

Probabilistic Flood Model Downscaling

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Riverine flooding harms people and property.

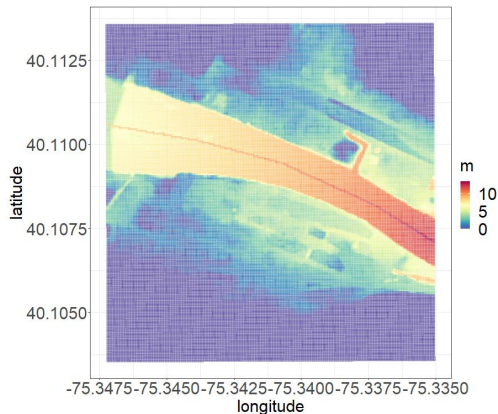
Spatial resolution is important.



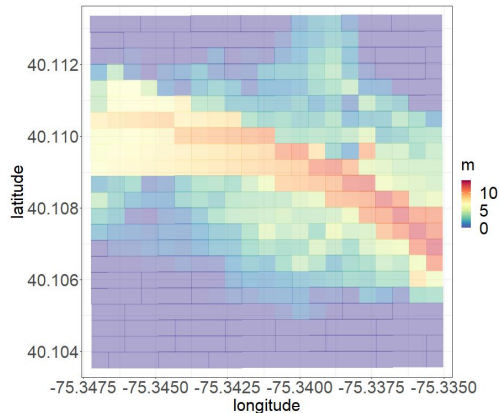
Image source: <https://www.wbir.com/article/weather/how-to-handle-flooding/51-22511bef-d964-4cfd-b60c-bd89b8c8637b>

Downscaling estimates high resolution projections.

5 m resolution flood heights

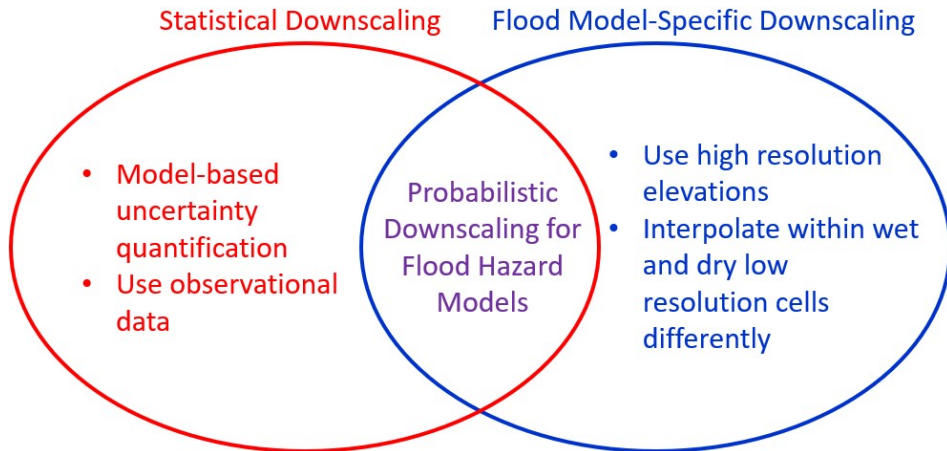


50 m resolution flood heights



- Flood projections inform decisions about how to manage flood risk.
- Decision-makers often require high spatial resolutions.
- High resolution model runs are computationally expensive.
- Skillful downscaling can tackle this problem.

Our approach combines advantages from different downscaling approaches.



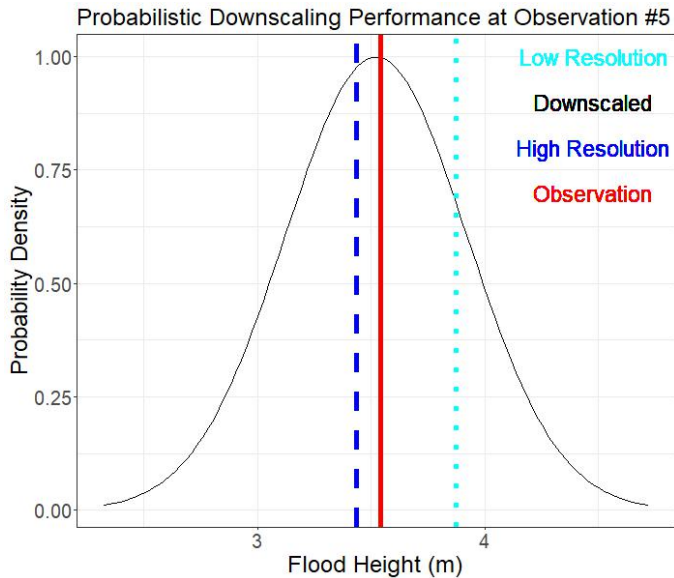
Our approach:

- Specifies different probability models for wet and dry low resolution cells
- Informs models using high resolution elevations and observational data.

Our approach is fast and accurate.

Downscaling approach	This study	Simple statistical model
Mean absolute error (m)	0.21	.30
95% PI coverage	0.97	.91
True negative rate	0.99	0
True positive rate	0.93	1
Speed-up compared to high resolution model	94	217

Our approach provides probabilistic flood hazard information.



Caveats:

- Simulated data
- Single, small study area
- Single flood type
- Single hazard type



Research needs:

- Use Hurricane Ida observations
- Use study areas of various sizes
- Test performance for other flood types
- Extend to other hazards such as fires

- We propose a new approach for probabilistic flood model downscaling.
- Our approach combines:
 - Flood-model specific techniques
 - Model-based uncertainty quantification.
- Our approach achieves advantages of statistical downscaling AND flood model-specific downscaling.

Acknowledgments

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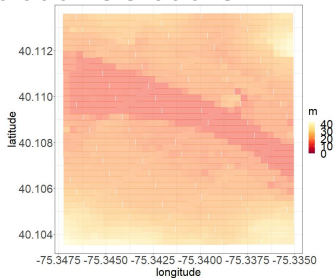


References I

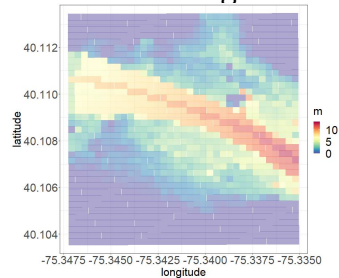
- Berrocal, V., Gelfand, A., and Holland, D. (2010). A spatio-temporal downscaler for output from numerical models. *Journal of agricultural, biological, and environmental statistics*, 15:176–197.
- Bryant, S., Schumann, G., Apel, H., Kreibich, H., and Merz, B. (2023). Technical note: Resolution enhancement of flood inundation grids. *Hydrology and Earth System Sciences Discussions*, 2023:1–18.

Given information

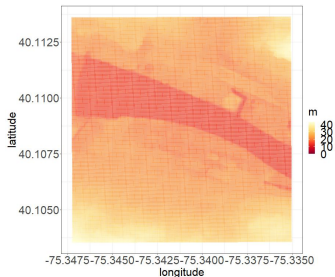
E_L : low resolution elevations



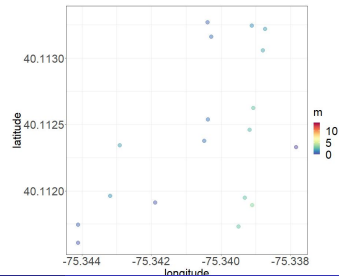
Y_L : low resolution flood heights



E_H : high resolution elevations

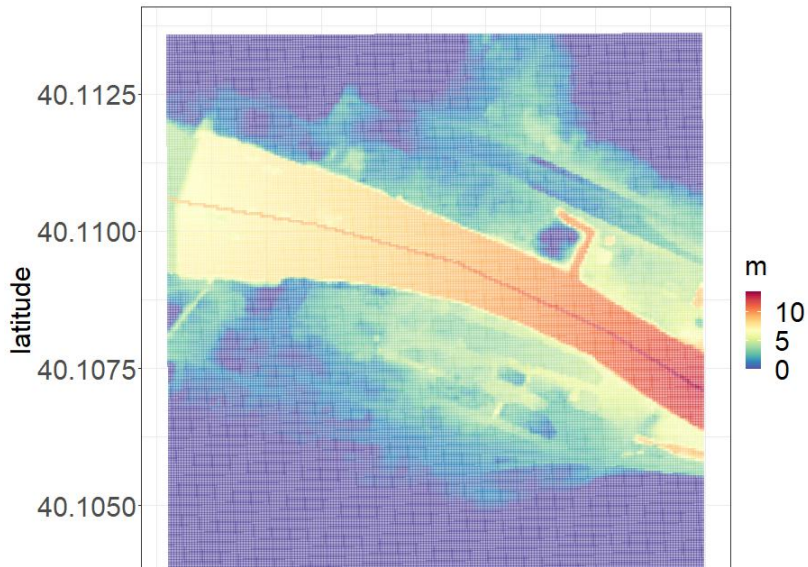


Z : Hurricane Ida observations



Want to estimate

Y_H : High resolution flood heights



Cost distance analysis

For each destination cell, a cost- minimizing algorithm is used to find:

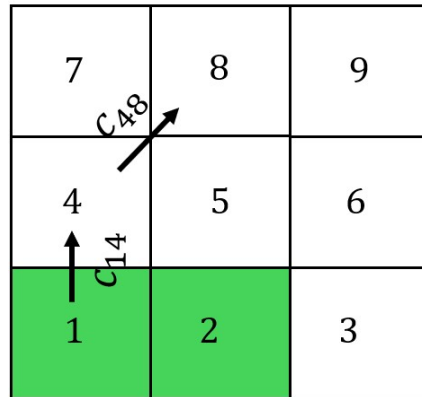
- Least-cost source cell
- Cost to travel from least-cost source cell to destination

Cost distance analysis requires:

- Cost-of-passage to each cell
 - Ours depend on elevation
- Labeled source cells

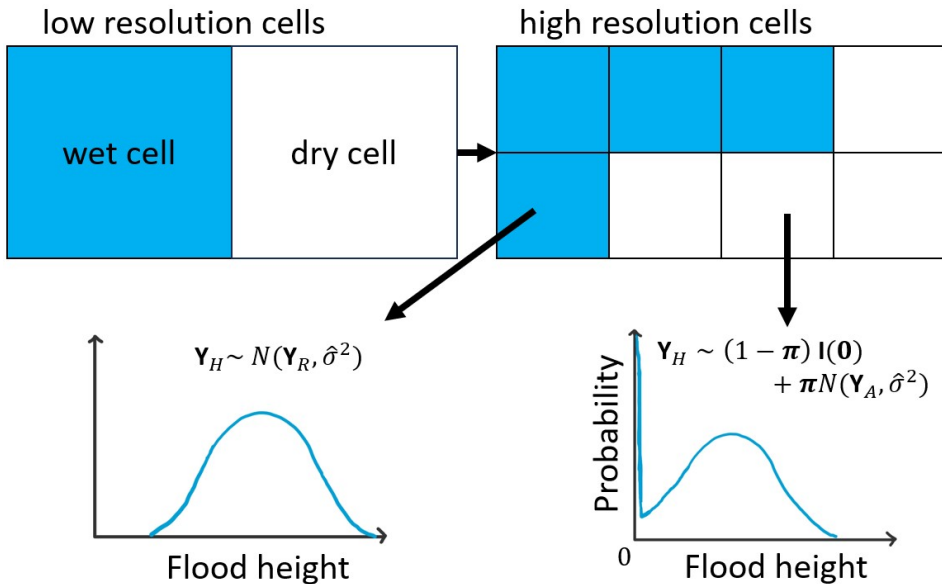
Total cost c to travel from source to cell 8:

$$c_{14} + c_{48}$$

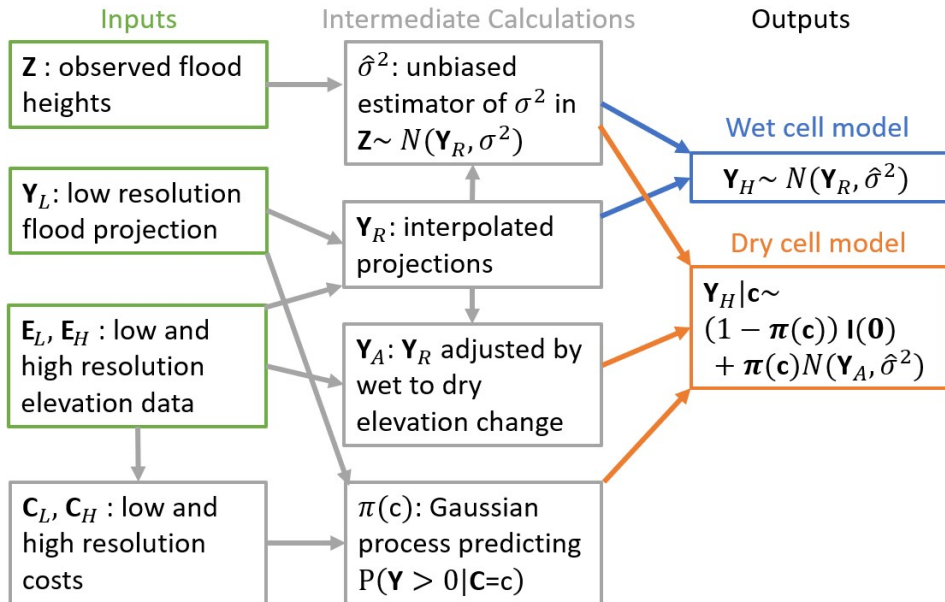


Foundation: ?, see for example ?

Probabilistic downscaling for flood models



Method summary



Our approach estimates the high resolution well

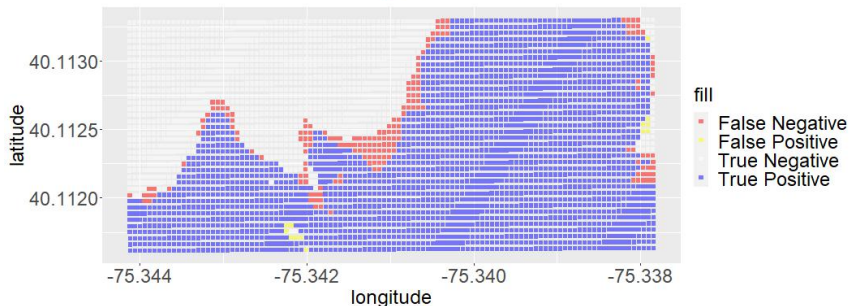
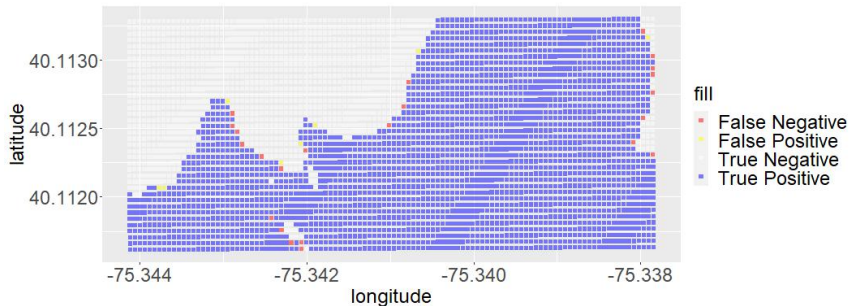
Downscaling approach	Ours	Simplified Berrocal et al. (2010)
Low resolution: 50 m		
Mean absolute error (m)	0.21	.33
95% PI coverage	0.96	.92
Sensitivity	0.87	1
Specificity	0.98	0
Low resolution: 30 m		
Mean absolute error (m)	0.21	.30
95% PI coverage	0.97	.91
Sensitivity	0.93	1
Specificity	0.99	0
Low resolution: 10 m		
Mean absolute error (m)	0.03	0.13
95% PI coverage	1	.90
Sensitivity	0.99	1
Specificity	0.99	0

Errors occur at wet-dry boundary

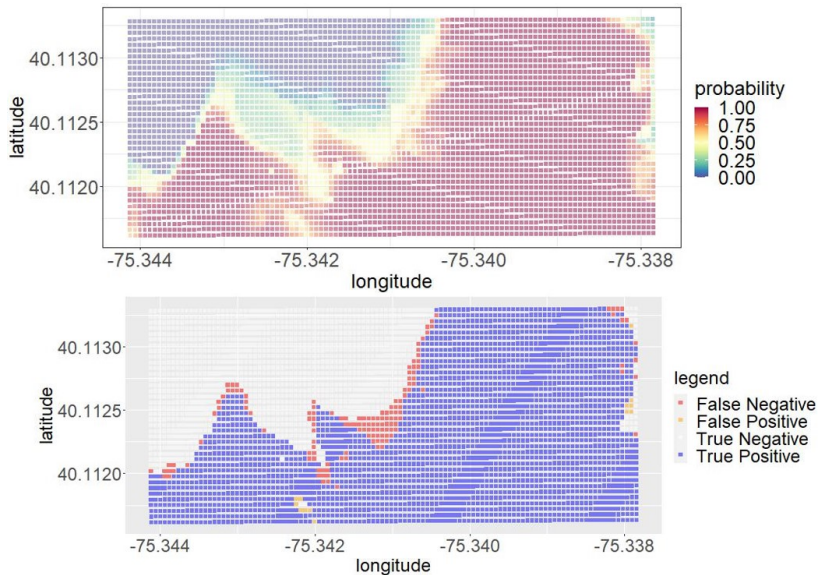
Starting at:

- 10 m:

- 30 m:



Our approach provides flooding probabilities



Our approach is fast

- Time to downscale starting with each resolution:
 - 50 m: 43.62 seconds
 - 30 m: 43.37 seconds
 - 10 m: 37.33 seconds
- Mean time to get projections at each resolution:
 - 50 m: 7 seconds
 - 30 m: 33 seconds
 - 10 m: 5.9 minutes
 - **5 m: 2 hours**
- Time difference influenced by:
 - Region size
 - Hydraulic model
 - Model parameters

Our approach sometimes better for observations

Table: Downscaled Projections VS High Water Marks

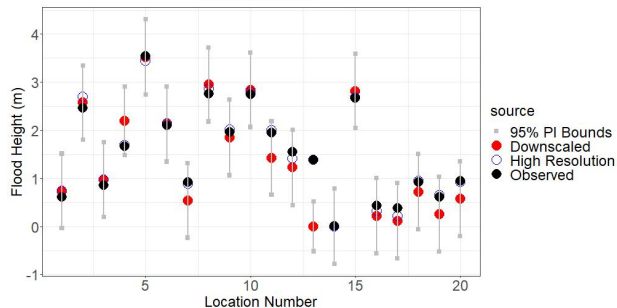
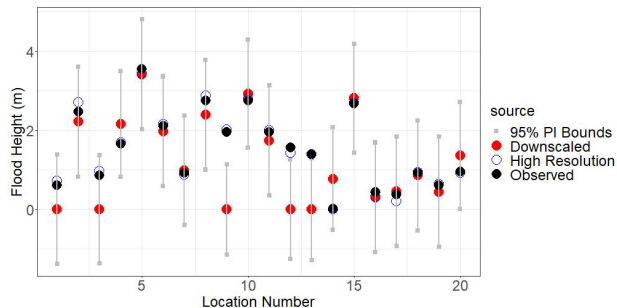
Downscaling approach	Ours	Simplified Berrocal et al. (2010)
Low resolution: 50 m		
Mean Absolute Error (m)	0.50	.33
95% PI Coverage	0.85	.95
Low resolution: 30 m		
Mean Absolute Error (m)	0.27	.25
95% PI Coverage	0.95	.85
Low resolution: 10 m		
Mean Absolute Error (m)	0.09	0.10
95% PI Coverage	.95	.90

Our approach estimates observations well

Starting at:

- 10 m:

- 30 m:



Our approach generalizes to other flood events

Discharge ($\frac{m^3}{s}$)	2503.21	2559.84	3681.19
Downscaling from: 50 m			
Mean Absolute Error (m)	0.20	.21	.30
95% PI Coverage	0.98	0.97	0.96
Sensitivity	0.85	0.87	0.89
Specificity	0.96	0.95	0.99
Downscaling from: 30 m			
Mean Absolute Error (m)	0.15	0.16	0.29
95% PI Coverage	0.99	0.98	0.92
Sensitivity	0.87	0.88	0.93
Specificity	0.98	0.97	1
Downscaling from: 10 m			
Mean Absolute Error (m)	0.025	0.032	0.054
95% PI Coverage	1	1	1
Sensitivity	0.98	0.98	1
Specificity	1	0.99	0.99