Improving Soil Salinity Prediction with High Resolution DEM Derived from LiDAR Data

Xiaoye Liu[1], Jim Peterson[1], Zhenyu Zhang[1] and Shobhit Chandra[1]

[1]Center for GIS, School of Geography and Environmental Science, Monash University, Australia

Abstract: The aim of this study is to investigate the capability of integration of LiDAR derived terrain and hydrological features with other salinity related datasets to improve prediction of areas at risk from salinity in a catchment area in Victoria, Australia. Terrain and hydrological features including slope, drainage density and hilltop were generated from LiDAR derived DEM and a relative low quality DEM separately. These features were combined with other salinity related datasets to predict areas at risk from salinity. The results showed that using LiDAR-derived high quality DEM can improve the accuracy of salinity risk prediction.

1. Introduction

Soil salinity is a global environmental hazard, and also a severe Australian environmental problem. It adversely affects crop yields and agricultural production in salt affected farm lands. Salinity also affects water quality (rivers, streams and lakes), and the structure integrity of buildings, roads and other infrastructures. Furthermore, ecosystems such as wetlands and forests are being degraded by increasing salinity problems. In Australia, more than 5 million hectares of land are adversely impacted by dryland salinity which causes damage totally $270 million each year (AAC, 1998). It was estimated that 665,000 hectares of land in Victoria State, Australia, are at risk of dryland salinity (AGV, 2001). As a result, agricultural production from farming industries such as grazing and cropping is diminished. Obviously, monitoring and managing salinity is one of the greatest natural resource management challenges in national, state and regional levels.

Soil salinity caused when rising ground water tables bring natural salts in the soil and groundwater to the surface. The salt remains in the soil and becomes progressively concentrated as the water evaporates (NAP, 2001). Therefore, determining the water movement which controls the mobility and transfer of the salt store is important in salinity studies. In the context of salinity management and risk assessment, accurately mapping water content and flow pathways is as important or more important as mapping salt itself (Spies and Woodgate, 2004). As water movement is controlled by surface elevation, in order to determine where salt accumulates, accurately representing landscape is always required. Previous researches have found that much information can be derived from elevation data to improve salinity mapping accuracy (Furby, 1998).

Digital Elevation Models (DEMs) are widely used to describe terrain surfaces. Traditionally, DEMs can be generated from such datasets as topographic maps, stereo aerial photography, satellite imagery or field survey. The drawbacks of using these kinds of ways for DEM generation are either their limitations of accuracy or their labour intensity. Light Detection and Ranging (LiDAR), an emerging technology, offers capability of capturing high density points and high accuracy digital elevation data in a fast and cost-efficient way. LiDAR in the simplest description is the use of lasers to determine distance from the sensor to specific targets (Barber and Shortrudge, 2004). For terrain mapping purpose, an air-borne LiDAR system is typically composed of sensor, Inertial Navigation System (INS), and differential Global Positioning System (GPS) (Hodgson et al., 2005, Barber and Shortrudge, 2004). Incorporating INS and GPS technologies into the LiDAR system results in the capability of determining target location in three dimensional spaces at high accuracy. Once the bare-earth points are determined by post-processing (Zhang et al., 2003, Axelsson, 1999, Lin, 1997, Lee and Younan, 2003, Means et al., 1999), LiDAR data allow the derivation of high accuracy and high resolution DEMs. Based on LiDAR-derived high quality DEMs, some terrain and hydrological attributes which play important roles in salinity prediction can be generated.

Salinity risk prediction aims to integrate salinity risk related factors to identify areas at risk from salinity. Irrespective of what approaches are used, terrain and hydrological attributes must be considered. DEM-derived terrain attributes and their derivatives can be used to improve soil salinity mapping, but the DEM resolution must match the degree of terrain variation in the area of interest since some features cannot be derived from a coarser resolution DEM for the flatter area (Furby, 1998). LiDAR-derived high resolution DEMs provide a potential to overcome this obstacle.

The aim of this project is to investigate the scope for integration of LiDAR derived terrain and hydrological data with other salinity related datasets to improve catchment salinity risk modeling. Terrain and hydrological attributes including slope, drainage density and water-shedding hilltops were generated from a LiDAR DEM and Vicmap (20m) DEM separately. Each of these two groups of terrain and hydrological features was combined with datasets such as soil type and salt distribution by using spatial analysis functions to predict salinity risk areas. Comparison of prediction results showed that by using LiDAR derived high quality DEM, overestimation of the salinity risk areas can be avoided, and thus the salinity risk prediction was improved.

2. Study Area and Datasets

The study area is in the region of Corangamite Catchment Management Authority (CCMA), which is located in the south western Victoria, Australia. It covers an area of over 1.3 million hectares with a population of over 400,000. The landscape in the region can be depicted to north and south highlands and a large Victoria Volcanic Plain (VVP) in the middle. Over 21,000 hectares of land in CCMA, mostly in the VVP, has been designated as potentially salinised (Dahlhaus et al., 2003). These areas have high priority for a range of research projects pertaining to salinity management addressed in the Corangamite Salinity Action Plan in July 2003. LiDAR data for the total area of 6900 km², covering most part of VVP in the CCMA, were collected over the period 19 July 2003 to 10 August 2003 for analysis of terrain and water flow paths. The selected initial study area, one of the hot spot salinity zones, covers an area over 300km².

The accuracy of LiDAR data used for this project was estimated as 0.5 metres for vertical accuracy and 1.5 metres for horizontal accuracy (AAMHatch, 2003). A 10m resolution DEM was generated from these LiDAR data, then some terrain and hydrological attributes were derived from this DEM. These attributes, together with other salinity related data, will contribute to the prediction of salinity risk.

Soil salinity is affected by variety of factors. As this project focuses on the investigation of the improvement of soil salinity prediction with LiDAR-derived high resolution DEM, emphasis will be given to elevation or terrain related derivatives such as slope and drainage density. A water accumulation model is needed to analyze the water flow directions so that hydrological features can be derived. Other datasets determined as indicators of salinity risk are based on our current understanding of salinity and available data.

Elevation related derivatives used in this study include drainage density, slope and water-shedding hilltops. Drainage density refers to the number of defined stream lines within a region (Evans et al., 1995). It represents the drainage condition in a region. Poor drainage can promote rise of saline watertables. The drainage density data were produced using drainage networks which were derived from the water accumulation model. Using a raster data model, a slope map (representing the maximum change in elevation over distance between the cell and its eight neighbors) was generated from the LiDAR-derived DEM. In general, the steeper the terrain, the less likely is the salt accumulation. Hilltop refers to either top of hill or local rises. The hilltop data were also generated from LiDAR-derived DEM. It is of low probability for salinity to occur in hilltop area (Furby, 1998).

In order to assess the prediction results, all these derivatives were also generated from a 20m resolution DEM, called Vicmap DEM, delivered by the Victorian Department of Sustainability and Environment. It was produced by using elevation data mainly derived from existing contour map at scale of 1:25,000 and digital stereo capture. Estimated standard deviations are 5m and 10m for vertical and horizontal accuracy respectively (DSE, 2002).

Other salinity related-datasets including soil and salt data were adopted from previous CCMA research results. Soil types range between duplex soils, yellow clays and cracking clays each with its particular vulnerability to salinisation. For example, the (poorly drained and relatively impermeable) cracking clay soils, have higher levels of salinity risk than others in the region (Dahlhaus et al., 2003). Salt data show the spatial distribution of salt or existing salinity area in the region. Thus, the soil salinisation vulnerability prediction model used in this project calls for slope declivity patterns, soil attribute patterns, drainage density patterns and current saline soil distribution patterns, the assumption here being that the closer to salt the area, the higher the salinity risk in this area. The slope declivity patterns are DEM derived, coming from two separate sources: the 20m DEM which is in common use in Victoria, and a LiDAR-derived high resolution DEM.

3. Salinity Prediction

All the datasets derived from the DEM or adopted from previous research results were incorporated into a GIS database. Each dataset corresponds to a data layer in GIS database. GIS spatial analysis functions were used to predict salinity risk based on the importance of each dataset to the salinity process. By reclassification of each dataset, each attribute value in the dataset was assigned a scaled value indicating its relative importance to salinity risk. The data layers were weighted based on current understanding of salinity processes (Searle and Baillie, 1998). The higher the weight which is assigned to a dataset, the more influence this particular dataset will have for the salinity risk prediction. The data layers were then spatially overlaid so that an overall salinity risk prediction can be produced (Searle and Baillie, 1998). Figure 1 shows the results of salinity prediction, elevation related datasets being derived from LiDAR DEM and Vicmap DEM separately.

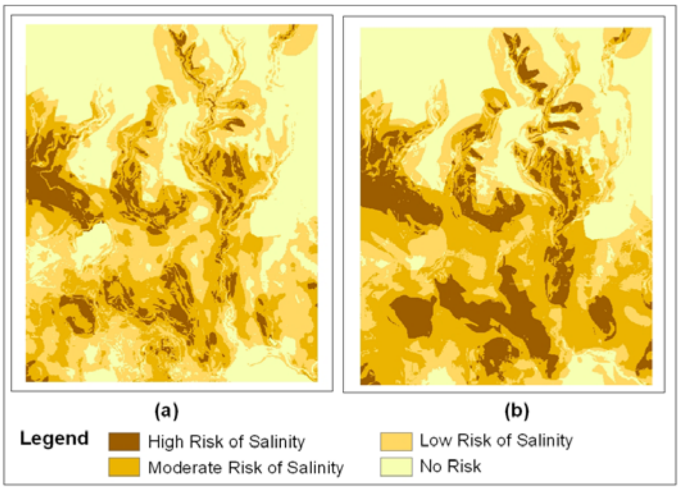

Figure 1. Predicted salinity risk area. (a) Derivatives from LiDAR DEM; (b) derivatives from Vicmap DEM.

Differences of salinity risk prediction by using LiDAR DEM and Vicmap DEM separately are shown in figure 1. Areas of both high risk and moderate risk of salinity shown in figure 1b were overestimated. Statistic results of different levels of salinity are shown in Table 1. The differences resulted from the utilization of the DEMs with different accuracy and resolution. The LiDAR-derived high quality DEM lead to the derivation of high quality terrain and hydrological attributes. On the other hand, terrain and hydrological attributes derived from the relatively lower accuracy and resolution of Vicmap DEM, due to their low quality, made little contribution to improve salinity prediction.

The effects of different quality of terrain and hydrological features derived from different quality of DEMs on salinity risk prediction are significant. Slopes derived from low resolution DEM tend to flatten the terrain. Flatter terrains are more likely to become salinity than steeper terrain. This is one reason why salinity risk areas were overestimated in figure 1b. The Vicmap DEM produced lower density results for drainage density than the LiDAR DEM did. Lower drainage density means poor drainage condition which is also prone to salinity risk. This is another reason for overestimating salinity areas in 1b, and it is significant especially in the upper right part of map.

Table 1. Statistics of Salinity Risk Prediction

DEMs used for derivatives	High risk	Moderate risk	Low risk	No risk
10m LiDAR DEM	9.7%	26.0%	31.8%	32.5%
20m Vicmap DEM	16.9%	32.7%	24.9%	25.5%

4. Conclusion

Soil salinity is influenced by a verity of factors. Elevation related factors play important roles for salinity risk prediction. However, if using a low accuracy and low resolution DEM, salinity risk prediction is less succeeded. Compared with the results from high quality LiDAR DEM, the salinity risk areas mapped by using terrain and hydrological features derived from lower quality DEM were actually overestimated. The reason comes from the factor that by using lower quality DEM, the terrain surface was flattened by derived slopes, and drainage conditions were shown poor by calculated drainage density value. LiDAR is a powerful tool to generate high accuracy and high resolution DEMs. Terrain and hydrological attributes derived from the LiDAR DEM significantly improved the salinity risk prediction.

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Address:

Xiaoye Liu, Jim Peterson, Zhenyu Zhang and Shobhit Chandra, Wellington Road, Clayton, VIC 3800, Melbourne, Australia. (Email: Xiaoye.Liu@arts.monash.edu.au; Jim.Peterson@arts.monash.edu.au; Zhenyu.Zhang@arts.monash.edu.au; Shobhit.Chandra@arts.monash.edu.au)