Characterizing and Communicating Global IMERG Error Estimates for End User Applications

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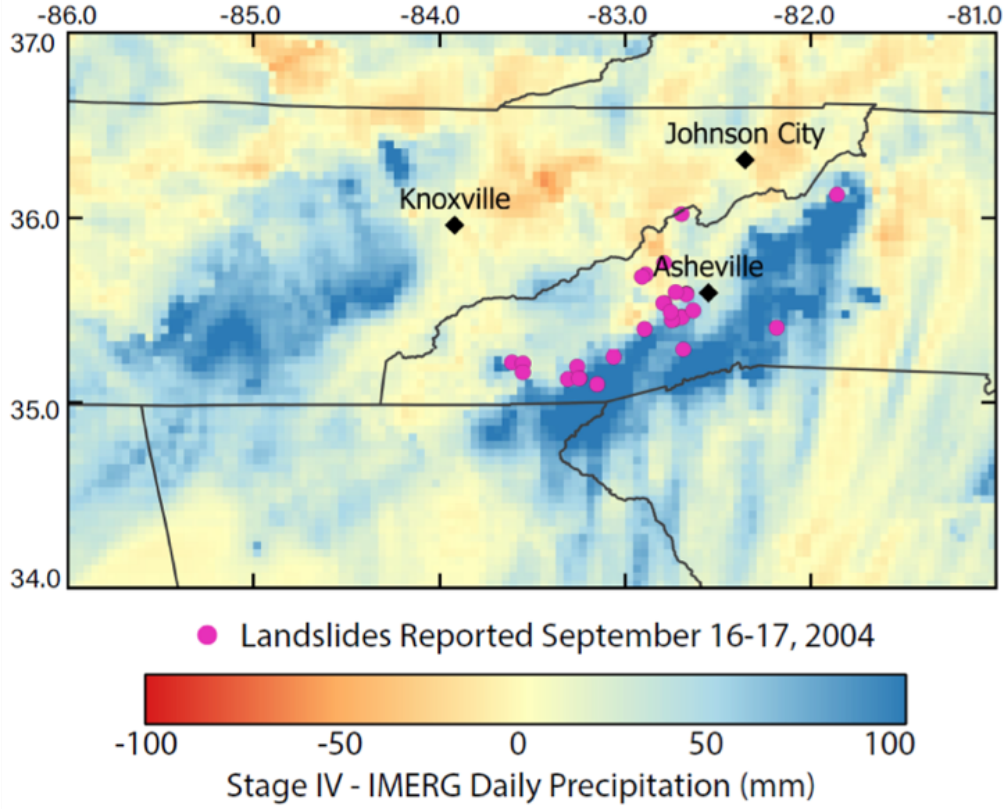
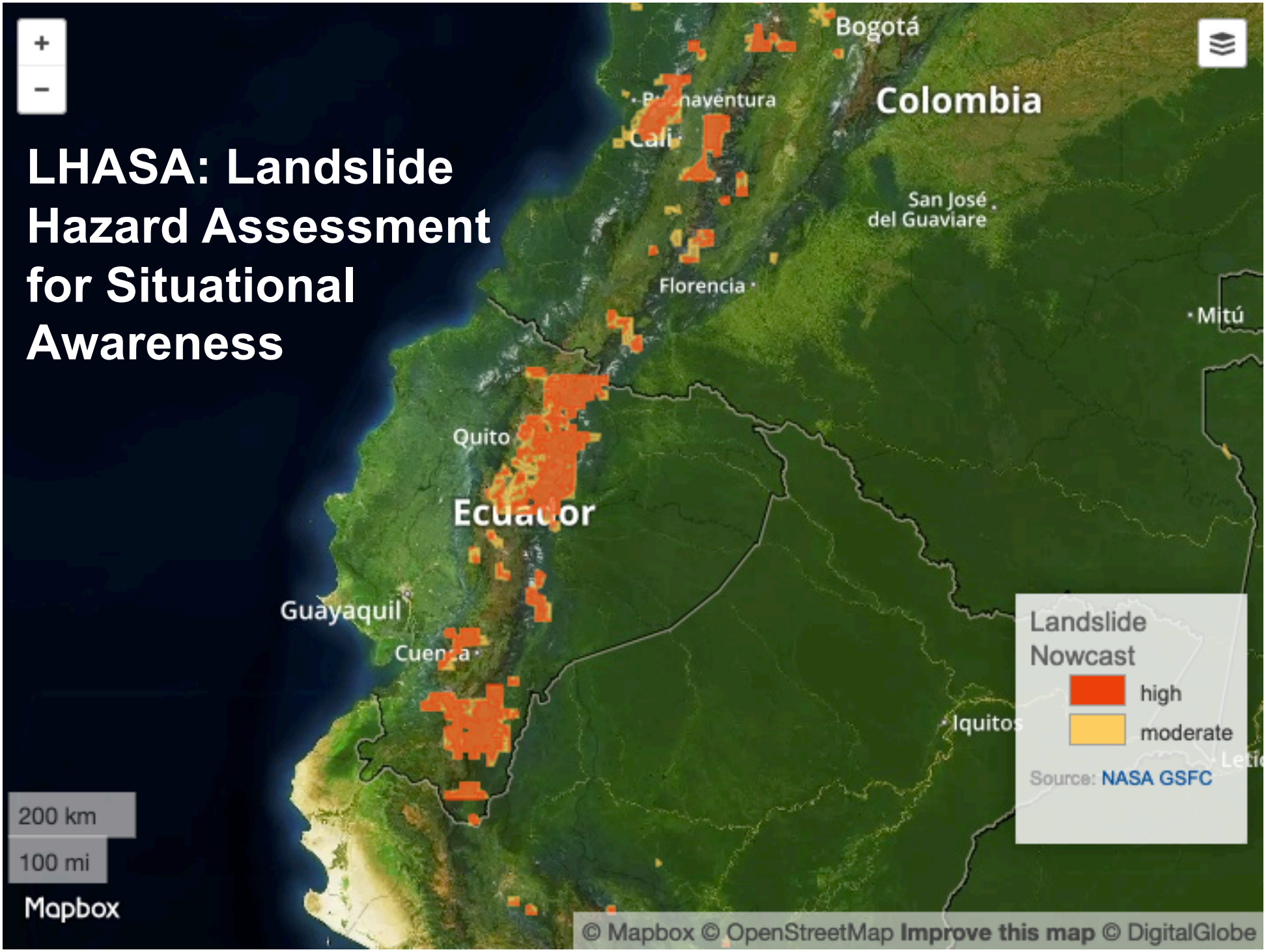
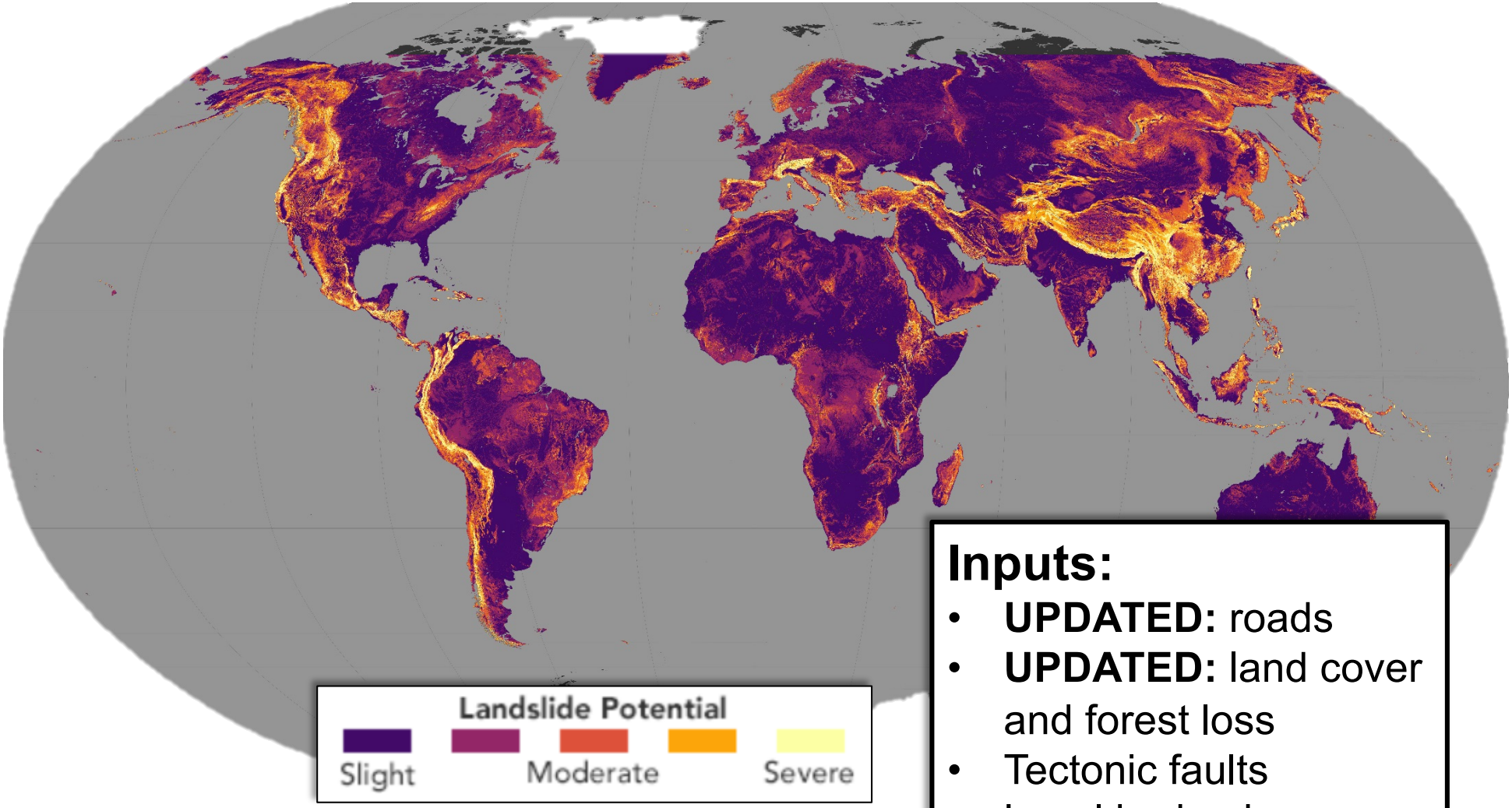
Satellite precipitation error/uncertainty matters a lot in user applications



LHASA: Landslide Hazard Assessment for Situational Awareness



LHASA Static Susceptibility



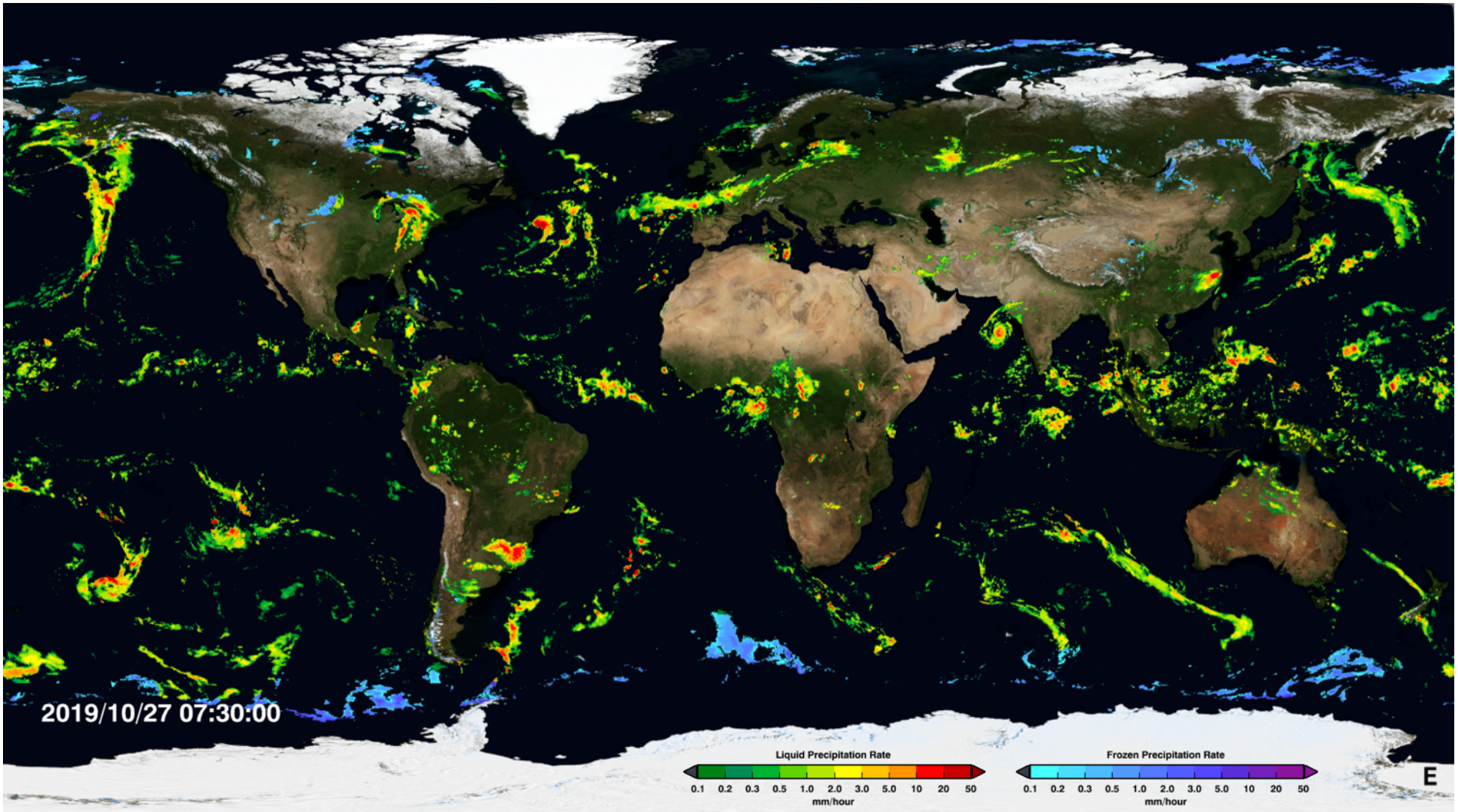
Inputs:

- **UPDATED:** roads
- **UPDATED:** land cover and forest loss
- Tectonic faults
- Local bedrock

Available for download at:
https://pmm.nasa.gov/applications/global-landslide-model

Stanley and Kirschbaum 2017

LHASA Dynamic Trigger: IMERG



Moderate/high susceptibility + IMERG rainfall > 95th percentile

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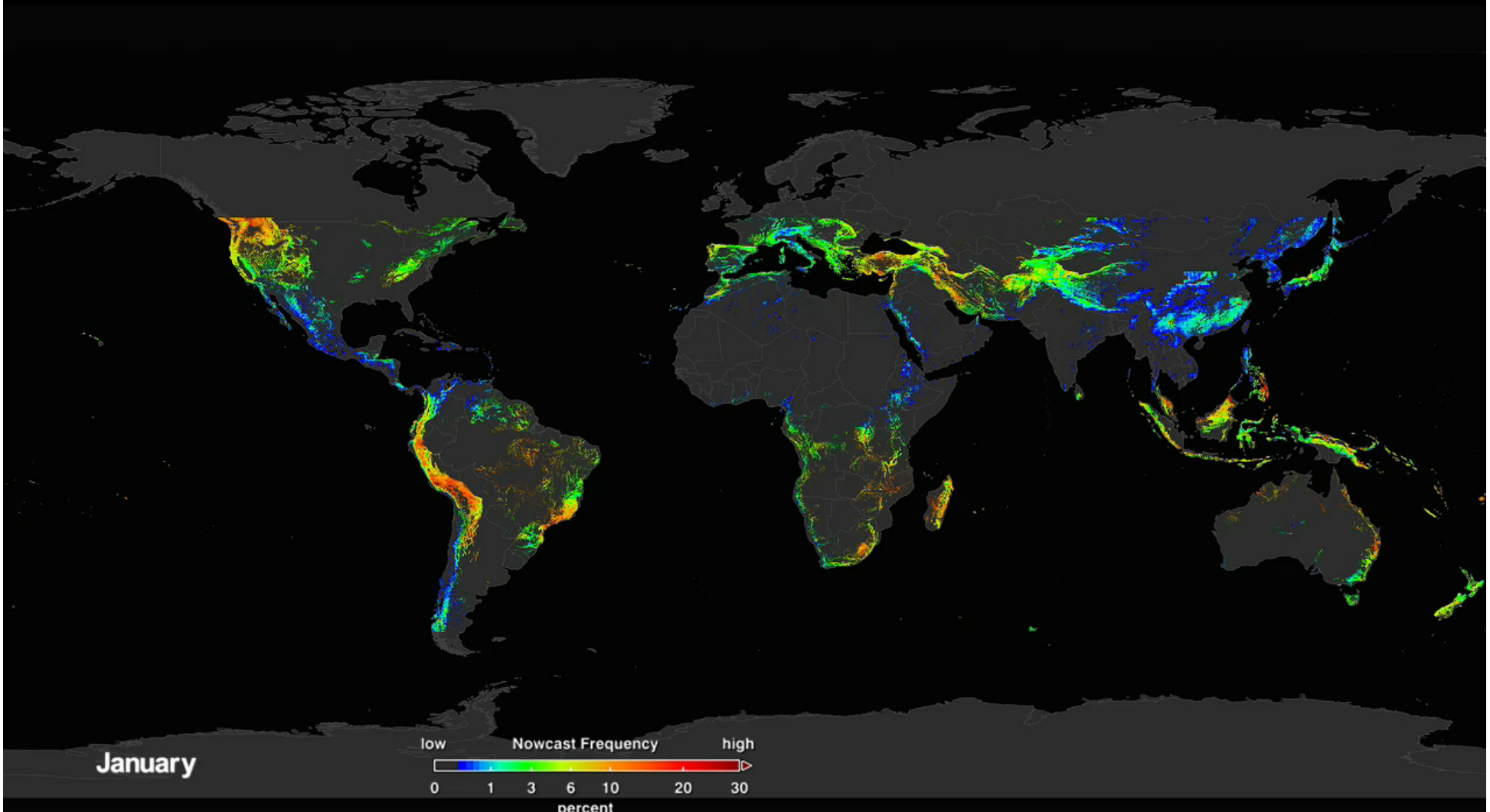
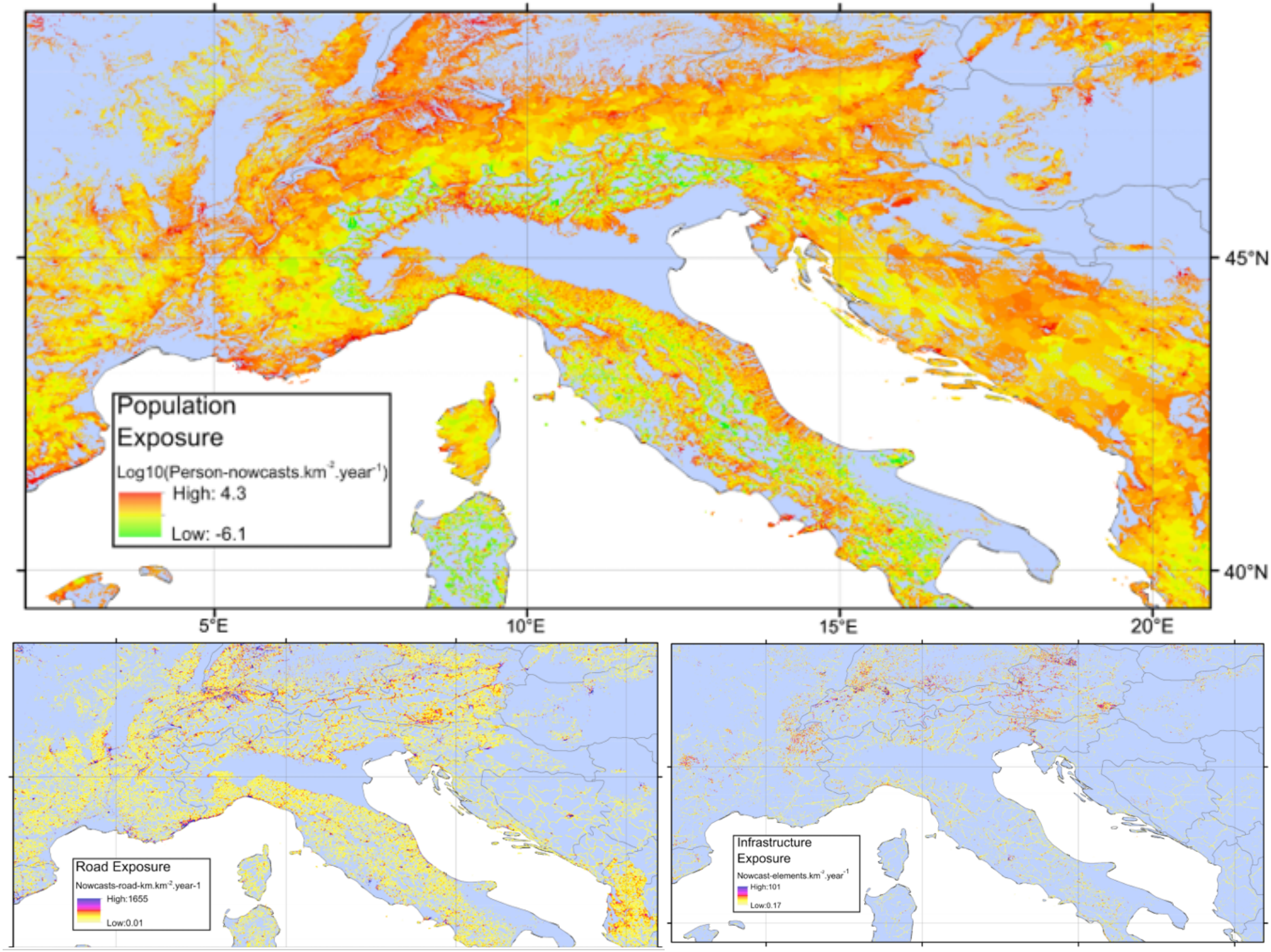
Landslide Hazard “Nowcast”

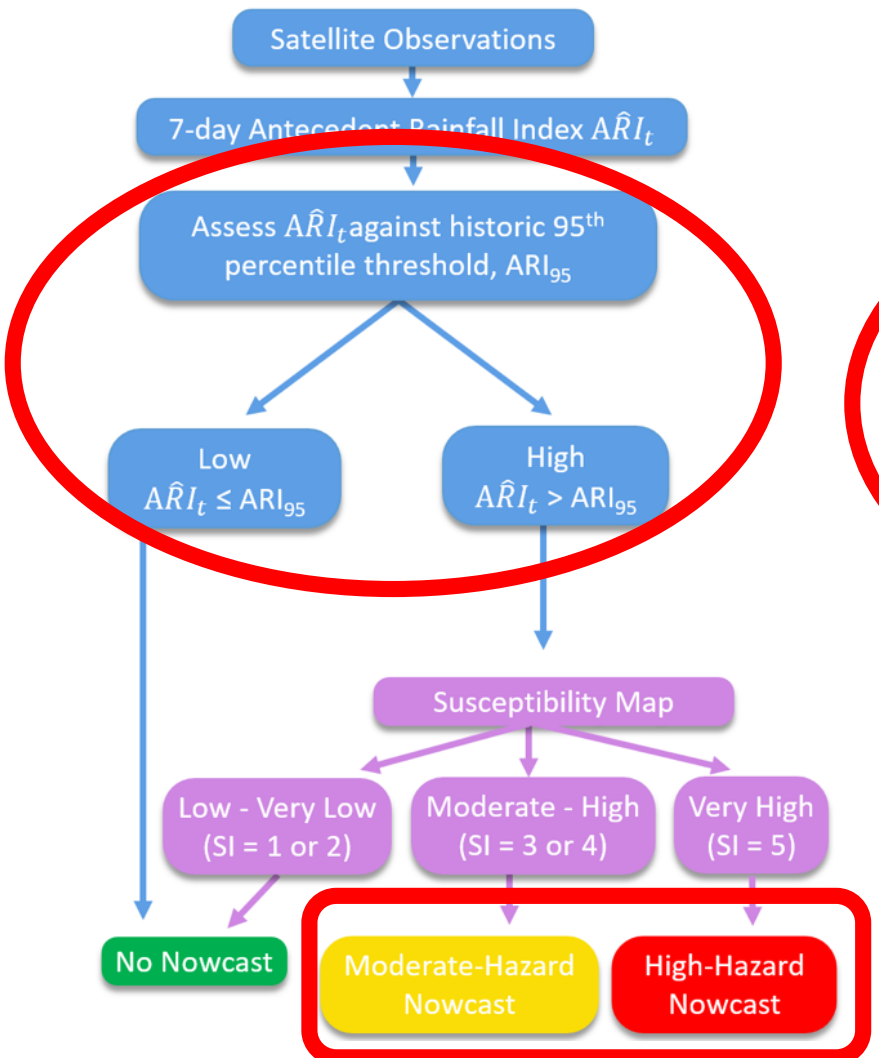
Landslide Climatology



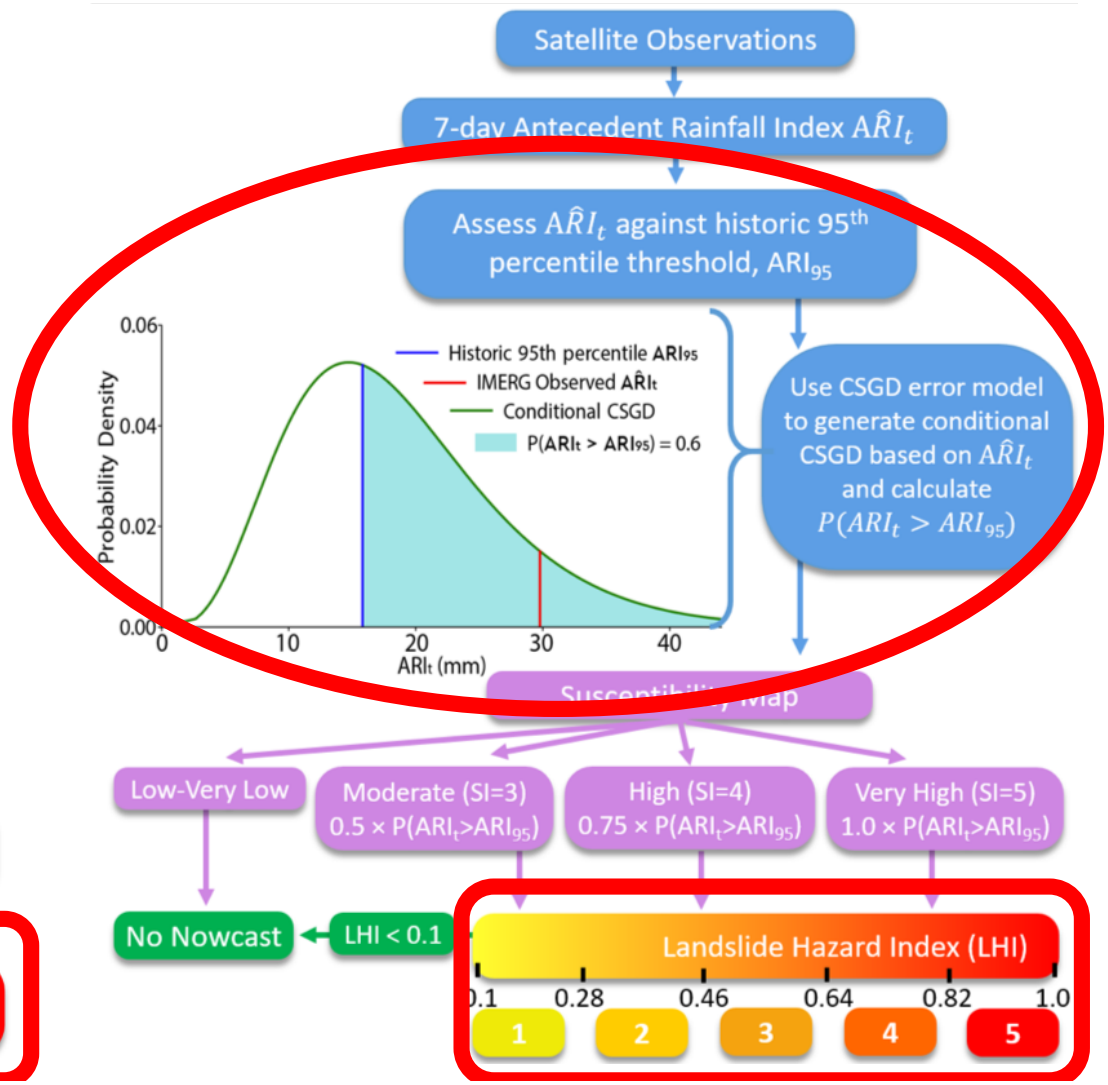

Population
Exposure
Log10(Person-nowcasts.km-2.year-1)
High: 4.3
Low: -6.1
45°N
40°N
5°E
10°E
15°E
20°E
Road Exposure
Nowcasts-road-km.km-2.year-1
High:1655
Low:0.01
Infrastructure
Exposure
Nowcast-elements.km-2.year-1
High:101
Low:0.17

LHASA: Landslide Hazard Assessment for Situational Awareness

Operational LHASA



Probabilistic LHASA



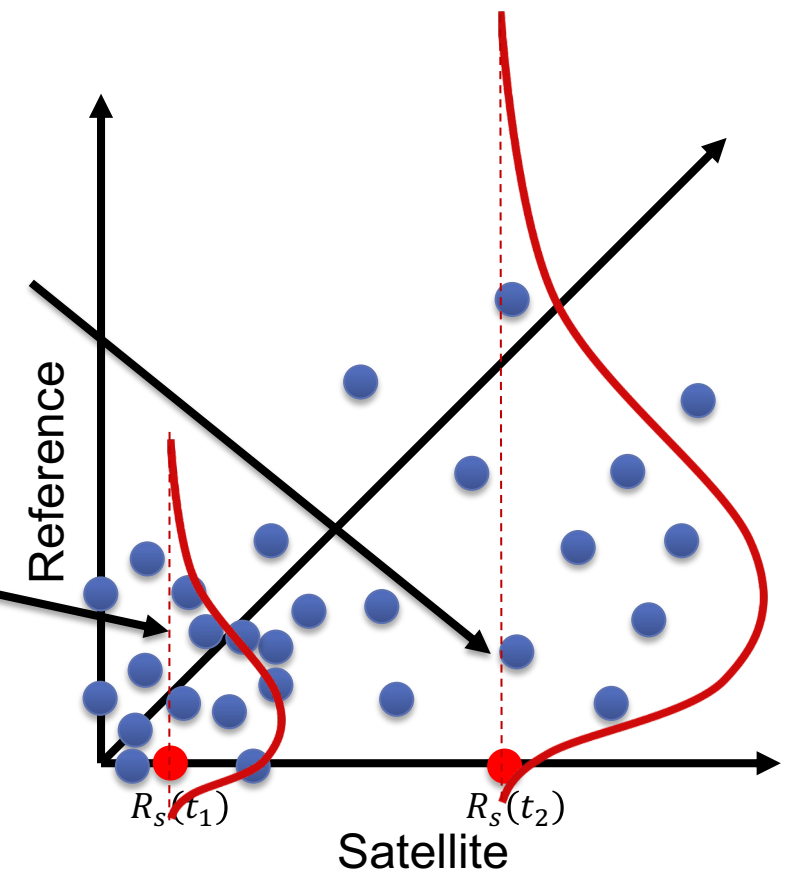
Censored Shifted Gamma Distribution (CSGD) Error Model

Estimated Distribution of true precip. at time *t*:

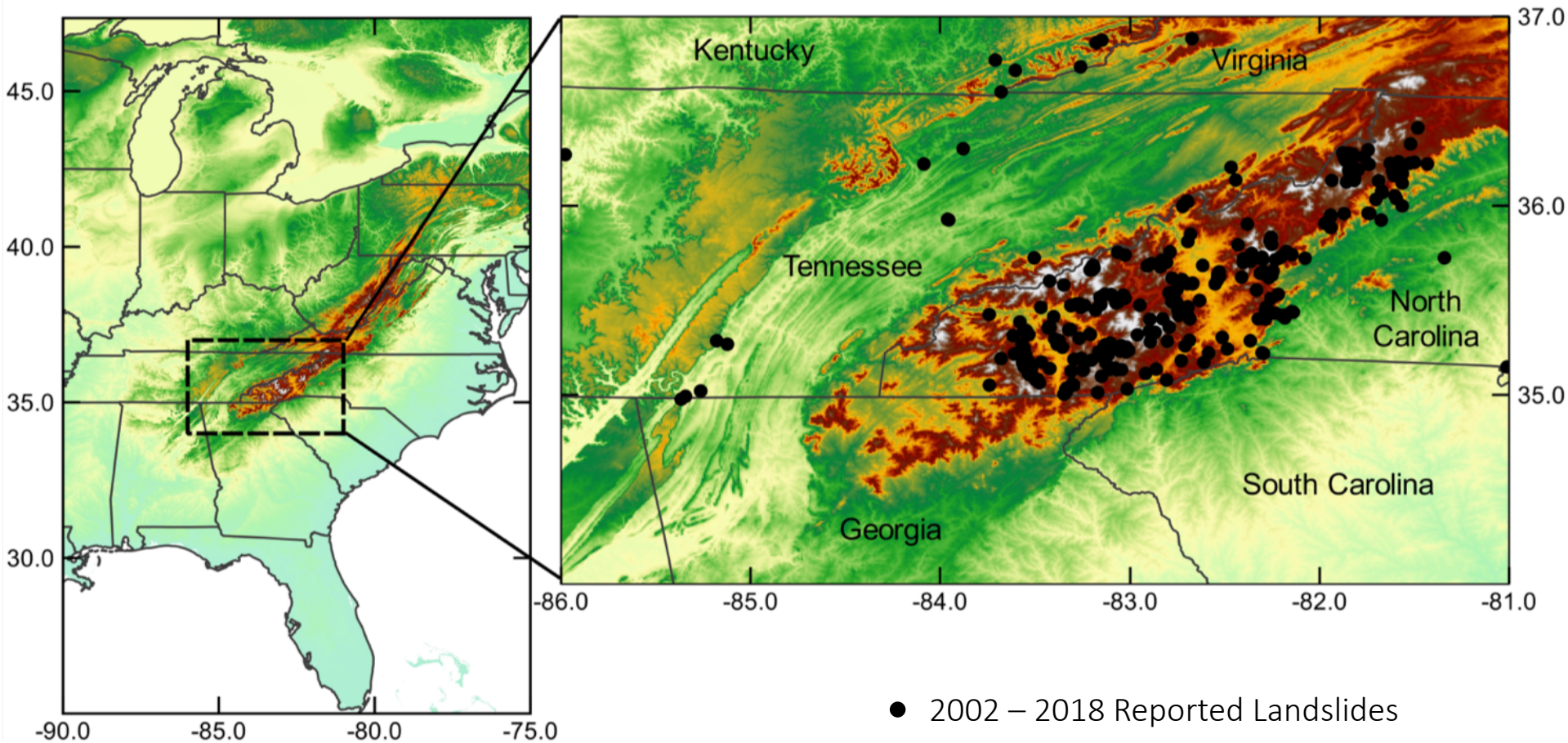
- $\mu(t) = \frac{\mu}{\alpha_1} log1p\left[expm1(\alpha_1)\left(\alpha_2 + \alpha_3 \frac{R_s(t)}{\overline{\boldsymbol{R_S}}}\right)\right]$
- $\sigma(t) = \alpha_4 \sigma \sqrt{\frac{\mu(t)}{\mu}}$
- $\delta(t) = \delta$

$R_s(t_2) \rightarrow \mu(t_2), \sigma(t_2), \delta(t_2)$

$R_s(t_1) \rightarrow \mu(t_1), \sigma(t_1), \delta(t_1)$



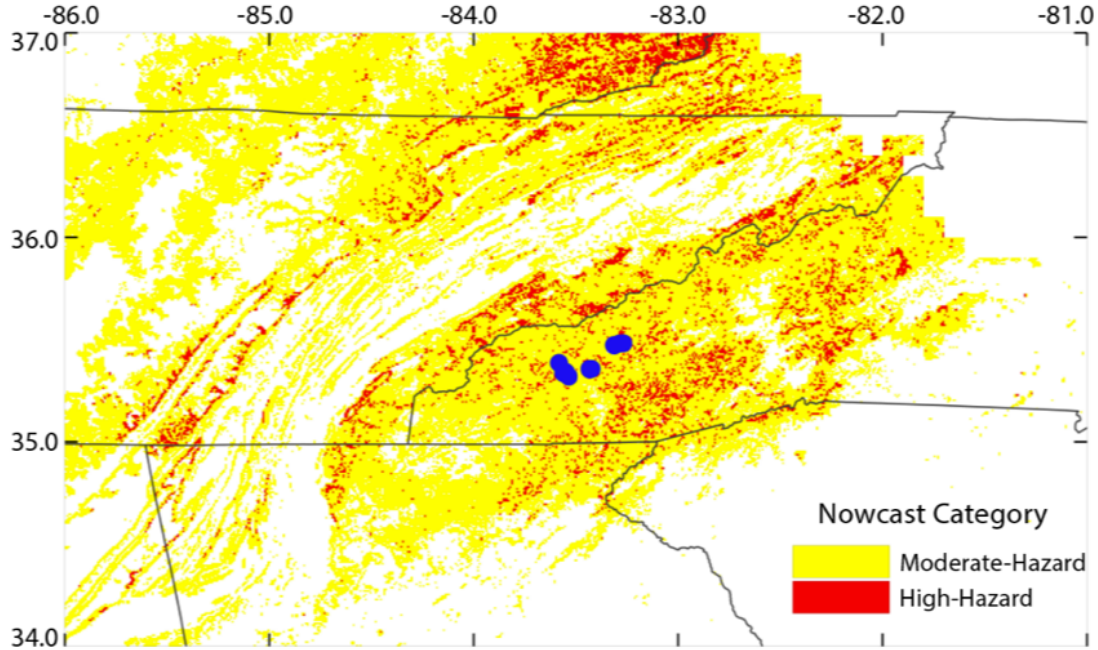
Wright, Kirschbaum, Yatheendradas, *J. Hydromet.* 2017.



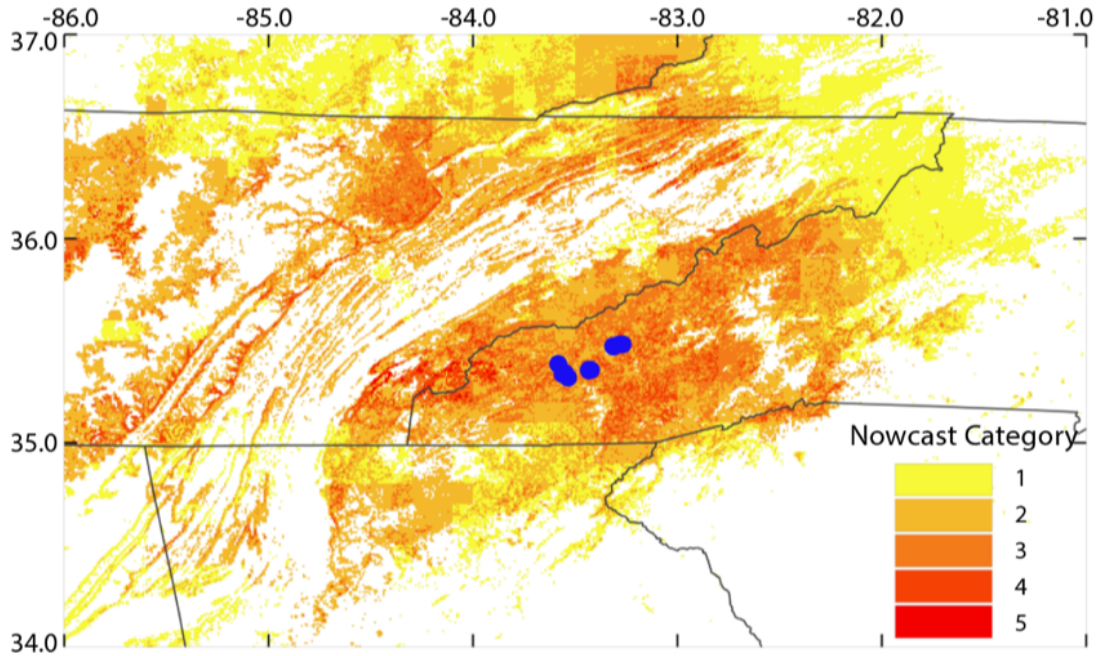
● 2002 – 2018 Reported Landslides

Example Results

Operational LHASA



May 5, 2003 Reported Landslides (n = 15)

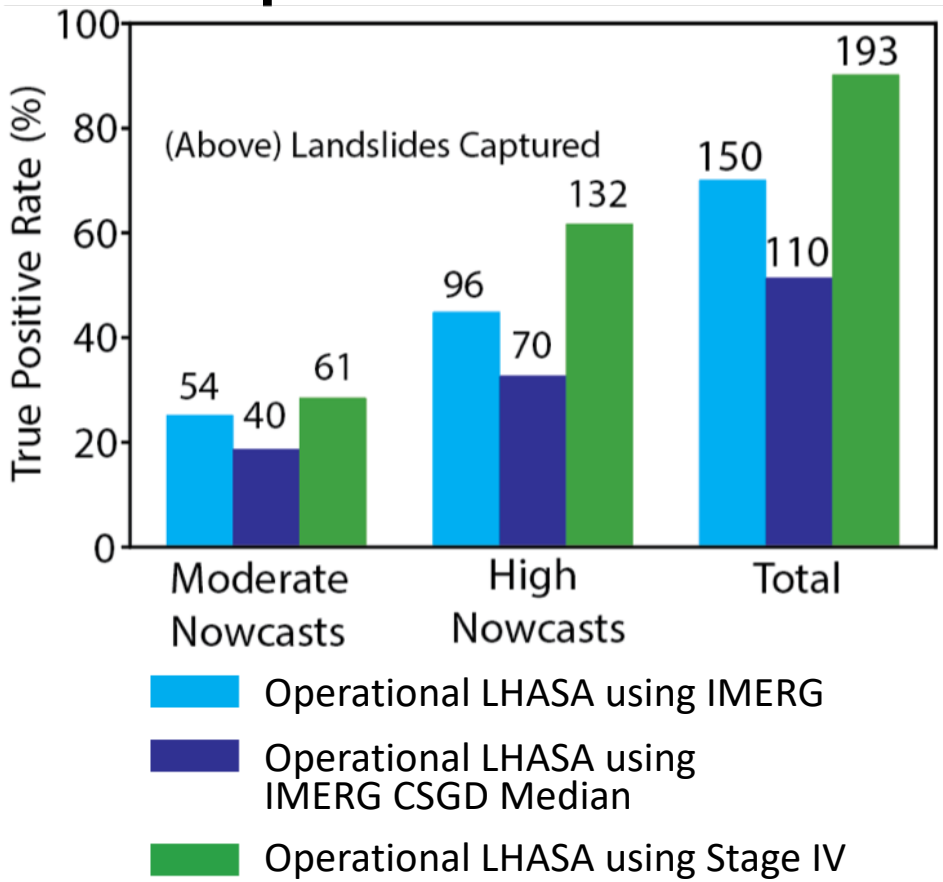


Probabilistic LHASA

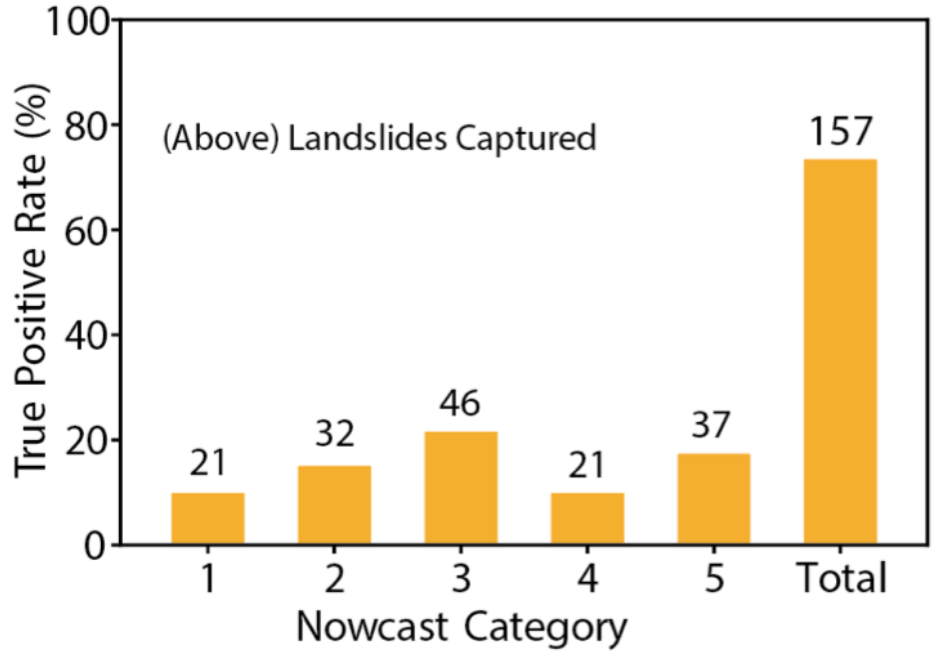
Probabilistic LHASA

- Climatologic bias correction doesn't work; need random error too
- Improved landslide detection

Operational LHASA



Probabilistic LHASA

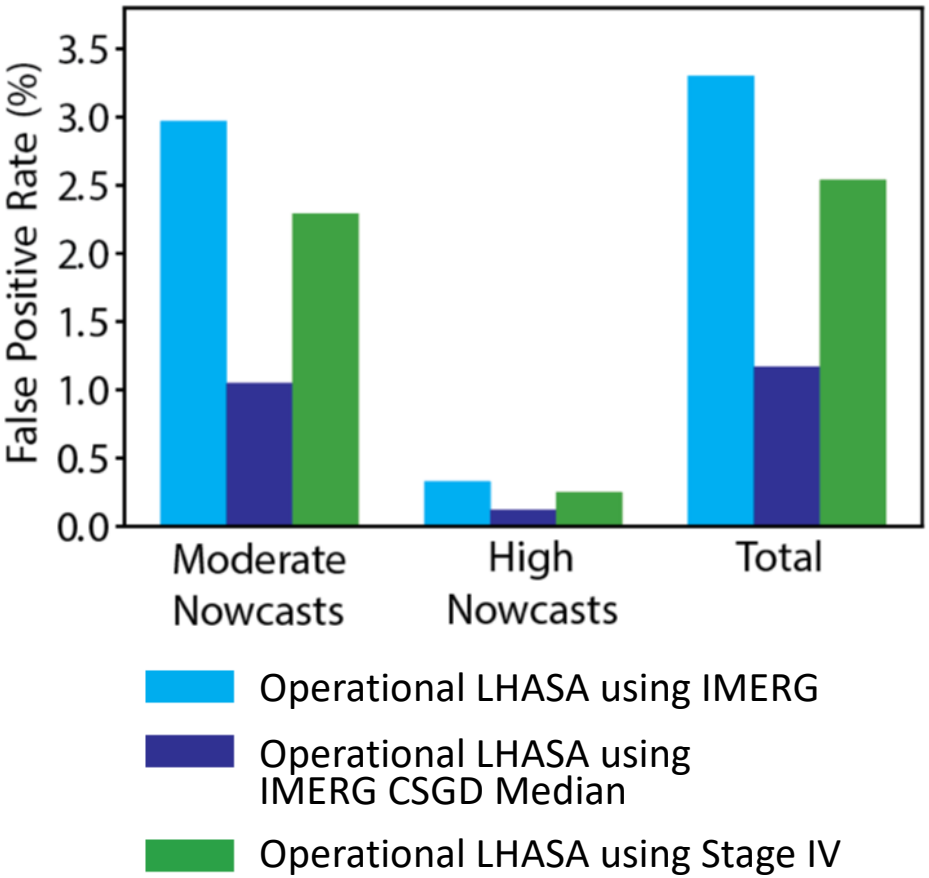


Hartke, Wright, Kirschbaum, Stanley, Li, in prep.

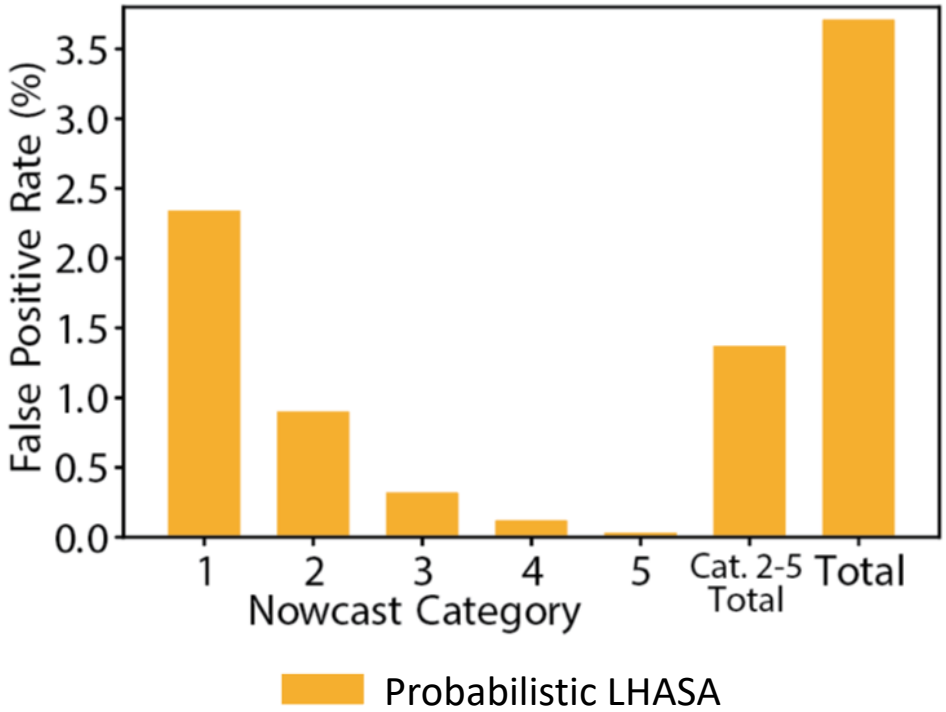
Probabilistic LHASA

- Fewer false positives in hazardous conditions
- Better control over false positive rate

Operational LHASA



Probabilistic LHASA



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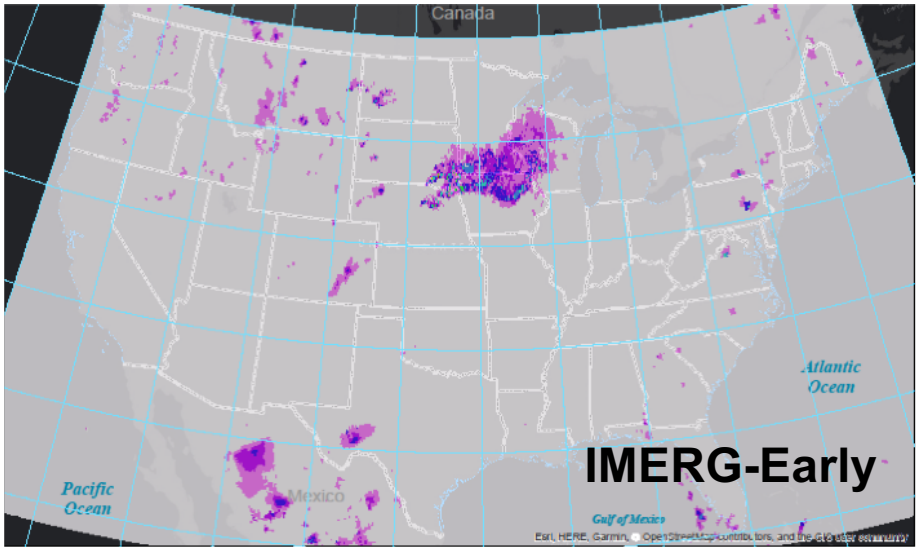
probabilistic precip + simple “customized” models = improved performance

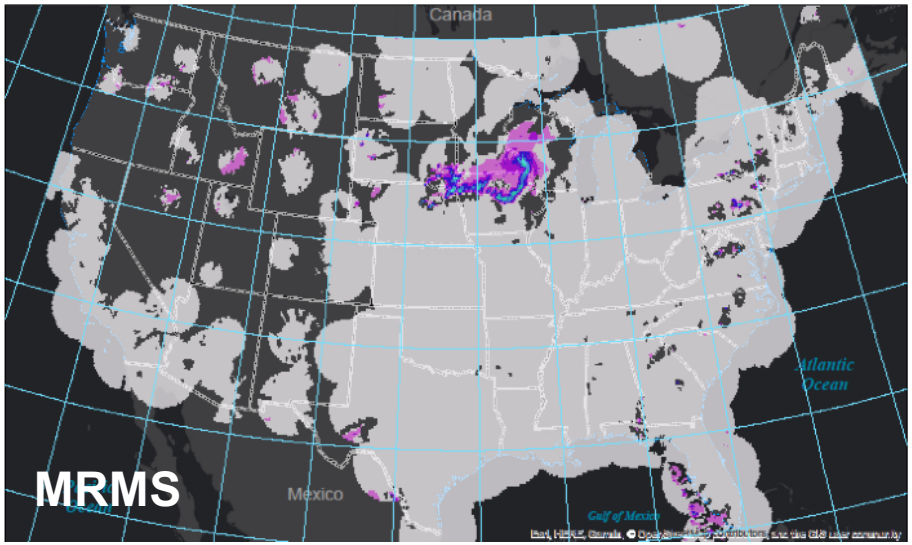
What do probabilistic predictions mean for end users?

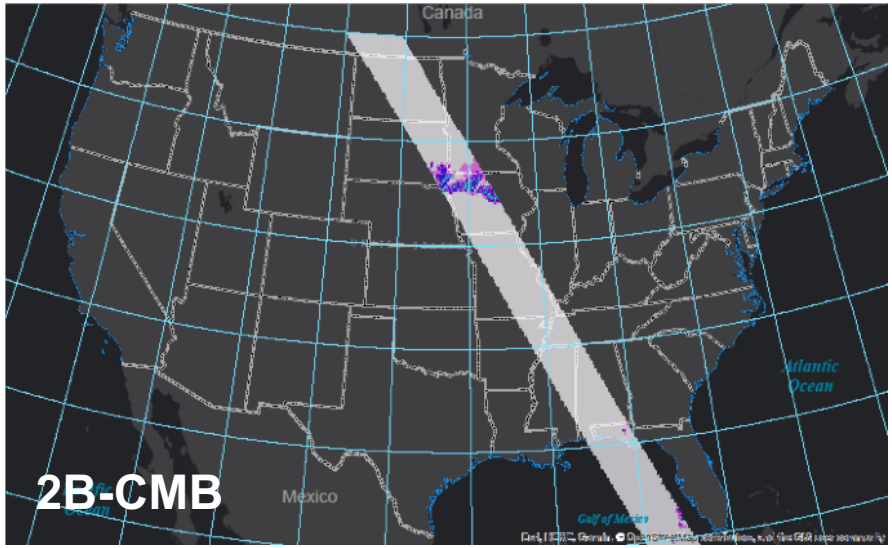
- Instituto de Hidrología, Meteorología y Estudios Ambientales
- Microinsurance Catastrophe Risk Organization
- Pacific Disaster Center

How can we generate probabilistic precipitation to support such applications?

Our approach: develop a prototype probabilistic dataset by considering DPR + GMI (2B-CMB) as “ground truth”



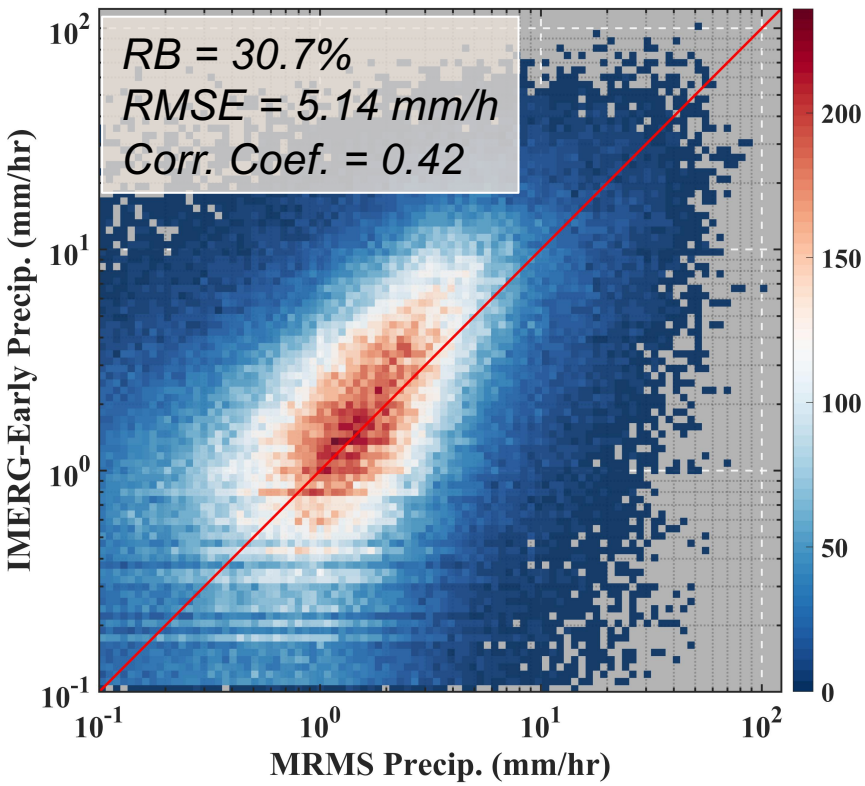




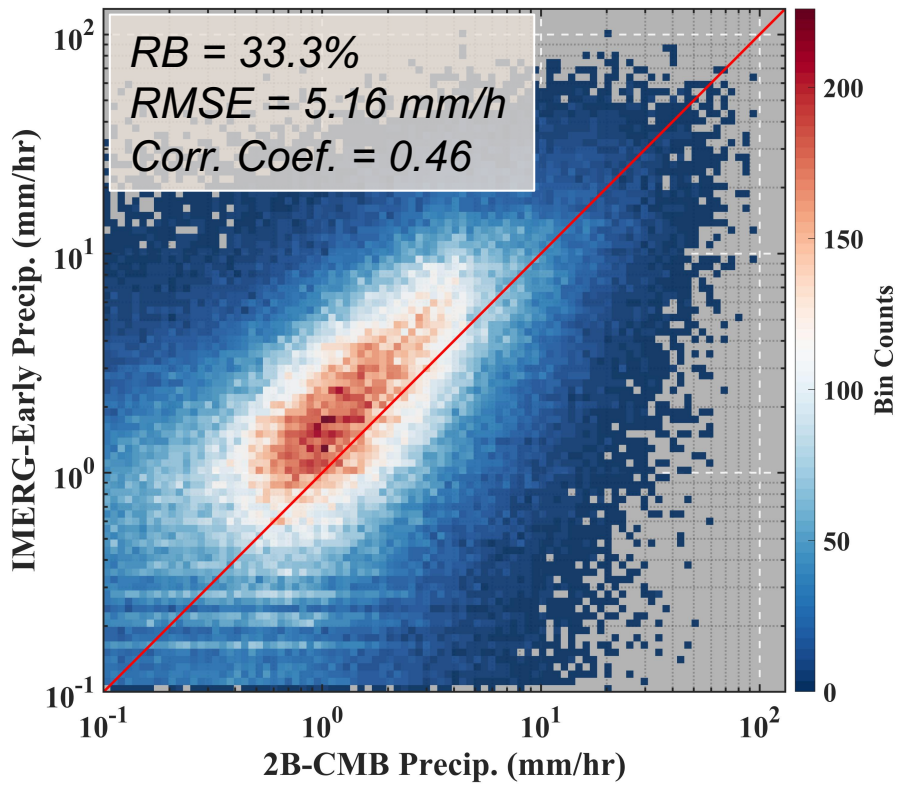
Li, Wright, Zhang, Kirschbaum, Hartke, in prep.

Our approach: develop a prototype probabilistic dataset by considering DPR + GMI as "ground truth"

MRMS vs IMERG-E estimates



2B-CMB vs IMERG-E estimates



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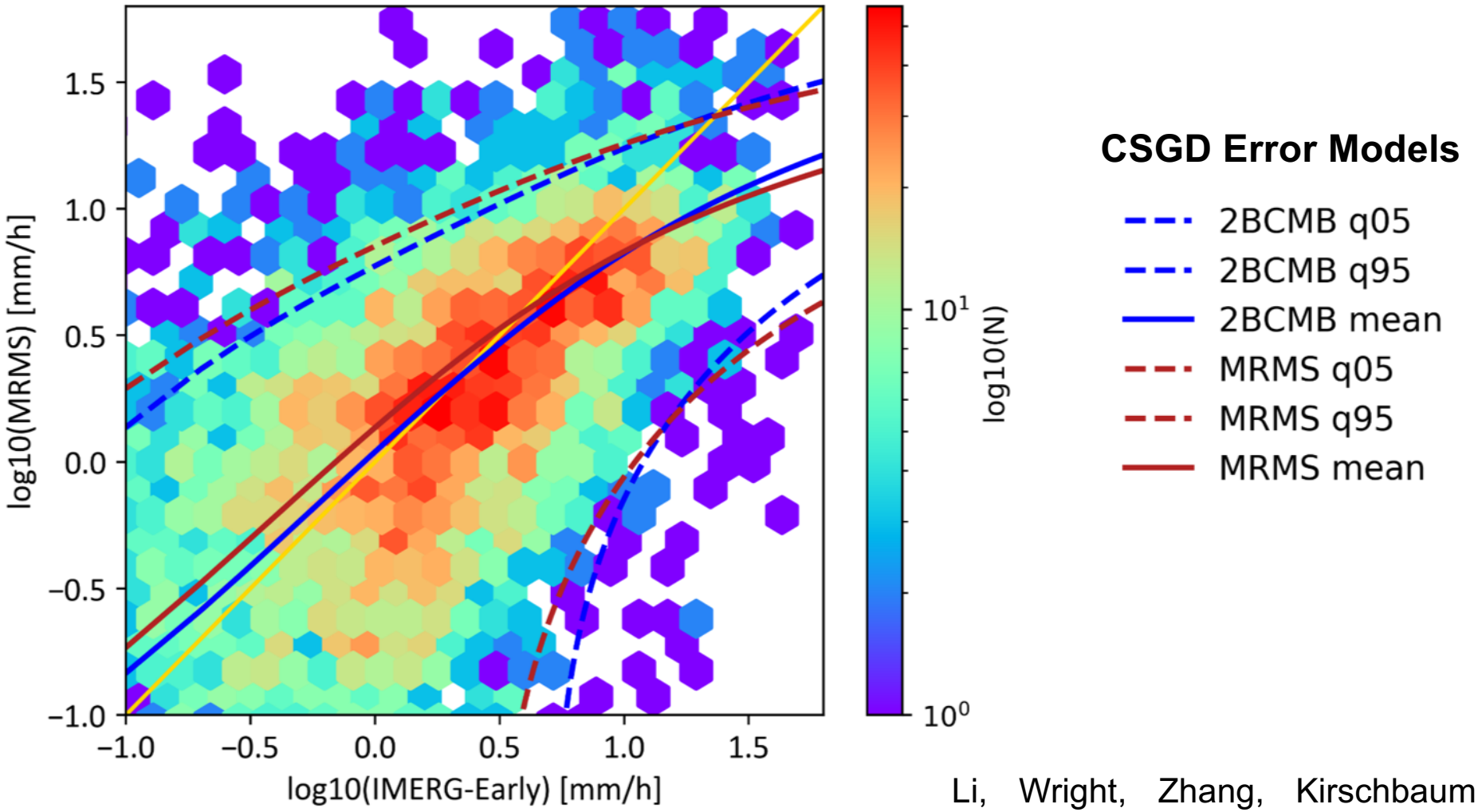
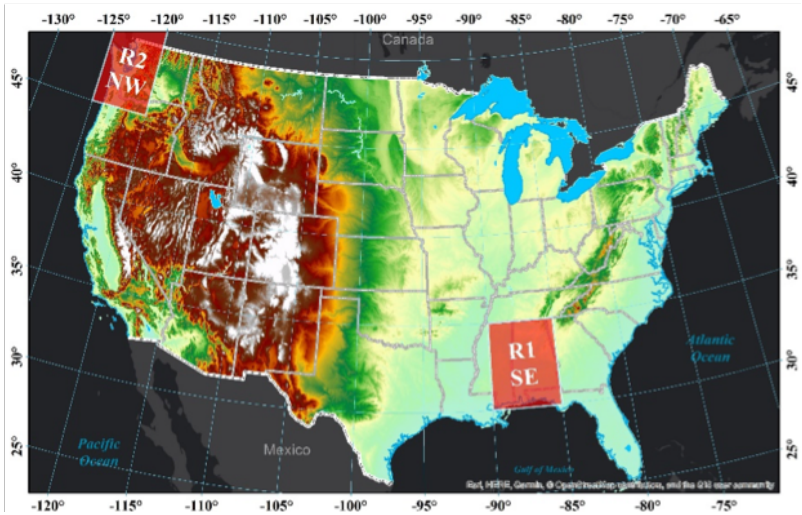


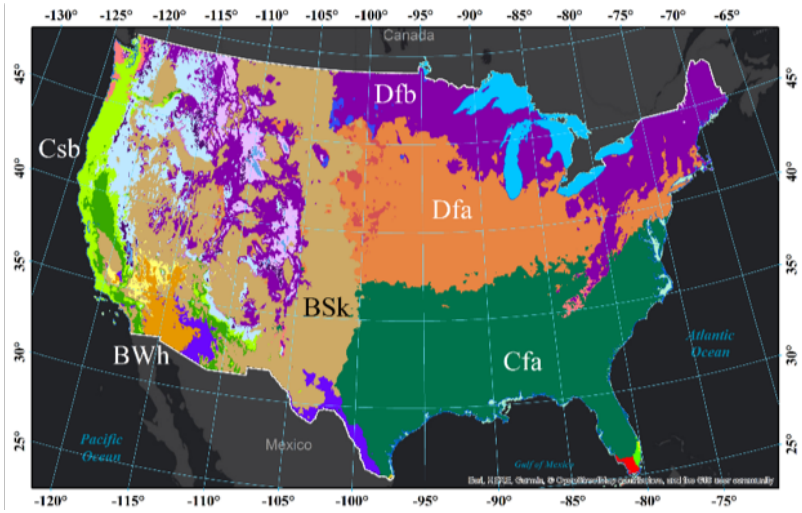
Li, Wright, Zhang, Kirschbaum, Hartke, in prep.

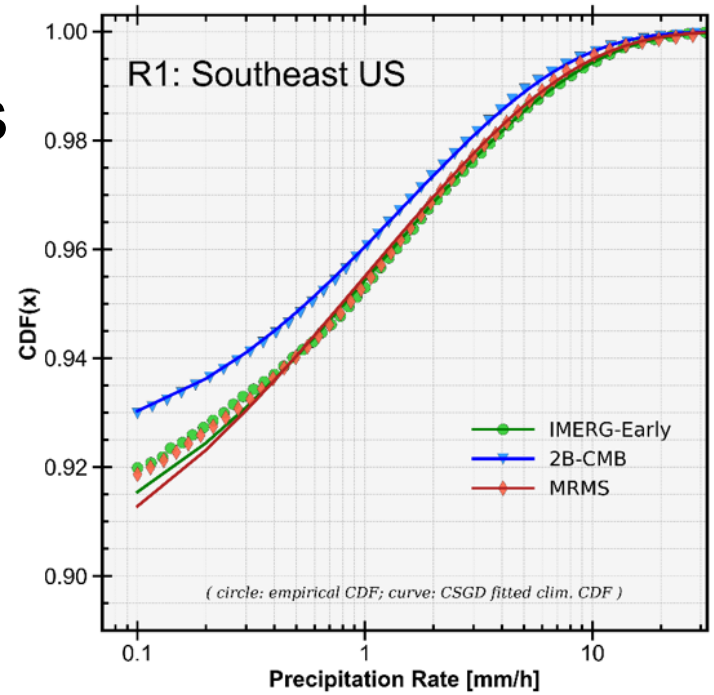
Next Steps: role of geography, PMW/IR source, ancillary variables

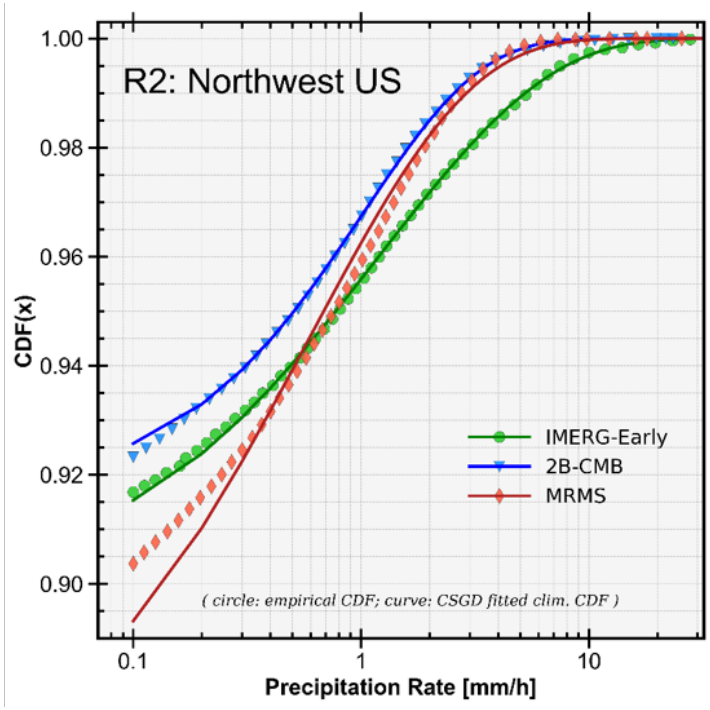
Topography over CONUS (4 km DEM)



Köppen Climate Types over CONUS







Summary

- **probabilistic precip + simple "customized" models = improved performance**
  - Example: Probabilistic LHASA
- **There are probably lots of ways of producing probabilistic satellite-based precipitation estimates**
  - We are working on one prototype
- **More work needed: how will end users interpret and communicate errors / uncertainty?**
  - Collaboration with international organizations

Acknowledgements

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