Assessing flood disaster impacts in Southeast Asia

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Introduction:

Like many tropical regions, the Lower Mekong River Basin (LMB) experiences seasonal flooding, which can pose negative and positive impacts to the environment and local communities. Floodwaters carry nutrient-rich sediment that is deposited as the floods recede, naturally replenishing and fertilizing the soils of the floodplain for sustaining agricultural production, and providing habitat for fish and various aquatic and terrestrial animals. During extreme events, however, large floods can lead to loss of life, cause damage to infrastructure, and destroy crops. Additionally, droughts and upstream hydropower development can cause abnormally low flood levels, which can also damage flood irrigated rice crops (Arias, 2014). As the river flows through six countries, coordinating disaster management and relief efforts is a transboundary issue. As these floods occur on such a large scale, having up-to-date information on flood extent and damage estimates is essential for effective disaster relief and management efforts. Estimating the extent and impacts, such as affected population, of such large floods from the ground, however, is extremely difficult and impractical. Satellite remote sensing and GIS technology, on the other hand, can be used to provide flood extent and direct socio-economic impact estimations in a timely manner across large regions (Kussul et al., 2011). This study demonstrates how remote sensing and GIS analysis can be automated as an ArcGIS toolbox to help improve rapid response flood disaster assessment across the entire Lower Mekong River Basin (LMB).

The LMB in Southeast Asia is particularly vulnerable to flood disasters and could greatly benefit from both long term, as well as rapid or near real-time synoptic flood monitoring and assessment. The sixty million inhabitants of the LMB rely on the natural resources provided by the Mekong River and its annual flooding, especially agriculture and fisheries, to support their well-being and the economy of the region (MRC, 2009; Dugan et al., 2010). Recent studies have indicated that annual losses from flooding in the LMB are estimated to be $60-70 million annually. In contrast, economic gain from flooding due to nutrient replenishment and fish habitat is estimated at $8-10 billion annually (MRC, 2012), making proper flood management essential. Intensified floods and droughts caused nearly 90% of rice production losses in Cambodia during 1996-2001 (Mainuddin et al., 2011; Brooks et al., 2003). Future climate change may only increase the occurrence and severity of flood damage in this vulnerable area. Over the past 30-50 years, the LMB has experienced an increase in temperature, an increase in rainfall during the wet season and decreases during the dry season, intensified flood and drought events, and sea-level rise (IPCC, 2014). As climate change and development continues to intensify flood risk and associated damage to agricultural output and urban areas, there is a need for transboundary coordination of flood monitoring and risk management planning (IPCC, 2014).

Current Practices

During and immediately after a flood disaster, it is essential to know how many people the flood affected and where in order to maximize efficacy of relief efforts. Estimating the population and other socio-economic damage measures is a daunting task, especially for flood disasters as expansive as those in Southeast Asia. Currently, estimates for the number of people affected by flooding in Southeast Asia are done individually by each country, and rely upon ground estimations reported by smaller administrative designations. Estimations of flood extent and socio-economic impacts from the ground are extremely difficult, however, and are often a "best guest." In addition, the aggregation of this information relies upon communication among various administrative levels across an entire country. The speed, accuracy, and reliability of this process for estimating socio-economic damage, therefore, may not be adequate for rapid response and efficient allocation of resources for disaster relief. While measuring floods and damage *in situ* face these limitations for disaster situations, space-borne and airborne observations can provide a timely and consistent method for monitoring large floods through time (Brooks and Adger, 2003). In addition, with GIS datasets becoming more readily available throughout the world, integrated remote sensing GIS systems can be used for disaster rapid response and socio-economic impact analysis. By automating satellite-based flood mapping techniques with GIS analysis, both flood extent maps and socio-economic impact estimates can be generated and disseminated on a near real-time basis or for historical analysis. In addition, this approach removes the time-consuming intermediate steps that involve many people, countries, and agencies, required by current methods for obtaining these initial maps and estimations.

To increase the speed of this analysis and make it easy to use, I created a tool for ArcGIS using Python. This tool requires a geodatabase that contains population distribution and other infrastructure and socio-economic data for a country, and a flood map as a shapefile for a flood event. The automation then outputs damage estimates and maps. This tool was tested for the 2011 and 2013 major flood events in Cambodia (Figure 1).

Figure 1. Study area of Cambodia, outlined in magenta.

Methods:

Deriving Flood Map

This study uses a flood mapping product for Southeast Asia developed by Doyle *et al.* (in preparation) to develop a flood assessment tool for the region. This product detects changes in NDVI that are caused by flooding, representing relative flood impact, using the MODIS sensor on board the Aqua and Terra satellites. The method can be applied to examine historical flood events, or can be produced using the most recent MODIS data available for near real-time disaster applications (Doyle *et al*., in preperation). This method was used to produce flood maps at 250m resolution from MODIS 8-day composites from October 16, 2011 (Figure 2.), and October 8, 2013. Then this map is integrated into a GIS containing socio-economic data for the region, where automated analysis produces impact estimates, maps, and figures. By automating both the flood detection and GIS analysis, non-experts can easily obtain this information for the time period of interest nearly instantaneously.

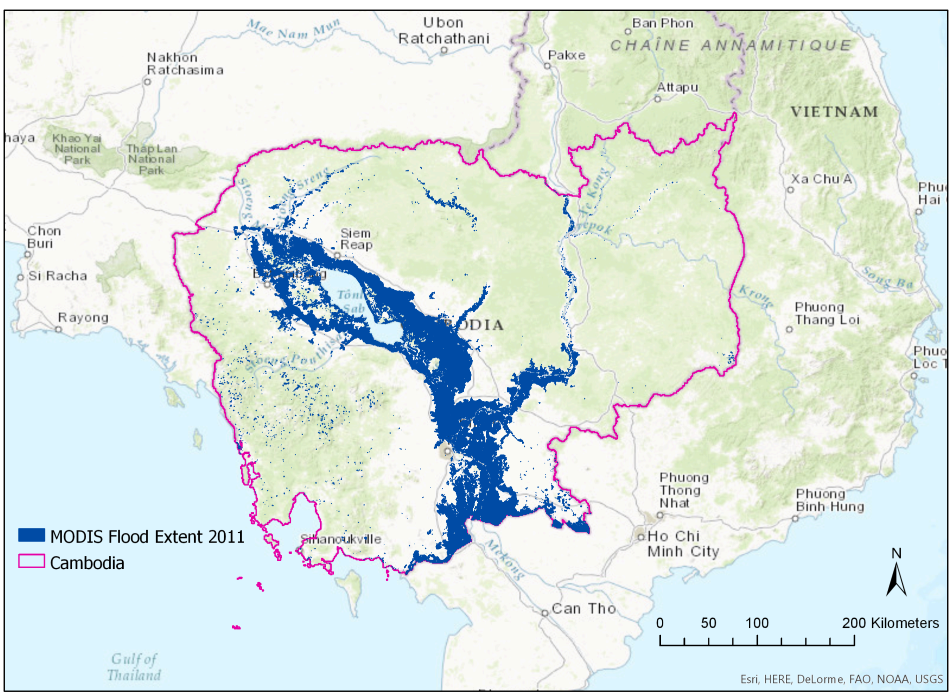


Figure 2. Flood extent derived from 8-day MODIS composite from October 16, 2011.

Estimating Socio-economic Impacts

A geodatabase was created to aggregate socio-economic information in a spatial format for Cambodia. Much data is available for free from various government and NGO agencies, and using open source data demonstrates how these methods can be applied to other regions. Once the data was uniformly formatted and projected, GIS processes were automated in the Python coding language to intersect a flood map with the data layers and estimate socio-economic impacts at the resolution of user-defined administrative boundary levels.

As estimating the number of people affected in different locations is essential for coordinating disaster relief, population distribution data was acquired from the WorldPop Project for Cambodia in 2010 (http://www.worldpop.org.uk). The WorldPop project uses various weighting datasets in combination with census data to create population distribution estimates by country at a 100m resolution (Figure 3). The estimations adjusted to match the official UN estimates were downloaded by country from the WorldPop website (http://www.worldpop.org.uk). Because this dataset and the flood extent maps are at different resolutions, several processing steps were necessary to compare the data.

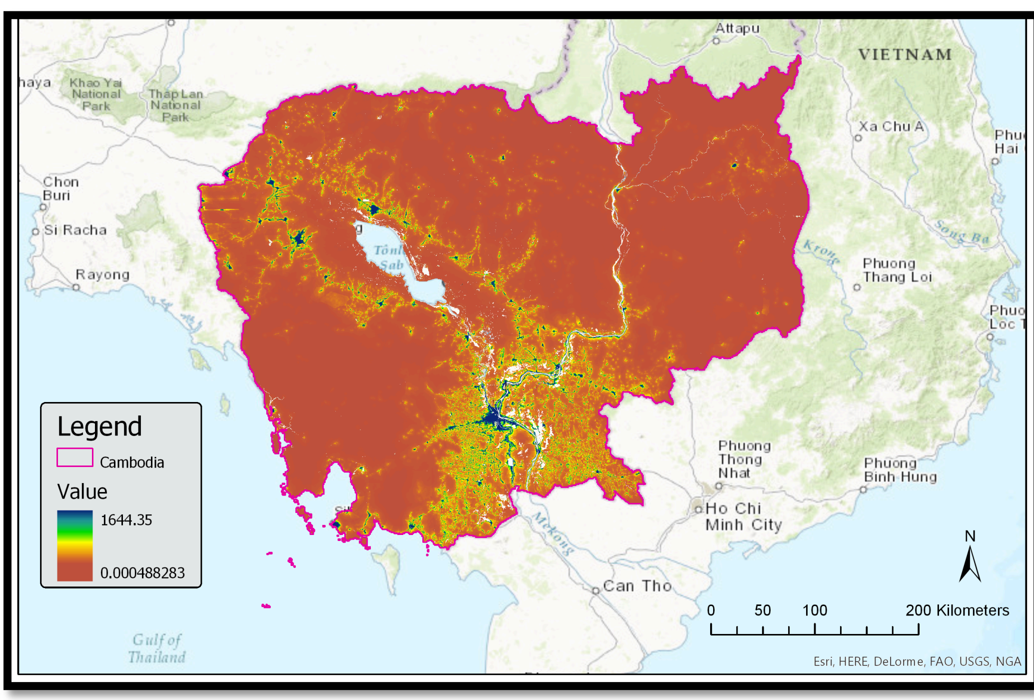


Figure 3. People per 100m x 100m pixel in Cambodia acquired from WorldPop

First, the population raster was converted into a shapefile in ArcGIS, and projected to WGS 1984 UTM Zone 48N. But, adjacent pixels that have the same population value will be joined as a single polygon feature in the shapefile, but the "GRIDCODE" value remains as the number of people in a single pixel. So, it was necessary to multiply the "GRIDCODE" by the "COUNT" to obtain the number of people in each polygon feature. Additionally, I calculated the area of each polygon in square kilometers. This shapefile was then saved in a geodatabase used as reference for the analysis.

In addition to population data, I acquired the locations of schools and health facilities in Cambodia through the Humanitarian Data Exchange (data.humdata.org/). These datasets are provided as point shapefiles, and were projected to WGS 1984 UTM Zone 48N and added to the reference geodatabase. In addition, Cambodia province, district, and commune boundary data was added to the reference geodatabase.

In ArcPro, I created a new Python Toolbox and opened the source code to edit with IDLE. I defined the labels and descriptions of the Toolbox and the Tool within it. Next, I used the "def getParameterInfo(self)" function to define three input parameters for the user to enter: the reference geodatabase, the flood map to be used for the analysis, and the folder in which the user would like to save the results to (Figure 4).

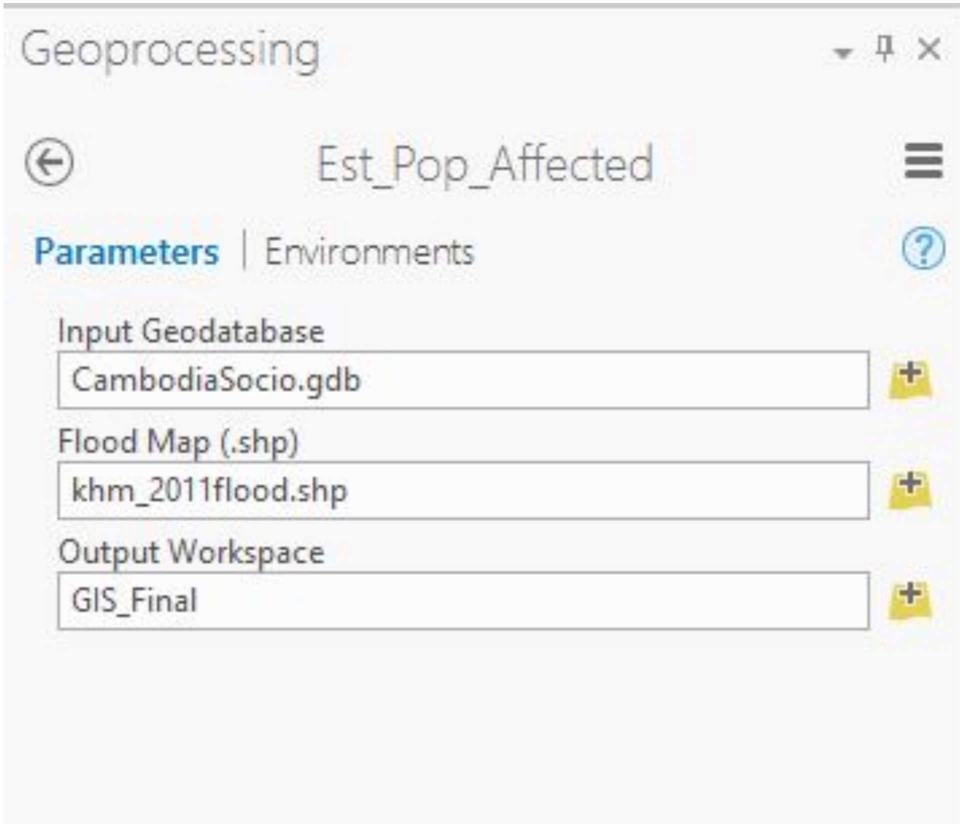
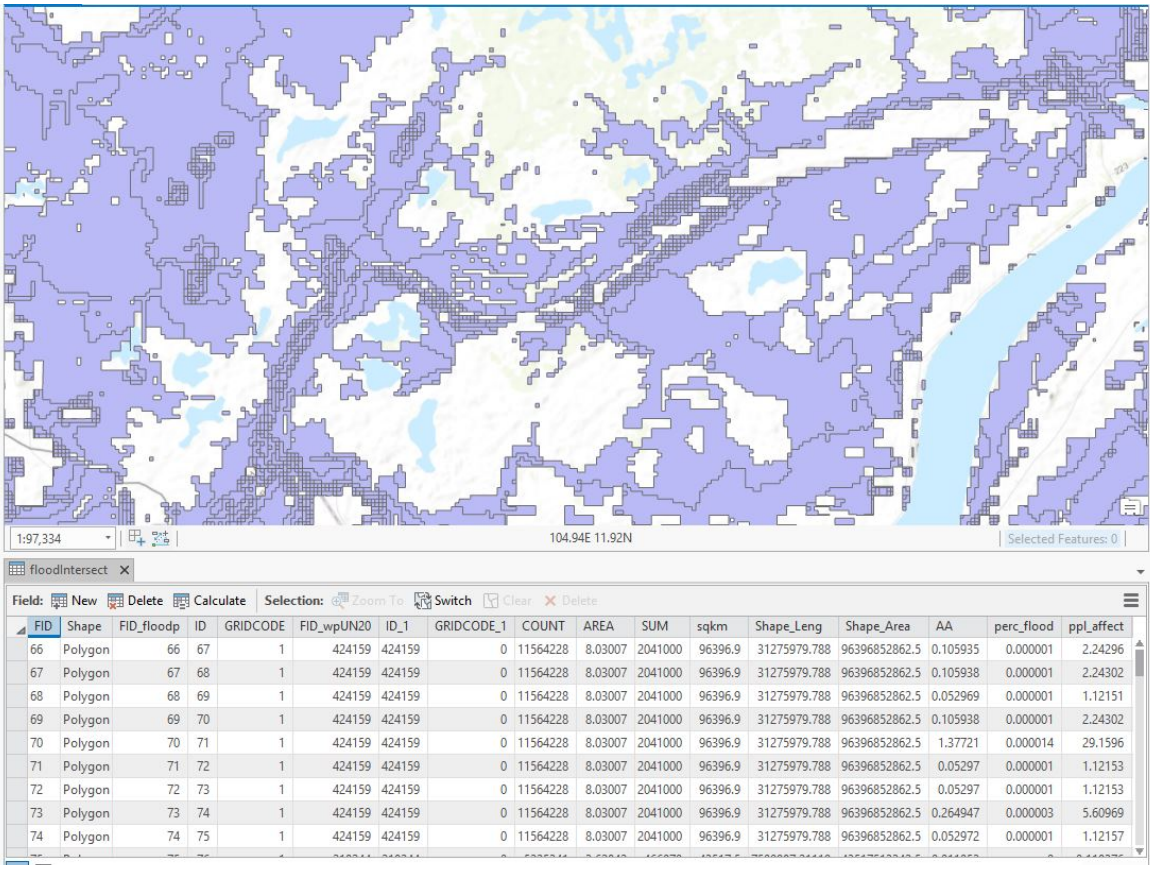


Figure 4. User-defined input parameters for flood impact estimation tool.

I then used the arcpy module to automate the estimation of affected people, schools, and hospitals with the user-defined flood map. First, I intersected the flood map shapefile with the population distribution shapefile. Using the area of the intersected polygons compared to the original area of the population polygons, I calculated the percent of each population polygon that is flooded. Then I multiplied this percentage by the number of people in each polygon to get the number of people affected by the flood in each polygon (Figure 5.). The number of people affected in each polygon were summed to calculate the total number of people affected by the flood for the event in Cambodia. This method assumes an even distribution of people across each 100m x 100m pixel, but allows me to take into account the difference in resolution between the data. Additionally, this approach allows for the input of a flood map at any resolution, not just from MODIS.



FID	Shape	FID_floodp	ID	GRIDCODE	FID_wpUN20	ID_1	GRIDCODE_1	COUNT	AREA	SUM	sqkm	Shape_Leng	Shape_Area	AA	perc_flood	ppl_affect
66	Polygon	66	67	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.105935	0.000001	2.24296
67	Polygon	67	68	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.105938	0.000001	2.24302
68	Polygon	68	69	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.052969	0.000001	1.12151
69	Polygon	69	70	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.105938	0.000001	2.24302
70	Polygon	70	71	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	1.37721	0.000014	29.1596
71	Polygon	71	72	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.05297	0.000001	1.12153
72	Polygon	72	73	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.05297	0.000001	1.12153
73	Polygon	73	74	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.264947	0.000003	5.60969
74	Polygon	74	75	1	424159	424159	0	11564228	8.03007	2041000	96396.9	31275979.788	96396852862.5	0.052972	0.000001	1.12157

Figure 5. Results of intersection between flood map and population data, and attribute table with calculations of people affected in each polygon.

To estimate the number of schools and hospitals affected by the flood, these datasets were clipped to the extent of the flood shapefile. The resulting clips contain the schools and hospitals affected by the flood, and the attribute tables contain the names of each facility, as well as the province, district, and village they are in, and additional information on each location. The script then creates a new geodatabase titled "FloodImpactResults.gdb" in the user-defined output folder, and saves the schools and hospitals affected to it. Additionally, the results for number of affected people, percent of population, schools, and hospitals are saved as a table in .csv format titled "CambodiaResults.csv" in the output folder.

Next, the script uses the "Extract by Mask" function to extract the population density from the original population density raster using the flood extent. This file is then saved to the results geodatabase. Lastly, "Zonal Statistics As Table" is used to determine the number of people affected in each province, and the table is joined to the province shapefile, and saved to the results geodatabase. The same process is carried out at the district and commune level. In the end, the output folder contains the results summarized in a .csv table, and a geodatabase that contains shapefiles of the affected hospitals and schools, a raster of people per pixel in flood zone, and province, district, and commune shapefiles that contain the number of people affected in each administration zone.

Results and Discussion:

It is difficult to validate the estimations of people, schools, and hospitals affected by the flood. To gain insight into if these estimations are at least reasonable, I compared my results to reports from the Asia Development Bank (ADB), Red Cross, and the UN Office of Communication for Humanitarian Affairs (OCHA) for the 2011 event (Table 1), and OCHA for the 2013 event (Table 2).

Table 1. Impact estimates of 2011 flood in Cambodia compared to NGO reports.

Cambodia	**GIS Estimates**	**Asia Development Bank**	**Red Cross**	**UN OCHA**
Population	1,648,826	1.5-1.7 million	>1.2 million	1 million
Schools	78	1,396		
Hospitals	71	115		

Table 2. Impact estimates of 2013 flood in Cambodia compared to public reports.

Cambodia	**GIS Estimates**	**UN OCHA**
Population	1,236,936	1.7 million
Schools	607	
Hospitals	47	

The estimations for both the 2011 and 2013 events calculated by my ArcPro tool were comparable to reports from various sources (Table 1; Table2). It is difficult to compare these results directly, however, as the methods for collecting this data is different with each organization, and the reliability of these estimates is unknown. But, the population-affected estimates are close enough to suggest that these GIS-based results are probably realistic. The schools and hospitals did not agree perfectly, but this is likely due to the reference datasets used in the geodatabase being incomplete. Regardless, these results suggest that this tool can be used to achieve realistic estimates in a timely manner through an easy to use automated process.

The data provided in the results geodatabase can be used to visualize the flood impacts in different ways. The “popInFlood” raster reveals the number of people affected throughout the country at 100m resolution. This map shows how the capital of Phnom Penh is very well protected, but it is the rural farming communities along the river that are at greatest risk (Figure 6). In addition, the other shapefiles can be used to see the location of affected schools and hospitals, or visualize the total number affected at different administrative levels, such as provinces (Figure 7).

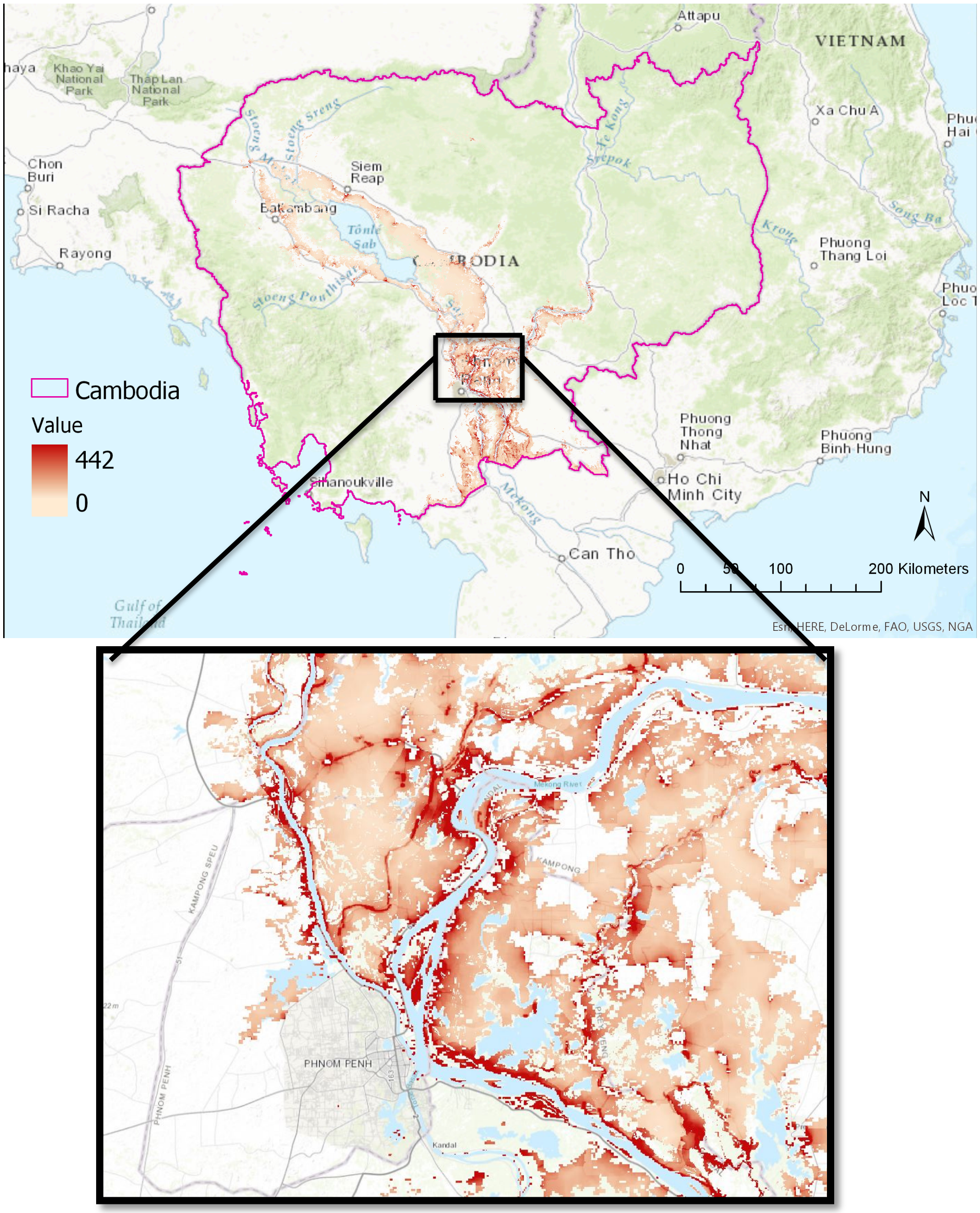


Figure 6. Number of people affected by 2011 flood in Cambodia in each 100m x 100m pixel.

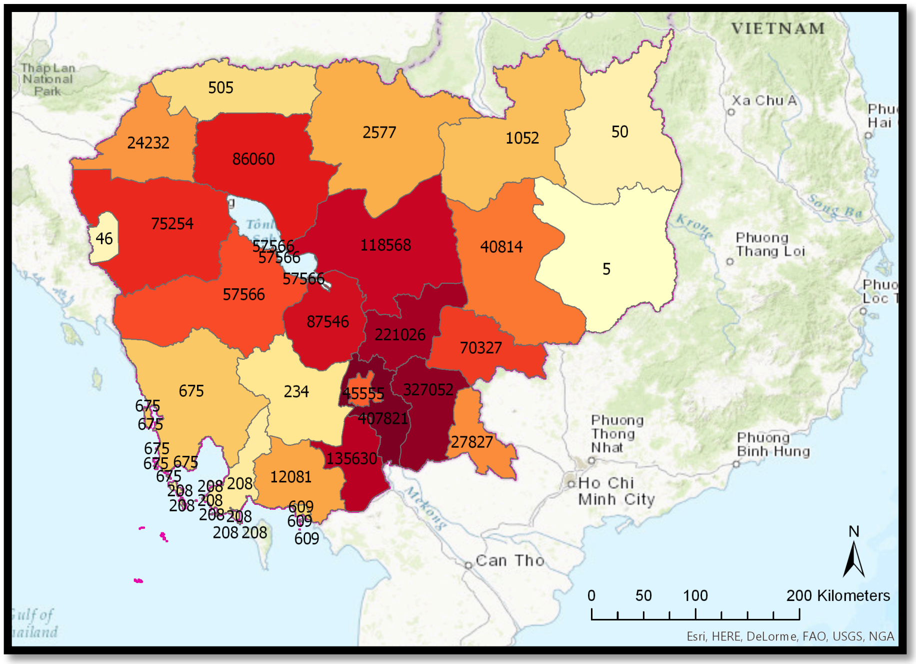


Figure 7. Total number of people affected by 2011 flood by province.

Conclusions:

This study demonstrates the utility of automating GIS analysis with python for enhance flood impact analysis in Cambodia. This tool implemented in ArcPro can be used to calculate socio-economic impacts in Cambodia in a timely and easy to use way using flood maps at any resolution. Tools such as this can help speed up analysis time for increasing testing of methods and results, but also allows non-expert end users to perform complex analyses to obtain results necessary for rapid disaster relief and assessment. The estimations of population affected by flood disasters in Cambodia for 2011 and 2013 agreed well with public reports from various agencies, suggesting great utility for this method for disaster recovery. In addition, the agency reports were produced months after the flood events, and the in-flood estimates, when available, are generally poor. This method allows for uniform estimation of flood impacts during a flood, as well as after, in a matter of minutes with minimal manual analysis.

Future work involves expanding this tool to other countries. In addition, I would like to add more data to the socio-economic database from various sources such as Open Street Map, and use higher resolution flood maps. In addition, the analysis portion of the code can be used to integrate into near real-time flood mapping systems to provide damage estimates in near real-time on the web.

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