Flood Susceptibility Analysis on Hexagonal Grid Meshes
A Case Study in Southern New Brunswick, Canada

Mingke Erin Li, PhD candidate | University of Calgary

STORY MAP

A. BACKGROUND

IN southern New Brunswick, seasonal flooding takes place around St. John River. Flooding can cause serious damage and hazard (Fig.1). Flood prediction can help to make response strategies.

Fig. 1 Flooding scene in NB, 2018[1]

FLOOD modeling was studied by machine learning methods. **Recently, h**ydrological modeling on hexagonal grid meshes has drawn attention among researchers. Discrete Global Grid Systems (DGGS) was increasingly adopted in integrating multi-sources data and solving real-world problems[2].

THIS project aimed to model flood susceptibility in a hexagonal DGGS, with 28 predictors in four categories : geomorphology, hydrography, meteorology, and terrain-derived variables. The study area is around 27705 km^2, coving partial drainage basin of the St. John River (Fig.2).

Fig. 3 ISEA3H DGGS.

B. METHODOLOGY

1 Quantization of sample points & predictor variables

- Configuration: Icosahedral Snyder Equal Area Aperture 3 Hexagonal Grid (ISEA3H; Fig.3).
- Modeling resolution: levels 19, 21, 23.
- Datasets: DTM, NDVI, landcover, geology types, soil types, mean snow and ice, distance to waterbody.
- Quantization: nearest / bilinear interpolation.
- R library: dggridR[3].

2 Computation of meteorology variables

- Variable classes: precipitation, temperature, degree days, total snow.
- Interpolation: Inverse Distance Weighted.
- Representative distance: hexagonal rings.

3 Topographical & hydrological parameters

- Terrain-based: slope, aspect, roughness, curvature, TRI, TPI.
- Flow-based: flow direction, upslope area, SPI, TWI.
- Flow direction algorithm: D6 algorithm[4].
- Depression filling method: Priority-Flood algorithm[5].

4 Random forest modeling, evaluation & prediction

- Machine learning model: random forest.
- Data split: 2795 sample points,70% training, 30% testing.
- Evaluation: accuracy (ACC), F-score, area under ROC (AUC).
- Tools: python, ArcGIS pro, R-ArcGIS Bridge (VSURF[6]).

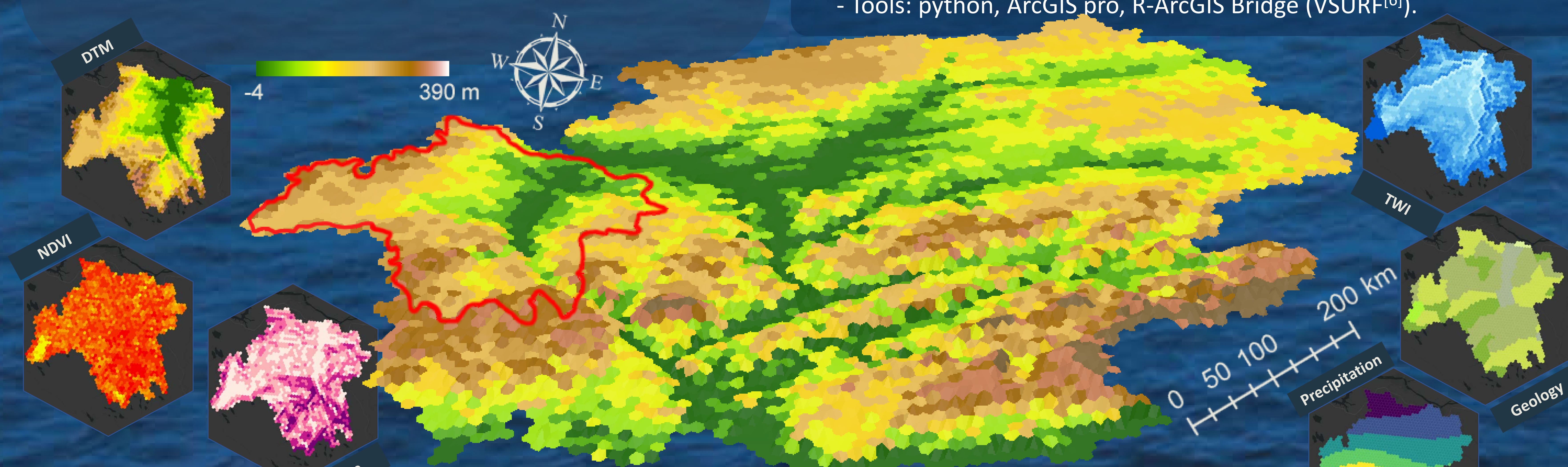

Fig. 2 Study area in New Brunswick, rendered by elevations on hexagonal meshes. Quantization results of representative predictors in one watershed are illustrated.

D. PREDICTIONS

CELL-BASED flooding events were predicted At three resolution levels. Fig.4 visualized the predicted flooding sites. Although there were slight differences in the visualized flooding extent in various scenarios, predicted flooding sites were clustered around St. John River and its branches.

Fig. 4 Prediction of the flood extent in ISEA3H DGGS at levels a. 19, b. 21, and c. 23.

C. IMPORTANT VARIABLES

RESULTS showed that DTM was the most important variable, generally followed by hydro-geomorphological variables distance-to-waterbody (NHN), landcover, and geology types (Table 1). Meteorology variables precipitation and total snow showed high importance when being added.

MODELS performed well according to three evaluation indicators, where ACC, AUC, and F-score were higher than 0.9 across all resolution levels (Table 1). Generally, models had better performance at finer resolutions with all predictors included in the training process.

Table 1. Summary of selected predictors and model performance at levels 19, 21, and 23.

Level	Important variables*	ACC	AUC	F
19	dtm, ts, precip, nhn, lc, rgh, sd50, tri, msi	0.920	0.920	0.917
21	dtm, ts, nhn, precip, geo, sd50, slp, r10	0.926	0.925	0.922
23	dtm, ts, nhn, precip, lc, rgh	0.942	0.942	0.938

*dtm = elevation; ts = total snow, precip = precipitation, nhn = distance to waterbody, lc = landcover, rgh = roughness, sd50 = snow depth > 50cm, tri = terrain roughness index, msi = mean snow and ice, slp = slope, geo = geology, r10 = rainfall > 10 mm

E. TAKEAWAYS

- This project modeled flood susceptibility in DGGS.
- DGGS helped to integrate multi-source data and conduct cell-based predictions.
- DTM was the most important predictor variable.
- Meteorology variables showed high importance.
- Model performance was better at finer resolutions.
- Flood susceptibility was predicted and visualized.

Data Availability Statement

All data used were obtained from Canada's Open Government Portal, under the Open Government License - Canada.

ACKNOWLEDGEMENTS

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