Distributed Hydrological Modelling Using Land-use Classification Automatically Derived from Satellite Imagery

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INTRODUCTION AND BACKGROUND

A hydrological modelling approach based on the distributed rainfall-runoff model Wetspa Extension (Wang, 1996) and automatic surface detection is described. This approach was aimed at refining determination of runoff hydrographs at critical locations in the network of small watercourses flowing through Zurich, Switzerland. Many of these watercourses are partially culverted, creating flood risk, but until now they had only been studied using spatially lumped models. The process is illustrated here using the Holderbach catchment, which has a high flood risk, combining a fast runoff response with a high proportion of built-up areas, and occasionally areas with a steep slope, such as deep valleys (Scherrer, 2007).

Amongst the necessary spatial data, land coverage is one of the most important, since it plays a decisive role in establishing the runoff coefficient. However, this data is difficult to collect on-site, and can change frequently and significantly. This has stimulated research into procedures for automatically calculating land cover categories from satellite images. A variety of different remotely sensed data, such as infrared radiation, and many different techniques, such as wavelets (Kim, 2003), texture (Varma , 2005), or shape detection have been applied in the literature.

AUTOMATIC IMAGE SEGMENTATION

A series of calculations according to an offline maximum likelihood scheme were performed on tiled satellite orthophotos in order to classify each pixel or group of pixels as a certain land type (Fig. 1). The algorithm was calibrated using images which had been manually divided into single land-use polygons according to already defined surface use data. These original types were reclassified into five simplified categories, because the hydrological model uses a different land-use classification, including some categories which are impossible to detect from the images alone.

The accuracy of the three segmentation stages was assessed by calculating the percentage of accurate land use detection in each category. Blobs for each land use category from the stage result having the highest detection percentage were combined into the final resulting image. In practice, where there was an equal distribution of all classes, an 84% classification rate is achieved. In areas with many buildings the result could be around 65%.

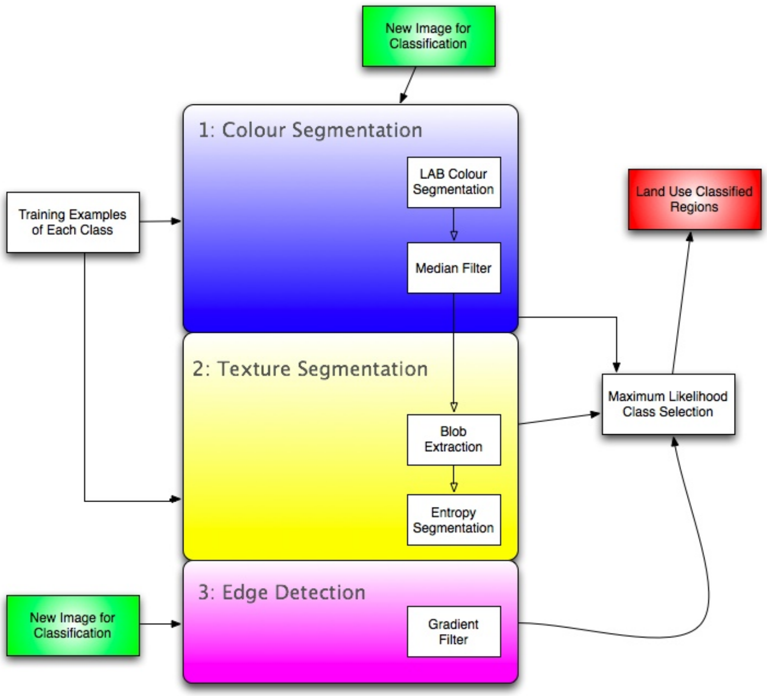

Figure 1: Schematic of the aerial orthophoto segmentation process.

RESULTS

Comparison of land use classifications

The raster coverage that resulted from the automatic land use classification is shown in Fig. 2 (b). For comparison, the original land use information shapefile supplied by the city of Zurich is shown in Fig. 2 (a). The reclassified rasters are shown in Fig. 3, which also shows a comparison, with the differing pixels marked in red. As can be seen, there is a majority of correctly classified pixels but there are errors due to the image processing and the re-classification process (see below).

Comparison of hydrological modelling results

Fig. 4 shows the result of modelling the Holderbach catchment in WetSpa Extension using the automatically derived land use categories together with the rest of the necessary data, and the synthetic T10-60 (ten year return period, 60 minute duration) rainfall event, which is also shown, and Fig. 5 shows the results for the same catchment when the original, hand-labelled land use categories are used instead.

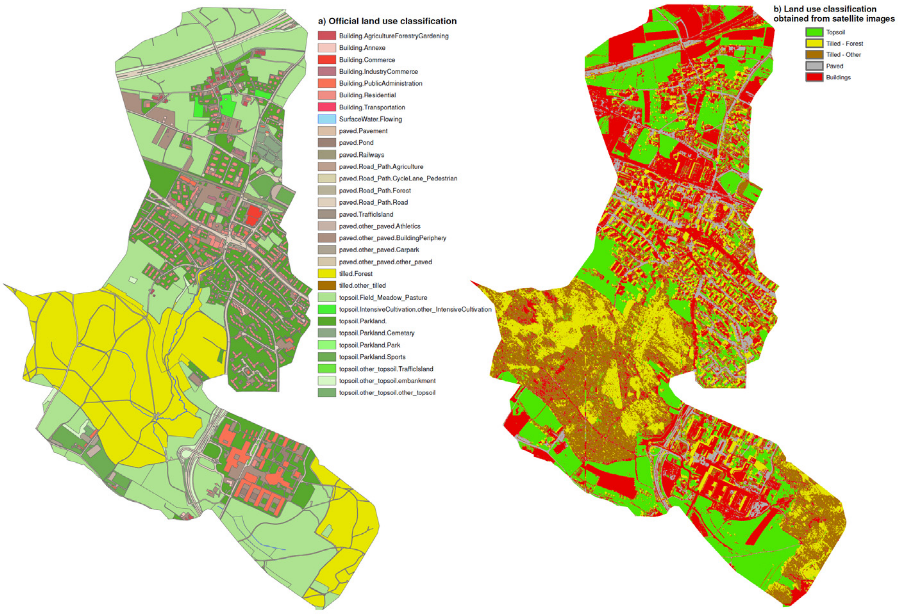

Figure 2: Original land use classification compared to automatically derived classification.

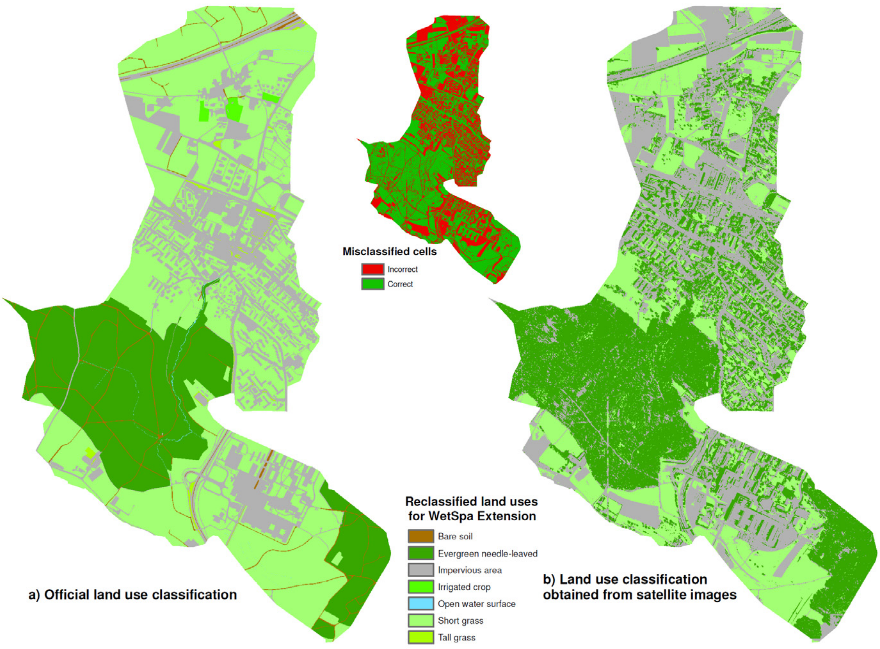

Figure 3: Original and automatically derived land classifications, reclassified for use in WetSpa Extension.

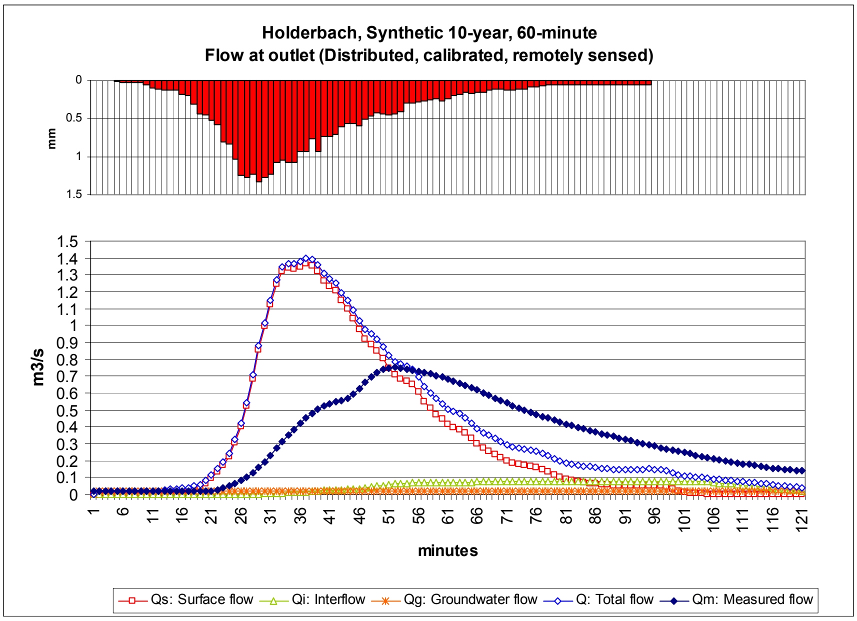

Figure 4: Modelling results using automatic classification.

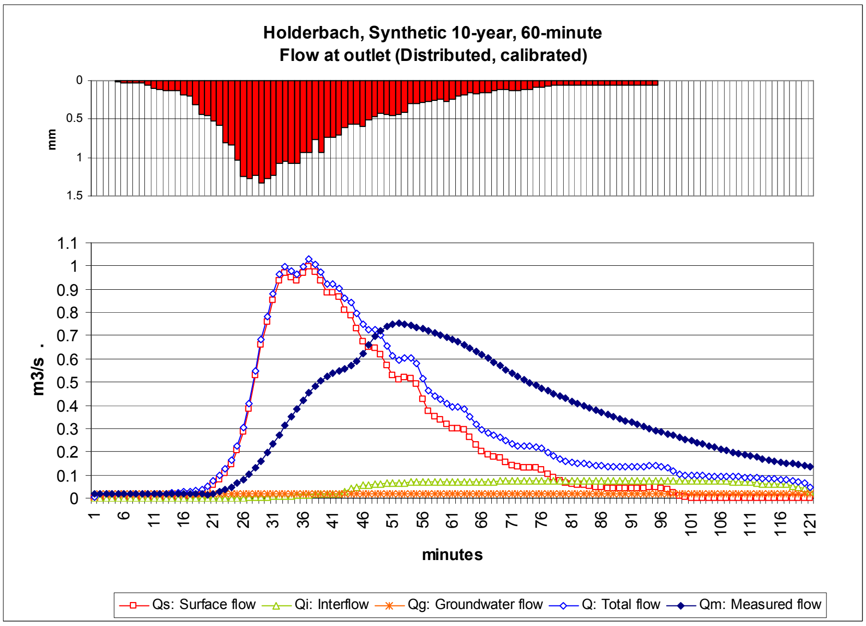

Figure 5: Modelling results using manual classification.

CONCLUSIONS

The automatic land-use classification algorithm developed is a first approach but serves to highlight the challenges involved. A likely source of error has been the reclassification necessary when using the data within the hydrological model because its specific land-use classification requires detailed vegetation data, which was not available. The main source of error, however, is the misclassification of paved areas as buildings. Although this does not seem to cause difficulty for the hydrological model (due to similar permeability) some improvements could be made using shape as a feature, since buildings are predominantly textureless rectangles when viewed from above. Some minor misclassifications also occur due to shadow. There are established techniques which could potentially be applied to remove shadow but further work is necessary to explore their applicability in this domain (Finlayson*,* 2006). Vegetation, on the other hand, was detected with around 90% accuracy, which explains the relative success of the technique.

The resulting automatically classified data, when used to model the catchment, results in similar hydrographs to those obtained using the manually classified data, despite the proportion of misclassified cells. In fact, as can be seen in the figures, in some cases the hydrograph obtained with the automatically classified land uses is more similar to the comparison 'measured' flow than the original hydrograph. This is an indication of the fact that the model is not very sensitive to changes in soil permeability, and other factors. However, the 'measured' flows used for comparison were derived from a different, simpler model than the one used here, and therefore are not necessarily more accurate than the results obtained for this study.

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