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Digital soil mapping of soil carbon at the farm scale: A spatial downscaling approach in consideration of measured and uncertain data

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ABSTRACT

In this paper a spatial downscaling method is explored for generating appropriate farm scale digital soil maps. The digital soil map product to be downscaled is an Australian national extent soil carbon map (100 m grid resolution). Taking into account the associated prediction uncertainties of this map, we used a simulation approach based on Gaussian random fields to generate plausible mapping realisations that were in turn downscaled to 10 m resolution for a farm in North-western NSW, Australia. We were able to derive both a downscaled map of soil carbon and associated prediction variance with this approach. Building further upon this development, we then incorporated a bias correction step into the spatial downscaling procedure which permits the inclusion of field observations as a way to moderate the downscaling results to better reflect actual conditions on the ground. Based on an independent validation dataset, it was found that incorporating field observations increase the concordance correlation coefficient to 0.8 from 0.2. This relatively lower correlation achieved using spatial downscaling alone was due to the national scale mapping for the study area being positively biased in the area of interest. It was found that downscaling that incorporates observational data was marginally better if not comparable to using a point-based digital soil mapping approach. The advantage of spatial downscaling is that it can be implemented in situations of data scarcity. This will be ideal for on farm soil monitoring in situations where detailed soil mapping is initially not available. For example, soil carbon auditing schemes requiring prior soil information for implementation of design-based soil sampling could potentially be universally applied with such a spatial downscaling approach.

1. Introduction

Contextualizing the sampling theory established by De Gruijter et al. (2015), follow up work by De Gruijter et al. (2016) proposed an efficient and optimizable soil sampling protocol for the unbiased estimation of on farm soil carbon stocks. Their interest was the estimation of whole farm soil carbon stocks with sufficient statistical confidence. Such information is necessary for the establishment and ongoing monitoring of soil carbon. Unbiased estimation of on-farm carbon stocks is also necessary in the broader context of carbon inventory and participation of agriculture sector in the carbon economy (Antle et al., 2003). Coincidentally, in addition to the environmental benefits associated with sequestration of carbon into soils, there are foreseeable economic benefits for farming communities too (Stockmann et al., 2013).

A design-based soil sampling approach, the *ospats* algorithm from De Gruijter et al. (2015) enables one to use prior information by way of existing soil carbon mapping (and associated prediction variances) to derive an optimal number and spatial configuration of strata, and ultimately an optimal number of samples to collect from a farm. The focus of this particular research is in regards to the prior information that is required by *ospats* – that is, the mapping of soil carbon and associated uncertainties. For universality of application, *ospats* needs relevant farm scale digital soil map of carbon stock and associated prediction uncertainties. With the exception of some farms, most agricultural landholdings will not likely have an established digital spatial information system. It is proposed in this research that such information may be obtained more-or-less globally by exploiting the availability of global and/or national digital soil mapping products.

Throughout the world there has been an upsurge of digital soil mapping projects (Minasny and McBratney, 2016). This is due mainly to enabling technologies in quantitative methodologies and geographic information systems, in addition to a global need of relevant spatial soil information systems to address critical environment issues of which soil is manifold. The vanguard of such projects has been the GlobalSoilMap project (Sanchez et al., 2009; Arrouays et al., 2014), which set as the ambitious goal to use digital soil mapping to map key soil attributes at 100 m spatial resolution and specified depth intervals

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to 2 m (0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, and 100–200 cm) across the entire ice-free land surface of the world. Working in parallel with that project or inspired from some of its methodological approaches, similar very large extent digital soil mapping projects have also resulted throughout the world.

Such large spatial extent digital soil mapping products are invaluable for aiding the decision-making process at the spatial scales they were intended for. However, they are not particularly relevant for considering issues at the farm scale. In other words, the observed spatial variability at the farm scale is not sufficiently captured in nationally or regionally calibrated models and the resultant digital soil maps. This can often be simply a matter of grid cell resolution being too coarse for meaningful on farm analyses.

In order to create digital soil maps relevant to the farm scale in the absence of sufficient data, one possible option to consider is spatial downscaling. This means the spatial disaggregation of the national mapping using a statistical model and a library of environmental covariates that will help in defining the spatial variability of the target variable. The implicit assumption here is that the covariate information is strongly related to the target variable, which is being derived at the fine scaled resolution. This general statistical downscaling approach is embodied is the *dissever* algorithm (Malone et al., 2012) which itself is a generalization of the linear downscaling algorithm proposed by Liu and Pu (2008). Poggio and Gimona (2015) used a modified *dissever* approach which considers a correction step when downscaling climate model outputs.

The *dissever* algorithm was originally parameterized for inclusion of the uncertainties of the map to be downscaled. The underlying model within *dissever* is a weighted generalized additive model (Hastie and Tibshirani, 1990). In addition to allowing one to investigate non-linear relationship between target variable and covariates, in this model, the uncertainties of the input data (the coarse map) are used as weighting factors (inverse weighted) in the nonlinear fitting function (Malone et al., 2012). Despite this generalization, incorporating the prediction uncertainties did not ultimately mean they were propagated through to the downscaled outputs directly. In fact, the only measure of uncertainty associated with downscaling from Malone et al. (2012) was that associated with the deviation from mass balance between coarse scale mapping and associated downscaled mapping. The quantification of uncertainties is necessary for obvious reasons of assessing the reliability of mapping. Importantly for soil carbon stock auditing and using *ospats* specifically, the magnitude of the prediction uncertainties determines the spatial configuration of the sampling strata and optimal sample number.

Subsequently, this research is focused on the delivery of relevant farm scale digital soil mapping of carbon via a spatial downscaling approach. A key question of this research is how to efficiently take into account the prediction uncertainties of the national mapping so that they are in turn propagated through to the downscaled mapping in addition to the uncertainty estimated from downscaling. Exploring further the work of Poggio and Gimona (2015) a second research question is, to what effect does incorporating field observations into the downscaling process while simultaneously taking into consideration the uncertainties of the national mapping? For the first question we may hypothesize that by explicitly taking into account the prediction uncertainties within the modeling process, we may expect an associated prediction variance with the downscaled mapping, which would be an ideal outcome especially for universal implementation of *ospats*. Regarding the second question, from results obtained by Poggio and Gimona (2015) we would expect the bias corrected downscaled mapping will reflect the more present-day spatial pattern of soil carbon variation, and have relatively lower uncertainty than the mapping created from downscaling alone.

2. Material and methods

2.1. Methodological overview

First we describe the study area that is under investigation, and then outline the various data that has been collected and subsequently used. We then detail a simple approach for generating plausible realisations from national scale mapping conditioned to the spatial and statistical properties of these mapping. This is followed by description of a spatial downscaling approach of the simulated national scale mapping outputs for generating relevant farm scale predictions and associated uncertainty. The spatial downscaling entails approaches pertaining to with and without correction based on the usage of point observation data. For comparisons, we compare downscaled products with those derived from a point-based digital soil mapping approach. Validation of all outputs in this investigation is performed using an independent data set from the area under investigation.

2.2. Study area and data acquisition

The farm under investigation in this study is the University of Sydney owned and managed E.J. Holtsbaum Research Station, “Nowley” (31.35°S 150.11°E). Situated in the highly agriculturally productive Liverpool Plains region in north west NSW (Fig. 1), Nowley (approximately 2300 ha) is run as a mixed farming enterprise centered around crops of wheat, barley and canola in winter, sorghum and sunflower in summer, and a cattle herd of breeders, replacement heifers and bulls. Nowley has a combination of fertile basaltic soils together with more challenging to manage soil types that are poorly drained and with considerably high amounts of subsoil sodium. A more comprehensive description of the region and Nowley farm can be found at (Stockmann et al., 2016).

At the present time, national mapping of soil carbon (that is publically available and downloadable) pertains to total soil carbon concentration. This data is available via the repository of the Australian Soil and Landscape Grid (http://www.clw.csiro.au/aclep/soilandlandscapegrid/). Technical information regarding the Australian Soil and Landscape grid can be found in Grundy et al. (2015). This national scale digital soil mapping is based on the GlobalSoilMap specification resolved to a 100 m grid cell resolution, and is available as layers corresponding to depth intervals of: 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, and 60–100 cm. Using a boundary extent of the Nowley Farm we clipped the national mapping which included the lower and upper bounds of a 90% prediction interval, and the predicted values as generated by *scorpan* modeling. In this study, because soil sampling was based on a 0–7.5 cm depth interval, we extracted only the mapping corresponding to 0–5 cm and 5–15 cm. With the extracted mapping we set about deriving mapping that corresponded to 0–7.5 cm which is based on collected topsoil samples. This was facilitated using the mass preserving spline depth function described in Bishop et al. (1999) for each 100 m grid cell. This procedure was done for the predictions and the associated lower and upper prediction intervals. After this, using the 90% lower and upper prediction limits we estimated the variance and standard deviation of the predictions the same way as in Malone et al. (2014).

Data collected from Nowley included a number of environmental layers related to topography and gamma radiation. The topographic data were collected (and later mapped) by Tranter (2005) by ground survey using an all-terrain vehicle with attached Ashtech Real-Time Kinetic Global Positioning System (RTK GPS). Driven across the farm in 20 m swaths, positional data with coupled elevation data were recorded every 3 s. After the completion of the survey, a series of post-processing steps were performed followed by interpolation to create a map of elevation. Interpolation was performed via local ordinary kriging onto a regularly spaced 10 m grid across the whole farm. Further processing of the 10 m elevation model entailed calculation of a number of terrain derivatives. In this particular study the following terrain derivatives were used: slope gradient, terrain wetness index, and multi-resolution valley bottom flatness index. High resolution gamma radiometric mapping was collected via aerial survey. Australia has a continental coverage of remotely-sensed radiometric data at 100 m grid resolution, but the raw data that contributes to this mapping is composed of a patchwork of aerial surveys that range in information content (Minty et al., 2009). In the area where this study is based, the information content

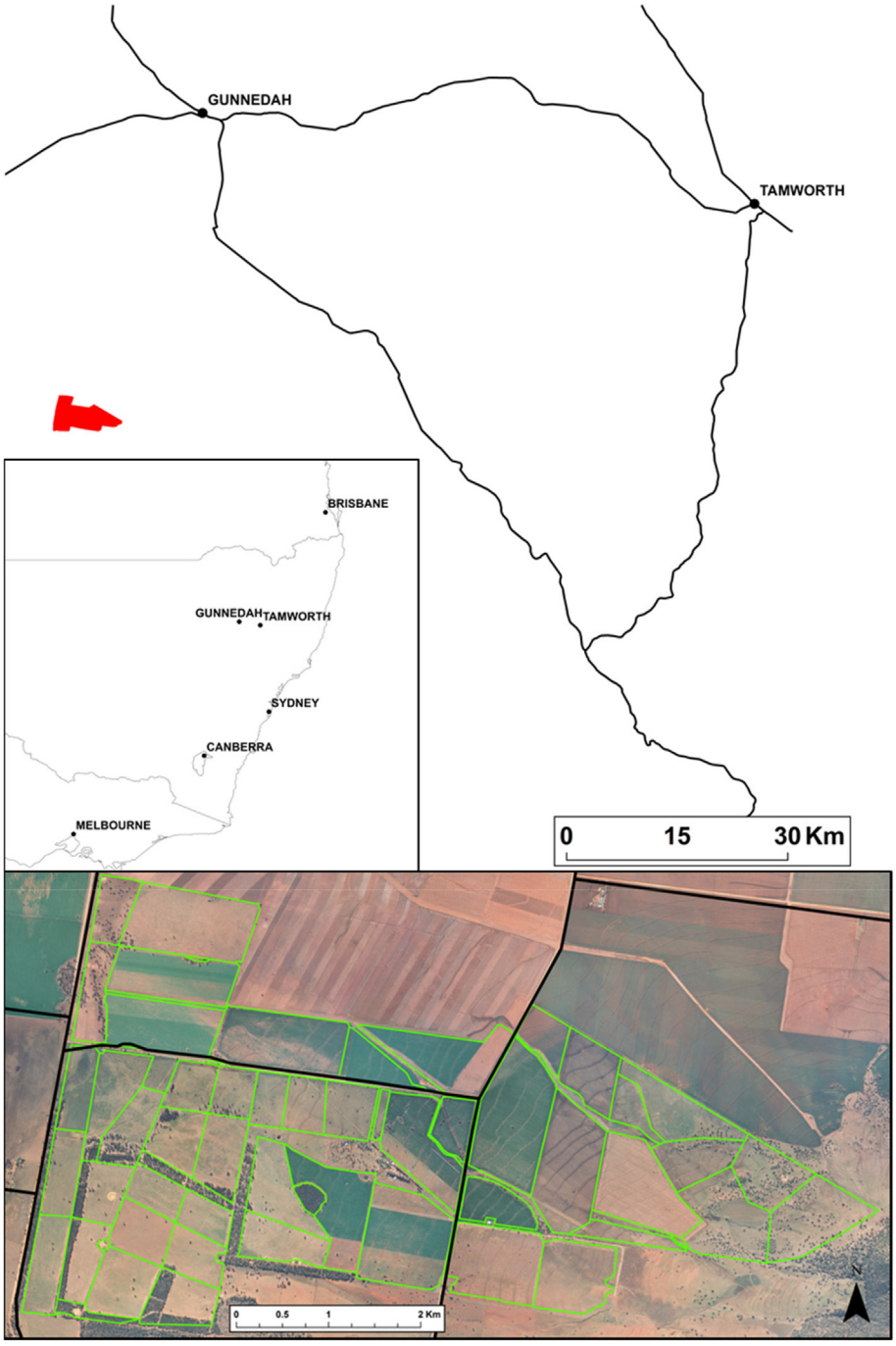

Fig. 1. E.J. Holtsbaum Research Station, "Nowley" is a 2300 ha mixed farming enterprise in north west NSW, Australia.

is relatively high than other parts of Australia, where the flight line spacing is every 200 m with tie lines every 2 km. Radiometric mapping predominantly reflects the variation of the amount of naturally occurring radioisotopes of potassium (^{40}K), uranium (^{238}U-series) and thorium (^{232}Th-series) in the soil (generally the top 40 cm). Generally, their intensity is directly related to the mineralogy and geochemistry of the parent material and its degree of weathering (Dickson and Scott, 1997). Tranter (2005) resampled the 100 m radiometric data (potassium, thorium and uranium) to the same 10 m grid that was used for the elevation mapping. Collectively, the topographic and radiometric 10 m resolution mapping henceforth will be described as the farm survey mapping.

In addition to the farm survey mapping this study also uses soil point observations of total soil carbon concentration that were collected over two separate soil sampling campaigns during 2014 and 2015. The sampling for each campaign was based on stratified random sampling, where at each site a 7.5 cm core of soil (0–7.5 cm) was collected. A total of 127 samples were collected from these two sampling campaigns. For all samples, they were air dried, followed by moderate grinding to pass soil through a 2 mm sieve. From the 2 mm ground soils, a further sub sample was taken and subjected to mechanized mortar-and-pestle grinding for 3 min. 500 mg of the fine-grinded soils were then taken for measurement of total carbon concentration using the dry combustion method which was performed using a vario MAX CNS analyzer (Elementar, Germany). From measurement, the mean carbon content of these samples was 1.60%, while the minimum and maximum was 0.52% and 4.20% respectively. A random subset of 39 samples was set aside for this study to be used for validation purposes. The remaining

88 were used – as to be described further on – in the downscaling (with correction) and digital soil mapping components of this research.

2.3. Simulations from national scale mapping

A simulation approach is used to create plausible realisations of the national mapping. The realisations are made in consideration of the prediction variance associated with the mapped predictions, such that the mean and variance of the simulated mapping will be same as the prediction and variance of the national mapping product. We may explore the uncertainty space attributed to the mapped predictions using a random sampling approach of the assumed distributions at each grid cell. However, this assumes the simulated values are completely spatially independent of each other. This is likely to be unrealistic, and pending the magnitude of uncertainty, the resulting mapping could appear as random noise. Therefore, it becomes necessary to include a random component that has some specified spatial correlation structure. This can efficiently be done using unconditioned Gaussian random fields with specified covariance parameters including nugget, partial sill and anisotropy etc. (Andrew and Chan, 1994). The procedure for generating the unconditioned random fields is commonly referred to as sequential Gaussian simulation (Chiles and Delfiner, 1999). After generating a random field, we can then derive a mapping realisation using the following equation:

$$sim_{map} = \sigma x + \mu$$

where sim_{map} is the simulated map, σ is the standard deviation of predictions of the national mapping, x is the Gaussian random field map, and μ is the national map predictions. With this procedure we generated 100 realisations. Obviously many more realisations could be performed if greater precision about the mean and standard deviation of the realisations is required. Nevertheless in the current study, 100 realisations was just an arbitrary number that configured well with our available compute resources. For the covariance parameters of the random fields we selected the distance parameter that was found from the fitted variogram of the national map predictions of total soil carbon for Nowley. The partial sill was set to equal 1. We did not consider any directional dependent (anisotropy) variation of the random field in this study.

2.4. Spatial downscaling

Spatial downscaling in this study was implemented using a generalized version of the *dissever* algorithm as described in Malone et al. (2012). In its original conceptualization, a relationship between the fine resolution covariates and the coarse resolution base map is built using a weighted generalized additive model (GAM). The GAM is used in an iterative process to converge towards a solution that is mass-preserving, i.e. the mean of fine scale predictions is equivalent to the associated value of their encapsulating coarse scale pixel. In words, the algorithm is implemented as follows (mathematical notation of the algorithm is detailed in Malone et al., 2012):

Initialization Steps:

1. Fine-grid coarse resolution map (source map) via nearest neighbor resampling. Resolution and extent of the fine gridded map is the same as that of the available predictive covariates to be used for regression modeling.
2. Regress (GAM model) fine gridded values against suite of available covariates.
3. Upscale via averaging the fine gridded estimates to source map resolution.
4. Estimate deviation from mass balance for each coarse grid pixel i.e. mean of fine grid values = value from associated pixel of source map.

Iteration steps:

5. Correct fine gridded estimates with deviation factor from step 4 (or step 10 if iteration number is greater than 1)
6. Regress (GAM model) fine gridded values against suite of available covariates.
7. Upscale via averaging the fine gridded estimates to source map resolution.
8. Check whether upscaled estimates from step 7 are changed from previous iteration (or step 3 if performing iteration 1).
9. If estimated change (from step 8) is greater than some pre-defined threshold proceed to next step, otherwise STOP. In Malone et al. (2012) an averaged absolute difference between upscaled map from present iteration and previous iteration was used. As in Malone et al. (2012) an arbitrarily selected threshold of 0.001 was used to determine if iteration should proceed or not.
10. Estimate deviation from mass balance for each coarse grid pixel i.e. mean of fine grid values = value from associated pixel of source map. Go back to Iteration step 1.

One way to improve *dissever* is to optimize the downscaling by comparing outcomes from different model structures then selecting the one where error is minimized. In the present study the selected model structure used was the quantile regression forest model (QRF) which is a generalized implementation of the random forest model from Breiman (2001). The selection of QRF was based on its superiority from our own internal model comparisons with other candidate models including Cubist models, Random Forests and GAMS. A full description and theoretical discussion of the QRF model can be found in Meinshausen (2006).

For each simulated national map, *dissever* was implemented using the farm survey mapping as the predictive covariates for estimating the carbon distribution across the study area at the fine scale. The resolution of the farm survey mapping was 10 m × 10 m raster grid, which ultimately meant the resolution of the downscaled mapping of carbon was equivalent to this too. This procedure ultimately created 100 downscaled maps. Without considering any correction steps, all 100 downscaled maps were stacked together from which the mean and variance were then calculated. Added to the variance was a measure of the downscaling error in terms of the deviation from mass balance. This deviation measure is estimated for every pixel at each iteration of the *dissever* algorithm. Once *dissever* terminates we estimate the mean square error which in this case is:

$$\mathrm{MSE}_{\mathrm{down}} = \frac{1}{N}\sum_{i=1}^{N}(CV_i - FV_i)^2$$

where N is the number of pixels of the coarse scaled map, and CV_i is the mapped value from the coarse map (national map) at pixel i, while FV_i is the averaged downscaled predictions from the last *dissever* iteration encapsulated by the same pixel i.

Downscaling with a correction step is just a means of adjusting the predictions given a collection of observations from the same area of the same phenomenon being investigated. In addition to Poggio and Gimona (2015), many examples of downscaling with correction appear to be concerned with climatic data applications e.g. Déqué (2007), Wilcke et al. (2013) are just a few of these. A basic implementation is to estimate a residual – the difference in value of observation and downscaled prediction – then use an interpolator to estimate the residual onto the same grid as the downscaled predictions. The downscaled mapped and the interpolated residuals are then added together. If considering kriging as an interpolator, such a procedure is actually similar to regression kriging that is used extensively for digital soil mapping (Odeh et al., 1995). In this study, the residuals were estimated by intersecting the available observations with the downscaled map that was created in the last iteration of *dissever*, then estimating the difference between the two values. Automated fitting of a variogram to the residuals performed followed by ordinary kriging is used to obtain a

map of residuals at the same resolution as the downscaled map. This procedure was done for all realisations of national map simulations. The estimation of the mean and variance of the downscaled predictions was the same as before in which did not consider the correction step. A flowchart of the downscaling with uncertain data procedure with and without correction is shown on Fig. 2.

2.5. Digital soil mapping example

Using the available 88 site observations of total soil carbon together with the farm survey data as covariates, regression kriging was used to create digital maps of this target variable and associated prediction variance. Specifically we used the universal kriging model for these purposes. Universal kriging is well explained in the literature (e.g. Webster and Oliver, 2001). It is suitable to use in this study because it simultaneously provides mapping of both the predictions and prediction variance. Ultimately these mapping outputs were to be compared to those generated from both downscaling procedures in this study.

2.6. Validation

The 39 withheld observations were used for evaluating similarities and differences in predictions associated with downscaling and with digital soil mapping. The statistical measures used in this study were concordance correlation, bias (often referred to as the mean error), the root mean square error, and prediction interval coverage probability. Concordance correlation (ρ_c) both evaluates the accuracy and precision of the relationship between observation and predictions. It is often referred to as the goodness of fit along a 45° line. It is evaluated as:

$$\rho_c = \frac{2\rho\sigma_{pred}\sigma_{obs}}{\sigma^2_{pred} + \sigma^2_{obs} + \left(\mu_{pred} - \mu_{obs}\right)^2}$$

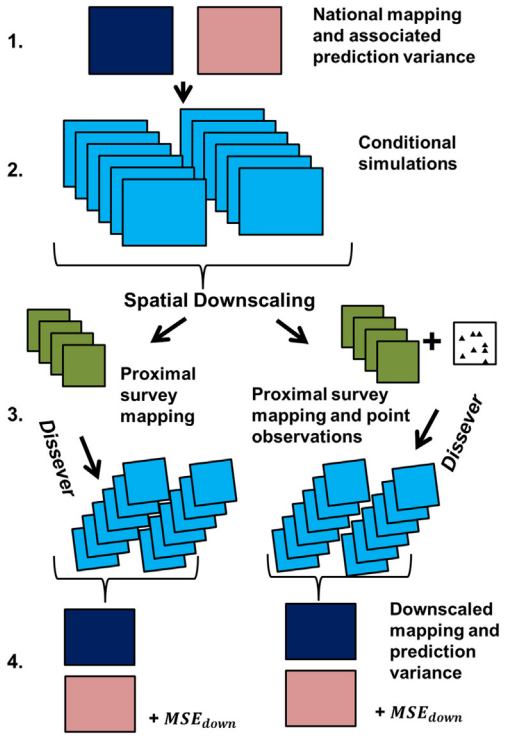

Fig. 2. Flow chart of procedures for spatial downscaling. Step 1 entails acquisition of the national scale mapping and prediction variances. Step 2 is using simulation approach to generate multiple realisations of national scale mapping. Step 3 the spatial downscaling which is informed using farm survey mapping or both farm survey mapping and observational data. Step 4 is taking the mean and variance of the downscaled mapping outputs.

where μ_{pred} and μ_{obs} are the means of the predicted and observed values respectively. σ^2_{pred} and σ^2_{obs} are the corresponding variances. ρ is the correlation coefficient between predictions and variances. Root mean square error is evaluated as:

$$RMSE = \sqrt[2]{\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{n}}$$

where *obs* is the observed value of sample *i*, and *pred* is the associated predicted value, and *n* is the number of observations. Bias is defined as:

$$bias = \frac{\sum_{i=1}^{n} obs_i - pred_i}{n}$$

The prediction interval coverage probability (PICP) is the probability that observed values fit within their estimated prediction interval. Prediction intervals were constructed for each validation point based on the associated mapped variance estimates that were quantified. A 90% prediction interval was defined in this case. In theory it should be expected 90% of all the observations fit within their given prediction limits.

2.7. Implementation of methods

Custom-made R scripts (R Core Team, 2015) were developed for carrying out the various procedures of this research. In developing these scripts a number of contributed R packages were exploited for specific functionality. The raster (Hijmans, 2015) package with associated rgdal (Bivand et al., 2015) and sp (Bivand et al., 2013) packages were used for handling and manipulating all GIS processes. Downscaling was performed using the *dissever* R package (Roudier et al., in review; available at https://github.com/pierreroudier/dissever), that in turn links with the caret R package (Kuhn et al. 2016) to exploit the numerous model structures that package supports, including the QRF model used in this study. While the downscaling procedures described in this study can be performed on a desktop computer, for efficiency some of the R scripting was modified so that it could be run on the University of Sydney High Performance computer cluster. Parallel compute functionality was aided through the use of specialist R packages parallel (R Core Team, 2015) and doParallel (Revolution Analytics and Weston 2014). Creating the Gaussian random fields was made possible by using the geoR package (Ribeiro and Diggle 2015). Automated variogram fitting and universal kriging was performed using functions from *automap* (Hiemstra et al. 2009) and *gstat* (Pebesma 2004) respectively.

3. Results

3.1. Simulations from national scale mapping

The national scale carbon concentration digital map clipped to the spatial extent of Nowley is shown on Fig. 3A and D. These digital maps (Fig. 3A, B, D, E) constitute the predictions and prediction variance respectively. The general spatial pattern of the national map shows a low to high carbon concentration in the west to east direction. This is generally what is actually observed on the ground and corresponds to both land use and topographical variations across the farm. The observed blockiness of this national mapping is an artifact of the environmental covariates that were used for building the underlying model, where it is likely such data were of varying spatial scales or information content.

Taking the mean and variance of the 100 mapped realisations of the national mapping resulted in the maps shown on Fig. 3B and E respectively. Fig. 3C and F are xy-plots of the predictions and variances between the national mapping and subsequent realisations thereof. The plots show a good agreement between the maps. We estimated a

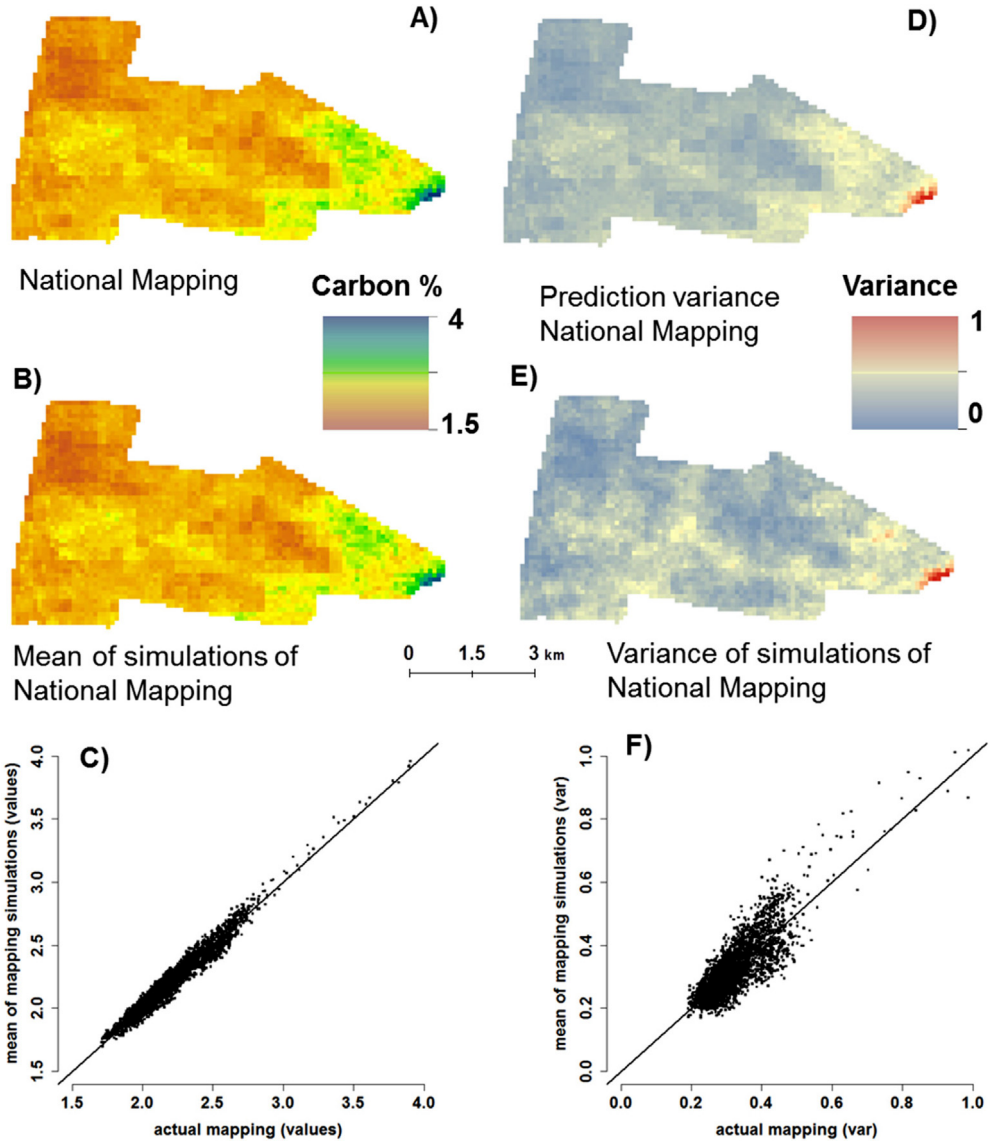

Fig. 3. National soil mapping products. A and D are the prediction and prediction variance products of the national mapping clipped to the extent of the study area. B and E are the mean and variance of the 100 simulations based on the mapping in A and D. C and F are xy-plots of the data in A and B and for D and E respectively.

concordance correlation of 0.98 and 0.82 when comparing the predictions (Fig. 3A and D) and variances respectively (Fig. 3B and E).

3.2. Spatial downscaling

Estimated mean and variance of the 100 downscaled maps from *dissever* is shown on Fig. 4A and D respectively. Incorporating the 88 soil observations to correct the downscaling outputs resulted in the associated maps on Fig. 4B and E. There is a discernible difference mainly in the predictions between both mapping outputs with values derived from using *dissever* only being relatively higher across the majority of the mapping domain than those using *dissever* with inclusion of point observations. Using the 39 validation points we were able to estimate the statistical measures (concordance, RMSE, and bias) for each downscaled map. Table 1 summarizes the mean and standard deviation of these statistical measures for each mapping type. For now, just comparing the different downscaling procedures, it is clear that using *dissever* with the incorporation of point observations results in more accurate predictions on the basis of the concordance and RSME values. A positive bias associated with downscaling the national mapping is corrected with the inclusion of point observations. The bias associated with the predictions has ultimately affected the result of the PICP where 60% of observations were within their prediction envelope. When including point observations the expected 90% of validation observations were within the respective prediction envelopes.

An operational consequence of these results is that naturally a more accurate map will make the sampling more efficient and less costly. For example, and with respect to the *ospats* algorithm, from our own calculations we estimated using equation 21 from De Gruijter et al. (2016) there to be a 10% reduction in the number of samples needed for estimating the on farm carbon storage if incorporating observational data into the downscaling procedure. Note that this optimized number is based on maximizing the financial gain which is derived by subtracting the cost of sampling from the data value — where data value is in part a function of the magnitude of prediction uncertainty of the given soil carbon map (De Gruijter et al. 2016).

3.3. Universal kriging

Downscaling with the inclusion of point observations resulted in outputs similar to that achieved using universal kriging across based on the considered statistical measures as summarised on Table 1.

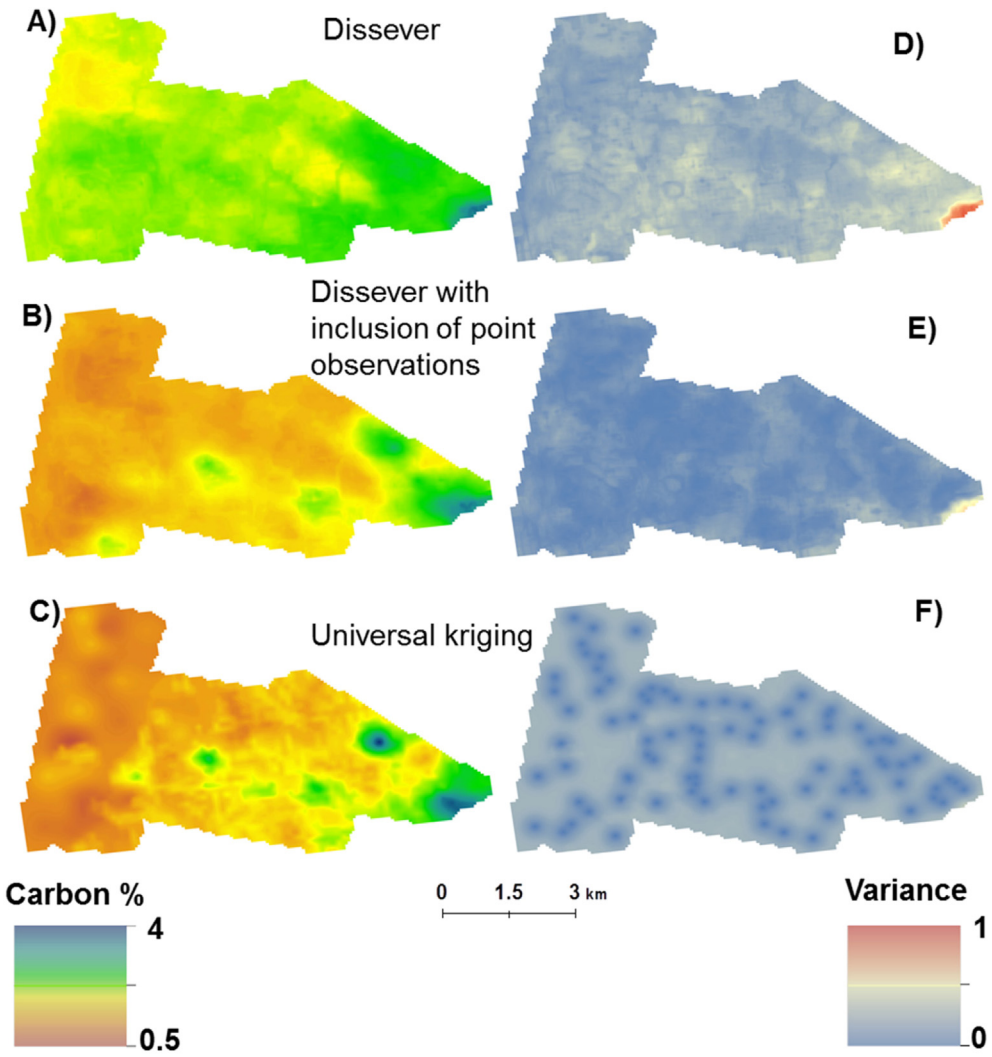

Fig. 4. Farm scale digital soil mapping of carbon. Predictions and prediction variance maps. A and D using *dissever*. B and E using *dissever* with inclusion of point data. C and F using universal kriging.

Prediction maps as shown on Fig. 4B and C illustrated the similarity in predictions, of which both are quite distinct from Fig. 4A — the downscaled with *dissever* only maps. As expected as shown on Fig. 4F the prediction variance is the lowest about the locations of the observations. Prediction variances associated with downscaling are relatively lower for the procedure incorporating observations when compared to using *dissever* only. They are slightly lower when comparing them to the prediction variances from universal kriging.

4. Discussion

In the context of soil carbon auditing, the purpose of this research has been to derive digital soil mapping to use as prior information for guiding an optimal soil sample based on stratified random sampling.

Table 1
Statistical measures associated with farm scale digital soil mapping based on an independent validation data set of 39 samples.

	Concordance correlation		RMSE		Bias		PICP (%)
		sd		sd		sd	
Dissever	0.20	0.16	0.96	0.14	0.60	0.18	60
Dissever with inclusion of point observations	0.81	0.07	0.39	0.06	−0.03	0.03	90
Universal kriging	0.70		0.50		−0.13		92

Operationally spatial downscaling would be recommended in situations where there is an availability of fine scale covariates, yet scarcity of point data. The existence of national scale mapping or similar is also necessary. Examples of such include that of Australia (Grundy et al. 2015) as used in this study. Odgers et al. (2012) describe some digital soil mapping efforts of soil carbon for the contiguous USA. De Brogniez et al. (2015) describe the mapping of topsoil organic carbon content across Europe. In 2002, New Zealand established its soil carbon monitoring system (Scott et al. 2002) as part of their efforts in the implementation of the Framework Convention for Climate Change and the Kyoto Protocol. More recently, McNeill et al. (2012, 2014) describe the process of updating the work of Scott et al. (2002) using methods more akin to digital soil mapping. There are other such similar National extent digital soil mapping examples around the world including those of France (Mulder et al., 2016), Denmark (Adhikari et al. 2014), Nigeria (Akpa et al. 2016) and Scotland (Poggio and Gimona 2014).

For universal implementation of *ospats* and soil carbon auditing in general, the spatial downscaling is a way of attaining the farm scale prior soil information (mapping) that is required to implement the sampling design, then go out to the field and begin soil sample and ultimately execute the first soil carbon audit. Come the appropriate time to revisit and perform the next round of sampling, there will now be available prior information both in terms of national mapping and soil observational data. However, the density of the sampling may still be impractical for deriving accurate digital soil map to use as the prior

information in these second and subsequent rounds of sampling. With this in mind, it is foreseen that there are a number of possible routes to follow if digital soil mapping alone is not going to be suitable.

1. Perform downscaling as was done for initiating the first sampling campaign. It is inevitable that with national soil mapping being digitally based, the underlying models will be dynamic in the sense that they can be updated pending the acquisition of new data. This will achieve the result of a new realisation of the national mapping and associated prediction variance which may or may not be improved. It is likely in the future that nationally directed efforts for updating and improving soil mapping will occur as a globally collective response to addressing environmental issue and land resource monitoring.
2. Perform downscaling together with incorporation of observed data as demonstrated in this study. There still may be issues with data density if variography and kriging is to be considered as the approach for interpolating the downscaling corrections. Otherwise it is also possible to consider other interpolators such as inverse distance weighting or cubic spline interpolators if appropriate. If still not feasible to use the observed data within the downscaling process, at a minimum these data could be used to assess to quality of the national mapping that is being downscaled.
3. Use an ensemble approach to fuse together downscaled outputs with digital soil mapping outputs. Ensemble modeling is a useful approach if one has multiple outcomes from different models and wants some way of consolidating them into one output (Rojas et al. 2008). Most approaches preferentially weight the outcomes based on accuracy such that the final outcome is one that is at least as good as or better than the best individual model.

Point-based digital soil mapping feasibility is still going to be largely data dependent in terms of the observed data density. There is likely going to be a critical density at which spatial downscaling of the national mapping is not perceived to be necessary – the prediction variance achieved by digital soil mapping may be acceptable. Figuring out what the critical threshold of data density is for a given target area of landholding, could be an interesting pursuit for further research, but it would still be recommended that spatial downscaling still be implemented (because it incorporates prior soil information) and use a model averaging approach to incorporate the point-based digital sol mapping outputs as described in point 3 above.

Ultimately the spatial downscaling approach described in this study, particularly that which incorporates observational data provides the facility for landholders or their consultants to exploit the availability of public digital soil mapping, and simultaneously incorporate their own (private) collected data for monitoring the soil resource at the farm scale.

5. Conclusions

- This study demonstrates a digital soil mapping approach based on spatial downscaling of coarse national-scale map that is able to generate digital maps relevant to a farm-scale context, of a target variable with associated prediction variance.
- A facility built into the downscaling procedure allows one to incorporate observational point data to moderate the downscaling results that better reflect the present soil condition. The quality of the digital soil map produced with this procedure results in significant improvements in terms of map accuracy and quantified uncertainties.
- Using publically available digital soil maps such as those that might have been created for national scale studies, it is possible to implement spatial downscaling to derive appropriate and low-cost farm-scale maps. The real application of this would be for helping landholders initiate a soil monitoring framework. A good example here is soil carbon auditing, where prior information in terms of soil carbon map will greatly improve the sampling efficiency where design-based sampling approaches are used.
- Spatial downscaling used in the context for soil carbon auditing does not necessarily require observed point data (although it makes an improvement). This should make things easier for landholders to initiate a monitoring program, and ultimately see a greater participation of the agriculture sector in the carbon economy.

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