A soil spatial prediction functions (SSPFs) for soil organic carbon in Eastern Australia

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Abstract

The development of spatial soil prediction functions (SSPFs) for soil organic carbon (SOC) in Australian bioregions has the potential to inform pragmatic measurement and monitoring schemes for the terrestrial carbon system. Recent availability of Australia-wide fine resolution datasets of key environmental covariates has created an unparalleled opportunity for the creation of bioregional SSPFs to guide sampling design for farm scale studies that may assist in economical verification efforts for SOC.

Key Words

Soil organic carbon, carbon auditing, spatial soil prediction function, terrain analysis, carbon offsets

Introduction

The predicted consequences of greenhouse gas derived climate change have increasingly turned recent attention to the potential early and positive role of terrestrial carbon sequestration. Whilst great promise is touted and indeed warranted, the challenges of creating verification systems that are at once pragmatic as well as capable of defining a fungible commodity for a given length of time in a dynamic environmental system are manifold. For example, the common truism of high spatial variability in soil organic carbon being a barrier to verification efforts indeed reflects very real soil variation that covers roughly nine orders of magnitude (i.e. see (Crawford et al. 2005). It does not follow however, that we lack scientific knowledge of this variation. As a result, the fundamental question of 'where to cut?' such commodity measures faces all verification and subsequent payment efforts for terrestrial carbon sequestration. In regards to soil organic carbon, the recent availability of global elevation models at fine resolution in combination with national scale gamma radiometric datasets offers an unparalleled opportunity for the development of soil spatial prediction functions (SSPFs) that may assist in more economical measurement and verification efforts. Such a system would provide bioregional or sub-bioregional trends in SOC that could guide sampling design and subsequently be amended by local/farm scale measurements – allowing creation and further refinement of localised SSPF's, creating the basis of a coordinated SOC database and opening opportunities for monitoring of measured local carbon stocks.

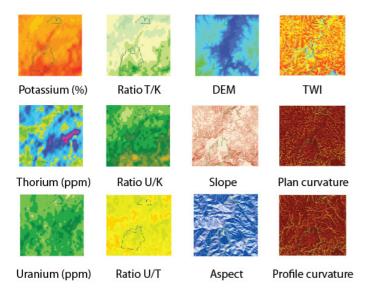


Figure 1. Example environmental attributes utilised in the SSPF for soil organic carbon.

Methods

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Datasets utilised for this study include: the joint METI and NASA ASTER Global Digital Elevation Model V001 and its derived terrain attributes at 30 m resolution (Figure 1); the Radiometric Map of Australia at 100 m resolution (Figure 1) and direct observations of soil organic carbon from the Australian Soil Resource Information System (ASRIS) dataset (Figure 2). In addition, 250 m resolution climatic, landuse and SOC% to 30 cm depth as previously estimated (Henderson *et al.* 2005)(Figure 3) were also utilised. Prior farm scale data for SOC within the bioregion have been collated to refine the sub-bioregional SSPF linear trend to create localised and farm scale SOC maps as well as assist in sampling design for future surveys. Additional SOC surveys intended to broaden the variety of production systems, soil types and regional climates represented are in the process of design, collection and analysis and will be integrated into the relevant sub-bioregional SSPF in the near future. A novel approach to landuse classification in regards to local SOC spatial behaviour has also been developed and is currently being refined for farm sale application.

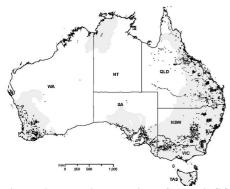


Figure 2. Relative location of topsoil SOC observations within the ASRIS dataset, grey areas indicate extent of prior maps generated from this dataset (Bui *et al.* 2009)

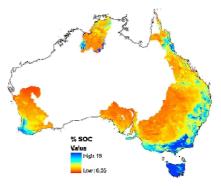


Figure 3. % soil organic carbon at 250 m resolution estimated by Henderson *et al.* 2005 using the ASRIS database

Results and discussion

Utilising the preliminary SOC results from collated farm scale surveys and the previously mentioned covariates a sub-bioregional SSPF was developed for SEH11 (Bathurst) (Figure 6) where $saga_wi$ is a variant of the wetness index; D_a is dryland annuals; D_input_pa is dryland pasture with regular inputs; D_noput_pa is dryland pasture with no regular inputs; D_noput_pa is tree cover greater than 30% with no regular inputs and U_th is the ratio of uranium to potassium as derived from the radiometric dataset. This sub-bioregional SSPF was used to predict the SOC distribution at a 30 m resolution (as depicted in Figure 5) on a farm where no prior SOC survey had been conducted but necessary environmental covariates were available. Stratification of the predicted farm scale SOC variation (Figure 5) was then utilised as the basis of sampling design via stratified simple random sampling (i.e. see (de Gruijter et al. 2006) and analyses of the dataset are ongoing. A similar approach is being utilised for additional farm scale surveys within other bioregions.

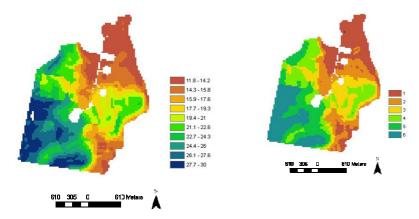


Figure 4. Predicted soil organic carbon (kg/m²/m¹) using sub-bioregional SOC SSPF and local environmental covariates

Figure 5. Stratification of SOC content for sampling design based on predicted SOC distribution (Figure 4)

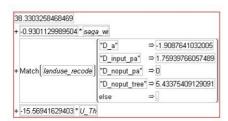


Figure 6. SSPF for SOC (see Figure 5)

Preliminary results indicate that at the local and farm scale controlling factors on soil organic carbon distribution appears to be dominated by landuse, water accumulation in the landscape and the uranium to thorium ratio. More specifically, landuse that involves a perennial component as opposed to annual dominated systems accumulate more SOC within the spatial model. The U:Th ratio also has a strong negative effect on SOC which is likely related to the age of the underlying regolith. Surprisingly, water accumulation is negatively associated with SOC occurrence in this instance. This runs somewhat contrary to the continental scale variation in SOC that appears to be controlled by soil moisture availability as outlined by (Bui *et al.* 2006).

Such fine and comprehensive spatial information of key environmental variables has the potential to support SOC specific SSPFs for sub-bioregional and bioregional scales enabling stratified sampling designs for initial farm scale SOC surveys where no prior soil carbon information exists.

Conclusion

The development of sub-bioregional and bioregional SSPFs for soil organic carbon has the potential to inform pragmatic measurement schemes for the terrestrial carbon system. This is especially pertinent in light of the growing awareness of the dichotomy between the very real opportunities presented by terrestrial carbon sequestration and the practicalities of implementing the currently desired comprehensive-style verification systems. As such, the regional trends in soil organic carbon derived from SSPFs could provide both an indication of local soil carbon potential as well as a foundation database for farm level deviations from regional means.

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