EXTRACTION OF FLOOD-MODELLING RELATED BASE-DATA FROM MULTI-SOURCE REMOTE SENSING IMAGERY

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ABSTRACT:

Flooding is one of the most destructive natural hazards, accounting for over a third of all disaster damage worldwide. In particular in less developed countries (LDCs) this is typically attributed to poor planning, lack of warning systems and limited awareness of the hazard. A number of flood risk models have been developed, but have as yet contributed little to mapping and quantifying the risk in LDCs, for several reasons. In addition to limited human and technical capacity, these models require considerable amounts of current spatial information that is widely lacking, such as landcover, elevation and elements at risk basedata. Collecting those with ground-based methods is difficult, but remote sensing technologies have the potential to acquire them economically. To account for the variety of required information, data from different sensors are needed, some of which may not be available or affordable. Therefore, data interchangeability needs to be considered.

Thus we test the potential of high spatial resolution optical imagery and laser scanning data to provide the information required to run such flood risk models as SOBEK. Using segmentation-based analysis in eCognition, Quickbird and laser scanning data were used to extract building footprints as well as the boundaries of informal settlements. Additionally, a landcover map to provide roughness values for the model was derived from the Quickbird image.

These basedata were used in model simulations to assess their actual utility, as well as the sensitivity of the model to variations in basedata quality. The project shows that existing remote sensing data and image analysis methods can match the input requirements for flood models, and that, given the unavailability of one dataset, alternative images can fill the gap.

1. INTRODUCTION

As one of the most destructive disaster types, flooding accounts for over one third of all estimated worldwide disaster damage, and over two thirds of all people affected by disasters. In particular in less developed countries (LDCs), where over 90% of all disaster victims are recorded, the consequences are most severe. This is a result of relatively high vulnerability coupled with limited preparedness and coping capacity. Globally, the number of flooding disasters has been increasing rapidly since the 1970s (CRED, 2004). While preparedness and flood response capabilities have been growing in developed countries, due to better understanding of risks, implementation of early warning systems, and incorporation of risk management in development plans, the risk in flood-prone areas in LDCs remains high.

While the frequency of flood disasters has grown, so has the number and sophistication of tools to model and understand flood risk. These 1- to 3-dimensional models allow hydrodynamic scenario simulation of non-steady water propagation, and thus a detailed assessment of areas to be affected by floodwater in a given situation. While some models only address the hazard component, i.e. the extent and depth of the water, others also incorporate value and vulnerability of elements at risk for a more realistic risk assessment. Based on such information appropriate planning or protection measures can be based, leading to reduced hazard (e.g. creation of special flooding zones upstream of urban areas) or lower vulnerability (e.g. if dykes are strengthened, populations educated about the risk, or vulnerable properties relocated).

A common feature of all models is the need for parameterisation. To simulate water propagation, flood depths, or building inundations, suitably current and accurate data layers on topography, roughness, infrastructure type, etc., i.e. mostly standard basedata are required. These are expensive to acquire and maintain, and are thus typically unavailable in LDCs. Historically the majority of data were collected using ground-based methods, which are characterised by high accuracy and spatial resolution, but also low update frequency and high cost. Geoinformatics techniques, in particular remote sensing, have steadily improved and matured, and may now offer a viable alternative to collect most of the required data timely, accurately and economically.

1.1 Modelling approaches to flood hazard assessment

Predictive models have been applied for flood hazard assessment for many years. The approaches range from the very simple, such as intersecting a plane representing the water surface with a digital elevation model, to very sophisticated three dimensional solutions. However, two main approaches in fluvial hydraulic modelling are the most popular. The oldest is based on the one-dimensional solution of the St. Venant equations (see e.g. Fread, 1992), such as the MIKE11 and HEC-

RAS models (Brunner, 2002). These models require characterization of the topography through a series of cross-sections perpendicular to the direction of flow to calculate the average water depth and flow-velocity. These are typically measured in the field. A continuous water surface is then constructed though interpolation between the cross-sections. A more accurate estimate of the spatial extent of the inundation can be obtained by intersecting this surface with a terrain model but it should be noted that in 1D-modelling the terrain model is not used in the flow computation. This type of modelling is often applied for catchment analysis where the research question is more focussed on *how much* water will flow through the river and not so much on *where* it will go. The underlying assumption is that all flow is parallel to a predefined river-network, so it is clear where the water will go. When this assumption is not valid, for example due to complex topography or to diverging flow at a dike breach or on an alluvial plain, models are required that are based on a two-dimensional solution of the St. Venant equations. These models, including the SOBEK model that we used (Hesselink et al. 2003), but also Telemac 2D (Hervouet and Van Haren, 1996) and MIKE21 (Abbott and Price, 1994), require a continuous representation of the topography in the form of a digital surface model (DSM), that forms the basis of the flow computation. The major drawbacks of this approach - the high data demand in the form of accurate surface models and high computation power - have become less relevant with availability of high accuracy surface models obtained with airborne laser scanning (LIDAR) and the availability of cheaper and faster computers. These DSMs contain all relevant topographical features that affect the flow of water over the surface.

SOBEK is an integrated 1D-2D software package developed at WL|Delft Hydraulics (see e.g. Dhondia and Stelling, 2002). The 2-D overland flow component is a 2D grid based inundation model based on the finite difference method. It is specially designed to simulate overland flow over initially dry land and through complex topography. In addition to water depth SOBEK also calculates the depth-averaged flow-velocity at each time-step. This allows the assessment of the propagation characteristics and distribution of kinetic energy for a given flood event.

1.2 Objectives

In a number of studies in recent years remote sensing data were used to extract landcover data for flood modelling, primarily for use in rural areas (e.g. van der Sande et al., 2003), mainly to get a spatial distribution of the variation in roughness coefficients, such as Manning's coefficient. However, critical infrastructure and potentially vulnerable populations are concentrated in urban settings, and thus more detailed models with consequently more detailed data need to be employed. In an urban flood the flow of water is also directed by the lay-out of the streets and buildings and it is, therefore, important to represent these features as accurately as possible in a flood model schematisation.

The purpose of this paper is to assess the utility of recent spaceborne optical and airborne laser scanning data to provide information on (i) topography, (ii) road and waterway locations, (iii) building footprints and height, and (iv) landcover in urban areas. Given that image data most suitable for a given purpose are not always available, we also investigate the interchangeability of alternative data types. In addition to topography and physical infrastructure we also use image data to map settlement types. This can reveal the location of informal housing areas, which are particularly vulnerable due to their frequent location in low value and high risk areas, high population concentration, substandard building materials, and insufficient access to life lines. Furthermore, in formal settlements the building type and size data can be used to estimate their value, and, if height data are considered, also the number of people per building or block.

Lastly the extracted data were tested in SOBEK, to assess their sufficiency in quality and resolution, i.e. accuracy and precision.. Due to computation limitations it is not possible to maintain the high resolution of the original surface model. Therefore, the DSM was reduced in resolution to 10 meters, thus still retaining an accurate representation of the urban topography. After the model was run, the results were then overlaid with the settlement type map to assess the impact of the flood, based on the quality of the constructions, as derived from the high resolution imagery.

2. DATA AND METHODOLOGY

SOBEK requires a detailed DSM, a river and road networks, building footprints height, as well as surface roughness values (Mannings' coefficients) that represent hydraulic roughness, the resistance to overland water flow. The latter parameter is derived from landcover data. To address vulnerability and value, settlement types are also extracted. The model also requires hydrographical data that define the boundary conditions, such as time series of discharge or water levels, or the Q(h) relation at the outflow boundary of the model.

The hypothesis that image data can be used to provide relevant basedata was tested on data from the city of Tegucigalpa, Honduras, which suffered extensive flood damage during Hurricane Mitch in 1998. The following is a list of the data sets used:

(1) High resolution data for detailed urban mapping
- Quickbird image of March 2000, pan-sharpened and resampled to 1m
- LIDAR gridded Digital Surface Model (DSM) of March 2001, 1.5 m resolution
- Contour map, produced in March 2001, scale 1:2,000
- 5, 25, 50 year flood maps, produced in 2001, scale 1:2,000
- Orthophotos at 1 m resolution as reference

(2) Lower resolution data for modelling of upstream areas
- Landsat TM scene of March 2000, 15 m Pan, 28.5 m MS

The image processing was done in eCognition, a software package that allows advanced segmentation-based analysis, and is appropriate given that information is required on objects (buildings, rivers, etc.) rather than individual pixels. The segmentation can be done at different spatial levels, which allows a semantic consideration of the smallest identifiable segments (e.g. cards, chimneys, etc.) as well as larger ones, such as houses or agricultural fields. The classification can then be based on spectral information, spatial data from additional sources (e.g. DEMs, vector data), as well as segment characteristics such as shape, texture or topology. Specific details on the processing are given in the relevant sections below, and more can be found in Shamaoma (2005).

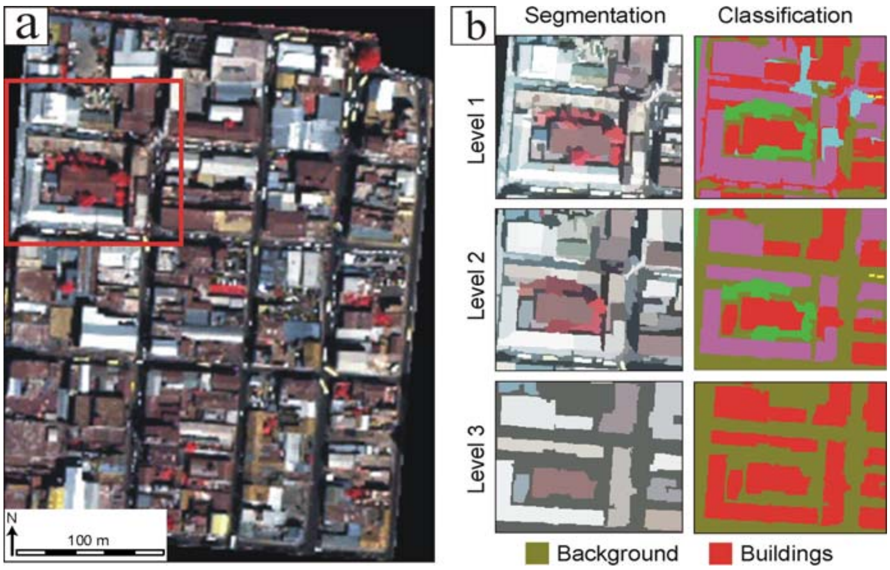

Figure 1. Tegucigalpa testsite for building footprint extraction (a), and three segmentation and classification levels (b, close-up area indicated by box in a). Small objects, such as cars are gradually removed in the rule-based classification stage, while at level 3 only whole buildings as semantic groups remain. Note that no manual editing or correcting is required.

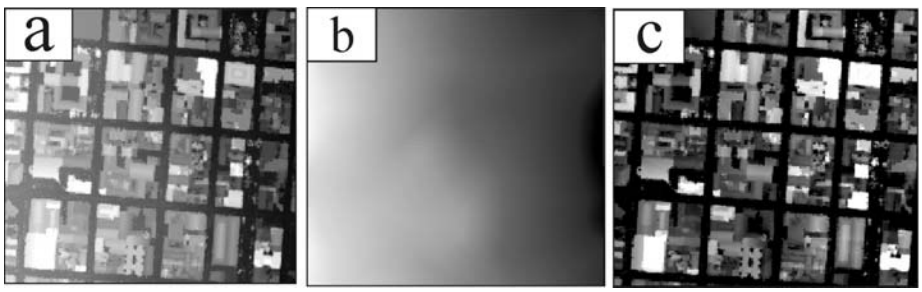

Figure 2. Original LIDAR Digital Surface Model (DSM, a), Digital Terrain Model (DTM, b), and difference model showing only elevations of above-terrain features (nDSM, c)

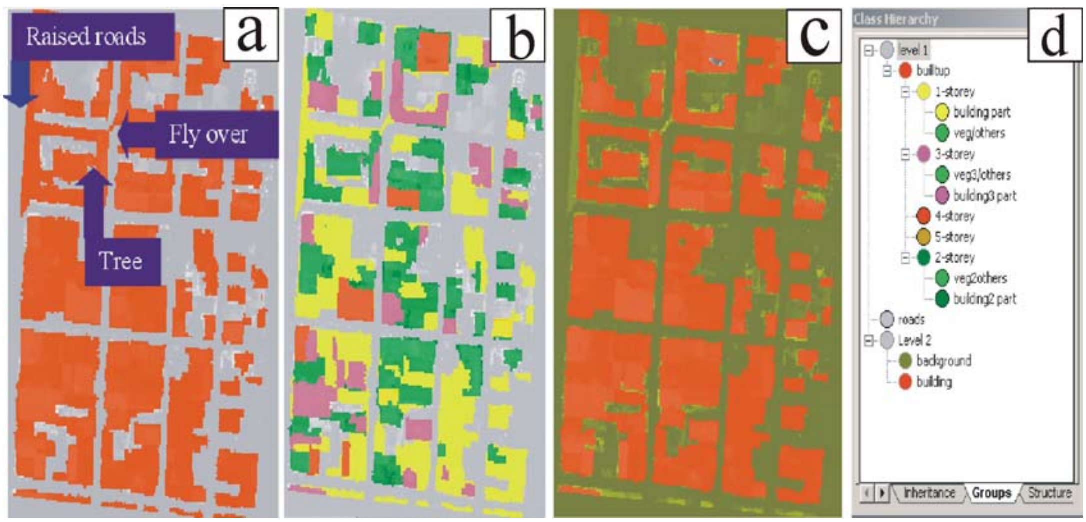

Figure 3. LIDAR nDSM classification steps. Separated ground and raised objects (a), buildings separated according to number of floors (b), only buildings, with cars, vegetation, flyovers etc. removed (c), and legend of different level elements (d).

3. RESULTS

3.1 Extraction of building footprints from Quickbird and laser scanning data

Buildings can be identified explicitly or implicitly, and many approaches have been developed and tested. eCognition uses a segmentation-based classification approach, whereby first homogenous objects are extracted, which are in turn classified based on a nearest-neighbour classifier or membership functions. The segmentation itself can be done at different scale levels, to allow the semantic incorporation of differently sized features. The Tegucigalpa Quickbird image was segmented at 3 levels; level 1 to discriminate small objects such as cars, level 2 for large features such as entire buildings or road sections, and level 3. This last level only contains building/no building classes, and was constructed through semantic grouping of level 2 elements (Figure 1). For details on the classification and rules used see Shamaoma (2005).

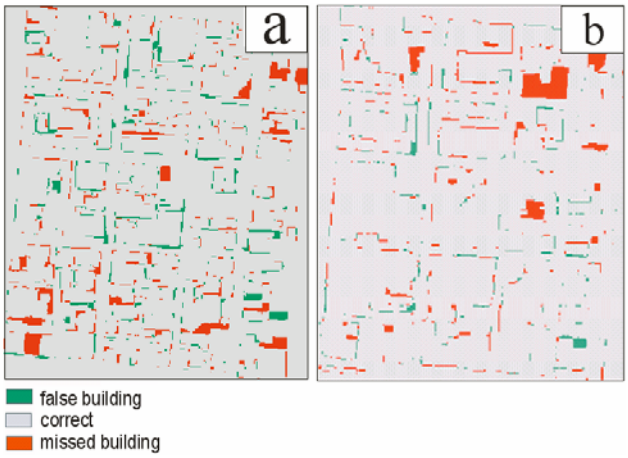

Figure 4. Building footprint classification error for Quickbird image (a) and LIDAR nDSM (b). The extent corresponds to 1a.

For the laser data two segmentation levels were sufficient, since features were well separated by their height, and because there was limited homogeneity in features of the same class. Given the absence of spectral information, rules had to be employed to separate trees, elevated roads and other features from buildings. This was done with texture measures including the grey-level co-occurrence matrix (GLCM, Haralick et al., 1973), and shape and elevation criteria. Whilst LIDAR data inherently provide accurate elevation information, the challenge is to calculate only the height of features such as buildings. This in fact means to separate two required information layers, (i) the actual terrain on which the water will flow, and which is needed for the water propagation and depth modelling, and (ii) the above-terrain elements that impede water flow and may constitute elements at risk. Figure 2 shows the original DSM (a), the actual terrain calculated from actual ground heights in between buildings and other features (Vosselman et al., 2004, b), and a difference nDSM that only contains the height of features above the actual ground surface (c). The nDSM was then further processed in eCognition to eliminate non-building elements (vegetation, cars,
flyovers, etc.), and to estimate building height and number of floors (Figure 3). This is useful to calculate possible inundation heights, as well as possible losses if information on the building type and value is available.

3.2 Accuracy assessment of footprint extraction

The results shown in figures 1 and 3 were individually assessed against hand-digitised building outlines based on an aerial orthophotos of 1m resolution. The comparison, presented in Figure 4, shows that the majority of buildings was correctly identified (accuracies of 84% and 89% for Quickbird and LIDAR, respectively). However, misclassifications are also apparent. The small green lines corresponding to building outlines are artefacts of digitisation of the reference dataset, but also of planimetric inaccuracies, in particular of the Quickbird image. It also has to be noted that more than 1 year passed between acquisition of the datasets, explaining that some buildings have disappeared or been newly constructed. In particular for laser data that are not simultaneously acquired with multispectral information, it is also difficult to formulate rules that separate buildings from all other features. The overall good success shown here is also a result of limited vegetation cover in the area covered. In regions of extensive and in particular high vegetation, a reduced accuracy must be expected. For the Tegucigalpa area studied here, however, both datasets provide good results for building footprints and are largely interchangeable.

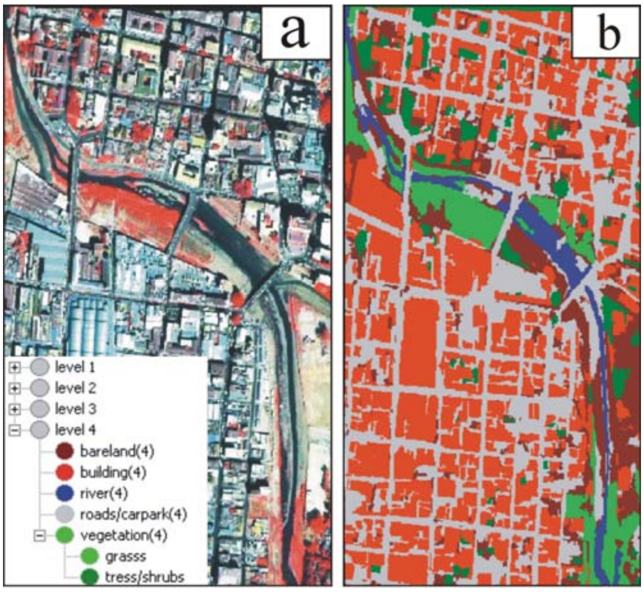

Figure 5. Quickbird false colour composite (a), and segmentation-based landcover classification (b)

3.3. Urban landcover assessment

Although they cannot provide explicit height information, Quickbird data are multispectral and thus suitable for detailed landcover assessment, the source for roughness information, as well as river and road networks. Figure 5 shows the original Quickbird and derived landcover map based on multi-level segmentation. Extracted were waterways, trees and grass, buildings and bareland. The accuracy was assessed using the aforementioned orthophoto, leading to an overall accuracy of 85%, and a kappa coefficient of 78%. Some buildings were misclassified as roads/car parks, while some bareland segments were incorrectly identified as buildings and roads. The overall results are good; however, it has to be realised that additional post-processing is needed before such data can be used in flood models. For example, because of bridges and occasional low water levels, the river is not classified as a continuous segment.

A further limitation of vertical imagery is that only 'solid' elements are extracted. Thus where buildings may permit partial water intrusion, in absence of more detailed information here they can only be considered as solids. In the case of bridges special care has to be taken to make sure that they do not become false barriers in the riverbed.

Airborne laser scanning data are not inherently well suited to map landcover. However, it is possible to extract buildings, roads and vegetation based on height and texture information, as shown above. Furthermore, the runoff directions of water surface flow can be calculated from the DTM. The roughness coefficients of features other than the above (such as bare land) can also be well calculated.

3.4. Detection of settlements types

Demographic factors are closely linked to the magnitude of disaster impacts. This is dictated by the risk equation (risk = hazard * value * vulnerability), and can be readily observed in any disaster that affects areas composed of both richer and poorer neighbourhoods. Informal living space (such as shanty towns or squatter settlements) typically comprise of self-constructed shacks and shelters in high-density arrangements. This partly explains their vulnerability, but also leads to physical characteristics that allow their detection in remote sensing imagery. In addition, such informal settlements have important impacts on flooding dynamics (e.g. through change of local erosion pattern, by obstructing draining channels, etc.). Previous mapping of such areas has focused on individual shacks (e.g. Rüther et al., 2002), the detection of their extent (e.g. Weber and Puissant, 2003), or on the estimation of population numbers in such settlements (Ramala, 2001). Besides mapping these parameters, image data also allow the monitoring of settlement spreading, and its impact on the environment and land cover change.

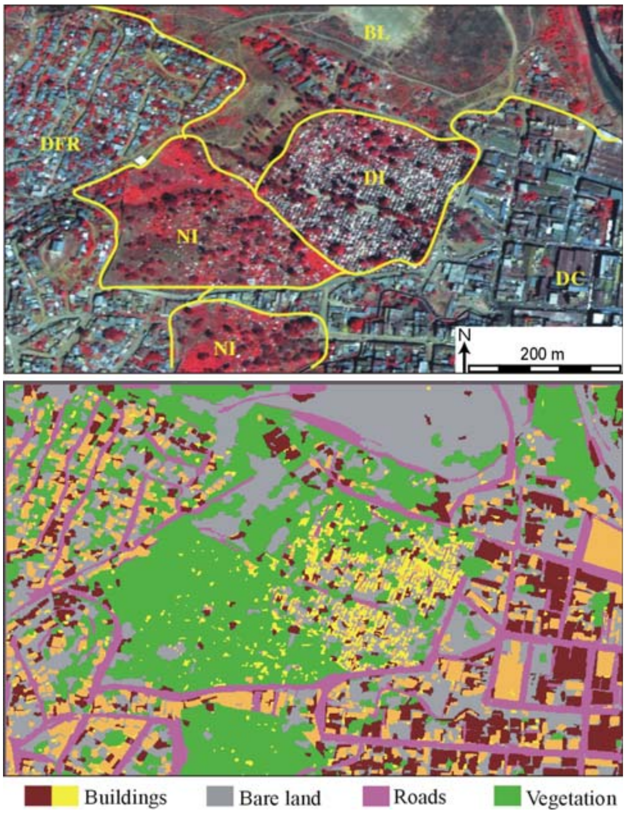

Figure 6. Quickbird false colour composite with settlement types shown (DFR – dense formal residential, DI – dense informal, NI – new informal, DC – dense commercial, BL – bare land), and level 2 classification. In particular the density of shacks (yellow) is apparent, which contributed to the detection of the NI and DI classes.

Our mapping of different settlement types is based on size and shape of individual housing units, inasfar as they are detectable, as well as texture and location of the settlement. The ratio of vegetation cover is also a critical attribute. In Tegucigalpa, residential areas contain more extensive vegetation cover than commercially used spaces, although such characteristics can vary with location. Figure 6 shows the Quickbird image with visually identified settlement types outlined. The individual feature classes are either identified based on spectral properties (vegetation, roofs), shape (roads), size (shacks), or combination of these characteristics. The final classification was again based on a 2-level segmentation (level 1 is shown in Figure 6).

Contrary to the optical image, individual shacks were not discernable in the 1.5 m gridded LIDAR data. Hence the classification was based on feature height and texture, and spatial arrangement. Figure 7 outlines the reasoning.

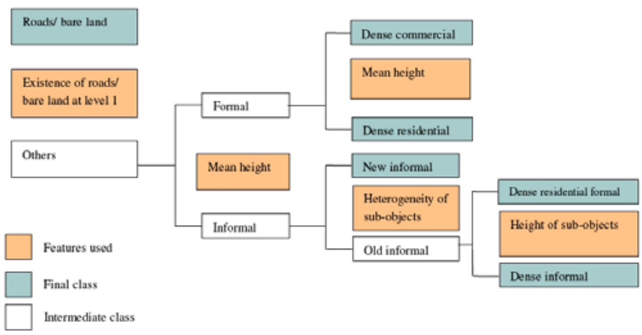

Figure 7. Class hierarchy and features used to separate classes at level 2 for the LIDAR DSM

Both the optical and laser data are suitable to identify formal and informal settlements. There are, however, some misclassifications, with both dataset showing some limitations (Figure 8). The dense vegetation cover made it difficult to identify small dwellings in the Quickbird data, while gridded laser date were insufficient to resolve individual shacks. Multi-return pulse laser data would be more useful than the data available here.

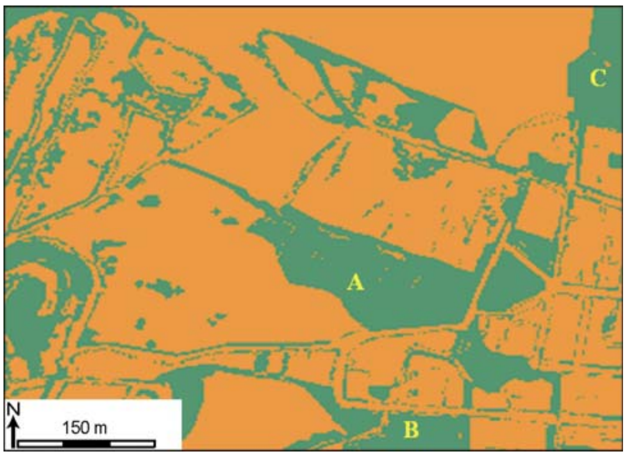

Figure 8. Overview of settlement misclassification. Respectively for the Quickbird and LIDAR data, A was classified as *DI* and *NI*, B as *DC* and as *DFR*, and C as *DFR* and *BL*.

3.5. Extraction of other relevant information

LIDAR data provide explicit height information, which, as detailed above, is required for flow modelling over the surface and around obstacles. Quickbird images, if acquired in stereo, can also provide DSM. However, such data are rarely acquired and expensive. For Tegucigalpa we used contour lines from a 1:2,000 topographic map, which is does not contain building information. We interpolated the contours to derive a detailed surface, and added building objects using the footprints extracted from the Quickbird image (see 3.1). While this does not allow to specify the accurate building height, in the absence of such data the assumption that any building will be high enough to pose a solid obstacle to water surface flow is reasonable. It must be stressed again here that high accuracy building footprints are critical for successful flow modelling, as any misclassification, such as a road section identified as a building, may lead to severe errors in the modelled water propagation. Detailed check and possibly some manual corrections are thus needed.

While detailed data are required to model flood risks in urban settings, a lower resolution is sufficient for more general catchment modelling upstream. Here the use of (generally more expensive) high resolution data is not only unnecessary, but also impractical, given the smaller aerial coverage and processing load. Extracting relevant flood risk information based on multispectral analysis has been done frequently. The focus of our study was the extraction of detailed flood risk basedata for urban areas. However, we also tested the utility of degraded Quickbird data against Landsat TM imagery, both pan-sharpened (15 m) and at standard 30 m resolution. As before, eCognition was used to segment the images before classification, using spectral information, shape and topology.

It was found that 15 m data are sufficient to map principal landcovers, including main rivers. The overall accuracies for the degraded Quickbird and enhanced TM were 90% and 82%, respectively. Conversely, the 30 m TM data were insufficient.

4. SOBEK MODELLING RESULTS

The hourly water depth and flow velocity maps generated by SOBEK were transformed into a flood hazard map, using flood hazard thresholds as a function of water depth and flow velocity (Smith, 2000 and Smith, 2004). The resulting hourly hazard maps were aggregated over the whole flood duration into a final flood hazard map that indicates the highest degree of hazard during the flood. The hazard thresholds are for objects with varying degree of vulnerability, i.e. pedestrians, cars, shanty houses, single storey woodframe houses and brick veneer buildings. Since the locations of these objects are known, a flood risk assessment can be carried out. Figure 9 shows an example of the flood hazard map for the centre of Tegucigalpa. In this example the terrain model and building outline and height were derived from the LIDAR data as explained above. It shows clearly how streets funnel the water flow and create thus increased hazard for pedestrians and constructions. However, the building information extracted from the LIDAR DTM does not provide information on the quality of the construction, making an actual risk assessment based on LIDAR data impossible. For this additional spectral and contextual information is required.

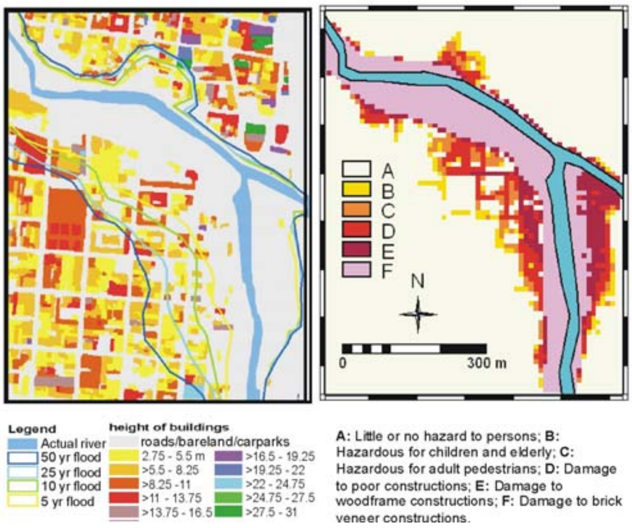

Figure 9. The centre of Tegucigalpa. Result of building height extraction (left, Shamaoma, 2005), and flood hazard map based on 2D flood modelling of the 50-year flood event using the hazard thresholds method according to Smith (2004, right).

5. CONCLUSIONS AND DISCUSSIONS

The principal objective of this work was to assess the utility of different high- and medium resolution optical and laser scanning data to provide flood risk related basedata. It was found that both Quickbird and LIDAR data are suitable to map building footprints, which are required for detailed urban flood modelling. LIDAR data can also provide DTMs (with all elevated features removed). While this is not possible with optical (mono) data, we used 1:2,000 topographic maps to extract information on the actual ground surface, and intergraded the dataset with the building footprints from Quickbird. Although the created building objects have no accurate height information, the combined DSM is nevertheless suitable to model overland water flow.

We further mapped urban landcover from the Quickbird image (accuracy of 85%). While laser data are lacking the spectral information to map features such as water or vegetation (unless combined with a MS camera), they still support the extraction of features such as buildings, roads and vegetation, as well as general surface roughness if used in a segmentation-based analysis as presented here. Hence the principal base data required to model flood risk can also be provided with laser data only as was demonstrated in the small flood hazard assessment example presented.

Lower-resolution synoptic information for upstream catchment modelling can be extracted from Quickbird data as well, but also lower resolution imagery such as 15 m enhanced TM data.

While the overall information extraction was successful, some problems need to be pointed out:

- The buildings extracted are treated as solids, even though in reality they may not be. A possible solution may be to treat buildings as areas of high resistance to flow, i.e. to define them in the surface roughness map, rather then in the DSM.
- Given the limited number of spectral bands for Quickbird, separating urban objects such as roads, car parks or roofs is still difficult.

- Separating vegetation from dwellings with LIDAR data based on texture and height alone is difficult. Here it would be better to use multi-pulse data or integrated multi-spectral information.

This study shows that the combined acquisition of high resolution elevation and image data forms a good basis for flood hazard and flood risk assessment. The elevation data serve to feed the 2D flood models, such as SOBEK, whereas the image data can help to distinguish between the varying types of buildings and their robustness when it comes to floods. It is also concluded that the optimal resolution for urban flood modelling is appr. 10 m. This leads to smaller features (such as alleys) to be lost in the model, but the overall topography is sufficiently retained, and it leads to higher computational efficiency. Changing the resolution to 5 m increases the processing time at least by a factor of 4. However, for building footprint extraction and element at risk mapping from optical data, higher resolution imagery is needed.

Both LIDAR and Quickbird imagery are expensive. Nevertheless, given the rising cost of flood damage, especially in LDCs, as well as the price of alternative, i.e. traditional ground-based, data collection methods, we argue that image-based extraction of relevant base data at sufficient accuracy is possible. Given the unavailability of one dataset, alternative images can fill the gap. We argue that with modest financial investments for data and processing infrastructure, adequate flood modelling can be performed also in LDCs.

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