Uncertainty analysis of digital terrain modelling

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Introduction

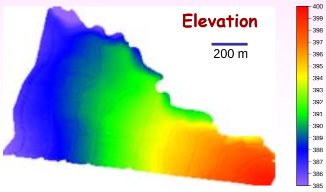
As remote-sensing technologies improve, DEMs are becoming available at greater resolution for more of the earth's surface. Concurrently, advances in global positioning system (GPS) technology are enabling the acquisition of accurate elevation information for smaller extents. Carrier phase GPS can achieve sub-decimetre vertical accuracies and provides an elevation measurement with an associated uncertainty, the RMSE for each observation. This provides the opportunity for the simultaneous creation of a DEM and an associated error surface.

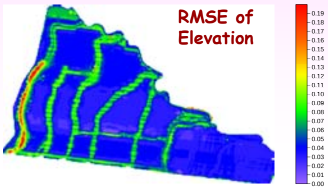
Digital elevation model is the basis for calculation of terrain attributes. For primary attributes that are derived locally, a quadratic trend local surface is usually fitted to the surface. The standard method involves calculating the parameters of a central cell and its 8 neighbourhood in a moving 3 × 3 cells window.

Uncertainty in the calculation of terrain attributes is composed of the input and model uncertainty. Input uncertainty comes from the quality of the DEM. The model uncertainty is mainly a function of how well a quadratic function fits the 'real' surface and the approximation of the finite-differences.

Study area

The dataset is from a 72 hectare field near Moree in northern New South Wales, Australia (Bishop, 2003). Elevation was surveyed with two carrier-phase Ashtech GPS, one was used as a base station and the other as the roving receiver. The post-processing software, P-NAV was used to obtain decimetre accurate elevation measurements. The output is an elevation estimate and an associated uncertainty estimate, in terms of the RMSE. The point elevation and uncertainty data was interpolated with 5 metre block kriging.

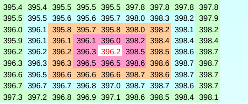




Digeman

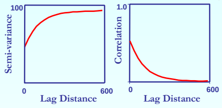
We implement the uncertainty analysis of terrain attributes as a result of elevation uncertainty and model uncertainty in a program called Digeman.
The model used a generalisation of Wood (1996) for multiple windows to calculate the surface attributes. Monte-Carlo simulation with Latin hypercube sampling of correlated variables (LHS) (Iman and Connover, 1982) was used to create spatially correlated uncertainty. Model uncertainty was estimated by fitting a quadratic function to the DEM surface and estimating the standard error of the parameters. Monte-Carlo simulation with LHS was used to generate multiple realisations of the attributes.

Elevation matrix



395.4	395.4	395.5	395.5	395.5	397.8	397.8	397.8	397.8
395.5	395.5	395.6	395.6	395.7	398.0	398.3	398.2	397.9
396.0	396.1	395.8	395.7	395.8	398.0	398.2	398.1	398.2
395.9	396.1	396.1	396.1	396.0	398.2	398.4	398.4	398.4
396.2	396.2	396.2	396.3	396.2	398.5	398.5	398.6	398.7
396.3	396.3	396.3	396.5	396.5	398.6	398.6	398.7	398.7
396.6	396.5	396.6	396.6	396.6	398.7	398.6	398.7	398.7
396.7	396.7	396.7	396.8	397.0	398.7	398.7	398.6	398.7
397.3	397.2	396.8	396.9	397.1	398.6	398.5	398.4	398.1

Calculate Semivariogram & corellogram

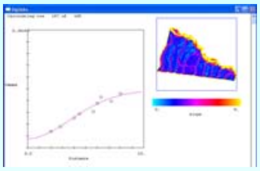


Fit quadratic surface

$$z = ax^2 + by^2 + cxy + dx + ey + f$$

Least-squares solution

Calculate terrain attributes



Algorithms in Digeman

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Determine windows size w, and the number of realisation for uncertainty in the
elevation n & number of realisation for uncertainty in the model m

For each elevation point:
•Extract the local neighbourhood from w
•Calculate the local variogram of altitude data
•Fit a variogram model to the data $\gamma(h)$
•LHS of altitudes from the specified windows w producing sample: $z_1, z_2 .... z_n$
   For $i$ =1 to $n$
      - Fit a quadratic response surface, with weight $1/\gamma(h)$ to $z_i$
          $z = ax^2 + by^2 + cxy + dx + ey + f$
      - Obtain parameter vector p = [a,b,c,d,e,f] and their std. dev.
      - LHS parameters a,b,c,d,e,f at m samples: $p_1, p_1, ... , p_m$
      For $j$ = 1 to $m$
            calculate terrain attributes with $p_j$:
                  slope, aspect, curvatures
       next $j$
   next $i$
•average the terrain attributes & calc their std dev
```

References:

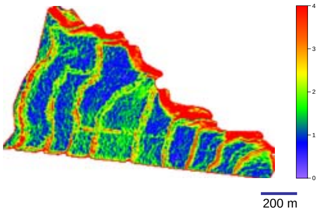
Bishop, T.F.A., 2003. Geodata Processing Methods for Site-Specific Crop Management. PhD Thesis, The University of Sydney, Australia.

Iman, R.L., Conover, W.J., 1982. A distribution-free approach to inducing rank correlation among input variables. Communications in Statistics B11, 311-334.

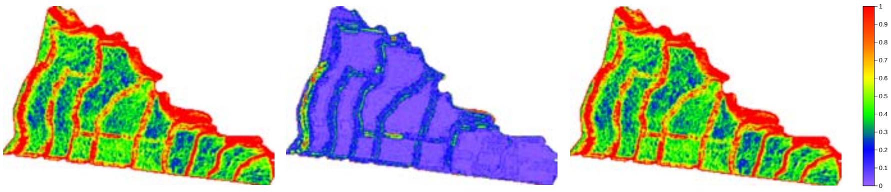
Wood, J., 1996. The Geomorphological Characterisation of Digital Elevation Models. PhD Thesis, University of Leicester, UK

Effect of input & model uncertainty

Slope (%)



Uncertainty of slope

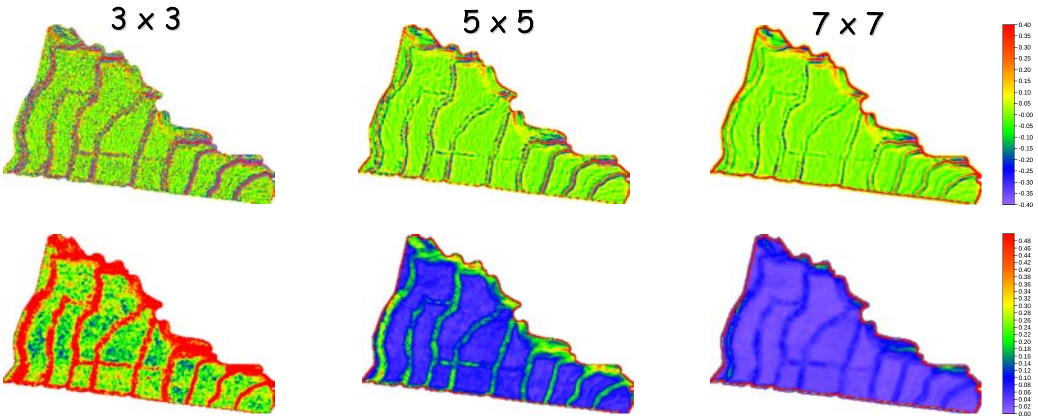


Source of uncertainty: **Elevation** **Model** **Elevation & model**

Effect of varying windows size

Profile curvature

Uncertainty of profile curvature



Digeman is available for download at: http://www.usyd.edu.au/su/agric/acpa/software

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