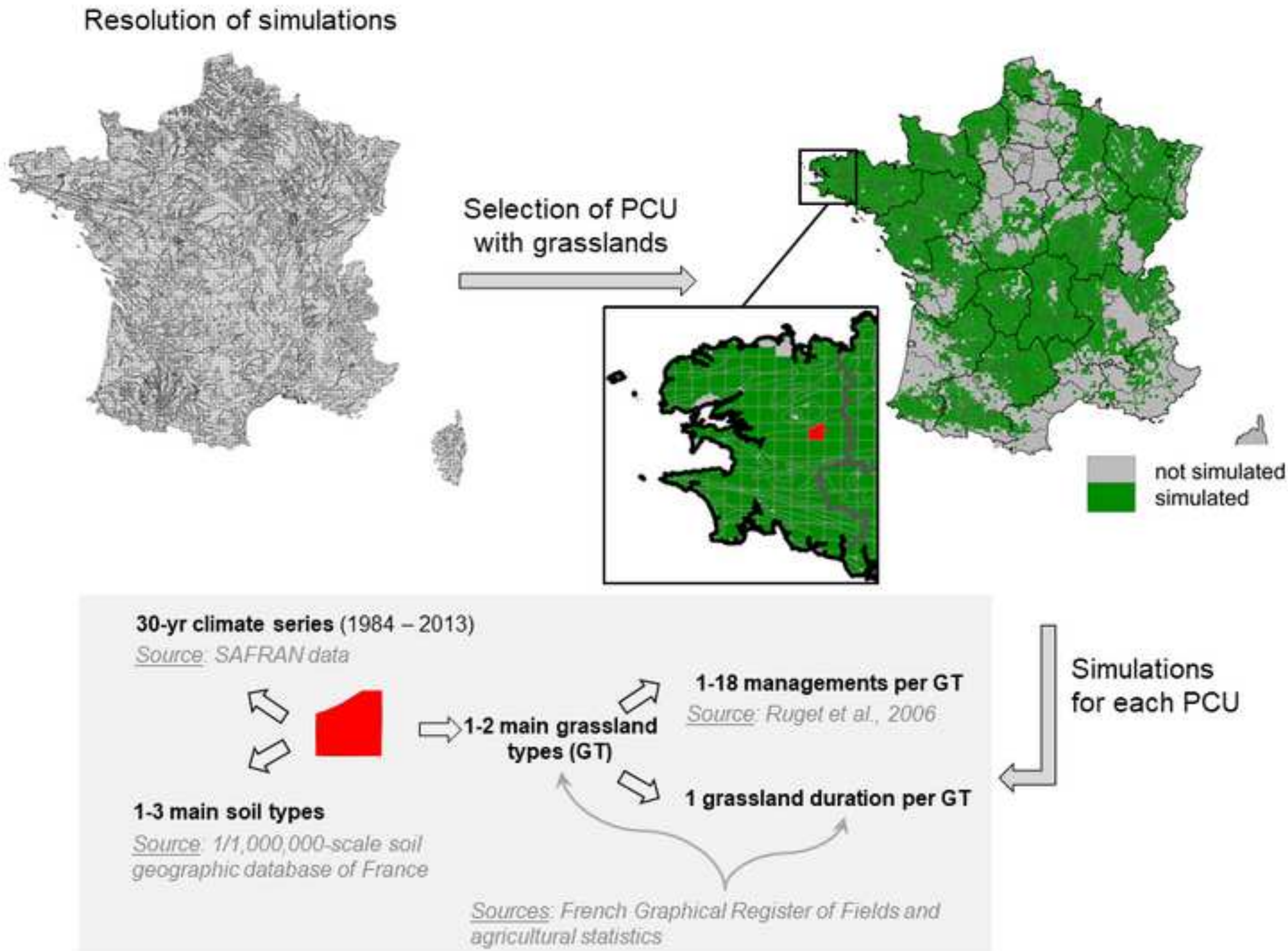

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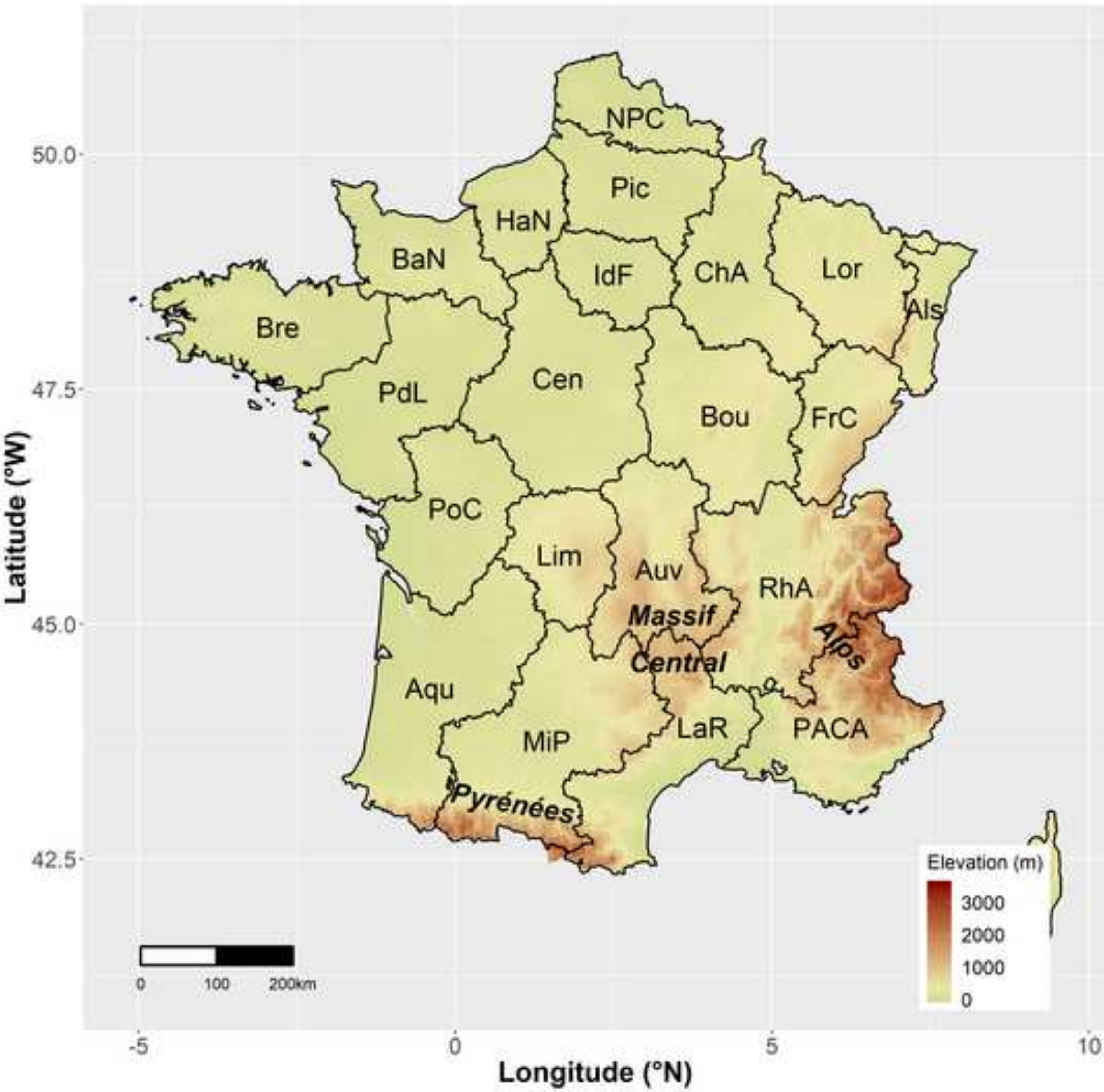

Figure2B

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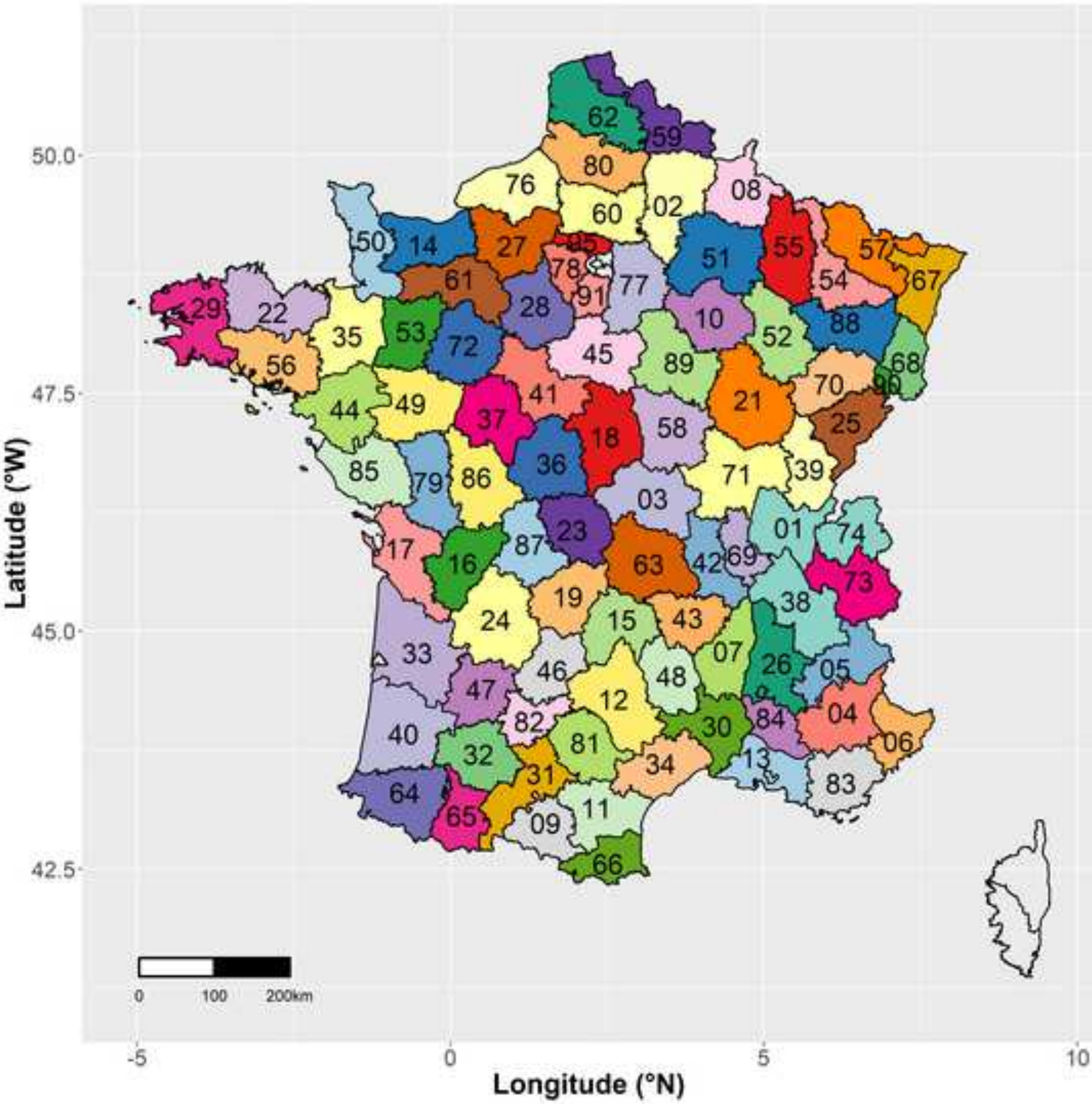

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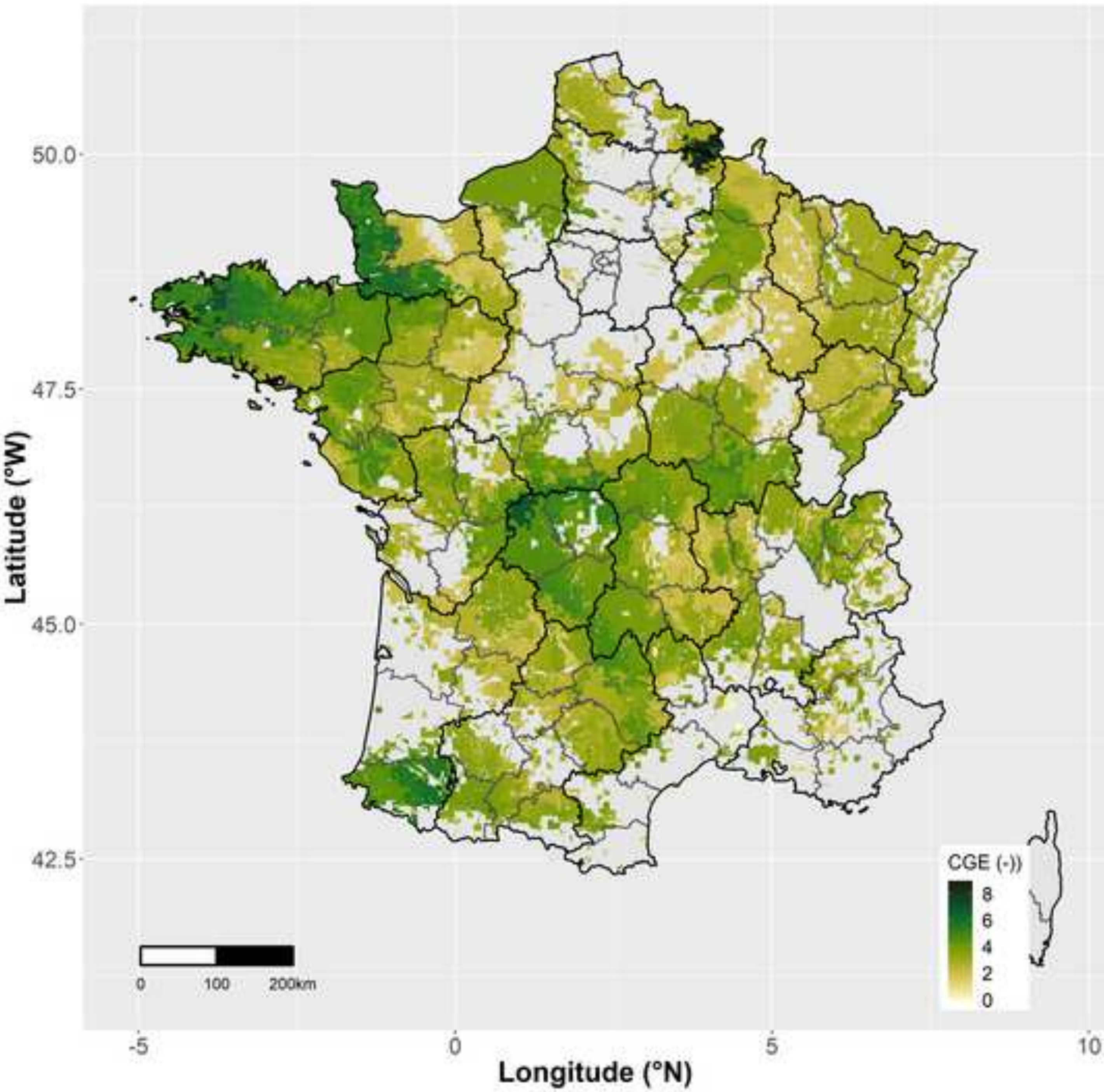

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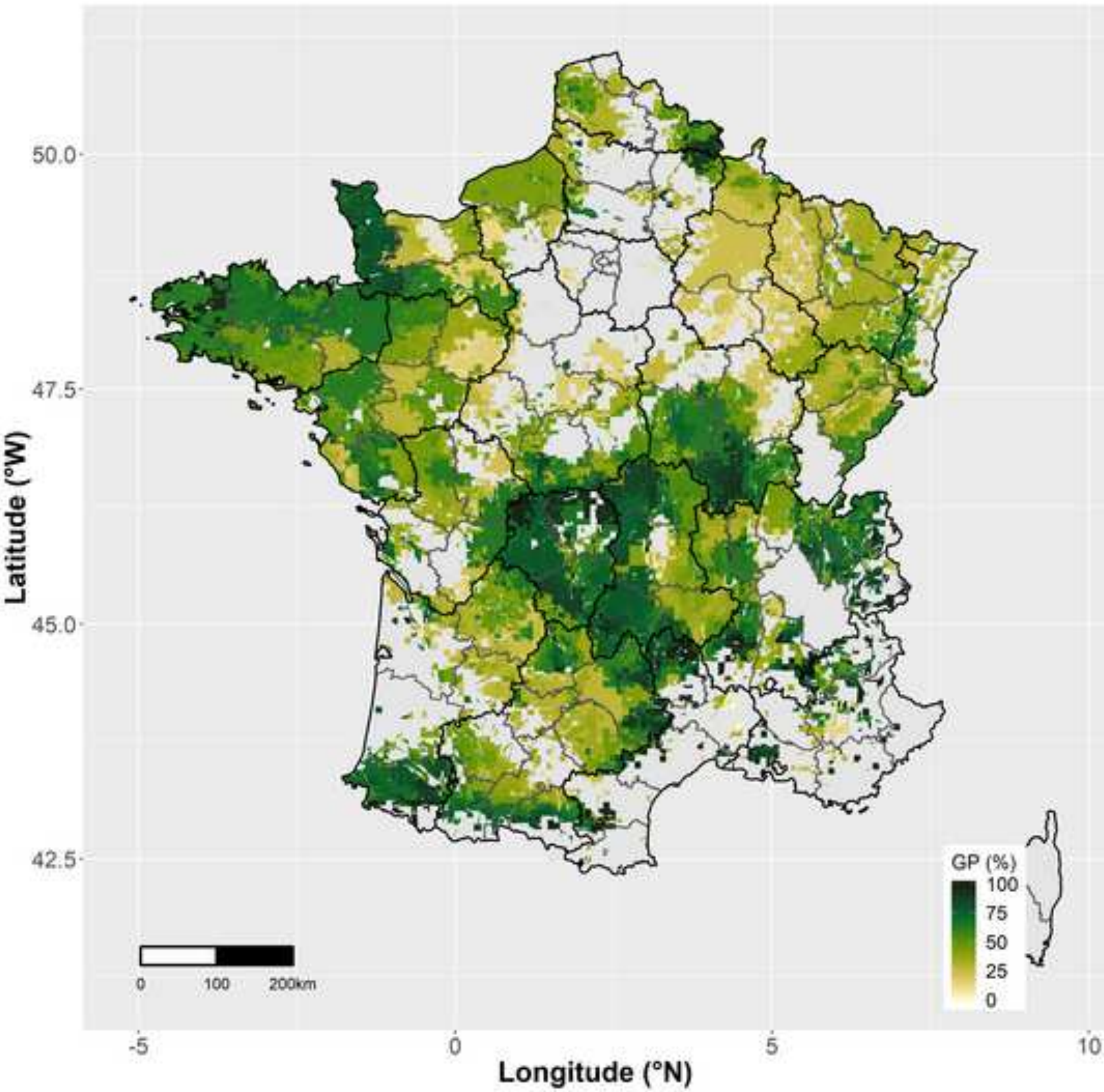




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Graux, A.-I., Resmond, R., Casellas, E., Delaby, L., Faverdin, P., Le Bas, C., Ripoche, D., Ruget, F., Therond, O., Vertes, F., Peyraud, J.-L. (2020). High-resolution assessment of French grassland dry matter and nitrogen yields. European Journal of Agronomy, 112, 125952. , DOI : 10.1016/j.eja.2019.125952

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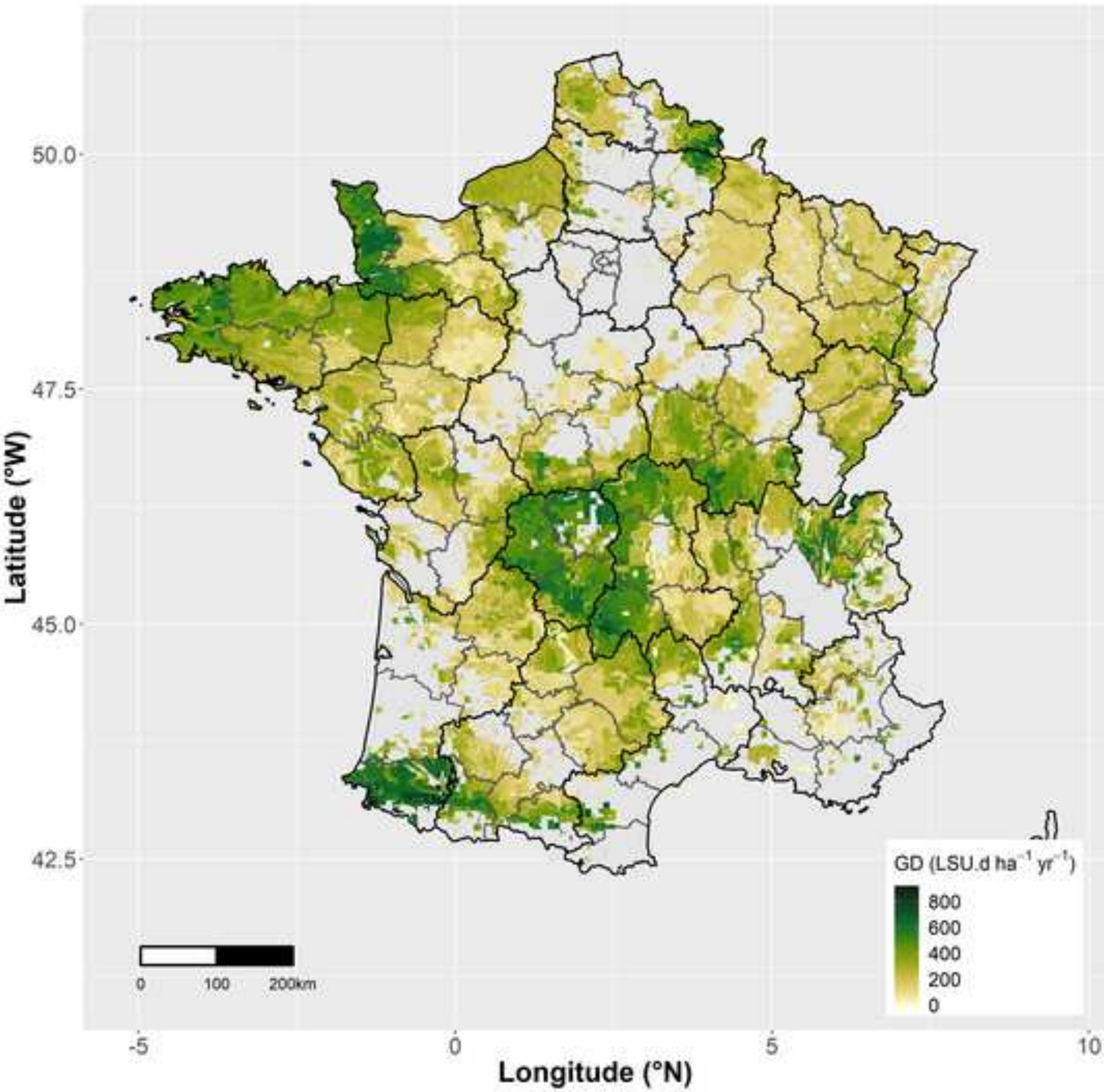

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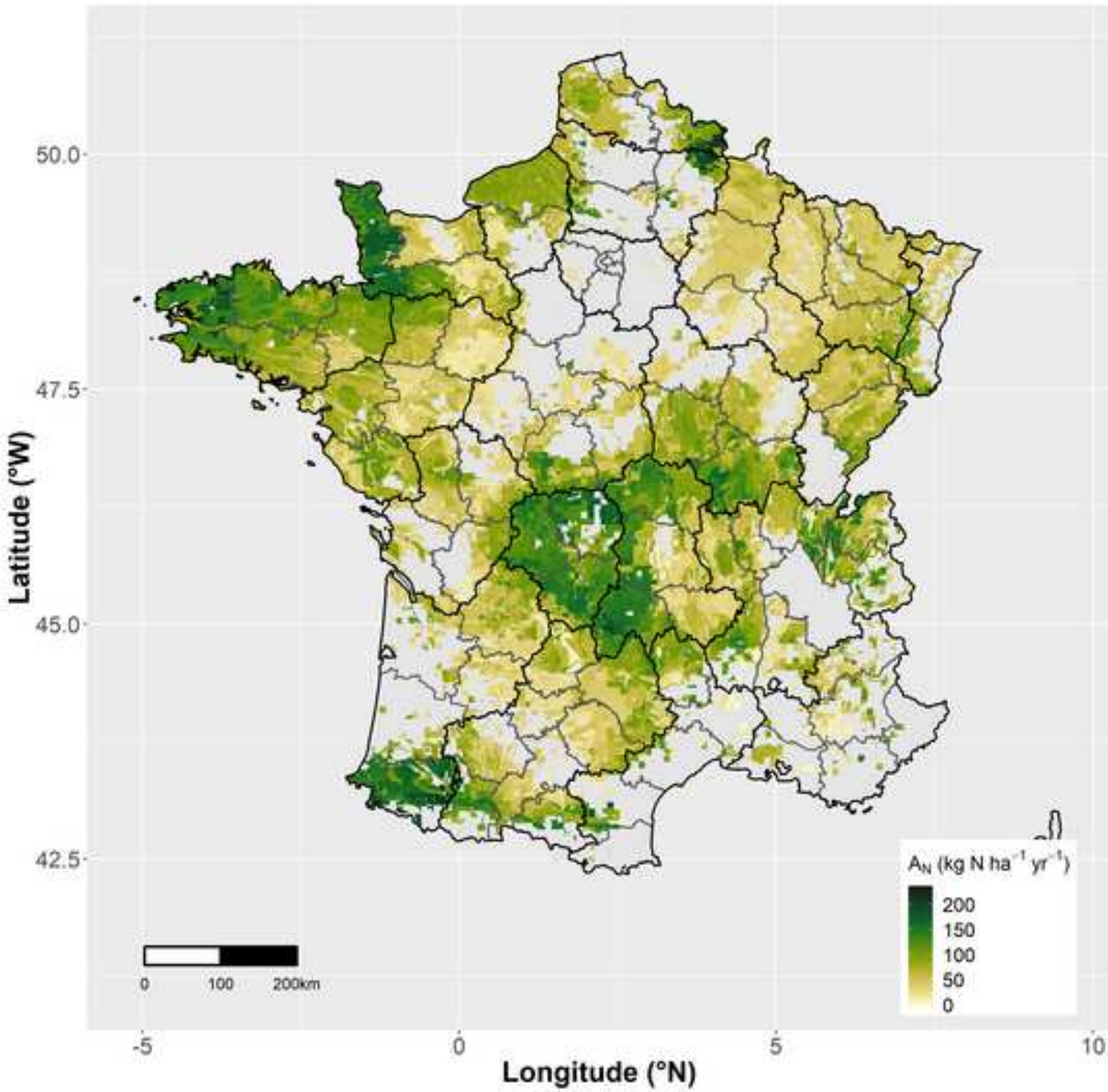

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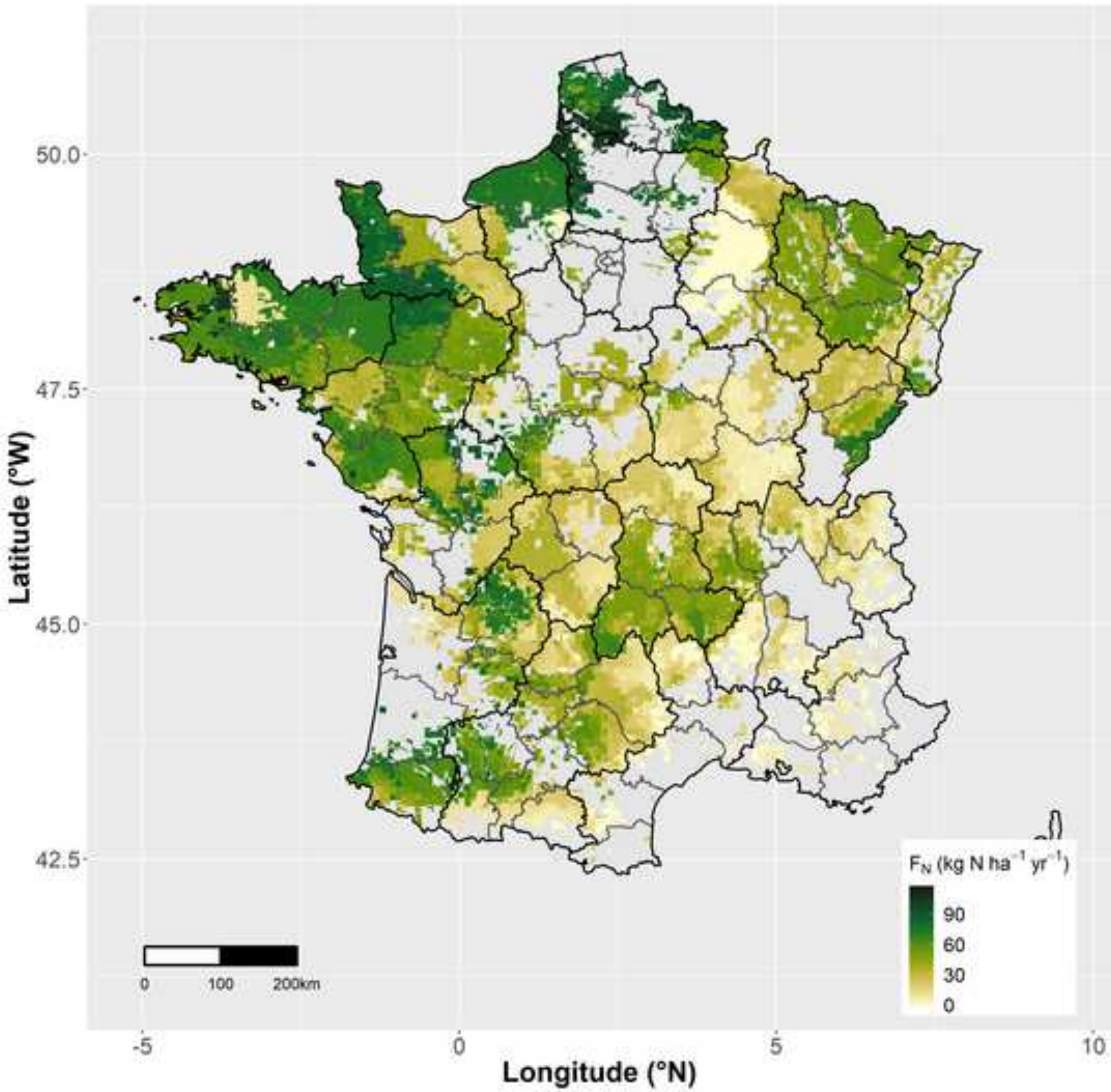

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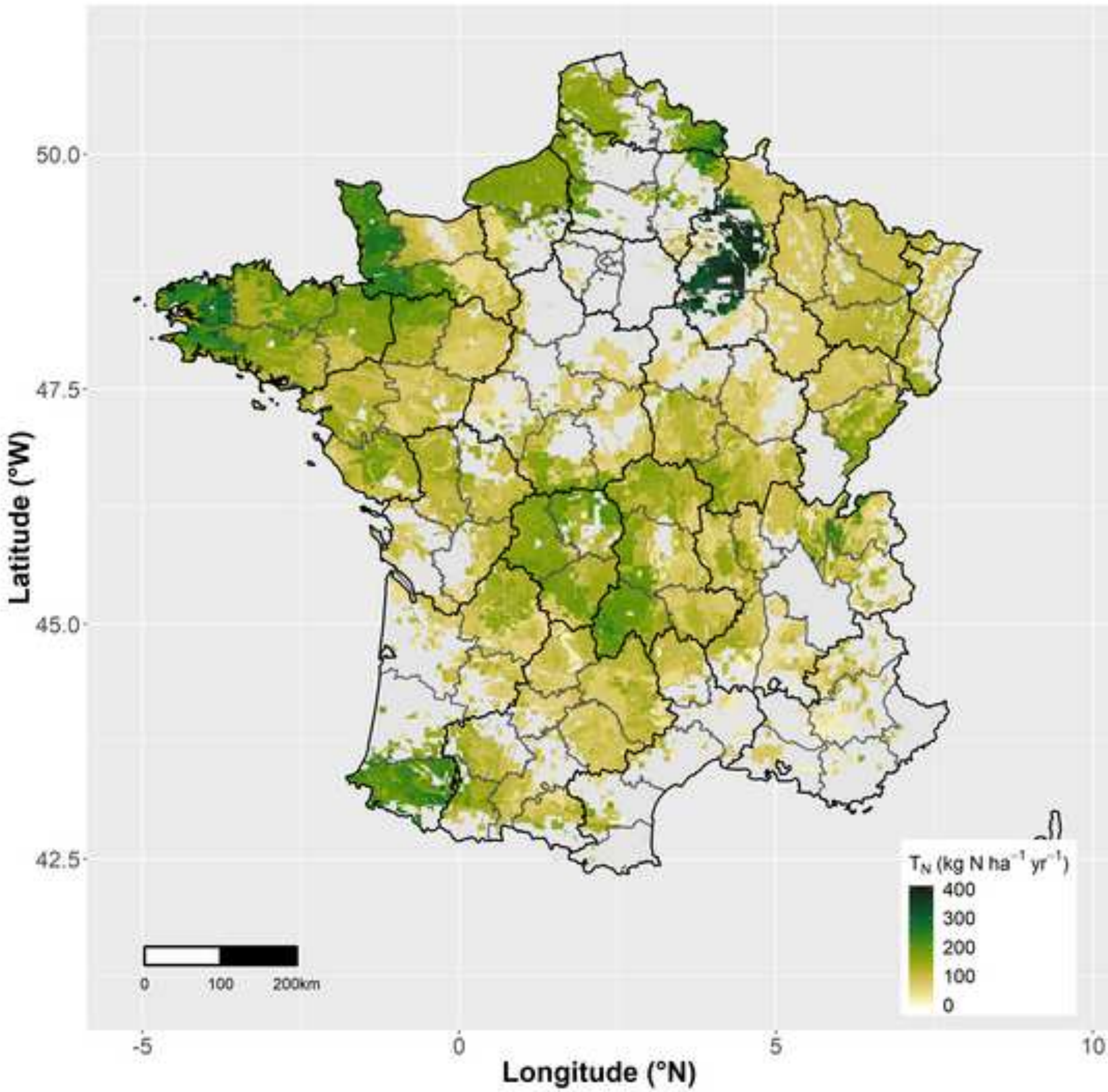

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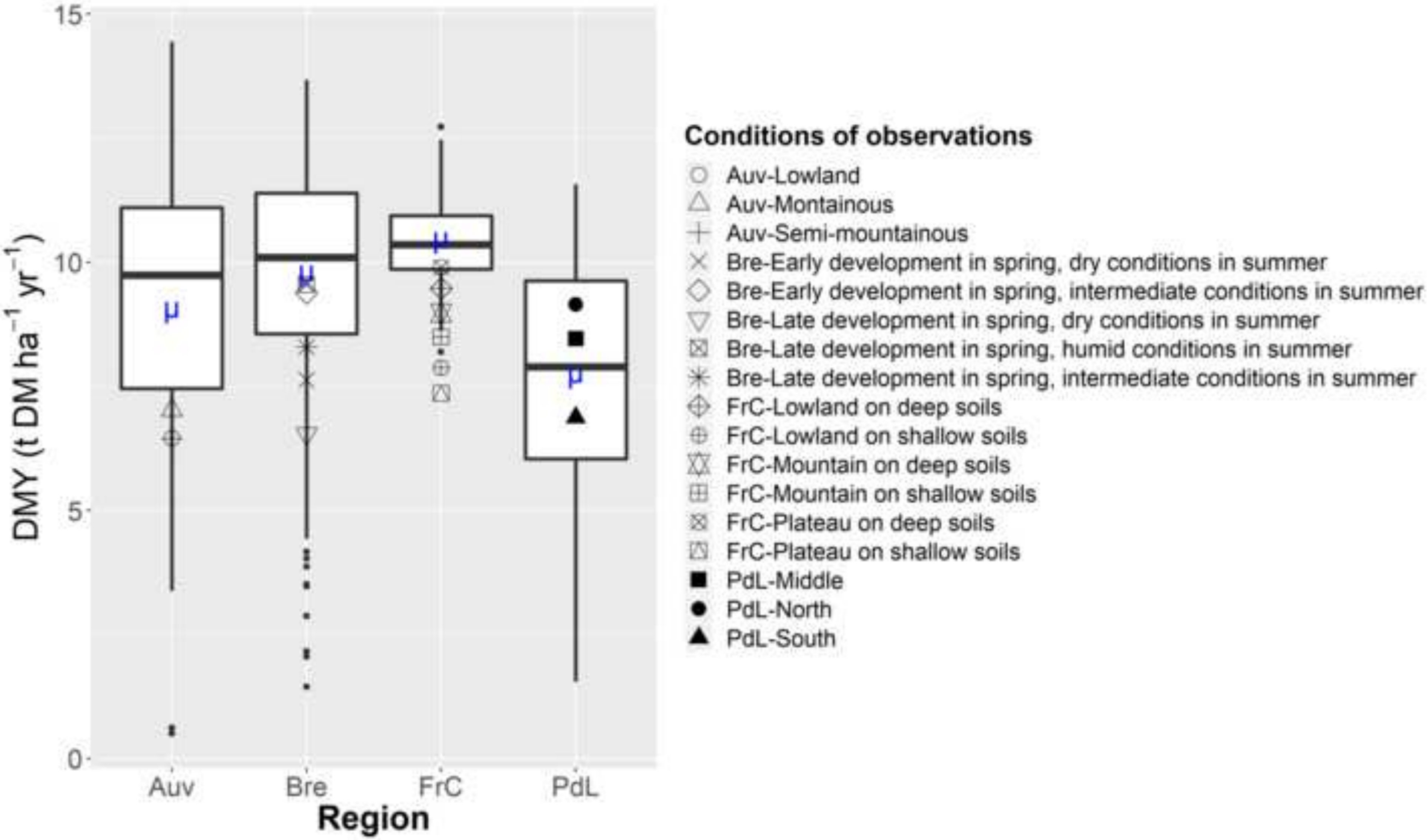

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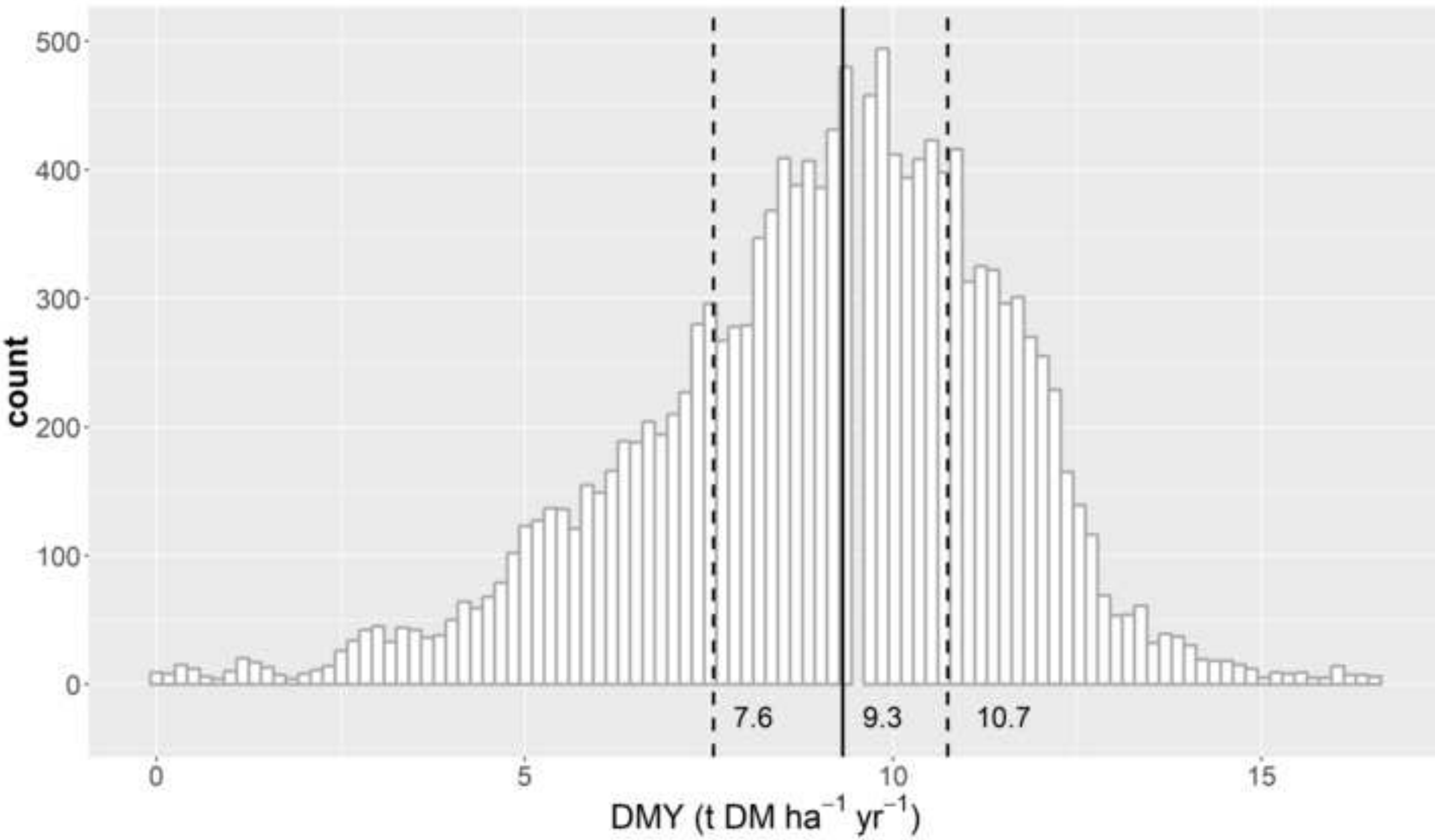

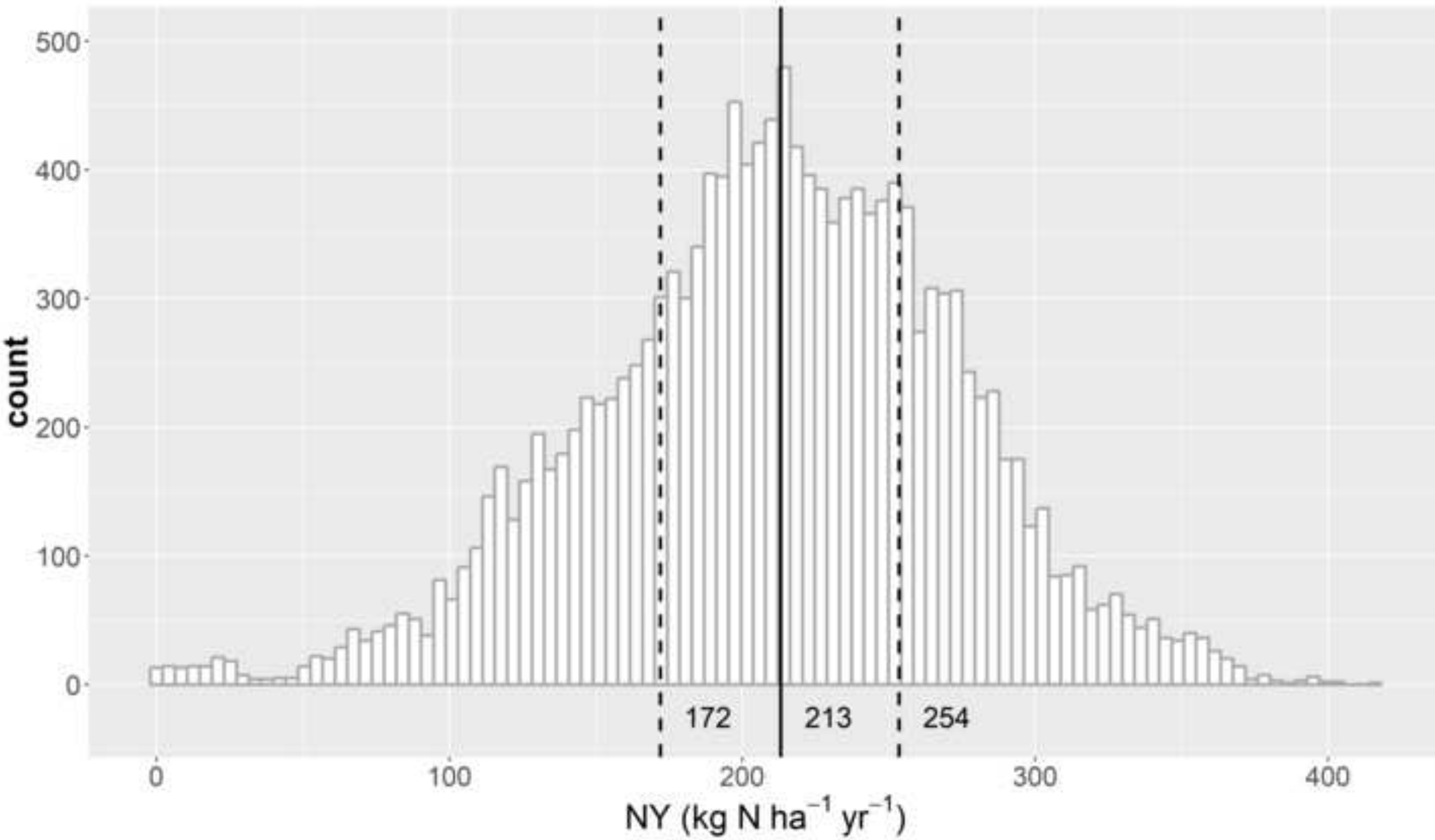
500
400
300
200
100
0
count
172
213
254
0
100
200
300
400
NY (kg N ha$^{-1}$ yr$^{-1}$)

Figure5B_left

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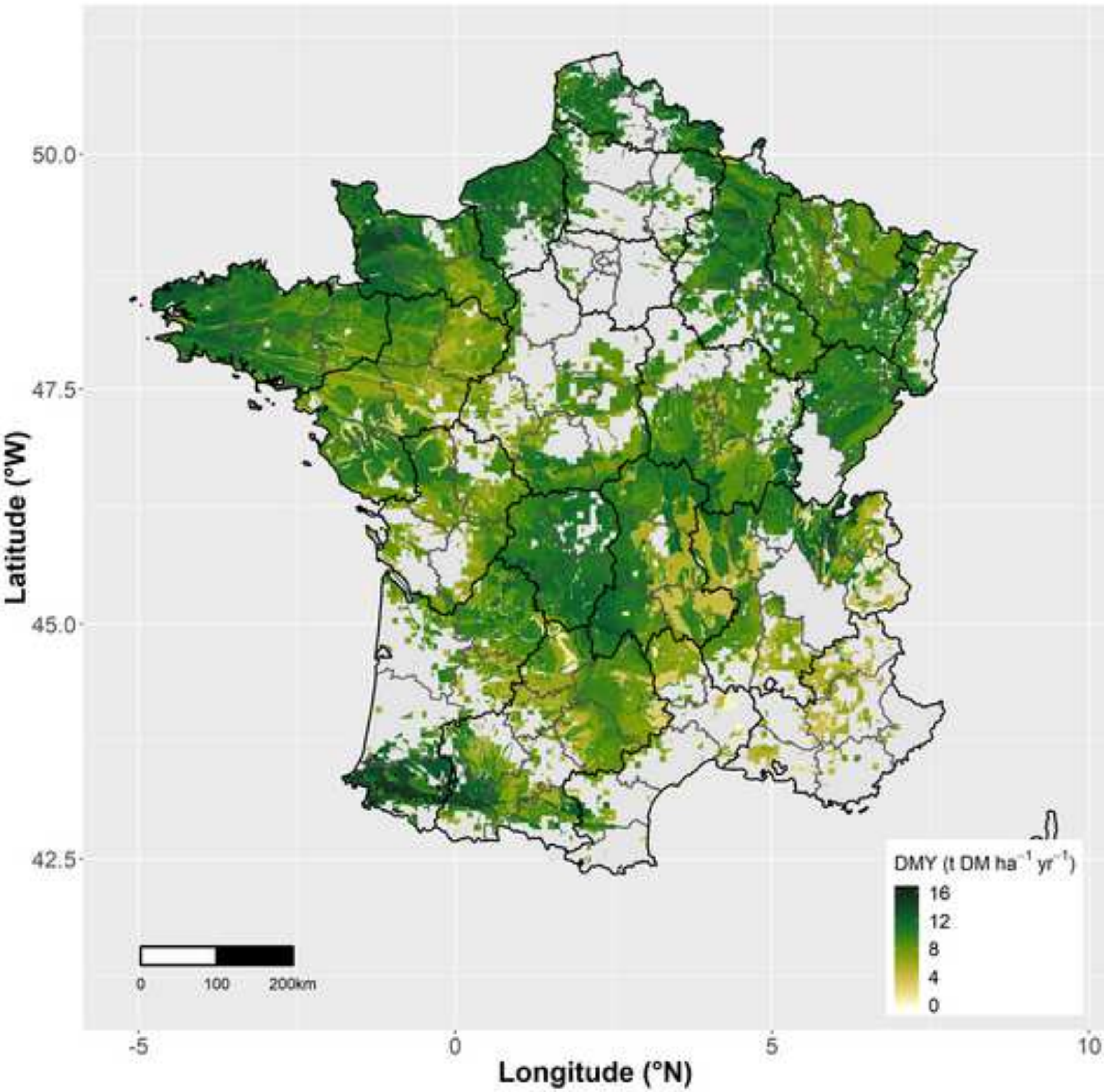

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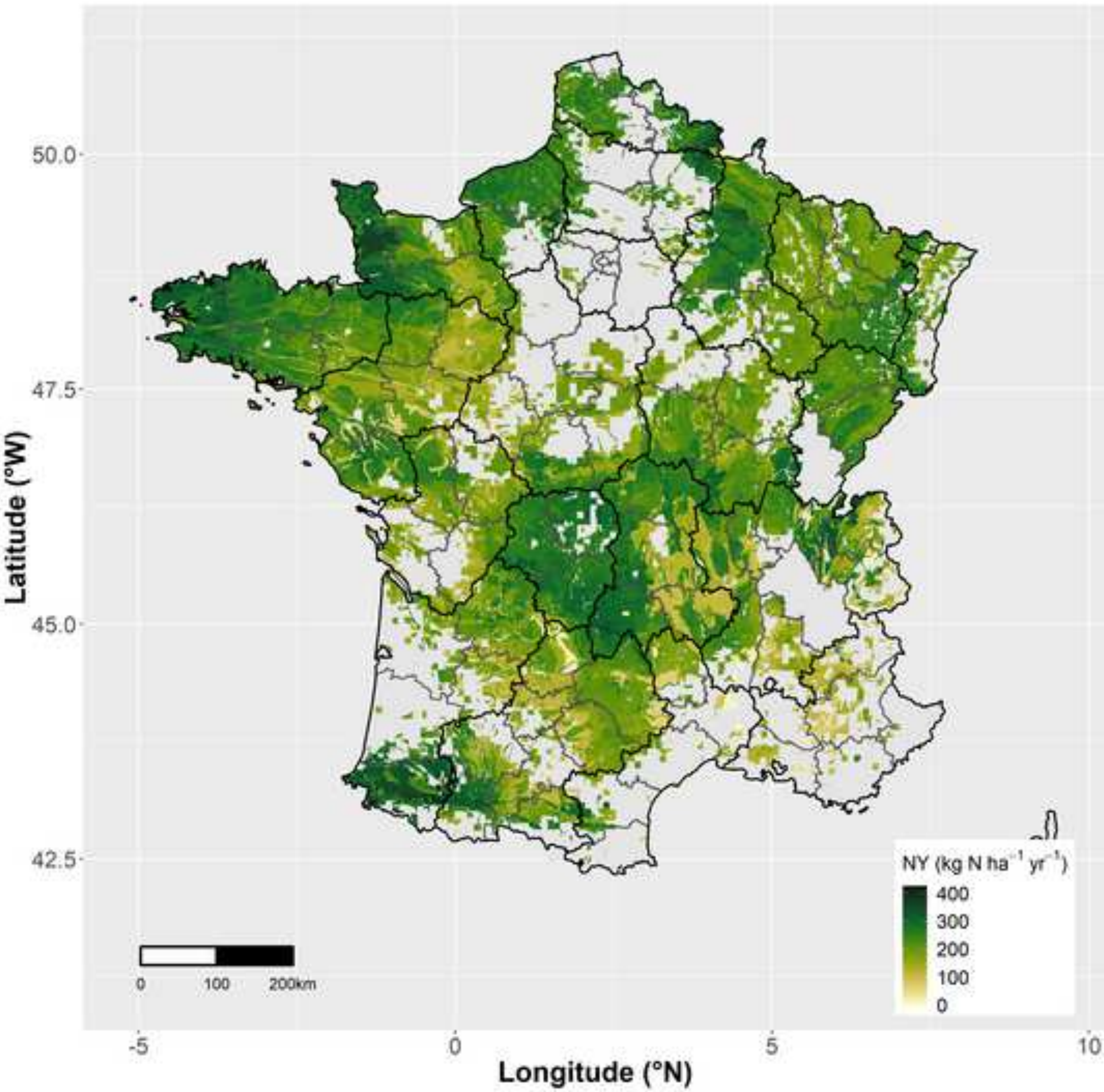

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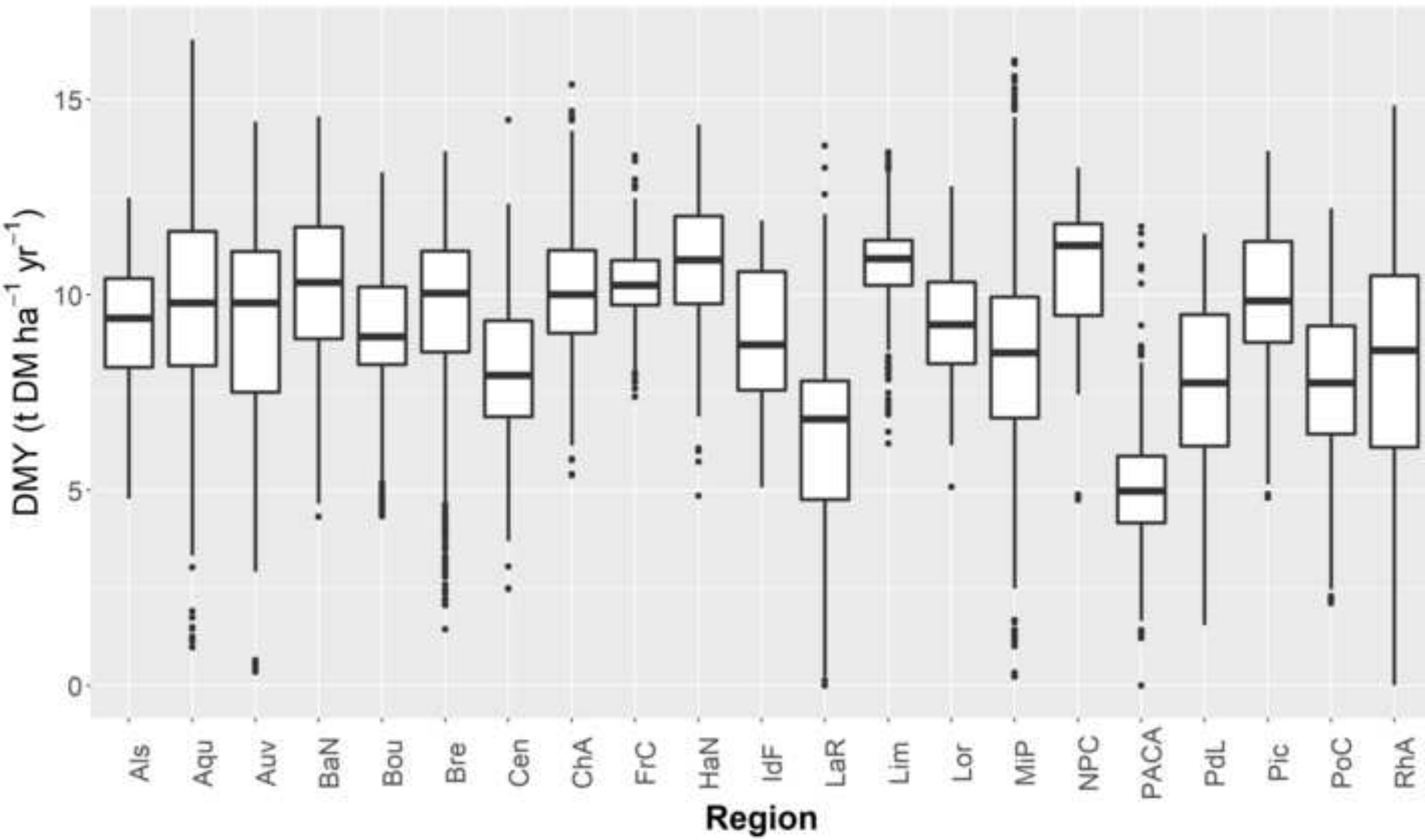

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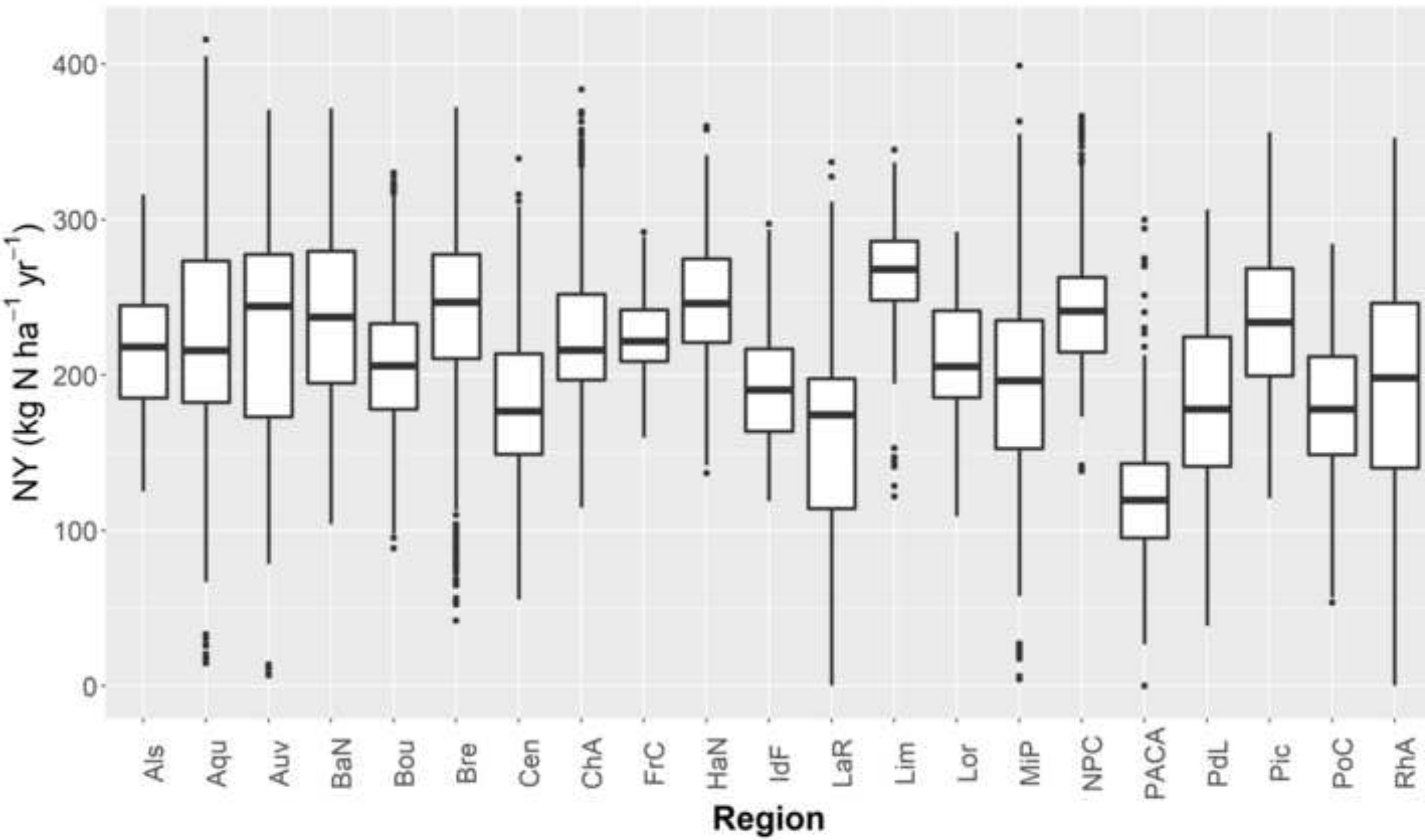

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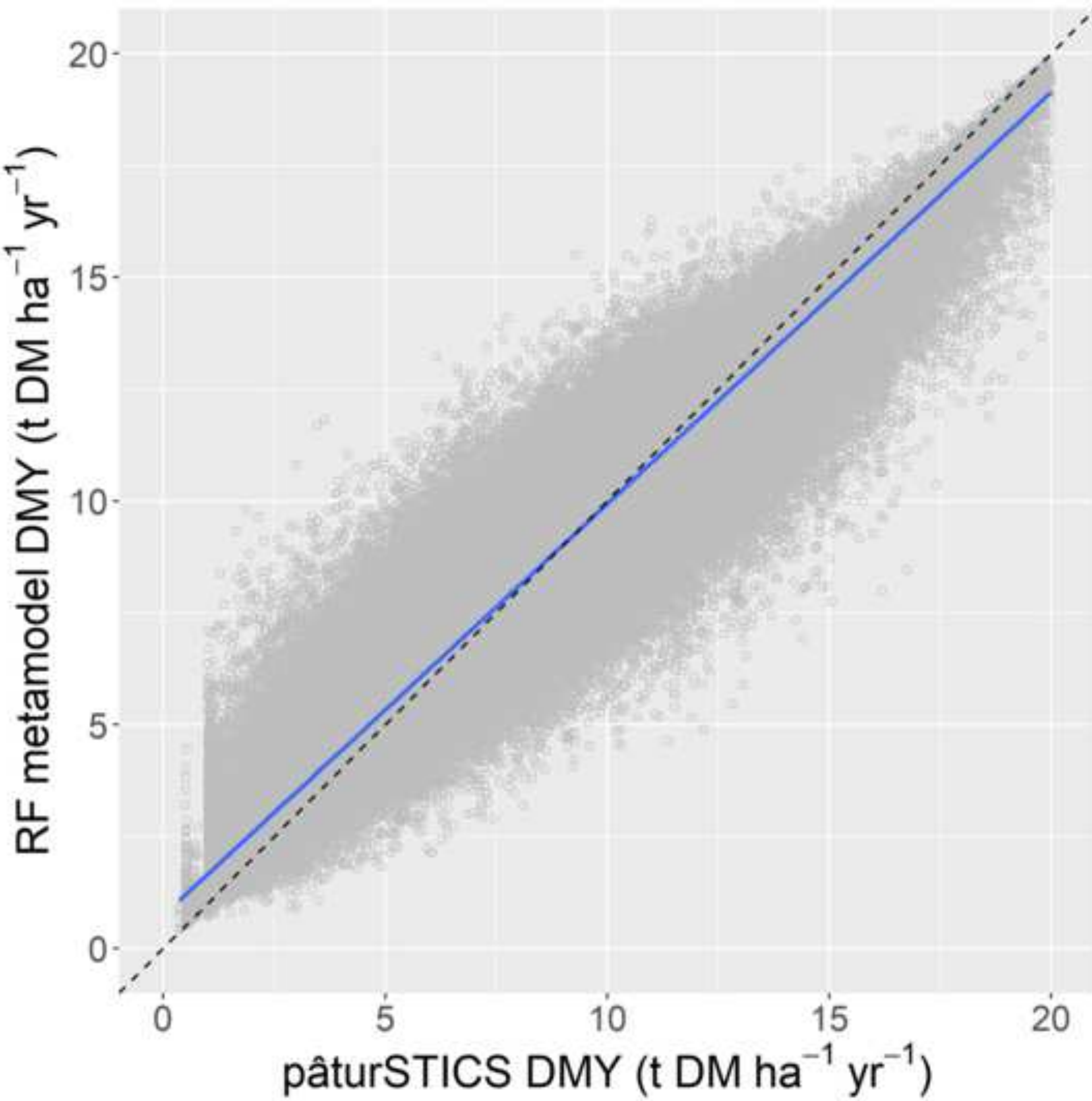

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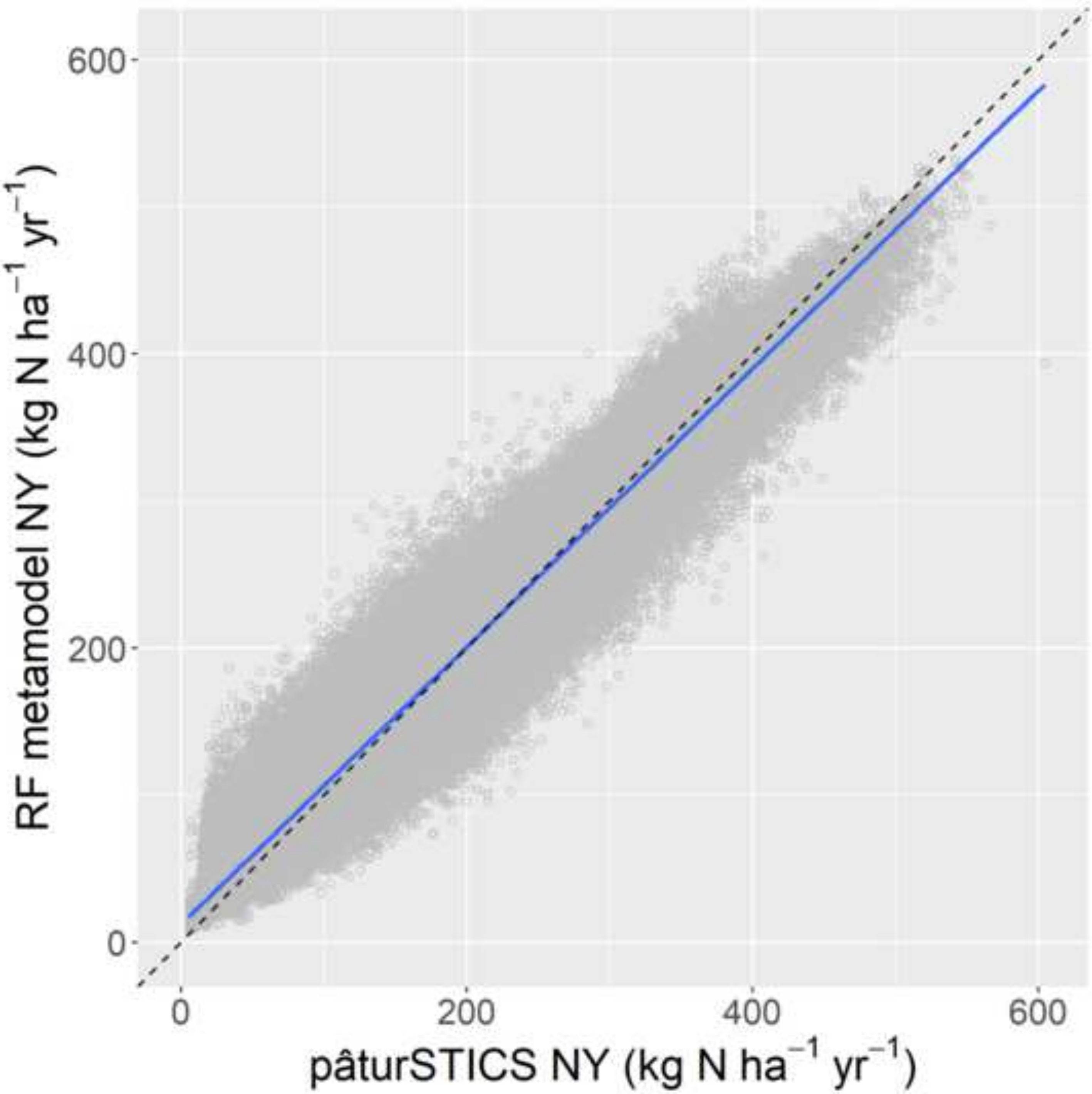

Table 1. Description of grassland typology simulated.

| Grassland type | Description | Percentage of legumes |
|---|---|---|
| Type 1 | permanent grasslands extensively managed (not fertilised) | 0 |
| Type 2 | temporary sown swards of pure legumes | 100 |
| Type 3 | temporary sown pure grass or grass-legume mixtures | 0 (pure swards) or 30 (mixtures) |
| Type 4 | permanent grasslands intensively managed | 0 |

Table2

Table 2. Mean and standard deviation (SD) of predicted DM yield (DMY, t DM $ha^{-1}$ $yr^{-1}$) and N yield (NY, kg N $ha^{-1}$ $yr^{-1}$) associated with cutting and grazing activities in grasslands in French departments simulated over the 1984-2013 period. n represents the number of pedoclimatic units simulated in a given department.

| | | | DMY | | NY | |
|---|---|---|---|---|---|---|
| Region | Department | n | Mean | SD | Mean | SD |
| Alsace | Bas-Rhin | 121 | 8.9 | 1.6 | 202 | 35 |
| | Haut-Rhin | 82 | 9.8 | 1.4 | 233 | 34 |
| Aquitaine | Dordogne | 360 | 9.1 | 1.9 | 202 | 48 |
| | Gironde | 130 | 8.6 | 1.6 | 187 | 38 |
| | Landes | 87 | 10.4 | 2.2 | 241 | 47 |
| | Lot-et-Garonne | 156 | 7.4 | 2.2 | 158 | 50 |
| | Pyrénées-Atlantiques | 292 | 12.8 | 2.6 | 306 | 62 |
| Auvergne | Allier | 285 | 9.8 | 2.0 | 238 | 49 |
| | Cantal | 191 | 10.4 | 2.3 | 269 | 55 |
| | Haute-Loire | 155 | 7.0 | 2.7 | 179 | 65 |
| | Puy-de-Dôme | 260 | 8.5 | 2.9 | 204 | 74 |
| Basse-Normandie | Calvados | 242 | 10.4 | 1.7 | 213 | 37 |
| | Manche | 278 | 11.5 | 1.8 | 300 | 44 |
| | Orne | 286 | 8.8 | 1.7 | 201 | 48 |
| Bourgogne | Côte-d'Or | 299 | 8.9 | 1.6 | 196 | 36 |
| | Nièvre | 244 | 9.0 | 1.8 | 208 | 43 |
| | Saône-et-Loire | 353 | 9.3 | 2.1 | 225 | 55 |
| | Yonne | 109 | 8.2 | 1.6 | 178 | 37 |
| Bretagne | Côtes d'Armor | 281 | 9.8 | 1.7 | 251 | 44 |
| | Finistère | 296 | 10.9 | 2.2 | 282 | 54 |
| | Ille-et-Vilaine | 310 | 8.6 | 2.1 | 209 | 53 |
| | Morbihan | 353 | 9.5 | 2.0 | 225 | 47 |
| Centre | Cher | 219 | 8.5 | 1.5 | 188 | 41 |
| | Eure-et-Loir | 41 | 7.8 | 1.6 | 168 | 35 |
| | Indre | 201 | 9.0 | 1.7 | 213 | 48 |
| | Indre-et-Loire | 157 | 6.8 | 1.3 | 150 | 31 |
| | Loir-et-Cher | 79 | 8.0 | 1.5 | 173 | 38 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Loiret | 58 | 7.9 | 1.5 | 169 | 37 |
| Champagne-Ardenne | Ardennes | 222 | 10.5 | 1.6 | 234 | 42 |
| | Aube | 140 | 9.6 | 1.6 | 213 | 48 |
| | Haute-Marne | 239 | 9.5 | 1.0 | 199 | 19 |
| | Marne | 227 | 10.6 | 1.7 | 253 | 50 |
| Franche-Comté | Doubs | 204 | 10.2 | 1.1 | 225 | 32 |
| | Haute-Saône | 204 | 10.3 | 0.9 | 223 | 20 |
| | Jura | 26 | 10.7 | 1.5 | 235 | 29 |
| | Terr. de Belfort | 25 | 10.3 | 0.9 | 231 | 27 |
| Haute-Normandie | Eure | 171 | 10.5 | 1.9 | 229 | 49 |
| | Seine-Maritime | 297 | 11.0 | 1.3 | 254 | 29 |
| Ile-de-France | Essonne | 1 | 11.9 | NA | 297 | NA |
| | Seine-et-Marne | 15 | 8.9 | 2.0 | 184 | 44 |
| | Val-D'Oise | 8 | 8.6 | 2.3 | 208 | 52 |
| | Yvelines | 12 | 9.3 | 0.8 | 193 | 21 |
| Languedoc-Rousillon | Aude | 66 | 7.6 | 2.7 | 182 | 70 |
| | Gard | 38 | 3.7 | 2.7 | 87 | 66 |
| | Hérault | 42 | 6.1 | 2.3 | 155 | 60 |
| | Lozère | 117 | 6.5 | 2.4 | 164 | 62 |
| | Pyrénées-Orientales | 12 | 7.9 | 3.1 | 202 | 81 |
| Limousin | Corrèze | 178 | 10.9 | 1.2 | 260 | 38 |
| | Creuse | 123 | 10.9 | 0.9 | 276 | 25 |
| | Haute-Vienne | 189 | 10.4 | 1.3 | 263 | 27 |
| Lorraine | Meurthe-et-Moselle | 202 | 9.2 | 1.6 | 213 | 39 |
| | Meuse | 255 | 9.3 | 1.2 | 195 | 26 |
| | Moselle | 227 | 9.0 | 1.5 | 211 | 36 |
| | Vosges | 210 | 10.1 | 1.1 | 234 | 32 |
| Midi-Pyrénées | Ariège | 121 | 9.1 | 2.5 | 204 | 64 |
| | Aveyron | 316 | 7.8 | 2.4 | 188 | 59 |
| | Gers | 239 | 8.7 | 2.1 | 204 | 51 |
| | Haute-Garonne | 190 | 8.5 | 2.3 | 193 | 58 |
| | Hautes-Pyrénées | 145 | 11.8 | 2.5 | 279 | 53 |
| | Lot | 192 | 7.6 | 3.0 | 171 | 74 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Tarn | 182 | 7.5 | 1.7 | 168 | 41 |
| | Tarn-et-Garonne | 108 | 7.4 | 1.8 | 162 | 44 |
| Nord-Pas-de-Calais | Nord | 186 | 11.1 | 1.6 | 262 | 48 |
| | Pas-de-Calais | 231 | 10.4 | 1.3 | 227 | 27 |
| Pays de la Loire | Loire-Atlantique | 308 | 7.7 | 2.3 | 190 | 58 |
| | Maine-et-Loire | 310 | 6.8 | 2.3 | 157 | 52 |
| | Mayenne | 260 | 8.9 | 1.6 | 212 | 42 |
| | Sarthe | 266 | 6.9 | 1.3 | 149 | 29 |
| | Vendée | 259 | 7.9 | 2.9 | 195 | 73 |
| Picardie | Aisne | 167 | 9.9 | 2.1 | 243 | 62 |
| | Oise | 98 | 9.7 | 1.8 | 235 | 45 |
| | Somme | 113 | 9.9 | 1.2 | 221 | 28 |
| Poitou-Charentes | Charente | 165 | 8.0 | 1.6 | 183 | 42 |
| | Charente-Maritime | 143 | 7.3 | 1.5 | 166 | 36 |
| | Deux-Sèvres | 210 | 7.8 | 2.3 | 185 | 55 |
| | Vienne | 215 | 7.7 | 1.6 | 181 | 38 |
| Provence-Alpes-Côte d'Azur | Alpes-de-Haute-Provence | 81 | 5.3 | 1.4 | 123 | 41 |
| | Alpes-Maritimes | 3 | 6.3 | 0.8 | 173 | 35 |
| | Bouches-du-Rhône | 42 | 4.7 | 1.4 | 118 | 37 |
| | Hautes-Alpes | 102 | 5.3 | 2.1 | 128 | 54 |
| | Var | 18 | 4.9 | 2.2 | 113 | 60 |
| | Vaucluse | 10 | 5.2 | 1.3 | 118 | 36 |
| Rhône-Alpes | Ain | 215 | 10.0 | 2.6 | 228 | 66 |
| | Ardèche | 126 | 7.6 | 2.7 | 185 | 73 |
| | Drôme | 129 | 6.6 | 1.8 | 147 | 42 |
| | Haute-Savoie | 121 | 9.1 | 3.3 | 217 | 82 |
| | Isère | 12 | 8.3 | 3.7 | 192 | 91 |
| | Loire | 153 | 8.3 | 3.0 | 198 | 69 |
| | Rhône | 79 | 8.1 | 2.8 | 185 | 60 |
| | Savoie | 142 | 6.9 | 3.7 | 166 | 88 |

Table 3. Predictors used for random forest regression models and their ranges. Ranks correspond to a variable importance measure determined by random forest models for each dataset.

| | Variable | Abbreviation | Unit | Range | | Rank of importance | |
|---|---|---|---|---|---|---|---|
| | | | | Min | Max | DMY | NY |
| Climate | Mean annual temperature | T | °C | -2.5 | 17.0 | 3 | 3 |
| | Annual global radiation | $R_g$ | MJ $m^{-2}$ $yr^{-1}$ | 2849 | 6531 | 2 | 1 |
| | Annual precipitation | P | mm $yr^{-1}$ | 271 | 3315 | 5 | 6 |
| Soil | Soil organic N content in the topsoil | $N_{org}$ | % dry soil | 0.068 | 0.40 | 7 | 4 |
| | Soil water holding capacity | WHC | mm | 7 | 172 | 4 | 7 |
| Grassland | Percentage of legumes | Leg | % | 0 | 100 | 10 | 10 |
| | Grassland age | Age | yr | 2 | 5 | 1 | 2 |
| Management | Annual nitrogen fertiliser application | $F_N$ | kg N $ha^{-1}$ $yr^{-1}$ | 0 | 200 | 6 | 5 |
| | Grazing days | GD | (LSU days) $ha^{-1}$ $yr^{-1}$ | 0 | 1176 | 8 | 8 |
| | Number of cutting events | CE | Dimensionless | 0 | 4 | 9 | 9 |

Table 4. Evaluation statistics (root mean square error (RMSE), relative RMSE (RRMSE), and Nash-Sutcliffe model efficiency (EF)) of random forest model performance of predicted dry matter yield (DMY) and nitrogen yield (NY) on test datasets.

| Variable | Unit | RMSE | RRMSE | EF |
|---|---|---|---|---|
| DMY | t DM $ha^{-1}$ $yr^{-1}$ | 0.77 | 21.8% | 0.95 |
| NY | kg N $ha^{-1}$ $yr^{-1}$ | 16.5 | 18.3% | 0.97 |