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Prediction of topsoil texture for Region Centre (France) applying model ensemble methods

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ABSTRACT

With the rapid development of digital soil mapping it is not unusual to find several maps for the same soil property in an area of interest. We applied two standard methods of model averaging for combining two regional maps and a European map of topsoil texture in agricultural land for the Region Centre (France). The two methods for model ensemble were the Granger-Ramanathan (G-R) and the Bates-Granger (B-G). A calibration dataset was used for fitting the coefficients of the G-R model, and for calculating a global variance: prediction error ratio which was then used to re-scale the weights of the B-G model. The prediction performance of the three primary maps and the two ensemble maps was compared with an independent validation dataset consisting on 100 observations from the French soil monitoring network. The prediction accuracy of the ensemble models improved only for clay in comparison to the primary maps ($\Delta R^2 = 0.02$–0.06, $\Delta RMSE = -1.56$–-4.97 g kg^{-1}). Overall, the G-R models obtained smaller RMSE and greater bias than B-G, and G-R estimated better the prediction uncertainty. The dissimilarities between the methods for estimating the prediction variance and non-optimal estimated uncertainties were important limitations for the B-G models despite applying a global correction factor for the prediction variances. The results suggested that both the calibration and validation datasets should represent the patterns of spatial variation and range of values of the soil property for the prediction space. Nonetheless, model ensemble methods proved to be useful for merging maps with different types of datasets, spatial coverage, and methodological approaches.

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1. Introduction

The expansion of digital soil mapping (Grunwald et al., 2011) and the increasing interest on data sharing often result in the availability of multiple digital soil maps for the same area, each of them with different qualities (e.g., resolution, extent, modeling approach, uncertainty). Initiatives like SoilGrids (Hengl et al., 2014) and *GlobalSoilMap* (GSM) (Arrouays et al., 2014) pursue producing soil maps at global extent and making them freely available in the Internet. Other organizations create maps at continental (Panagos et al., 2012), national (Poggio et al., 2010; Odgers et al., 2012; Adhikari et al., 2013; Viscarra Rossel et al., 2015; Mulder et al., 2016), or regional extent (Padarian et al., 2012; Vaysse and Lagacherie, 2015). However, potential end-users may have difficulties choosing between the available digital soil maps for an area of interest, especially when each map has specific advantages and disadvantages. At the same time, modelers and land-use managers request predictions of soil properties with the highest possible accuracy. In this context, it is worthy investigating the applicability of methods for combining existing predictions and their improvement of prediction accuracy.

Model ensemble or model averaging has been proposed for improving prediction accuracy when raster maps of soil properties are readily available (Malone et al., 2014), and can be especially useful when these maps have been produced at different scales. The premise is that the new model will be at least as good as any of the individual models, using all available information efficiently (Diks and Vrugt, 2010). In some cases model averaging may be the most effective way of combining soil datasets requiring different treatment of the data due to their spatial support (e.g., georeferenced soil profiles vs. polygon based information) (Heuvelink and Bierkens, 1992; Malone et al., 2014), some

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methods are relatively easy to implement, plus it provides a single map to end users. It allows putting in common the efforts of researchers that used different approaches to answer the same question, enhancing collaboration between regional, national, and international teams. Model averaging techniques are widely used for hydrological (Diks and Vrugt, 2010; Najafi et al., 2011) and climate modeling (Benestad, 2002; Min and Hense, 2006; Reichler and Kim, 2008), yet examples for mapping soil properties are not as numerous (Heuvelink and Bierkens, 1992; Malone et al., 2014; Padarian et al., 2014; Clifford and Guo, 2015). Heuvelink and Bierkens (1992) applied the Bates-Granger method (1969) for combining information from a soil map with point observations, and found that the combined map had greater accuracy than either of the primary maps alone (i.e., soil map and kriging of point observations). Malone et al. (2014) compared several averaging methods for merging a regression kriging map and disaggregated soil maps and, albeit modestly, improved the prediction accuracy for all studied depths. Clifford and Guo (2015) applied adaptive gating for averaging soil property rasters, which performed better than the Bates-Granger and regression based approaches.

France has several active programs for soil research and monitoring integrated in the French Group of Scientific Interest in Soil (GIS Sol). In addition there is a large record of soil data from all the soil surveys and monitoring projects carried by the French National Institute of Agricultural Research (INRA) since the 1950s (Saby et al., 2014). The aim of GIS Sol is to characterize the spatial distribution of soil properties and soil types and to monitor the status of French soils. As a result, there are multiple products at national and regional scale, traditional soil maps (Arrouays et al., 2004) and digital soil maps for different soil properties (Vaysse and Lagacherie, 2015; Lacoste et al., 2016; Mulder et al., 2016), including soil texture (Ciampalini et al., 2014, Román Dobarco et al.,2016). However, soil data from different programs are not always used together for digital soil mapping. In addition, the European Commission implemented a topsoil sampling survey in parallel to the Land Use and Cover Area frame Statistical survey (LUCAS), and produced digital soil maps of topsoil physical properties for Europe (Ballabio et al., 2016).

Soil texture is a master soil property that influences important physical, chemical and ecological processes like water infiltration and supply (Mills et al., 2006), biogeochemical cycling (Austin et al., 2004), retention of pollutants (Jacobson et al., 2005; Li et al., 2015), and soil biodiversity (Silva et al., 2012). Multitude of models and pedotransfer functions include texture data as input to predict other soil properties and related processes [soil water capacity (Reynolds et al., 2000), soil organic carbon and nutrients (Meersmans et al., 2008; Glendining et al., 2011), risk of pollutants leaching to groundwater (Bah et al., 2011), crop production (Gijsman et al., 2007)]. Therefore, accurate soil texture maps are required for reducing the uncertainty associated to these models and providing more precise and accurate spatial predictions (Kværnø et al., 2007; Guillod et al., 2013), which would especially benefit farmers and land managers working on environmental protection, crop productivity, soil management and hydrological planning (Adhikari et al., 2013; Akpa et al., 2014; Zhao et al., 2009).

The objective of this study was to combine three maps of topsoil texture in Region Centre (France) – two regional maps and a European map- with two standard methods for model ensemble and to assess the improvement of prediction accuracy for agricultural land. The applied methods for model averaging were respectively the Granger-Ramanathan (1984) and the Bates-Granger (1969).

2. Materials and methods

2.1. Study area

Region Centre is located in the Middle Loire basin and has a surface of 34,151 km^2 (Fig. 1). Its relatively flat topography (0–500 m elevation) is traversed by the Loire River and several tributaries, and the elevation softly increases towards the south in proximity to the Massif Central. The climate is continental oceanic with an average annual temperature of 11.4 °C and a mean annual precipitation below 800 mm (Joly et al., 2010). Agriculture is the main land use, dedicated mostly to the production of cereal, oleaginous and protein crops (72% of agricultural area) (Agreste, 2011). The principal soil types are Luvisols (33.8%), Cambisols (15%), Leptosols (11.9%), Fluvisols (10.6%), and Podzols (10.6%) (Ciampalini et al., 2014) according to the World Reference Base for Soil Resources classification (IUSS Working Group WRB, 2014).

Fig. 1. Situation of Region Centre in France.

2.2. Primary maps

There were three available maps of soil texture for Region Centre (France) produced with different modeling approaches and soil databases: i) the French soil mapping and inventory program (Ciampalini et al., 2014), ii) the French soil test database (Román Dobarco et al., 2016), and iii) the Land Use and Cover Area frame Statistical survey (Ballabio et al., 2016) (Fig. 2). For the three maps, the reference texture data used to fit the different models was previously transformed with the additive log ratio (*alr*-transform) (Aitchison, 1982) as it has been proposed for the spatial prediction of compositional data like soil particle size fractions (Odeh et al., 2003; Lark and Bishop, 2007). The *alr*-variables (i.e., $sand_{alr}$ and $clay_{alr}$) were back-transformed directly to sand, silt, and clay through the *alr* inverse transform (Lark and Bishop, 2007) prior to model ensemble. The characteristics of the three modeling approaches and their products are briefly explained:

i. Ciampalini et al. (2014) predicted soil texture for the Region Centre following GSM specifications (Arrouays et al., 2014). They produced predictions for the depth intervals 0–5, 5–15, 15–30, 30–60, 60–100, and 100–200 cm, at 3-arc-second (~90 m) resolution using data from 2487 soil profiles and 8718 horizons from the French soil mapping and inventory program (Inventaire Gestion et Conservation des Sols: IGCS) and environmental covariates in a regression kriging approach. In the IGCS program, sampling was based on soil surveyor expertise and mainly devoted to characterize soil mapping units. The coordinates of soil profiles are known with an accuracy ranging from 5 to 25 m. To estimate the soil texture on the depth intervals according to the GSM specifications, the measured values were interpolated using quadratic splines (Bishop et al., 1999; Malone

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