Assessing the role of global datasets for flood risk management at national and catchment scales

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Summary

- Some global flood risk datasets are now detailed enough to be relevant at national and catchment scales. Especially in regions lacking existing flood risk information.
- We explore the usefulness of global datasets and methods for calculating flood risk at national and catchment scales in five countries: **Colombia**, **England**, **Ethiopia**, **India**, and **Malaysia**
- We use datasets and methodologies from previously published studies of global flood risk.
- We calculate national flood risk in each of the five countries using **five** (100-year return period) global flood hazard models, **seven** global population datasets, and **three** methods for calculating vulnerability.
- Usefulness is assessed considering the variability of national flood risk estimates.

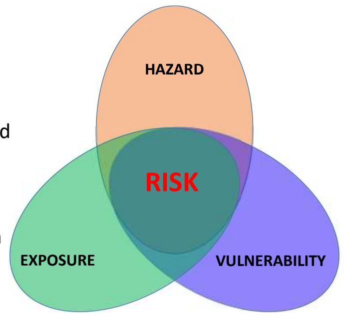

Figure 1. The three components of flood risk

Conclusions

- National flood risk estimates calculated using different global datasets vary significantly.
- Results are highly country dependent. No global dataset consistently overpredicts or underpredicts flood risk relative to the other datasets.
- Users should use a combination of multiple global datasets to report flood risk to reduce the uncertainty associated with using any single global dataset.

Further Work

- We explore the credibility of this data considering the local flood management context in each country. What capacity is there to use this data? How can the data be misused? What implications does dataset disagreement have on its use locally?
- We unpack the uncertainty associated with each risk dataset in greater detail.

Hazard

- We use five global flood hazard models: **CaMa-UT**, **CIMA-UNEP**, **Fathom**, **GLOFRIS**, and **JRC.**
- We compare their fluvial, undefended, 100-year return period flood hazard maps.
- We calculate agreement between the models using the Model Agreement Index score from *Trigg et al. (2016).*
- Country Model Agreement Index Scores (high to low): Colombia (0.364), India (0.322), Malaysia (0.299), England (0.258), Ethiopia (0.240). *Note: 1 = perfect agreement 0 = no agreement*

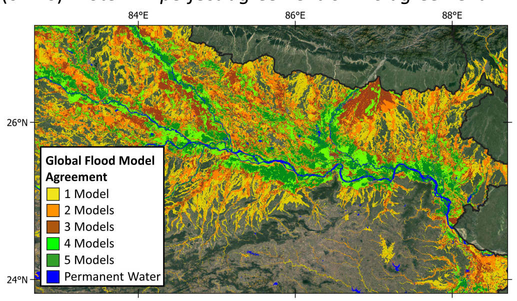

Figure 2. Flood extent agreement on the Ganges river in northern India

Key Findings

- ➢ Model disagreement is highest in low-lying coastal areas and on smaller rivers (which aren't represented in all the models)
- ➢ Total flooded area ranking varies between the countries and seems equally dependent on how many rivers are represented and how flow is estimated.

Exposure

- We use seven global population datasets: **GPW4**, **GHS-POP**, **GRUMP**, **HRSL**, **HYDE**, **LandScan**, and **WorldPop**.
- Flood exposure is calculated by intersecting the seven population datasets with the five global flood hazard maps. <u>35 possible combinations</u>.
- Flood exposure is greatest in India (both in absolute and relative terms)
- National exposure estimates differ by up to a factor of 7 (England), 6.9 (Ethiopia), 5.2 (Colombia), 4.5 (Malaysia), and 3.4 (India) depending which combination of global flood model and global population dataset is used in the exposure calculation.

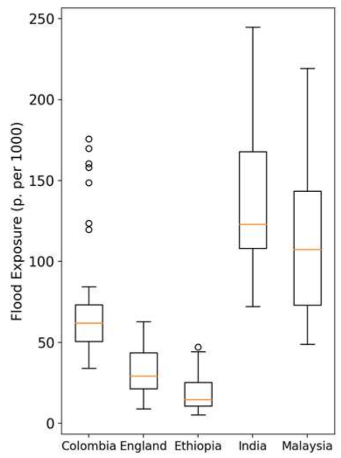

Figure 3. Spread of exposure results in each country using all 35 combinations

Key Findings

- ➢ The choice of global flood model has a greater influence on exposure estimates than the choice of population dataset.
- ➢ Population disagreement is highest in rural areas.
- ➢ No global flood model or global population dataset consistently predicts the most or least exposure.

Vulnerability

- Vulnerability is expressed in terms of direct economic damages.
- We use three different methods. Each method uses depth damage curves, a land use map, and flood depths to determine the proportion of land value damaged by floods (see *Figure 4*).
- The three land use maps used are: **GlobCover**, **GHSL**, and **HYDE**.
- Two approaches use depth damage curves from a global database of depth damage functions. The other approach uses a single depth damage curve globally.

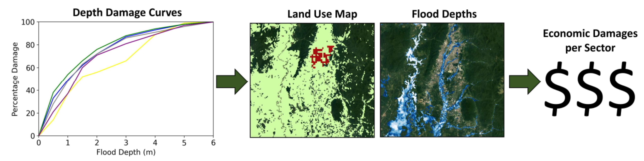

Figure 4. Vulnerability damage calculation process.

- Flood damages (relative to GDP) were highest in Malaysia (on average 10% GDP) and lowest in Ethiopia (on average 0.2% GDP).
- National flood damages differ by up to a factor of 39 (Colombia), 15.6 (England), 12 (Malaysia), 6 (Ethiopia), and 4.2 (India) depending on the vulnerability method and global model used in the damage calculation.

Key Findings

- ➢ The choice of vulnerability method has a greater influence on damage estimates than the choice of global flood model.
- ➢ The definition of urban areas in each land use map is an important factor influencing damage estimates.
- ➢ No approach consistently predicts the most or least damage.

References

Trigg M A et al 2016 Environ. Res. Lett. 11 094014

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