DEM and terrain analysis to predict spatial pattern of SOC

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Abstract
A simple approach to predict spatial pattern of SOC using a surrogate variable, soil Munsell value, with the aid of digital terrain analysis is presented. Digital elevation models (DEMs) were prepared using readily available digital topographic maps and then enhanced for a small sloping catchment in the Adelaide hills using plausibility algorithms. Seven terrain parameters were calculated from the DEMs. One hundred random points were identified across the 5.6 ha site and soil Munsell value was obtained. Correlation analysis showed elevation, specific catchment area, profile curvature, and wetness index influence soil Munsell value. It was also found that the application of plausibility algorithms to DEMs derived from topographic maps produced better correlation coefficients compared to unsmooth DEMs.

Key Words
Soil Munsell value, digital terrain parameters.

Introduction

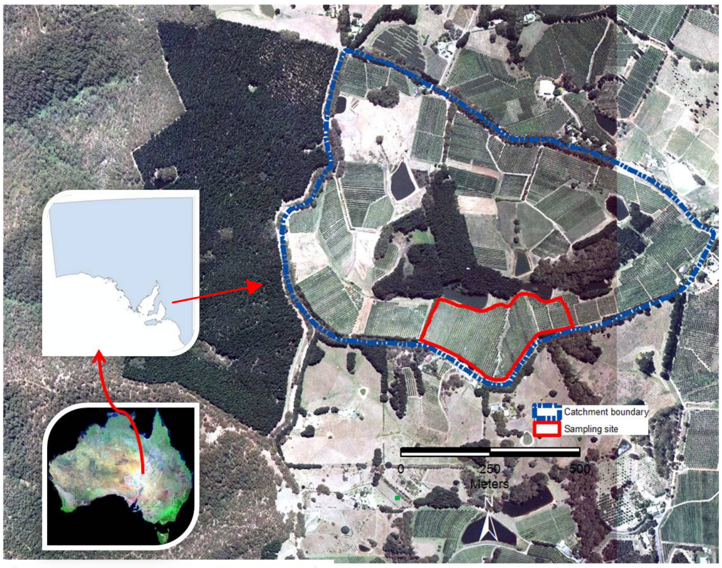
Soil organic carbon (SOC) influences crop yield and acts as binding material for nutrients and agrochemicals (Konen *et al.* 2003; Lal 2007). Quantifying and mapping the spatial distribution of SOC is therefore important to an effective farm management as well as in broad carbon cycle modelling (Wills *et al.* 2007). Accurate but practical means of elucidating spatial distribution of SOC is needed because current laboratory quantification is overwhelmingly expensive. Soil colour, particularly Munsell value, has been used as a surrogate for SOC (Konen *et al.* 2003; Schulze *et al.* 1993; Wills *et al.* 2007) where darker soils are associated with high SOC and lighter soils with low SOC. Although soil colour determination using Munsell Colour Chart is subjective, it can be used to assess the distribution of SOC across large landscapes (Wills *et al.* 2007). SOC pattern in the landscape is also strongly influenced by the distribution of water and soil material (Pennock and Corre 2001) such that it can be predicted from terrain. Terrain parameters can be readily derived from digital elevation models (DEM) and particularly those relating to water flow accumulation and dissipation are well suited to predict SOC and soil colour (Gessler *et al.* 1995; Moore *et al.* 1991). However, SOC distribution is site specific and fundamentally affected by agronomic management. The utility of soil colour measurement and terrain analysis, which are both easy and intuitive, to infer spatial distribution of SOC in an agronomically homogenous landscape has not been fully explored. Thus, this research was conducted if terrain attributes calculated from topographic maps can be used to infer spatial distribution of SOC through soil colour in a hilly apple tree orchard. This research also investigated the effect of plausibility algorithms in preparing hydrologically correct DEM.

Methods

A sloping area located within the Mt. Lofty Ranges (30 km east of Adelaide, South Australia) has been selected for this purpose (Figure 1). The subcatchment has a relief of about 100 m and a Mediterranean climate. The site has brown duplex soil overlying a Stonyfell Quartzite formation (Heath 1963). The apple orchard was established in the early 1950s and little soil trenching was done prior to tree establishment. Topographic maps (1:10,000 and 1:50,000) in digital format have been sourced from the Department of Environment and Heritage – South Australia. Both maps were derived from analogue photogrammetric techniques and scanned then converted to GIS formats. The 1:10,000 map has a contour interval of 5 m. The 1:50,000 map has a contour interval of 10 m. Both maps have unknown vertical and horizontal accuracy.
A 5x5 m and a 10x10 m pixel DEM were generated for each of the two topographic data using the Topo to Raster tool in ArcGIS 9.2 incorporating drainage enforcement and sink filling. One of the main problems in soil-terrain modelling is the accuracy of available topographic data suitable for regional soil mapping. This can addressed through plausibility algorithms that reduces errors in DEM generation (Hengl *et al.* 2004).Two plausibility algorithms were then carried out to enhance the quality of the DEMs. The first algorithm involved the reduction of outliers through low pass filtering. The second one involved the reduction of padi terraces using focal mean statistics. Both algorithms were done on a 3x3 moving window. This resulted to

four (4) DEMs namely: s5-5; s5-10; s10-5; and s10-10. These DEMs where then compared with the interpolated 5x5 m pixel DEM of the 1:10,000 topographic map and 10x10m pixel DEM of the 1:50,000 topographic map (hereinafter referred as r5 and r10, respectively). Seven (7) key terrain parameters (Table 1) were calculated in GIS environment for each of the DEM using a freely available software called Terrain Analysis System (Lindsay 2006) and the distributional algorithm developed by Ostendorf and Reynolds (1993).

One hundred locations were randomly selected across a 5.6 ha area within the subcatchment. Points were referenced on the ground using a handheld high-sensitivity GPS. Each point consisted of 5 soil samples 0.5 m apart in a Z configuration. The top 10 cm of soil found between apple tree rows was obtained with a soil auger. Soil samples were air-dried, composited and analysed in the laboratory. Air-dry soil colour was determined using Munsell® Colour Chart (1998 edition) under natural diffuse daylight. Soil Munsell value was extracted and tabulated against the aforementioned topographic parameters including elevation obtained by nearest neighbourhood sampling of the DEMs. Spearman rank correlation analysis was performed to determine the degree of relationship and to compare the various DEM qualities and resolutions.



(Sources: Geoscience, Australia and DEH, South Australia)

Figure 1. Location of the study site.

Table 1. Terrain parameters calculated in this study.

Attribute	Description
Slope,	
Plan curvature (PlanC), /m	a measure of topographic convergence and divergence
Profile curvature (ProfC), /m	a measure of flow acceleration or deceleration
Tangential curvature (TanC), /m	a measure of flow convergence and divergence
Specific catchment area (SCA), m^2/m	the ratio of the area upslope of a contour segment that contributes flow to that segment and the length of that segment
Sediment transport capacity index (STCI)	equivalent to RUSLE Length-Slope factor
Wetness index (WI)	the ratio of specific catchment area and slope

Results

The resulting DEM varied across the various pixel qualities and resolutions prepared as evidenced by the differing statistical measures of terrain parameters (Table 2). Slope and curvature parameters, for instance, became subtler after two smoothing operations (low pass filtering and focal mean statistics) were done on both topographic map scales. Moreover, increasing the pixel size resulted to a more generalised topography. Thompson et al (2001) attributed this to loss of details as a result of smoothing the topography.

Spearman rank correlation analysis reveals elevation, ProfC, SCA and WI correlates well with soil Munsell value (Table 3) in the study site. These observations were congruent to those of Gessler *et al* (2000), Moore *et al* (1993), Takata *et al* (2007), and Thompson *et al* (Thompson *et al.* 2001). The directions of correlation were similar for all DEMs prepared. However, the magnitude and significance varied depending on the quality of the DEM. A smoother DEM improved the correlation regardless pixel size.

Table 2. Summary statistics of terrain parameters across the different DEM resolution and quality.

Terrain parameters	Statistics	DEM					
		r5	s5-5	s5-10	r10	s10-5	s10-10
Slope	min	6.08	6.81	6.70	2.80	3.38	1.96
	µ	13.2	12.9	11.9	12.4	12.3	11.17
	max	20.9	19.2	16.9	21.6	20.3	18.1
	S	2.99	2.62	2.41	3.90	3.76	3.21
Plan curvature	min	-3.92	-3.27	-2.10	-3.02	-3.54	-3.42
	µ	-0.179	0.166	0.0460	-0.059	0.0715	-0.0258
	max	4.19	1.88	1.23	3.68	2.24	1.20
	S	1.11	0.86	0.611	1.16	0.915	0.738
Profile curvature	min	-0.909	-0.359	-0.268	-0.700	-0.387	-0.238
	µ	-0.0079	-0.00766	-0.0181	0.00617	0.0167	0.00854
	max	0.733	0.599	0.323	0.882	0.453	0.308
	S	0.260	0.159	0.117	0.230	0.213	0.136
Tangential curvature	min	-0.709	-0.374	-0.213	-0.499	-0.333	-0.214
	µ	-0.0302	-0.0344	-0.0157	-0.0143	-0.0177	-0.00743
	max	0.781	0.421	0.279	0.658	0.671	0.307
	S	0.222	0.159	0.104	0.206	0.174	0.109
Specific catchment area	min	9.99	5.08	10.0	18.5	5.11	10.0
	µ	58.3	54.1	76.2	84.6	76.5	78.4
	max	392.	770	480	1680.	1370	570
	S	56.5	79.3	81.2	170.	168	88.6
Sediment transport capacity index	min	0.999	0.589	1.56	0.750	0.771	1.19
	µ	5.71	5.15	5.49	5.89	5.33	4.99
	max	18.6	21.9	14.5	14.3	31.5	13.2
	S	3.02	3.09	2.53	2.83	4.35	2.43
Wetness index	min	3.82	2.94	3.51	4.22	2.99	3.97
	µ	5.28	5.12	5.59	5.62	5.29	5.66
	max	7.69	8.30	7.95	10.4	9.71	9.72
	S	0.67	0.824	0.846	0.849	1.06	0.987

Min– minimum; max – maximum; µ – mean; S – standard deviation; r5 – interpolated 5m pixel DEM from 1:10,000 map; r10 – interpolated 10m pixel DEM from 1:50,000 map; s5-5 – smooth 5m pixel DEM from 1:10,000 map; s5-10 – smooth 10m pixel DEM from 1:10,000 map; s10-5 – smooth 5m pixel DEM from 1:50,000 map; s10-10 – smooth 10m pixel DEM from 1:50,000 map

Table 3. Comparison of DEM using Spearman's rank correlation of Munsell value and terrain parameters.

Parameters	DEM					
	R5	S0505	S0510	R10	S1005	S1010
Elevation	0.488 ***	0.494 ***	0.488 ***	0.492 ***	0.487 ***	0.48 ***
Slope	0.014 ns	0.032 ns	0.025 ns	0.12 ns	0.108 ns	0.123 ns
PlanC	-0.089 ns	-0.196 *	-0.24 *	-0.075 ns	-0.102 ns	-0.147 ns
ProfC	-0.152 ns	-0.267 **	-0.35 ***	-0.261 **	-0.235 *	-0.364 ***
TanC	-0.102 ns	-0.204 *	-0.25 *	-0.078 ns	-0.061 ns	-0.116 ns
SCA	-0.354 ***	-0.432 ***	-0.402 ***	-0.287 **	-0.358 ***	-0.353 ***
STCI	-0.222 *	-0.273 **	-0.314 ***	-0.108 ns	-0.124 ns	-0.107 ns
WI	-0.39 ***	-0.466 ***	-0.407 ***	-0.224 *	-0.308 **	-0.357 ***

Please see DEM notation on Table 2; * $\alpha = 0.05$; ** $\alpha = 0.01$; *** $\alpha = 0.001$; ns – not significant

Conclusion

Various digital terrain models have been derived from existing topographic data (available from state mapping agencies; derived from early topographic surveys) and provided valuable tool in soil-landscape modeling. Smoothing the DEM enhanced terrain models.

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