TECHNICAL REPORT

FLOOD HAZARD INDEX

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Introduction

Floods are natural disasters that can lead to loss of life, the destruction of infrastructure and/or the natural environment. Recent studies have reported an increase in floods globally, with some regions being affected more than others. Increases in floods have given impetus for the research of flood mapping and monitoring, which has resulted in the improvement and development of new technologies and techniques for modelling these events. In South Africa, the total financial costs/losses suffered by government departments, municipalities and the agricultural sector were estimated at R 1.6 billion for the period 2003-2015 (Pharoah et al. 2016).

Flood Hazard Index (FHI) Development

Pre-processing

The Stellenbosch University DEM (SUDEM) (Van Niekerk 2016), a 5-m resolution digital elevation model (DEM), and the DEMSA2 L3 or (L1 and L2 in some areas), a 2-m resolution digital terrain model (DTM), were used to develop the FHI. The DEMSA2 dataset for the area of interest (AOI) was resampled to 5 m-resolution to match the resolution of the SUDEM. These datasets were then hydrologically corrected, which involved filling sinks and depressions.

Derivative generation

Slope gradient (percentage rise) and height above nearest drainage (HAND) are the two primary DEM derivatives required for the FHI. In turn, HAND requires several additional derivatives, namely flow direction, flow accumulation, stream network, DEM flat areas (slope <= 1%) and euclidean allocated stream network based on flat areas. The hydrological derivatives (flow direction, flow accumulation and stream network) were generated using the SUDEM on a provincial scale and were then clipped to the AOI.

Machine learning

Flood lines generated using hydrological modelling were collated from several regions within South Africa. Sample points representing flood high and low risk were randomly created below and above the flood lines. These samples were then used to train a machine learning model, with all the DEM derivatives as predictor variables. The machine learning model had an overall accuracy of 84%. The resulting model was then applied to the DEM derivatives of the AOI to produce the FHI map.

Post-processing

Several post-processing steps were applied to the FHI, mainly to reduce noise. All regions smaller than 2500 pixels were removed and a 3x3 majority was applied to smooth class edges.

Introduce expert rules

Two expert rules were added to improve the FHI. The first relates to waterbodies (as determined from satellite imagery), which were set to the HIGH risk class. The second rule related to coastal sand and dunes, which were assigned to the LOW risk class.

All processing was performed using Python scripting.

Use and Limitations

The FHI was not generated using sophisticated hydraulic modelling methods. It is important to note that the FHI does not reflect the probability of a flood occurring, but is simply a unit-less indicator of relative flood hazard in accordance with the morphology of the terrain. The FHI is ideal as a scoping mechanism for identifying areas where hydraulic modelling is required and to alert authorities of areas that are in danger of flooding.

Although the machine learning model used to determine the risk classes had an overall accuracy of 84%, the input (training) data used to generate the samples were based on hydraulic modelling outputs (produced by various other consultants). These flood lines are in itself only estimations (i.e. they are uncertain). This limitation, as well as the 16% overall error rate of the FHI needs to be taken into consideration when the index is used for operational purposes. It is merely the output of a model!

Despite its limitations, the index is a first attempt at providing a consistent, regional spatial index of flood hazard. It was generated using a transparent, empirical approach that can easily be replicated using updated data or be adapted for use in other areas. The FHI index is being used by the Western Cape Disaster Centre and feedback has been very positive. The intention is to continuously improve the FHI by expanding the training data used in the machine learning.

References

Van Niekerk, A., 2016. Stellenbosch University Digital Elevation Model (SUDEM): 2016 Edition (v16.xx). *Centre for Geographical Analysis*, 1, p.16. Available at: https://www.researchgate.net/publication/299336022_Stellenbosch_University_Digital_Elevation_Model_SUDEM_2016_Edition_v16xx.

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