Prediction uncertainty in elevation and its effect on flood inundation modelling

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Flood awareness in the UK has risen dramatically in the last few years after several major flood events. Flooding has seen a resurgence in research effort and, in particular, work has become increasingly focused on flood inundation modelling. However, all data used (and hence parameters and variables) in flood inundation models have inherent uncertainty. The challenge is to quantify this uncertainty and, perhaps more importantly, assess the effect that uncertainty may have on model predictions.

Floodplain topography is the principal variable that affects the movement of the flood wave and is, therefore, critical to the prediction of inundation extent. Ideally, a flood inundation model requires elevation data that represent closely the true ground surface. High quality remotely-sensed elevation data are often unavailable for the area of interest and may contain features higher than the true land surface (e.g., buildings and vegetation). Any land feature which restricts (but not prevents) the flow of water (e.g. forest) should be accounted for in the friction terms of the model rather than represented by an area of higher elevation.

In this paper, readily available contour data were supplemented with differential GPS measurements of elevation on the floodplain on a reach of the Hampshire Avon river, England (Figure 1). Experimental variograms were predicted for both the original contour data and the GPS supplemented data. The original contour data were fitted well by a Gaussian model, which has a concave upwards form near the ordinate, indicating over-generalisation. The addition of GPS measurements to the contour data resulted in a reduction of this concavity, indicating a corresponding reduction in generalisation.

The combined data were interpolated using ordinary Kriging to create a digital elevation model (DEM) that is more representative of the true floodplain surface (Figure 2). Flooding was then simulated for a 60 day event during the autumn 2000 floods using the grid-based model LISFLOOD-FP (Bates and De Roo, 2000, De Roo et al., 2000, Horritt and Bates, 2001). The 1D linear kinematic Saint-Venant equations were applied within the channel, and flow on the floodplain was approximated using a continuity equation. In particular, change in the volume in a cell over time is equal to the fluxes into and out of it. Flow rates were calculated based on the height of the water surface above the land, and the Manning friction coefficient.

Prediction uncertainty in the combined contour and GPS data was then assessed using the geostatistical method of stochastic simulation, which was developed to provide measures of spatial uncertainty rather than provide a single “best fit” interpolation of data. Conditional simulation (Deutsch and Journel, 1998) was used here as it honours the values of the data at their original locations, and aims to reproduce global features and statistics of the data. One hundred different elevation simulations were generated from the combined contour and GPS data, each maintaining the same original variogram. Therefore, given the original data, each simulation can be said to have an equal probability of representing the true floodplain surface. By comparing model results using each simulation, the effect of data uncertainty can be assessed.

The model was run for the same 60 day flood event on each elevation scenario at a spatial resolution of 25 m. Simulations were conducted on a large Beowulf cluster at the University of Southampton, each taking approximately 40 hours to complete on 1 GHz processors.

Mean and variance in predicted flood depth across all simulations was calculated at regular intervals during the flood event. In addition, mean and variance was calculated for the maximum flood depth, time of maximum flood depth, duration of flooding, flood volume, flooded area and channel outflow. These were compared to the predictions obtained using the original Kriged data. In addition, each prediction was assessed against aerial photography of flood inundation acquired close to the flood peak, using both global and local measures of fit. The greatest variation in predicted inundation was observed at the edge of the floodplain.

References

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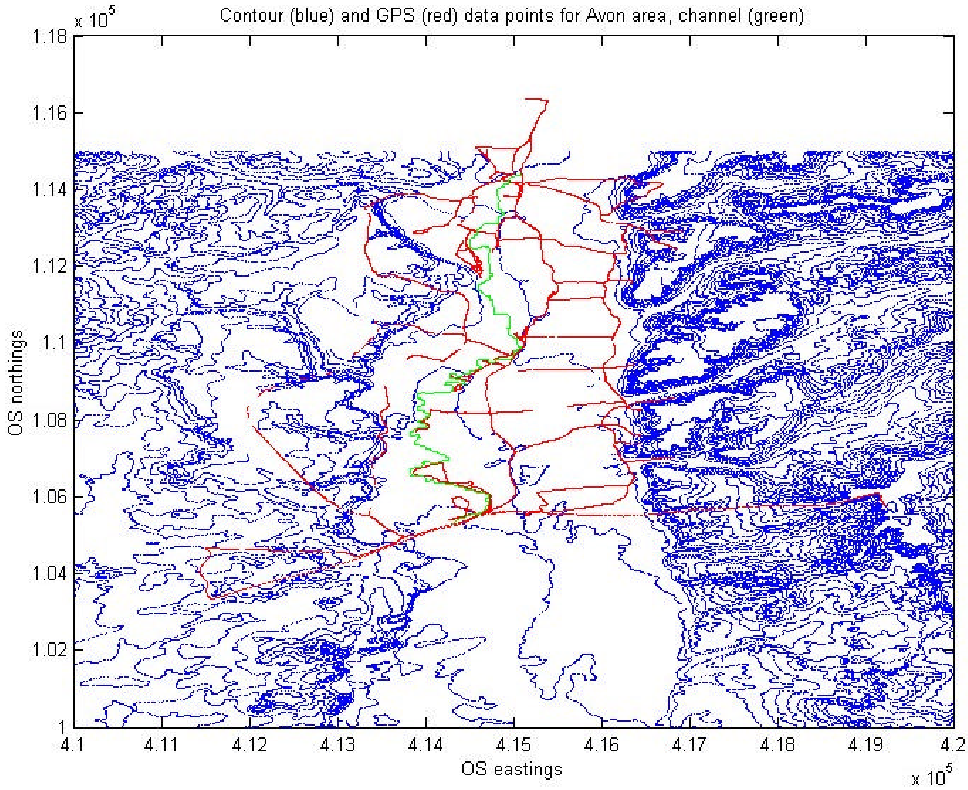

Figure 1. Contour data points, differential GPS data points, and channel location for a reach of the Hampshire Avon, England.

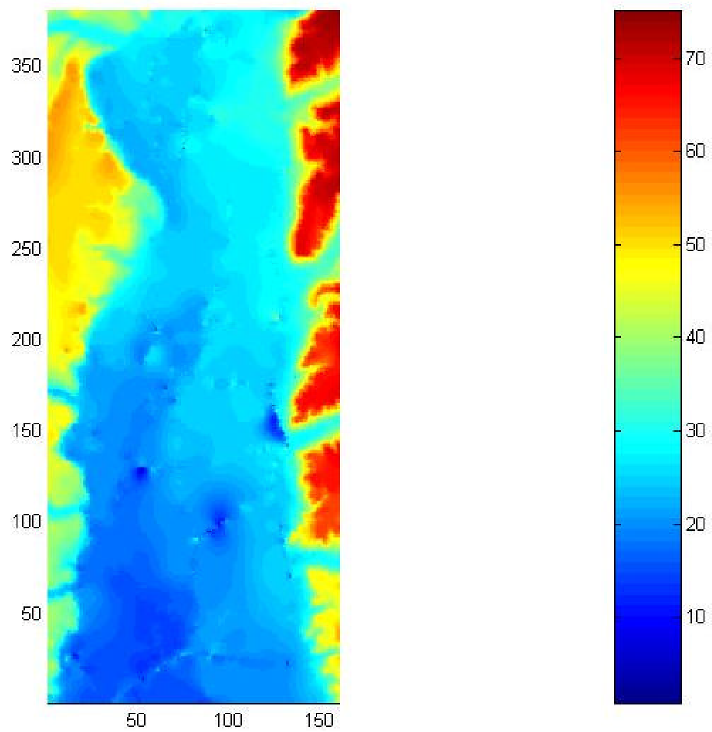

Figure 2. Kriging predictions using combined contour and differential GPS measurements, subset to area of interest on the Hampshire Avon, England.