High Performance Computing with Geospatial Information

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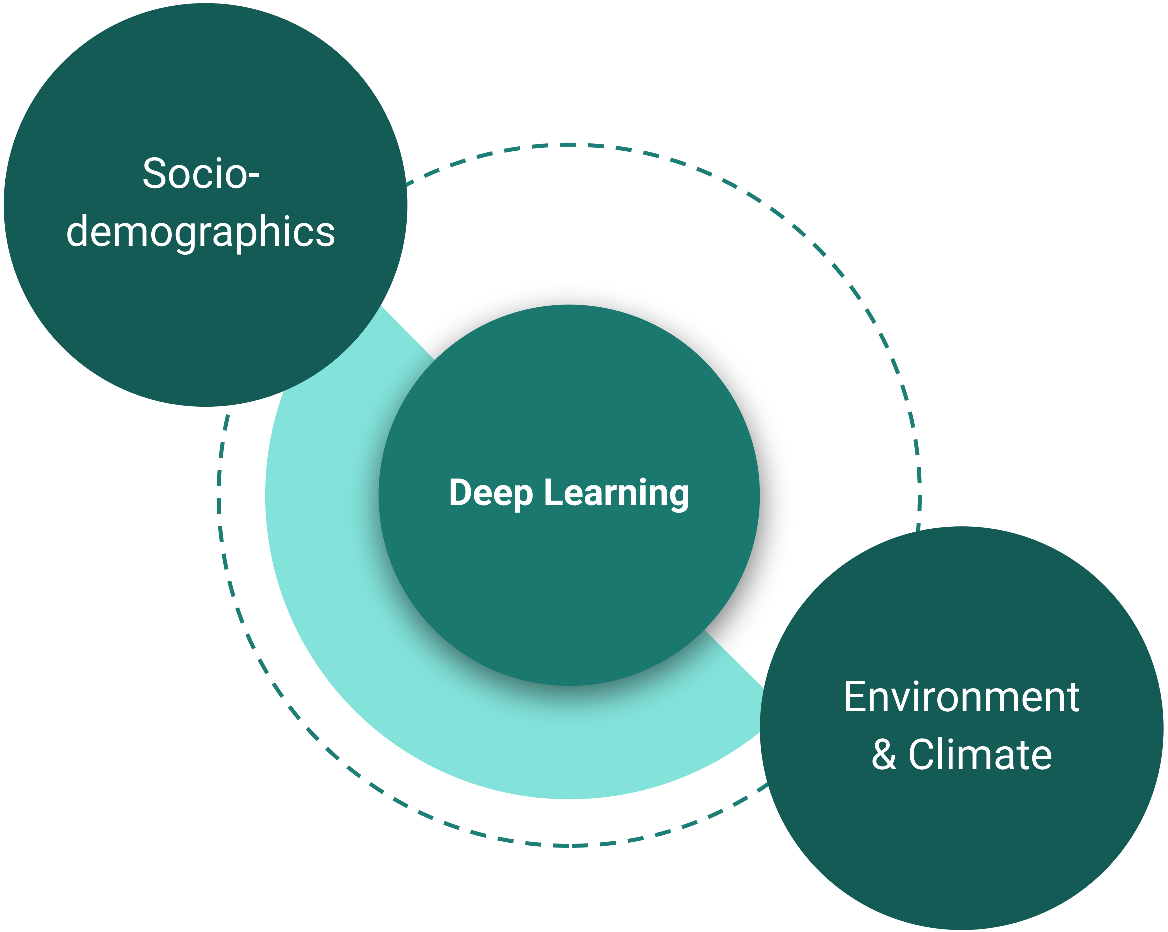
William & Mary


Socio-
demographics
Deep Learning
Environment
& Climate

Environment & Climate

Mapping & Modeling Human Shoreline Structures with Deep Learning

Assessing the Impact of Global Environmental Projects to Mitigate Climate Change

Lv, Z.[†], Nunez, K., Brewer, E.[†], Runfola, D. 2023. Mapping the tidal marshes of coastal Virginia: A hierarchical transfer learning approach. **GIScience & Remote Sensing**. https://doi.org/10.1080/15481603.2023.2287291

Lv, Z.[†], Nunez, K., Brewer, E.[†], Runfola, D. 2023. pyShore: A deep learning toolkit for shoreline structure mapping with high-resolution orthographic imagery and convolutional neural networks. **Computers & Geosciences**. https://doi.org/10.1016/j.cageo.2022.105296

Runfola, D.; Batra, G.; Anand, A.; Way, A.[†]; Goodman, S.[†] 2020. Exploring the Socioeconomic Co-benefits of Global Environment Facility Projects in Uganda Using a Quasi-Experimental Geospatial Interpolation (QGI) Approach. **Sustainability**, 12, 3225. https://doi.org/10.3390/su12083225

Marty, R.[†], Goodman, S.[†], LeFew, M.[†], Dolan, C., BenYishay, A., Runfola, D. 2019. Assessing the Causal Impact of Chinese Aid on Vegetative Land Cover in Burundi and Rwanda Under Conditions of Spatial Imprecision. **Development Engineering.** https://doi.org/10.1016/j.deveng.2018.11.001

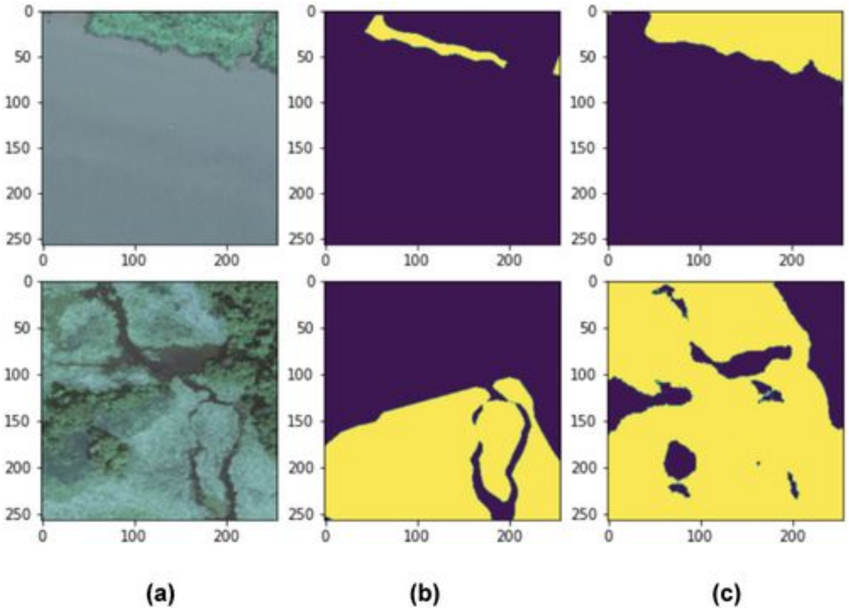
Buchanan, G., Parks, B., Donald, P., O'Donnel, B., Runfola, D., Swaddle, J., Tracewski, L., Butchart, S. 2018. The Local Impacts of World Bank Development Projects Near Sites of Conservation Significance. **Journal of Environment and Development**. https://doi.org/10.1177/1070496518785943

BenYishay, A., Heuser, S., Runfola, D.M., Trichler, R. 2017. Indigenous land rights and deforestation: Evidence from the Brazilian Amazon. **Journal of Environmental Economics and Management**. https://doi.org/10.1016/j.jeem.2017.07.008

Bunte, J., Desai, H.[†], Gbala, K., Parks, B., Runfola, D.M., 2018. Natural resource sector FDI, government policy, and economic growth: Quasi-experimental evidence from Liberia. **World Development**. Volume 107. pg 151-162. https://doi.org/10.1016/j.worlddev.2018.02.034.

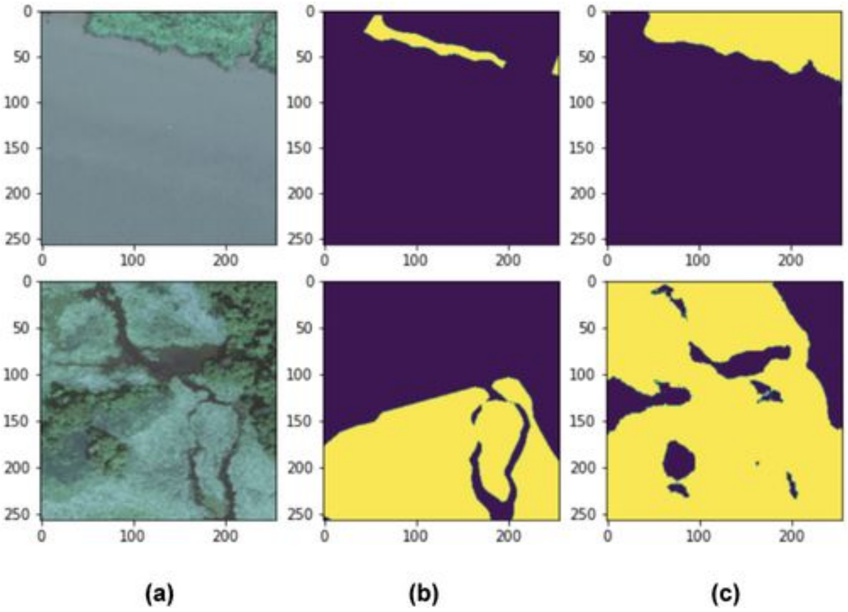
Mapping Marshland & Shoreline Structures w/ GPUs!

Marsh Community Types

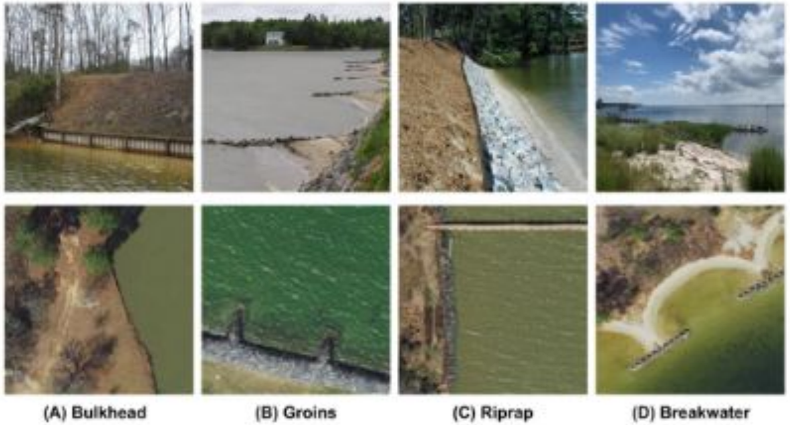


Mapping Marshland & Shoreline Structures w/ GPUs!

Marsh Community Types



Shoreline Structures



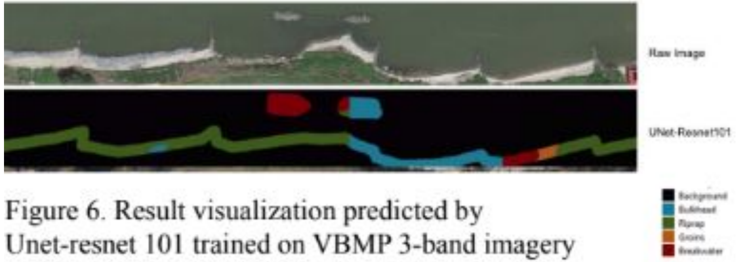
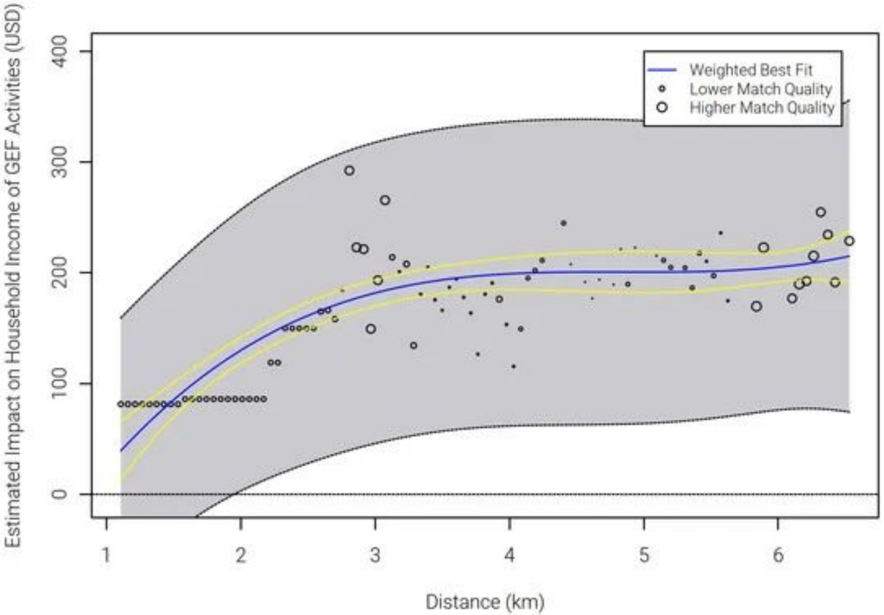
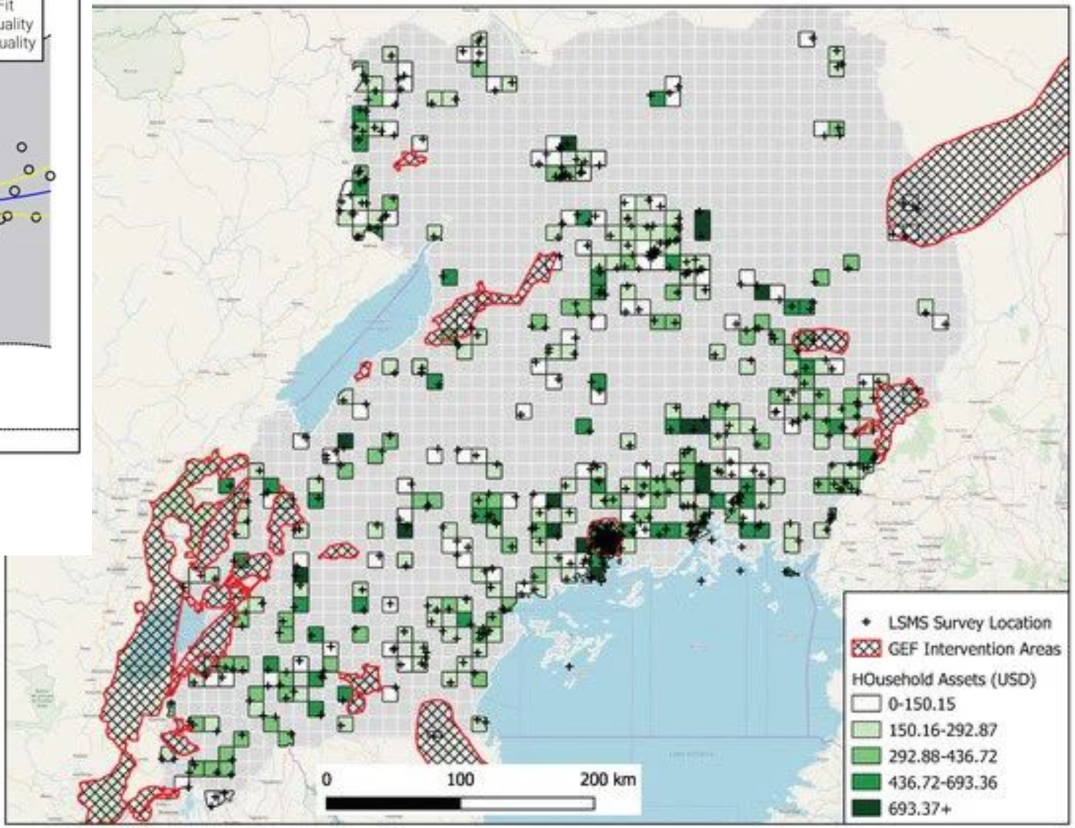


Figure 6. Result visualization predicted by Unet-resnet 101 trained on VBMP 3-band imagery (Lv et al., 2023)

Impact Assessment





People

Mapping & predicting sociodemographic factors based on satellite imagery

Modeling geographic boundaries in HPC environments

Runfola, D., Stefanidis, A., Lv, Z.[†], O'Brien, J.[†], and Baier, H[†]. 2024. A multi-glimpse deep learning architecture to estimate socioeconomic census metrics in the context of extreme scope variance. **International Journal of Geographical Information Science.**

Runfola, D., Baier, H.[†], Mills, L.[†], Naughton-Rockwell, M.[†], Stefanidis, A. 2022. Deep Learning Fusion of Satellite and Social Information to Estimate Human Migratory Flows. **Transactions in GIS.** http://doi.org/10.1111/tgis.12953

Runfola, D., Stefanidis, A., Baier, H.[†], 2021. Using Satellite Data and Deep Learning to Estimate Educational Outcomes in Data Sparse Environments. **Remote Sensing Letters 13(1)**. https://doi.org/10.1080/2150704X.2021.1987575

Brewer, E.[†], Kemper, P., Lin, J.[†], Hennin, J.[†], and Runfola, D. 2021. Predicting Road Quality using High Resolution Satellite Imagery: A Transfer Learning Approach. **PLoS One**. https://doi.org/10.1371/journal.pone.0253370

Goodman, S.[†], BenYishay, A., Runfola, D. 2020. A Convolutional Neural Network Approach to Predict Non Permissive Environments from Moderate Resolution Imagery. **Transactions in GIS**. https://doi.org/10.1111/tgis.12661


Mendenhall St
Mendenhall St
Spring St
Chamblee Charter
High School
North Dekalb Stadium
Pierce Dr
Pierce
Simple Finds
for the home

West Sector
High School


Baybayog High School


Gomez St
Gomez St
Magsaysay Ave
Magsaysay Ave
Bonifacio Ave
Bonifacio Ave
Calaocan Elementary School
Zamora St
Zamora St
JOM's Internet Cafe
Nesti Busto Beauty Salon
Google

Overall Study Design

44,751 public elementary schools in the Philippines.

We only know school test outcomes for a limited subset of these schools.

Our goal is to predict school scores based on imagery alone, using a CNN, to provide to a NGO partner.

Acquire School Test Outcome Data

5,875 school from 2013 - 2014

+

Acquire Remote Imagery

Google maps, Landsat

Design & Calibrate CNN Architecture

Cross-validation, multi-model ensemble approaches tested using NVIDIA GPUs.

Predict School Outcomes

Using the model calibrated based on the available 5,875 schools, predict outcomes for remaining schools. Apply model to future time steps as well to fill in temporal gaps.

CNN Architecture

In total, 18 CNNs and 12 ensemble's are fit, covering each of 5 class subjects and 1 "all subjects" model.

Ensemble Accuracies

Subject	Binary Accuracy (%)	Score Error (MAE)
English	**82%**	2.21
Filipino	76%	**1.42**
Math	81%	2.23
Science	80%	**2.26**
Social Studies	**75%**	2.07
All Subjects	80%	1.77

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5,875 school from 2013 - 2014

Acquire Remote Imagery

Google maps, Google Street View, Landsat

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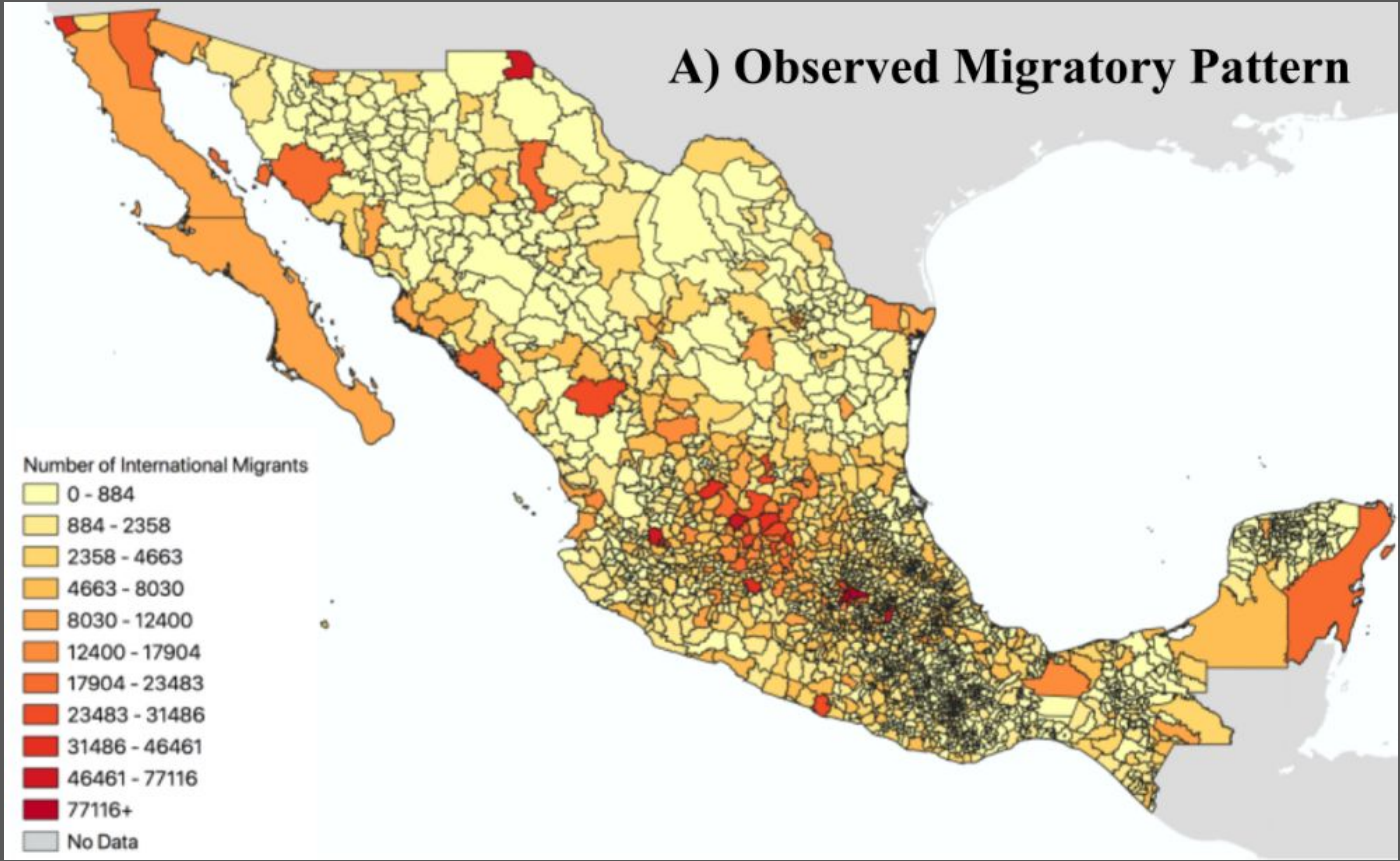
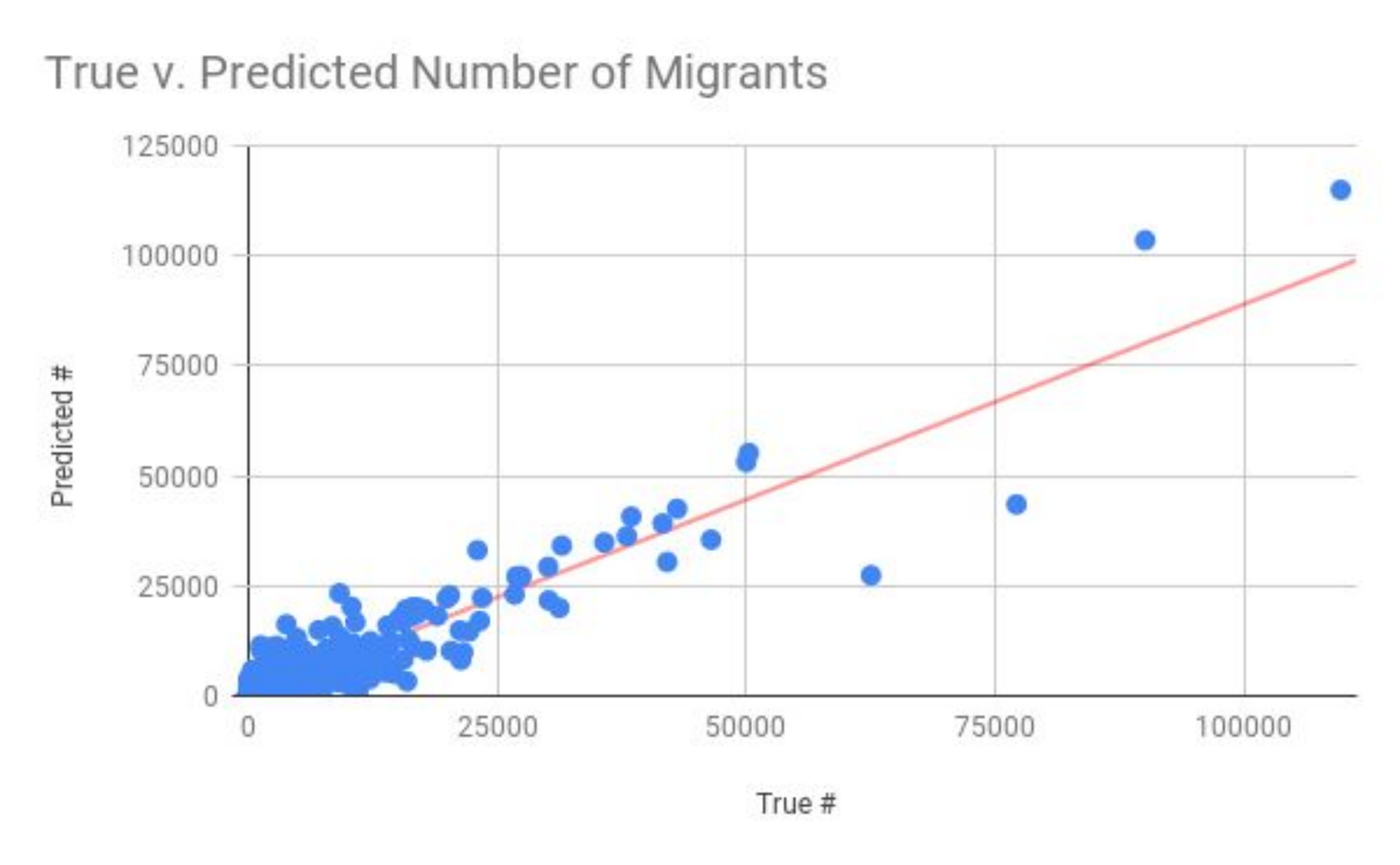

A) Observed Migratory Pattern
Number of International Migrants
0 - 884
884 - 2358
2358 - 4663
4663 - 8030
8030 - 12400
12400 - 17904
17904 - 23483
23483 - 31486
31486 - 46461
46461 - 77116
77116+
No Data


True v. Predicted Number of Migrants
125000
100000
75000
50000
25000
0
Predicted #
0
25000
50000
75000
100000
True #

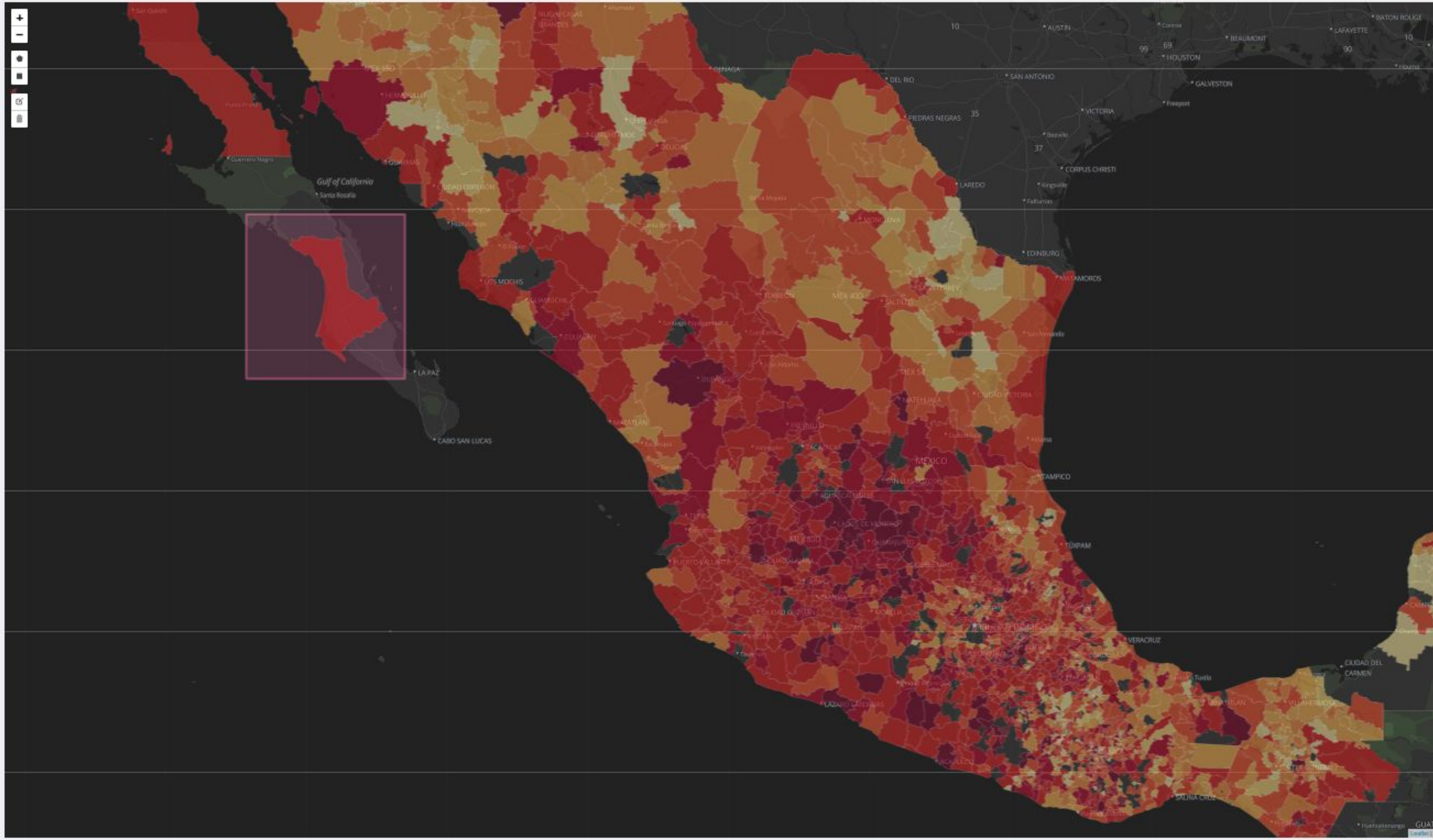
Migration Data Portal

Adjustable sociodemographic variables:

- Economic Variables
- Demographic Variables
- Marriage & Fertility Variables
- Health Variables
- Occupational Variables
- Education Variables
- Household Variables

Predict new migration pattern

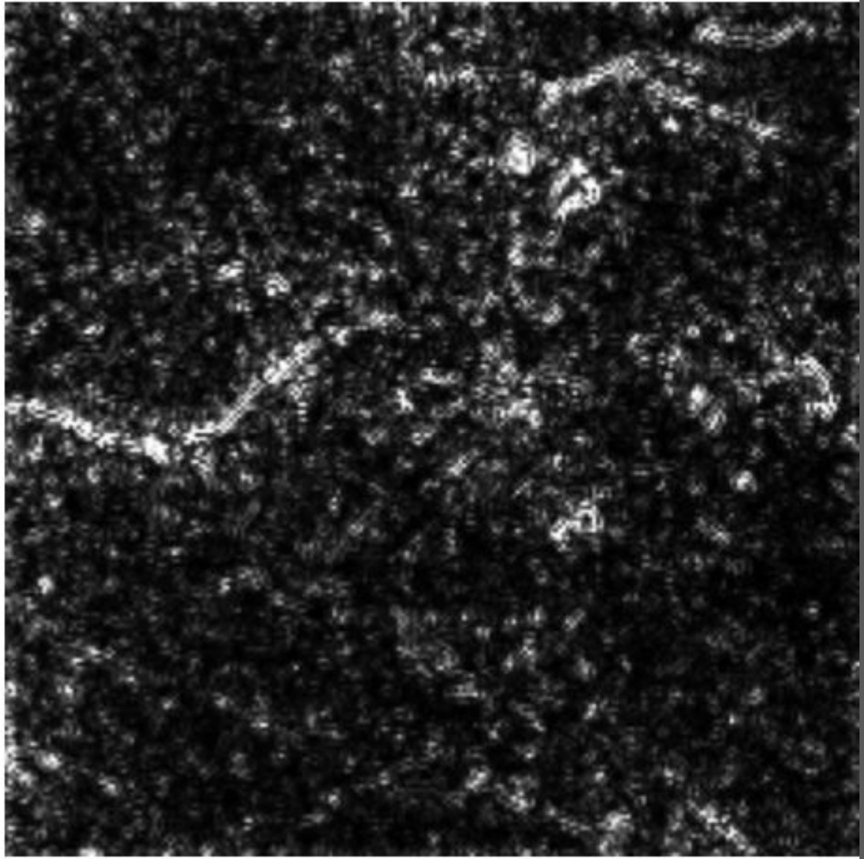
Total number of migrants	Change in number of migrants		Average age of migrants	Change in average age
680232	-29755	-4.19%	195.4	32.03



Directions to user:

1. Click on either the polygon or rectangle icons on the map to draw an area of interest (AOI) over municipalities you wish to manipualte data for. You can draw as many AOI's as you wish. To delete an AOI, click on the trash can icon on the map, then click on the AOI you wish to delte and hit 'save' next to the trash can icon.
2. Click on any of the variable drop downs above to view associated variables that are available to manipulate. Then, type in a percentage increase or decrease to change the value of the variable for the municiaplities you choose on the map. For example, if you'd like to increase the Total Income of selected municipalities by 10%, click on 'Economic Variables and type '10' into the input box next to income.
3. Once you are happy with your selections, click 'Predict new migration pattern' and wait for the update migration predictions.


Chile
Costa Rica
Ecuador
Honduras
Panama
Google
CNES / Airbus, Maxar Technologies

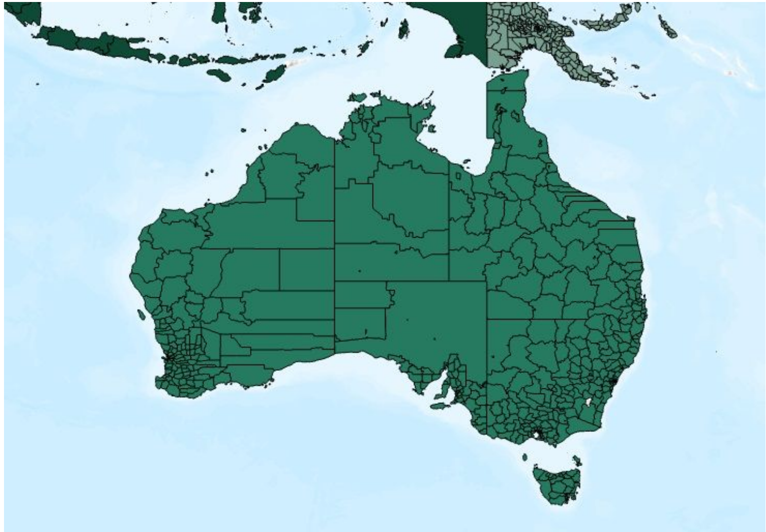


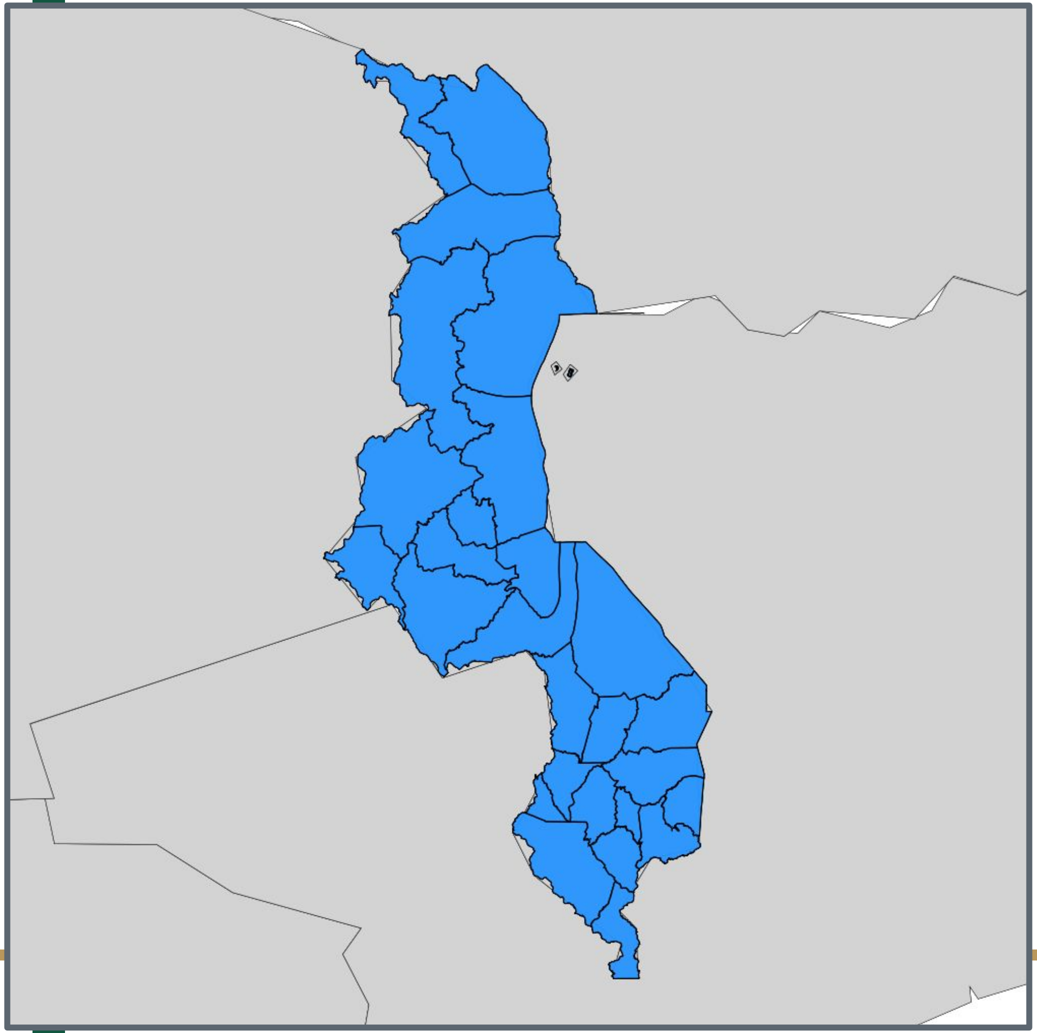
Boundaries: geoBoundaries.org

- Boundaries of hundreds of thousands of States, Counties, and other Districts around the world.

- Standardized, Machine Readable, API

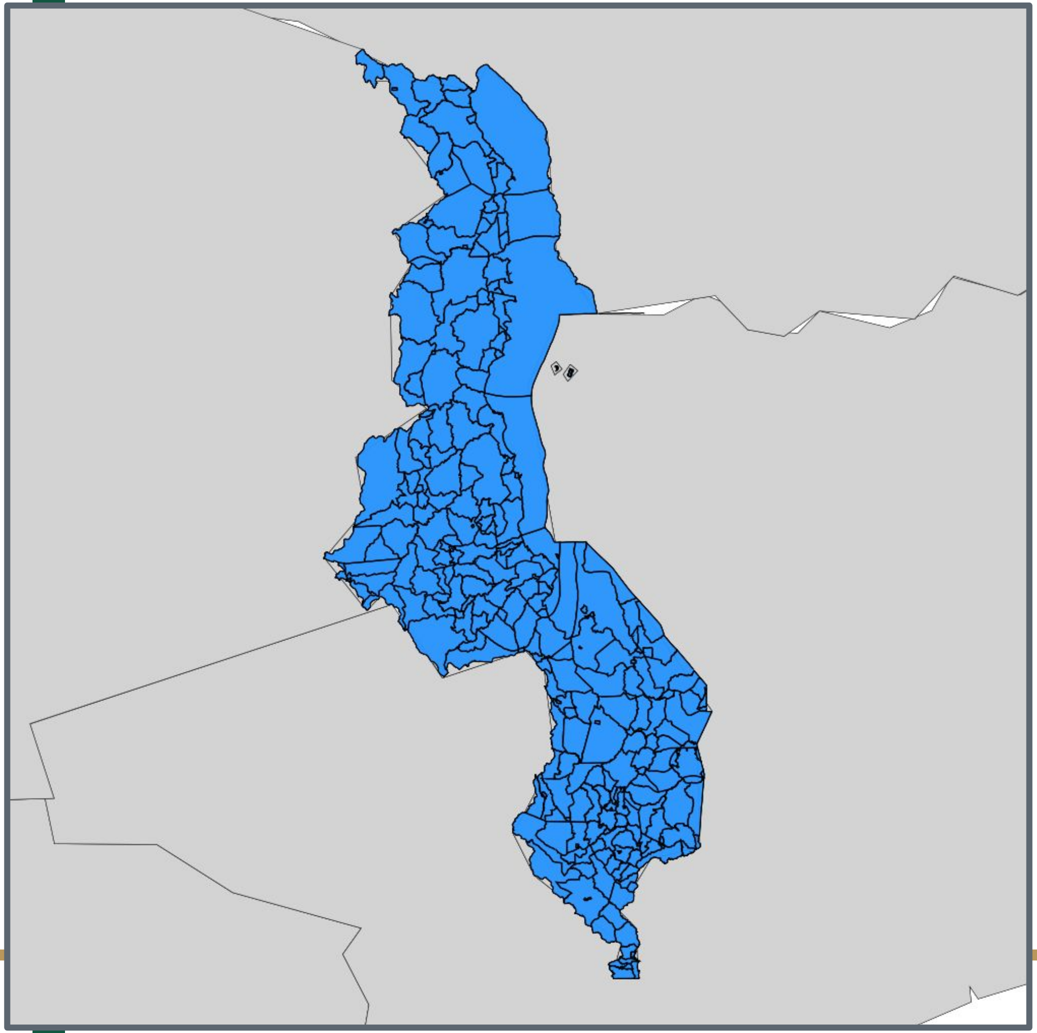
- About 60 TB of data serviced monthly today, to around 750 users/week.



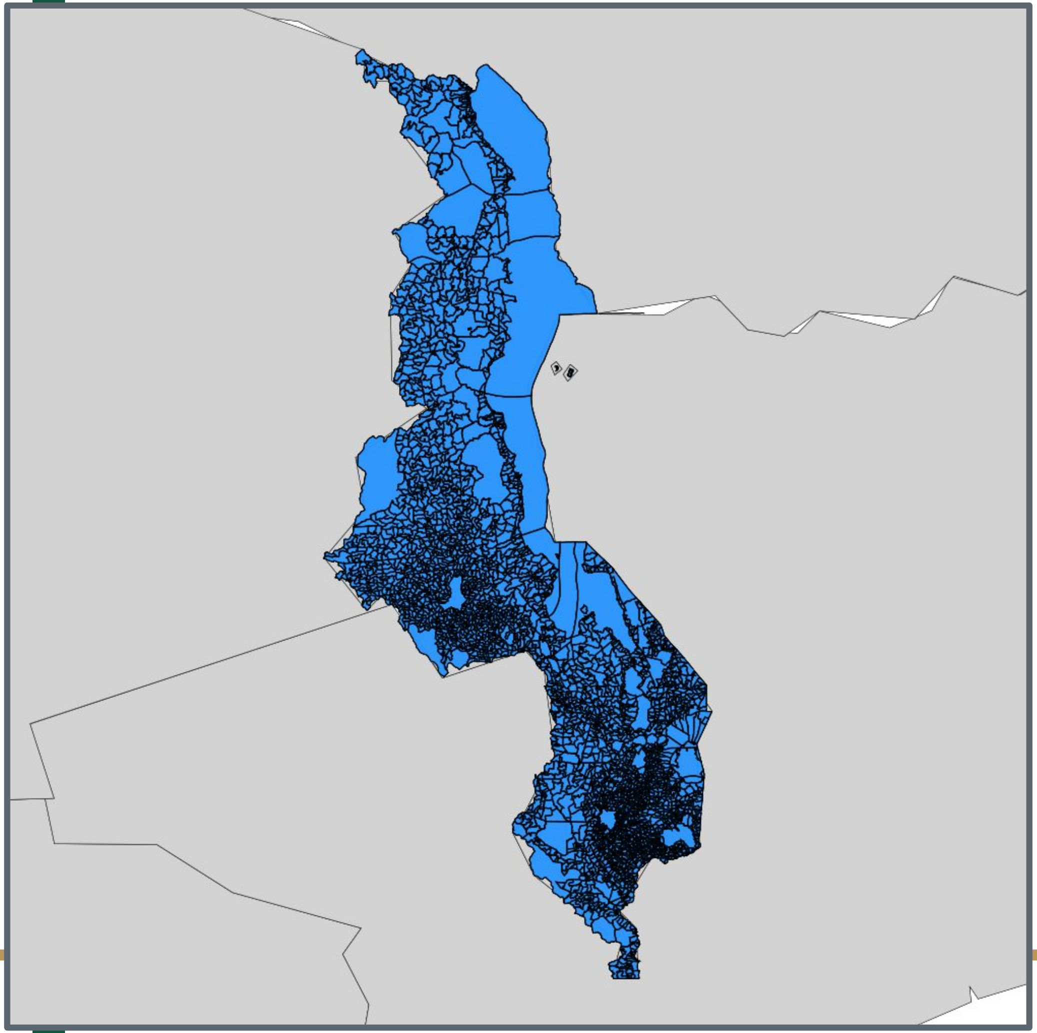


ADM1

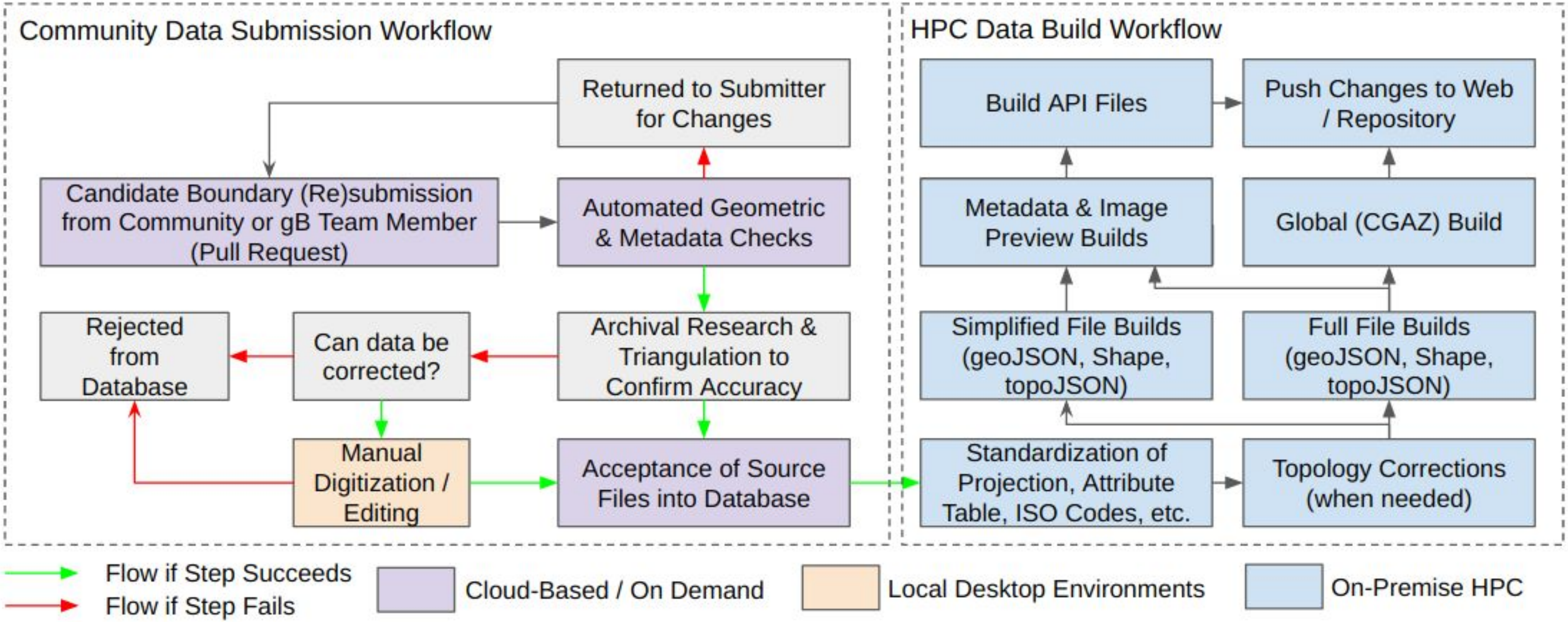
geoboundaries.org

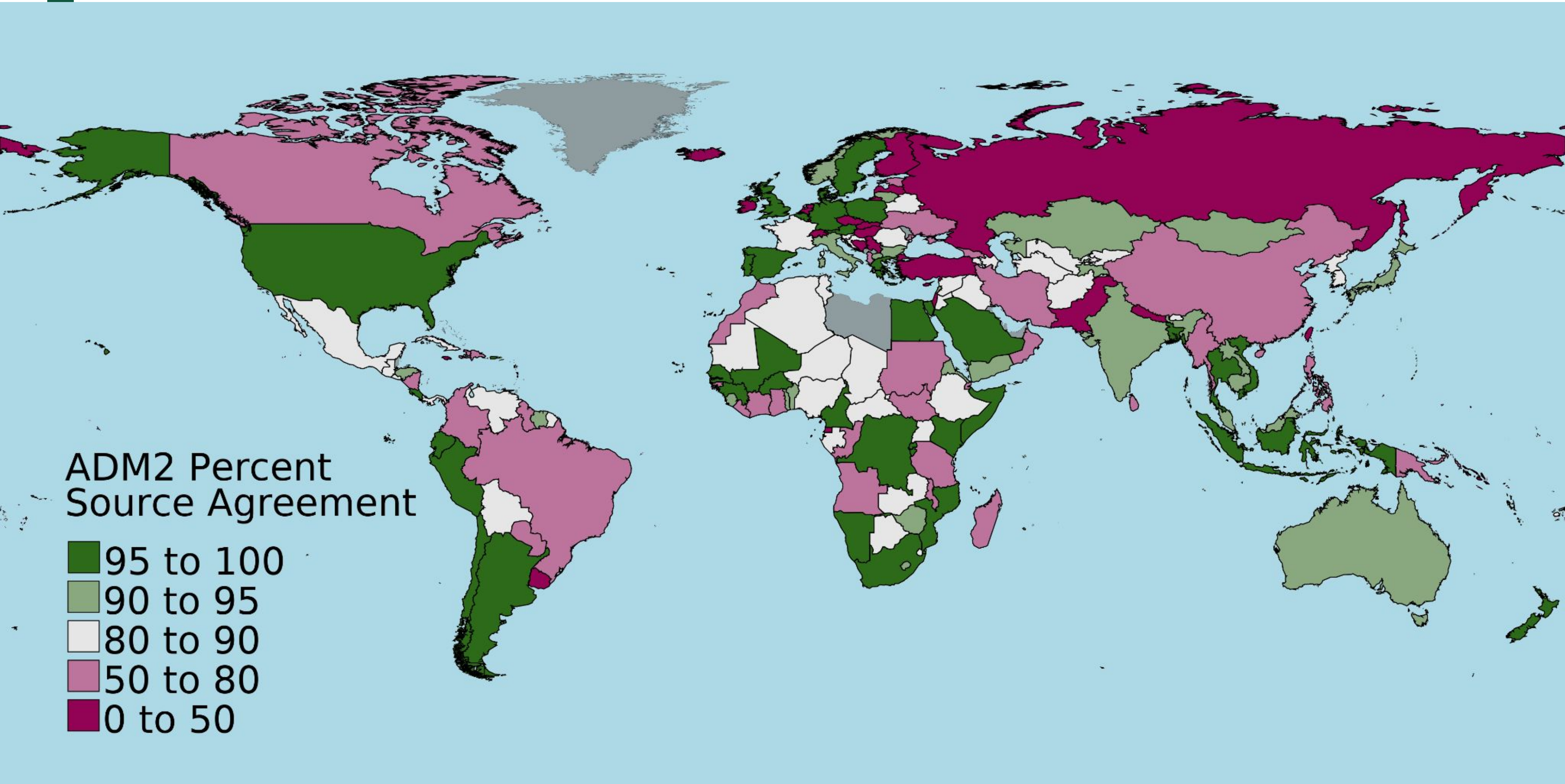


ADM2



ADM3


Community Data Submission Workflow
Returned to Submitter for Changes
Candidate Boundary (Re)submission from Community or gB Team Member (Pull Request)
Automated Geometric & Metadata Checks
Rejected from Database
Can data be corrected?
Archival Research & Triangulation to Confirm Accuracy
Manual Digitization / Editing
Acceptance of Source Files into Database
HPC Data Build Workflow
Build API Files
Push Changes to Web / Repository
Metadata & Image Preview Builds
Global (CGAZ) Build
Simplified File Builds (geoJSON, Shape, topoJSON)
Full File Builds (geoJSON, Shape, topoJSON)
Standardization of Projection, Attribute Table, ISO Codes, etc.
Topology Corrections (when needed)
Flow if Step Succeeds
Flow if Step Fails
Cloud-Based / On Demand
Local Desktop Environments
On-Premise HPC


ADM2 Percent
Source Agreement
95 to 100
90 to 95
80 to 90
50 to 80
0 to 50

Thanks!

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+ The many Ph.D. and undergraduate students of the geoLab (geolab.wm.edu), collaborators at VIMS, NASA, Columbia, and our funding partners.

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