The Impact of Natural Disasters on Light-based Geospatial Income Inequality

Jaqueson K. Galimberti[1]; Stefan Pichler[2]; Regina Pleninger[3]
[1]Asian Development Bank, [2]University of Groningen, [3]World Bank Group

Summary

Motivation	❑ How do natural disasters impact inequality? ❑ Different disasters can affect a country's population unequally. ❑ Mixed evidence from the literature.
Goals	❑ Evaluate the impact of natural disasters on inequality. ❑ Extend database of Light-based Geospatial Income Inequality (LGII).
Methods	❑ Sample of LGII Gini-coefficients for 233 countries and territories over the period from 1992 to 2019. ❑ Impacts of natural disasters estimated using (i) panel regressions and (ii) synthetic control groups. ❑ Heterogeneity analysis by disaster type and subtype.
Key Contributions and Findings	❑ LGII allows study of a sample about 50% larger than traditional data. ❑ Impact of natural disasters on inequality depends on type of disaster, income level, geography and sectoral structure. ❑ Preparedness may condition the impacts of disasters on inequality.

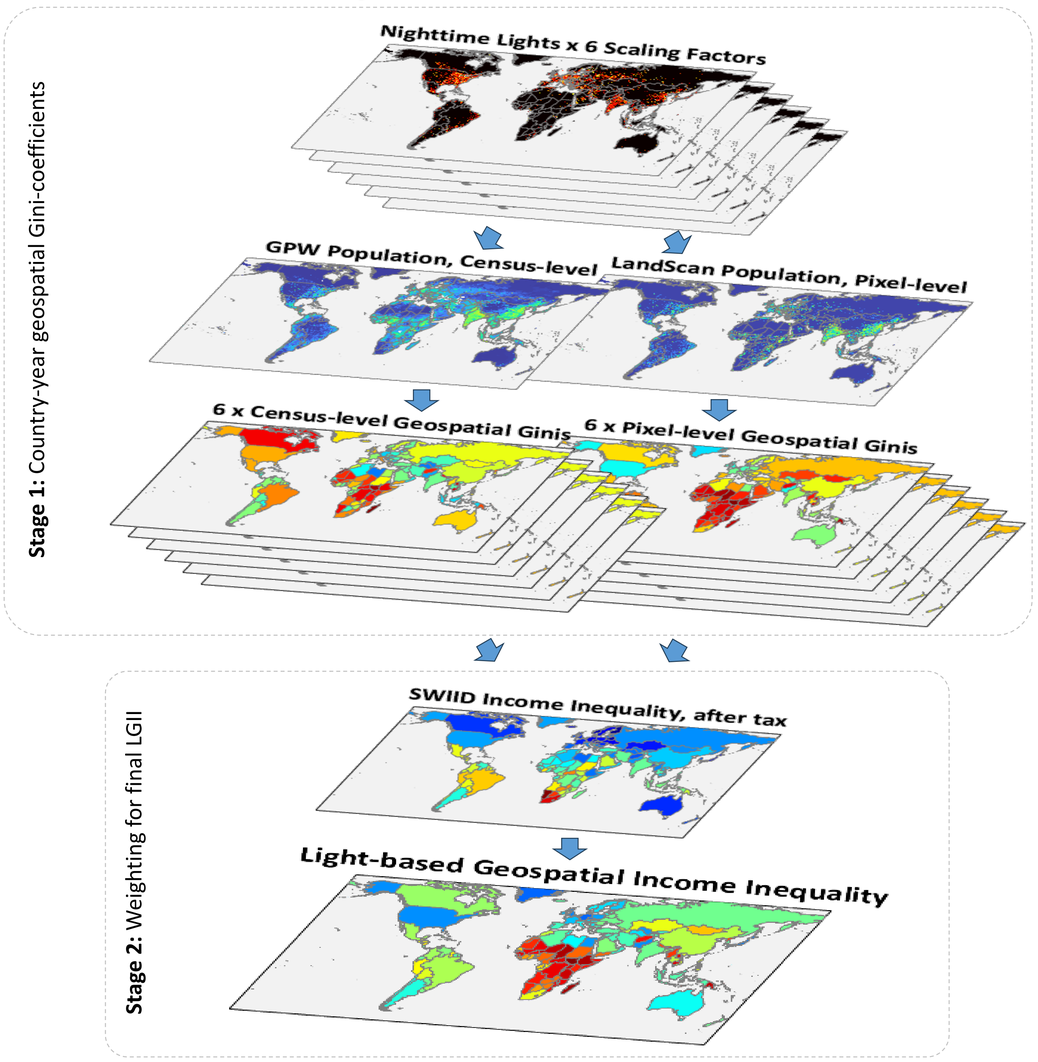
1. Light-based Geospatial Income Inequality

The **LGII** database is extended by combining data from:[1]

- Nightlights (NTL) from Defense Meteorological Satellite Program, 1992-2013.
- DMSP-like NTL derived from Visible and Infrared Imaging Suite, 2013-2019.[2]
- Gridded Population of the World (GPW) from CIESIN, 2000-2020.
- LandScan Global Database (LSC) from ORNL, 2000-2019.
- Standardized World Income Inequality Database (SWIID), 1992-2020.[3]

After pre-processing the data, the LGII measures are constructed in two stages (see Figure 1). The resulting (overall) correlation between the LGII and SWIID is 0.51.

Figure 1. Construction of LGII measures.



2. Natural Disasters Data and Controls

Natural disasters data come from EM-DAT, an international database compiled by CRED. Four types of **severe natural disasters**, defined as disasters affecting at least 5% of the country's population, are considered:

1. Climatological: droughts and wildfires.
2. Geophysical: earthquakes, dry mass movements and volcanic activity.
3. Hydrological: floods and wet mass movements.
4. Meteorological: extreme temperatures and storms.

Control variables include the occurrence of biological and technological disasters, and deaths due to conflicts as a share of the country's population.[4]

3. Panel Regressions

Panel regressions of the following specification are estimated to determine the impact of natural disasters on inequality:

$$Gini_{i,t} = \sum_j \beta_j Disaster_{i,j,t} + \delta \boldsymbol{X}_{i,t} + \alpha_i + \gamma_t + \varepsilon_{i,t}$$

where $\boldsymbol{X}_{i,t}$ are control variables, α_i and γ_t are country and year fixed effects, and $Disaster_{i,j,t}$ is the treatment variable defined by the occurrence of different types of disasters (j) and to capture varying dynamics:

- Transitory: $Disaster_{i,t}^{Trans} = \begin{cases} 1, if\ natural\ disaster\ occurred, \\ 0, \qquad otherwise. \end{cases}$
- Permanent: $Disaster_{i,t}^{Perm} = \sum_{\tau=1}^{t} Disaster_{i,\tau}^{Trans}$

Key findings (see Table 1):

- Little evidence that natural disasters have (only) transitory effects on inequality.
- Extreme temperatures are associated with permanent increases in inequality, especially in more developed economies.
  - ❖ Labor productivity channel: low-income households affected more strongly.
- Droughts are associated with permanent decreases in inequality, especially in more developed, non-landlocked, and non-island economies.
  - ❖ Sectoral shifts channel: droughts impacts on agriculture intensify urban migration, reducing urban-rural income gaps in industrialized economies.
- Other types of natural disasters have more heterogenous effects on inequality, but mostly statistically insignificant.

Table 1. Dashboard of panel regression estimates.

	Climatological				Geophysical				Hydrological				Meteorological			
	Drought		Wildfire		Earthquake		Volcanic		Flood		Wet mass mov		Extreme temp		Storm	
	Trans	Perm	Trans	Perm	Trans	Perm	Trans	Perm	Trans	Perm	Trans	Perm	Trans	Perm	Trans	Perm
Overall	○	↓	○	○	○	○	○	○	○	○	○	○	○	↑	○	○
By Income Group																
High	○	↓	○	○	○	↓	○	○	○	○	○	○	○	↑	○	↓
Upper middle	○	↓	↓	○	○	↑	○	○	○	○	↑	○	○	↑	○	○
Lower middle	○	○	○	↓	○	↑	↓	○	○	○	○	↑	○	○	○	○
Low	○	○	↑	○	↑	○			↓	○	↓	○	○	○	○	○
By Geography																
Not Landlocked	○	↓	○	○	○	○	○	○	○	○	○	○	○	↑	○	○
Landlocked	↓	○	○	○	○	○			↓	○	○	○	○	↑	○	○
Not Island	○	↓	○	○	○	○	○	○	↓	○	○	○	○	↑	○	○
Island	○	○	○	○	○	○	○	○	○	○	○	○	↑	○	○	○
By Adaptation*																
Low	○	○	○	○	○	○	↓	↑	○	○	○	○	○	○	↑	○
High	↓	↓	○	○	○	↓	↑	↓	○	○	○	○	○	↑	○	○
By Agriculture																
Low share	○	↓	○	○	○	↓	○	○	○	○	○	○	○	↑	○	○
High share	○	○	○	○	○	↑	↓	○	○	○	○	○	○	○	○	○

↑ = significant increase in inequality; ↓ = significant decrease in inequality; ○ = insignificant effect on inequality.
Statistical significance at 10% level. *Adaptation is based on the Notre Dame Global Adaptation Initiative's Country Index.

4. Synthetic Control Groups

Focus on treated countries where:

i. Severe disasters (>5% of pop affected) occurred only after 2000.
ii. No major conflicts killing more than 0.1% of the population.

Donor pool:

Countries (107) that did not experience any severe disaster or major conflicts.

Key findings (see Table 2):

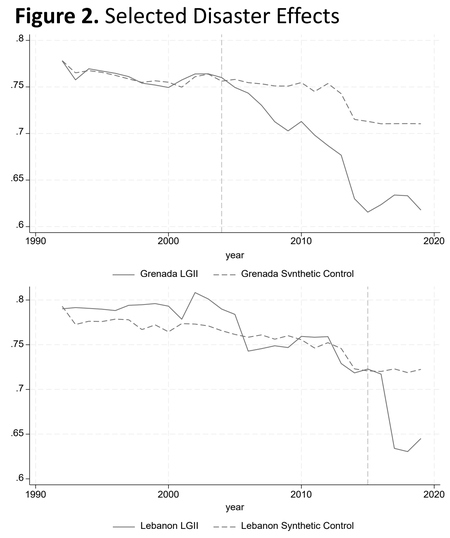
- Most disasters did not have statistically significant effects on inequality.
- Only 4 countries/territories show statistically significant results (out of 28).

Table 2. Synthetic control groups results overview.

Country/Territory	Year	Disaster type	Affected pop	Effect on LGII
Grenada	2004	Storm	58%	− 5.5**
Lebanon	2015	Storm	13%	− 4.1*
Trinidad and Tobago	2018	Flood	11%	− 1.4**
Taiwan	2009	Storm	10%	− 3.6**
Average (17 obs with both income and light)			19%	− 2.5
Average (all 28 obs)			17%	− 2.3

Note: Only cases with statistically significant effects are presented. ***, ** and * indicate effects statistically significant at the 1%, 5% and 10% levels of significance, respectively.

Figure 2. Selected Disaster Effects



Contact

Jaqueson K. Galimberti (ADB) → jgalimberti@adb.org
Stefan Pichler (Uni of Groningen) → s.Pichler@rug.nl
Regina Pleninger (WBG) → rpleninger@worldbank.org

Selected References

1. Galimberti, J. K., S. Pichler, and R. Pleninger (2023). Measuring Inequality Using Geospatial Data. *The World Bank Economic Review* 37(4), 549-569.
2. Nechaev, D., M. Zhizhin, A. Poyda, T. Ghosh, F.-C. Hsu, and C. Elvidge (2021). Cross-sensor nighttime lights image calibration for DMSP/OLS and SNPP/VIIRS with residual u-net. *Remote Sensing* 13 (24).
3. Solt, F. (2020). Measuring Income Inequality Across Countries and Over Time: The Standardized World Income Inequality Database. *Social Science Quarterly* 101 (3), 1183-1199. SWIID Version 9.5, June 2023.
4. Sundberg, R. and E. Melander (2013). Introducing the UCDP Georeferenced Event Dataset. *Journal of Peace Research* 50 (4), 523–532.