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Distribution variability of soil properties of oil palm (*Elaeis guineensis*) plantations in southern plateau of India

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ABSTRACT

The present study was carried out to assess distribution variability of soil properties like pH, electrical conductivity (EC), organic carbon (OC), available potassium (K) (NH_4OAc-K), phosphorus (P) (Olsen-P), exchangeable calcium (Ca) (Exch. Ca) and magnesium (Mg) (Exch. Mg), available sulphur (S) ($CaCl_2$-S) and hot water soluble boron (B) (HWB) of oil palm (*Elaeis guineensis* Jacq.) plantations in southern plateau region of India. The mean values of soil pH, EC(dS/m), OC (g/kg), NH_4OAc-K (mg/kg), Olsen-P (mg/kg), Exch. Ca (mg/kg) , Exch. Mg (mg/kg), $CaCl_2$-S (mg/kg) and HWB (mg/kg) were 6.94 ± 1.19, 0.53 ± 0.47, 11.6 ± 5.60, 179 ± 107, 92.9 ± 50.6, 820 ± 326, 159 ± 58.9, 21.8 ± 14.9 and 5.81 ± 2.53 respectively in surface (0 to 20 cm) soil layers. Geostatistical analysis revealed that surface soil properties had circular, Gaussian, spherical, and exponential best fit models and were influenced by intrinsic, extrinsic and both intrinsic and extrinsic factors. The wide spatial variability of soil properties warrants site specific nutrient management for higher oil palm production.

Key words: Geostatistics, Oil palm, Spatial variability, Soil properties

Oil palm (*Elaeis guineensis* Jacq.) is a heavy feeder of nutrients and requires balanced and adequate supply of macro and micronutrients for growth and yield. Optimum economic and sustainable oil palm yields can only be achieved with judicious use of fertilizers (Goh *et al*. 2003). Nutritional constraints are major limitations to oil palm productivity in oil palm growing countries including India (Prasad *et al*. 2012). Nutrient disorders/deficiencies like nitrogen (N)/potassium (K) imbalance, K deficiency, magnesium (Mg), deficiency and boron (B) deficiency are commonly prevalent in different oil palm plantations in India affecting oil palm production (Narsimha Rao *et al.* 2014). Fertilizer recommendations in oil palm, like other plantation crops, are based on calibrated soil and leaf tests (Maneepong 2008). Therefore, it is essential to continuously monitor soil nutrient status and leaf nutrient concentrations of oil palm plantations for efficient fertilizer recommendations and sustainable yield. However, information regarding soil nutrient status and leaf nutrient concentrations in oil palm plantations of India is scantily available.

Spatial variability of soil properties may be related to the combined action of physical, chemical and biological processes as well as anthropogenic land use patterns, which vary in space and time across the landscape (Goovaerets 1998). The scales of spatial variation may differ between different soil properties, because the processes that cause variability may occur at different scales, e.g. from the single plant scale to larger topographical scales (Zhang *et al.* 2014). Understanding the patterns and processes of soil spatial variability is key to efficient soil resource management. Disregarding spatial variability may cause undesirable results. Geostatistical estimation helps in predicting values at unsampled location by taking into account the spatial correlation between estimated and sampled points and minimizing the variance of estimation error and implementation costs (Saito *et al.* 2005). Geostatistical methods have been used to effectively assess the spatial variability of soil properties (Mueller *et al.* 2003). Spatial variability of soil chemical properties like pH, organic matter content, available K, phosphorus (P) and N and available and total micronutrients have been studied by different researchers in different soils under different management systems across the world (Li *et al.* 2011, Behera and Shukla 2014, Behera and Shukla 2015). However, spatial variability of soil properties of plantation crops across the world in general and oil palm plantations of India in particular is poorly understood. Therefore, understanding the spatial variability of soil properties in oil palm plantations of India is important for designing site specific sustainable soil management decisions. The

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objective of this study was to examine the spatial dependence and variability of some soil properties using classical and geostatistical methods for site specific soil management in oil palm plantations of Karnataka state of India. A better understanding of the spatial variability of soil properties would enable for refined soil management practices by identification of proper sites for management.

MATERIALS AND METHODS

A survey was carried out in Mysore, Mandya and Hassan districts of Karnataka state during 2012-13 to study soil and plant nutritional status in 42 oil palm plantations. The sampling area lies between 12° 9.8" 7' N latitudes to 77° 3.3' 33" E longitudes and 15° 40.1' 93" N latitudes to 74° 27.7' 45" E longitudes with average mean sea level of 2121 to 3141 feet. The climate of the area is tropical monsoon type with annual average rainfall of 760 mm spread over a period of seven months, i.e. latter half of April to October. April is the hottest month with mean daily maximum temperature at 34.5 °C and daily minimum at 21.1 ˚C with relative humidity of > 70% throughout the year. On normal days, the day temperature during summer may exceed 39°C. The soil types of the districts are broadly lateritic, red loam, sandy loam, red clay and black cotton soils.

A total of 84 soil samples were collected from 0-20 cm (surface) and 20-40 cm (subsurface) depths in the palm basins during the survey to assess soil fertility status of oil palm plantations. The latitude, longitude and elevation at each sampling site were recorded using a handheld global positioning system (GPS) (Oregon 550, Garmin Ltd, Kansas, USA). Each sample was formed from three random samples from an oil palm basin and pooled together to form one representative sample for analysis (Jackson 1973). The soil samples were dried in shade at room temperature, roots and debrises "removed" ground and passed through 2 mm sieve and stored in polyethene bottles for analysis. The 2 mm sieved soil was further ground using pestle and mortar to pass through 0.5 mm sieve for determination of organic carbon (OC). The soil samples were analyzed for pH, electrical conductivity (EC), OC, available K, P, exchangeable Ca and Mg, available sulphur (S) and hot water soluble B. Determination of soil pH and EC were done on 1: 2 soil water ratio (w/v) suspension using pH meter and EC meter following half an hour equilibrium (Jackson 1973). Soil OC content was estimated by Walkley and Black (1934) method. Available K was extracted using neutral normal ammonium acetate solution (NH_4OAc-K) (Hanway and Heidel 1952) and was estimated by flame photometry. Available P (Olsen-P) was extracted using Olsen's reagent (Olsen *et. al.* 1954) and estimated through spectrophotometry. Exchangeable Ca (Exch. Ca) and Mg (Exch. Mg) were extracted using neutral normal ammonium acetate solution (Jones 1998) and estimated through atomic absorption spectrometry. Available S ($CaCl_2$-S) was estimated by turbidity method (Williams and Steinbergs 1969). Hot water soluble B (HWB) was estimated through Azomethine-H reagent (Gupta 1967) using spectrophotometry.

Data were subjected to descriptive analysis. The minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis for soil properties were computed. ARCMap 10.1 was used to analyze the spatial structure of surface soil properties and to define the semivariograms. From semivariograms, differences in nugget/sill ratio and range were examined for soil properties. All semivariograms in isotropic form were fit using spherical, circular, exponential, and Gaussian models. Kriging interpolation was applied to the best fit model. Ordinary kriging was chosen to create the spatial distribution maps of soil properties.

RESULTS AND DISCUSSION

Descriptive statistics of soil properties

The minimum, maximum, SD, CV, skewness and kurtosis values of pH, EC, OC, NH_4OAc-K, Olsen–P, Exch. Ca and Mg and $CaCl_2$-S and HWB ranged widely in soils of oil palm plantations indicating their considerable variability (Table 1). Soil pH varied from 4.76 to 8.74, with mean values of 6.94 ± 1.19 (in surface soil layers) and 6.81 ± 1.33 (in subsurface soil layers). The values of CV for soil pH in both the soil layers revealed their moderate variability and these values were less compared to CV values of other measured soil properties. According to Nielsen and Bouma (1985), the CV values of 10 to 100 are considered moderate variability. Low CV values for soil pH was due to transformed measurement of hydrogen ion concentration. Mulla and McBratney (2000) reported low variability of soil pH and moderate to high variability for organic matter content, available K, available P and soil nitrate nitrogen in acid soils of Australia. Tesfahunegn *et al.* (2011) also reported CV values of 8.6 to 73.4% for a several soil properties in Ethiopia. Wide variability of soil chemical and physical properties in wetland soils of two agro-ecological zones of Lesotho (Nikheloane *et al.* 2012) and grass land and cultivated land in Tokat province of Turkey (Kilic *et al.* 2012) were also reported. This variability is due to the interaction of geological, pedological, microclimatic and land use factors including soil management practices, fertilization and crop rotation on spatial and temporal scales (Mallarino *et al.* 1999, Behera *et al*. 2011). Soil EC ranged from 0.10 to 2.54 dS/m in surface soil layers and from 0.11 to 1.55 dS/m in subsurface soils layers. Soil OC content varied from 1.17 to 28.9 and 1.17 to 21.1 g/kg in surface and subsurface soil layers respectively. The mean values of all the measured soil properties in subsurface soil layers were less than the mean values in surface soil layers. In agreement with our findings, Savita *et al.* (2013) reported wide variability in values of soil pH, available N, P and K in sapota (*Manilkara achras* M. Fosberg)) orchards of Raichur, Dharwad and Belgaum districts of Karnataka, India. Nayak *et al.* (2011) also recorded significant variation in soil pH, EC, OC, available N, Olsen's-P and available K status in aonla (*Emblica officinalis* Gaertn.) orchards of central Indo-

Table 1 Descriptive statistics* for selected soil properties of surface and subsurface layers (n=42)

Soil properties	Soil layer	Min.	Max.	Mean	SD	CV (%)	Skew.	Kurt.
pH	Surface	4.91	8.74	6.94	1.19	17.1	-0.27	-1.30
	Subsurface	4.76	8.72	6.81	1.33	19.5	-0.19	-1.36
EC, dS/m	Surface	0.10	2.54	0.53	0.47	89.5	2.33	7.08
	Subsurface	0.11	1.55	0.46	0.36	79.1	1.58	2.33
OC, g/kg	Surface	1.17	28.9	11.6	5.60	48.2	0.90	1.75
	Subsurface	1.17	21.1	7.86	4.05	51.5	0.78	1.43
NH_4OAc-K, mg/kg	Surface	31.2	386	179	107	59.8	0.69	-0.86
	Subsurface	5.00	456	121	81.5	67.6	2.02	6.07
Olsen-P, m/kg	Surface	7.69	242	92.9	50.6	54.4	0.69	-0.87
	Subsurface	2.56	155	73.9	31.8	72.5	1.47	3.22
Exch. Ca, mg/kg	Surface	156	1273	820	326	39.7	0.68	-0.87
	Subsurface	124	1389	701	343	49.0	0.43	-0.69
Exch. Mg, mg/kg	Surface	52.8	307	159	58.9	37.1	0.69	-0.87
	Subsurface	34.8	328	156	69.7	44.8	0.73	0.25
$CaCl_2$-S, mg/kg	Surface	2.25	73.5	21.8	14.9	68.1	1.27	2.45
	Subsurface	2.25	36.7	13.9	8.69	62.5	1.04	1.26
HWB, mg/kg	Surface	2.29	16.0	5.81	2.53	43.6	1.94	6.01
	Subsurface	2.24	8.45	4.72	1.67	35.5	0.40	-0.85

*Min., Minimum; Max., Maximum; SD, Standard deviation; CV, Coefficient of variation; Skew., Skewness; Kurt., Kurtosis.

Gangetic plains of Uttar Pradesh, India. Skewness of soil properties was low to high and the values ranged from -0.27 to 2.33. Highly skewed properties in both the soil layers include all the measured soil properties except soil pH. Highly skewed properties indicated that these properties had a local distribution, the high values were recorded for these properties at some points, but most of the values of these properties were low (Grego *et al.* 2006). Similar trend was recorded for coefficient of kurtosis (Table 1) and the values ranged from -1.36 to 7.08 for different soil properties.

Spatial distribution of surface soil properties

Evaluating the spatial variability of soil properties and mapping such variations are very useful and applicable techniques for the precise determination of soil behaviour fluctuations. Such evaluations can be used for optimum fertilizer application recommendations because appropriate use of nutrients can contribute to enhanced crop quantity and quality, while being environmentally sustainable (Miransari and Mackenzie 2010). Also, knowledge of spatial dependency and distribution of soil properties is crucial for natural resource evaluation and environmental management of un-surveyed locations. Classical statistics like CV could not identify the spatial variability of soil properties at the un-sampled sites. Geostatistical analysis however permits examination and understanding of spatial dependency of a soil property (Liu *et al.* 2006). Best fit models were found to be circular, Gaussian, spherical and exponential for different soil properties in surface soil layers (Table 2). Soil pH, OC and $CaCl_2$-S had circular best fit models, whereas EC, Olsen-P and HWB had Gaussian best fit models. Exch. Ca and Mg and NH_4OAc-K had exponential and spherical best fit models respectively. In agreement with our findings, Tesfahunegn *et al.* (2011) also reported best fit models such as spherical for soil pH, OC and exchangeable K, exponential for exchangeable Ca and Mg and Gaussian for total nitrogen and total phosphorus in Mai-Negus catchment of north Ethiopia. The semivariogram provides a clear description of the spatial

Table 2 Semivariogram parameters of surface soil properties

Soil properties	Model	Nugget	Sill	Nugget: Sill ratio	Spatial class	Range (m)
pH	Circular	0.225	0.818	0.275	Moderate	43491
EC	Gaussian	0.021	0.196	0.107	Strong	51380
OC	Circular	20.8	51.1	0.407	Moderate	581
NH_4OAc-K	Spherical	3500	3500	1.000	Weak	4525
Olsen-P	Gaussian	97.6	149.9	0.651	Moderate	771
Exch. Ca	Exponential	10906	341322	0.032	Strong	581
Exch. Mg	Exponential	19839	20685	0.959	Weak	1110
$CaCl_2$-S	Circular	61.2	95.1	0.643	Moderate	32586
HWB	Gaussian	2.01	3.47	0.579	Moderate	29497

structure of variables and provides some insight into possible processes affecting data distribution (Webster and Oliver 1990). The nugget/sill ratio expressed in percentage was the criterion used to classify the spatial dependence of variables. Ratio value lower than or equal to 25% was considered strongly spatially dependent. If the ratio value was between 25 and 75%, the variable was considered moderately spatially dependent. More than 75% ratio value is considered weakly spatially dependent (Cambardella *et al.* 1994). The semivariogram, the main component of kriging, is an effective tool for evaluating spatial variability (Boyer *et al*. 1991). Strong spatial dependence of soil properties can be attributed to intrinsic factors such as soil properties and mineralogy, whereas, weak spatial dependence is due to extrinsic factors such as anthropogenic activities. Moderate spatial dependence is owing to both intrinsic and extrinsic factors. Measured soil properties exhibited weak to strong spatial dependency. Spatial dependency classes of soil pH, OC, Olsen-P, $CaCl_2$-S and HWB were moderate indicating the influence of both intrinsic and extrinsic factors on these properties. Soil EC and Exch. Ca had strong spatial dependency class whereas; NH_4OAc-K and Exch. Mg had weak spatial dependency class. This is in line with the findings of Tesfahunegn *et al.* (2011) and Foroughifar *et al.* (2013). Range value is a measure of the spatial extension within which autocorrelation exists (Webster and Oliver 1990). Estimates of range tend to be landscape dependent and may be interpreted to indicate the distance across distinct soil types. In these soils, the range of different soil properties varied from 581 to 51380 m (Table 2). Samples separated by distances closer than the range are related spatially, and those separated by distances greater than the range are not spatially related. Higher range values were recorded for soil pH, EC, $CaCl_2$-S and HWB. A large range value of a soil property indicates that the value of measured soil property is influenced by natural and anthropogenic factors over greater distances. Different ranges of measured soil properties may be due to combined effect of parent material, climatic conditions and land management practices adopted in different soil series. The kriged distribution maps (not given) for different soil properties indicate the variability and distribution of soil properties in the region, which is of great use for planning appropriate strategies for efficient soil management for higher yield. The areas with low nutrient availability require more amount of nutrient application as compared to areas having high nutrient availability. The usability of such a distribution maps can also be increased if the farmers in the area become familiar with the characteristics related to the analyzed soil properties and accordingly can plan appropriate agricultural strategies, including variable rate amendment technologies like fertilizer application (Ramamurthy *et al.* 2009). According to our findings, the soils are variable and heterogeneous and hence use of traditional practices cannot supply plants with their necessary nutrients. Hence, site specific soil management can be very useful for planning site-specfic agricultural practices including fertilizer application, which are profitable as well as environmentally and economically sound.

It was concluded that soil pH, EC, OC, NH_4OAc-K, Olsen–P, Exch. Ca and Mg, $CaCl_2$-S and HWB in both the soil layers of oil palm plantations in Southern plateau of India varied widely. All the measured surface soil properties had wider variability in spatial distribution pattern and therefore site specific fertilizer management decisions need to be taken for sustainable oil palm cultivation.

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REFERENCES

Anonymous. 2013. Oil world 2013 at http://www.oilworld.biz/annual (accessed 24 June 2014).

Behera S K and Shukla A K. 2014. Total and extractable manganese and iron in some cultivated acid soils of India - status, distribution and relationship with some soil properties. *Pedosphere* **24**(2): 196–208.

Behera S K and Shukla A K. 2015. Spatial distribution of surface soil acidity, electrical conductivity, soil organic carbon content and exchangeable potassium, calcium and magnesium in some cropped acid soils of India. *Land Degradation & Development* **26**(1): 71–9.

Behera S K, Singh M V, Singh K N and Todwal S. 2011. Distribution variability of total and extractable zinc in cultivated acid soils of India and their relationship with some selected soil properties. *Geoderma* **162**(3-4): 242–50.

Boyer D G, Wright R J, Feldhake C M and Bligh D P. 1991. Soil spatial variability in steeply sloping acid soil environment. *Soil Science* **161**: 278–87.

Cambardella C A, Moorman T B, Novak J M, Parkin T B, Karlen D L, Turco R F and Konopka A E. 1994. Field scale variability of soil properties in central Iowa soils. Soil *Science Society of America Journal* **58**: 1 501–11.

DOPR. 2012. Oil Palm Area Assessment Report –DOPR (2012). DOPR and Department of Agriculture and Cooperation, Ministry of Agriculture, Government of India, New Delhi.

DOPR. 2013. *Annual Report 2012-13. Directorate of Oil Palm Research (DOPR), Pedavegi Andhra Pradesh.*

Foroughifar H, Pakpour A, Jafarzadeh A A, Miransari M and Torabi H. 2013. Using geostatistics and geographic information system techniques to characterize spatial variability of soil properties, including micronutrients. *Communications in Soil Science and Plant Analysis* **44**: 1 273–81.

Goh K J, Hardter R and Fairhust T H. 2003. Fertilizer for maximum return. *(In)* Oil Palm: Management for High and Sustainable Yields, pp 278–306. Potash and phosphate Institute, Potash and Phosphate Institute of Canada, International Potash Institute, Singapore.

Goovaerts P. 1998. Geostatistical tools for characterizing the spatial variability of microbiological and physio-chemical soil properties. *Biology and Fertility of Soils* **27**: 315–34.

Grego C R, Vieira S R and Lourencao A L. 2006. Spatial distribution of *Pseudaletia sequax* Franclemlont in triticale under no-till management. *Scientia Agricola* **63**: 321–27.

Gupta U C. 1967. A simplified method for determining hot-water soluble boron in podzol soils. *Soil Science* **103**: 424–28.

Hanway J J and Heidel H. 1952. Soil analyses methods as used in Iowa state college soil testing laboratory. *Iowa Agriculture* **57**: 1–31.

Jackson M L. 1973. *Soil Chemical Analysis*. Prentice Hall of India, New Delhi.

Jones Jr J B. 1998. Soil test methods: Past, present, and future. *Communications in Soil Science and Plant Analysis* **29**: 1 543–52.

Kilic K, Kilic S and Kocyigit R. 2012. Assessment of spatial variability of soil properties In areas under different land use. *Bulgarian Journal of Agricultural Science* **18** (5): 722–32.

Li X F, Chen Z B, Chen H B and Chen Z Q. 2011. Spatial distribution of soil nutrients and their response to land use in eroded area of South China. *Proceedings of Environmental Sciences* **10**: 14–9.

Liu X, Herbert S J, Hashemi A M, Zhang X and Ding G. 2006. Effects of agricultural management on soil organic matter and carbon transformation – a review. *Plant, Soil and Environment* **52**: 531–6.

Mallarino A P, Oyarzaba, E S and Hinz P N. 1999. Interpreting within-field relationships between crop yields and soil and plant variables using factor analysis. *Precision Agriculture* **1**: 15–26.

Maneepong S. 2008. A nutrient survey for establishment of standard recommendation of soil and plant analysis for pomelo. *Agricultural Science Journal* **37**(3): 62–5.

Miransari M and Mackenzie A F. 2010. Wheat (*Triticum aestivum* L.) grain N uptake as affected by soil total and mineral N, for the determination of optimum N fertilizer rates for wheat production. *Communications in Soil Science and Plant Analysis* **41**: 644–53.

Mueller T G, Hartsock N J, Stombaugh T S, Shearer S A, Cornelius P L and Barnhise R I. 2003. Soil electrical conductivity map variability in limestone soil overlain by loess. *Agronomy Journal* **95**: 496–507.

Mulla D J and McBratney A B. 2000. Soil spatial variability. *(In) Handbook of Soil Science*, pp 321–52. Summner M E (ed). CRC Press, Boca Raton.

Narasimha Rao B, Suresh K, Behera S K, Ramachandrudu K and Manorama K. 2014. Nutrient management in oil palm. Technical Bulletin, DOPR, Pedavegi, pp 1–24.

Nayak A K, Sharma D K, Singh C S, Mishra V K, Singh G and Swarup A. 2011. Diagnosis and recommendation integrated system approach for nitrogen, phosphorus, potassium and zinc foliar diagnostic norms for aonla in central Indo-gangetic plains. *Journal of Plant Nutrition* **34**: 547–56.

Nielsen, D R and Bouma J. 1985. Soil spatial variability. *(In) Proceedings of a Workshop of the ISSS and the SSSA,* Las Vegas, USA, 30 November to 1st December, 1984, Pudoc, Wageningen, The Netherlands, p 243.

Nikheloane T, Olaleye A O and Mating R. 2012. Spatial heterogeneity of soil physic-chemical properties in contrasting wetland soils in two agro-ecological zones of Lesotho. *Soil Research* **50**: 579–87.

Olsen S R, Cole C V, Watanable F S and Dean L A. 1954. Estimation of available phosphorus in soils by extraction with sodium bicarbonate. Circular US, Department of Agriculture No. 939.

Prasad M V, Sairam C V, Arulraj S and Jameema J. 2012. Estimation of cost of production of oil palm in Andhra Pradesh. *(In)* Abstracts of paper, Plantation Crops Symposium XX, Coimbatore, pp 136.

Ramamurthy V, Naidu L G K, Ramesh Kumar S C, Srinivas S and Hegde R. 2009. Soil-based fertilizer recommendations for precision farming. *Current Science* **97**: 641–7.

Saito H, McKenna A, Zimmerman D A and Coburn T C. 2005. Geostatistical interpolation of object counts collected from multiple strip transects: ordinary kriging versus finite domain kriging. *Stochastic Environmental Research and Risk Assessment* **19**: 71–85.

Savita B, Raghupathi H B, Verma S and Anjaneyulu K. 2013. Nutritional status of sapota (*Manilkara achras* M. Fosberg) gardens and optimum ranges of nutrients for higher production. *Journal of the Indian Society of Soil Science* **61**(2): 112–6.

Tesfahunegn G B, Tamene L and Vlek P L G. 2011. Catchment-scale spatial variability of soil properties and implications on site-specific soil management in northen Ethiopia. *Soil and Tillage Research* **117**: 124–39.

von Uesxkull H R and Fairhurst T H. 1991. Fertilizing for higher yield and quality. The oil Palm. IPI, Bern, 79 p.

Walkley A J and Black I A. 1934. An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. *Soil Science* **37**: 29–38.

Webster R and Oliver M A. 1990. *Statistical Methods in Soil and Land Resource Survey.* Oxford University Press, London.

Williams C H and Steinbergs A. 1969. Soil sulphur fractions as chemical indices of available sulphur in some Australian soils. *Australian Journal of Agricultural Research* **10**: 340–52.

Zhang X, Sahajpal R, Manowitz D H, Zhao K, LeDue S D, Xu M, Xiong W, Zhang A, Izaurralde R C, Thomsom A M, West T O and Post W O. 2014. Multi-scale geospatial agroecosystem modelling: A case study on the influence of soil data resolution on carbon budget estimates. *Science of the Total Environment* **479-480**: 138–50.