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Deployment of a Machine Learning Model for North America-wide Hydrometric Flow Forecasting with LiDAR-based Floodplain Mapping Capabilities

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ABSTRACT

The Integrated Science and Watershed Management System (ISWMS™) incorporates a temporal fusion transformer-based machine learning model designed to generate hydrometric flow forecasts across North America. Trained on an extensive archive of flow measurements from thousands of gauging stations, the model integrates real-time hydrometric observations, climate inputs, and catchment characteristics to produce localized probabilistic flow predictions. Alongside forecasting capability, ISWMS™ includes a Flood-Frequency Analysis (FFA) functionality used to derive return-period design flows. Together, these components support operational decision-making by providing both real-time forecasts and long-term hydrologic design information. The decision support system is deployed within The Healthy Rivers Ecosystem AssessmenT System (THREATS™), a web-based platform that includes tools for watershed data access, visualization, and analysis.

To translate forecasted or design flows into actionable flood intelligence, ISWMS™ requires flow forecasting and hydraulic model / flood mapping components capable of rapidly equating discharge inputs into inundation extents that can be rendered on a map. To address this need, we evaluated the Blackbird hydraulic model and results of cross validation of the TFT flow forecasting model. Blackbird has an efficient, reach-integrated, hydraulic framework that has been designed for large-scale, regional flood line mapping. Blackbird's potential for use in ISWMS™ was assessed by comparing its predicted flood extents to those generated by the widely used HEC-RAS 1D model for the Mattagami River Basin under 25-, 50-, and 100-year return periods and the Timmins storm event. Validation employed nine statistical measures.

By integrating a continental-scale machine learning forecasting engine, flood-frequency analysis functionality, and a computationally efficient hydraulic flood mapping model, ISWMS™ will provide a scalable and operational system for real-time and design-based flood risk assessment. This combined approach enables timely, geographically extensive flood intelligence, particularly valuable for remote regions where conventional hydraulic modelling is impractical.

KEYWORDS: ISWMS™, Temporal Fusion Transformer, Flood risk, Blackbird, Inundation mapping, real-time flow forecasting

1 INTRODUCTION

Although floods can play an important ecological role by sustaining riverine and wetland ecosystems during periodic scouring events, their increasing impacts on human communities highlight the urgent need for reliable flood risk assessment and mapping tools (Aristizabal et al., 2023; Bhupsingh et al., 2022). Flood inundation models have therefore become essential for hazard mapping, flood forecasting, damage assessment, and water resources planning (Apel et al., 2022; Arduino et al., 2005).

Hydraulic models, such as HEC-RAS, have been widely used to generate flood maps based on numerical solutions of the shallow-water equations (Brunner and RAS, 2008). In practice, both 1D and 2D versions of HEC-RAS are applied, but each has notable drawbacks. The 1D approach requires detailed cross-sectional data and relies on interpolation between sections, which can lead to unrealistic predictions of inundation in areas lacking hydraulic connectivity (Hashim et al., 2021; Yang et al., 2006). While 2D models generally provide higher accuracy, they demand significant computational resources and extensive setup effort, making them difficult to implement at large scales or for real-time applications (Ghimire et al., 2022; Teng et al., 2017). These limitations often result in flood maps that are outdated or unavailable in many high-risk regions.

To address these challenges, the Integrated Science and Watershed Management System (ISWMS™) originally developed by GREENLAND® International Consulting Ltd. (Greenland) over 2 decades ago, was re-developed as a multi-component platform that integrates hydrometric flow prediction and hydrologic analysis with hydraulic flood mapping capabilities. The ISWMS™ decision support system is now deployed within the Healthy Rivers Ecosystem AssessmenT System (THREATS™), a web-based platform, developed and maintained by Greenland, that offers tools for watershed data access, visualization and analysis.

A key element of ISWMS™ is a Temporal Fusion Transformer (TFT) deep learning model capable of producing real-time probabilistic flow forecasts across North America, with prediction horizons of up to 14 days. Complementing this forecasting capability, ISWMS™ incorporates flood-frequency analysis for deriving design flows used in regulatory and planning contexts. Together, these functions allow ISWMS™ to characterize both short-term forecasted extremes and long-term risk. To translate either forecasted or design flows into inundation extents, ISWMS™ requires a hydraulic mapping tool that is both computationally efficient and readily scalable.

Blackbird, developed by Chlumsky et al. (2024), is a reach-integrated hydraulic model that combines the Geospatially Augmented Standard Step (GASS) method with the Height Above Nearest Drainage (HAND), eliminating the need for cross-sectional data, streamlining model development, and producing flood maps orders of magnitude faster than comparable 2D models while maintaining reasonable accuracy relative to hydrodynamic benchmarks. Its efficiency and reduced data requirements make it particularly suitable for large-scale and real-time flood mapping, as well as for remote locations where traditional hydraulic modelling may be infeasible.

In this study, we present evaluation results from both the TFT and the Blackbird models and consider how their combined use could provide a comprehensive visualization of flood inundation for emergency preparedness and long-term planning.

2 MATERIALS AND METHODS

2.1 Study area and data

The Mattagami River is a major riverine system in northern Ontario, Canada. Its watershed encompasses approximately 36,800 km² (Clavet-Gaumont et al., 2017), draining a diverse landscape of lakes, wetlands, and forested terrain before flowing northward through the City of Timmins and eventually joining the Moose River system located within the “Ring of Fire” natural resources economic region. The latter was designated recently by the Government of Ontario as a Special Economic Zone (SPZ). The river reach examined plays a critical role in drinking water supply, hydroelectric generation, and flood management for the region. Figure 1 illustrates the portion of Mattagami River Basin that was used for the study.

In this study, LIDAR-derived digital elevation model (DEM) data with 2-m resolution was employed to ensure accurate representation of terrain and channel geometry in the Mattagami River watershed. The DEM was used to compute flow accumulation, flow direction, and HAND layers, as well as channel polylines, which are critical inputs for reach-integrated hydraulic property calculations. A high-resolution DEM was necessary to preserve landscape connectivity, minimize interpolation errors, and improve the accuracy of flood depth mapping across complex terrain. For hydrological input, the Mattagami River hydrometric station 04LA002, located upstream of the City of Timmins, was used. This station provides a continuous record of daily flow data from 1969 to 2025, making it suitable for flood frequency analysis. The long record length allows for robust statistical fitting of probability distributions to estimate return period flows (e.g., 25-, 50-, and 100-year floods). These return period discharges were applied as boundary conditions in both HEC-RAS 1D and Blackbird simulations to generate flood inundation maps for comparison.

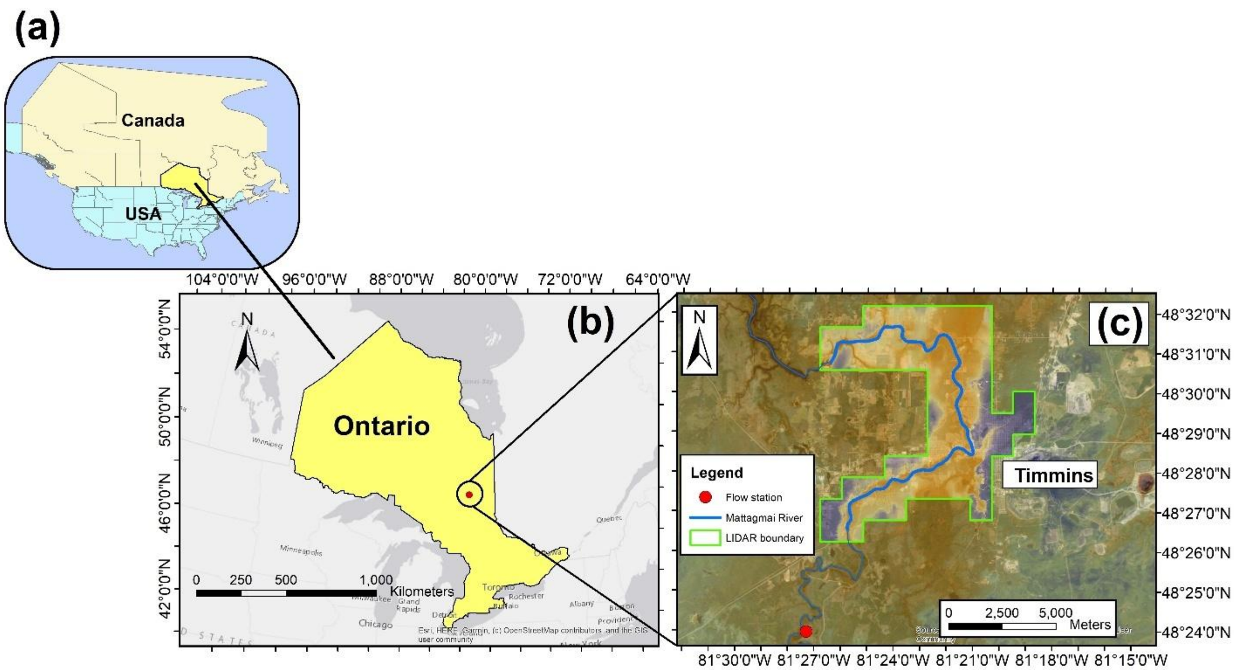

Figure 1: Location and hydrological context of the study area in northern Ontario: (a) National overview showing Ontario within North America, (b) Regional map of Ontario highlighting the Timmins area, (c) Detailed map of the Mattagami River near the City of Timmins, including the LiDAR survey boundary, the river channel, and the upstream hydrometric station 04LA002.

2.2 Methodology

2.2.1 ISWMS™ machine learning flow forecasting model

The machine learning component of ISWMS™ is based on the Temporal Fusion Transformer (TFT) architecture developed and evaluated by French (2023). The TFT is a sequence-to-sequence deep learning model designed for multivariate time-series forecasting and can learn complex temporal relationships among climate variables, catchment attributes, and historical streamflow. The model was trained on several decades of hydrometric and climate data from thousands of stations across North America, using large datasets such as Hydrological Streamflow Extent Time Series (HYSETS), Global Land Data Assimilation System (GLDAS), Canada's National Water Data Archive (HYDAT), Natural Resources Canada (NRCAN), and numerical weather prediction products.

Key features of the TFT include attention mechanisms, gating layers, and variable-selection networks, which allow the model to identify the most influential predictors at each timestep and to provide interpretable probabilistic forecasts. Within ISWMS™, the TFT model generates real-time flow predictions with 14-day lead times. These forecasts can serve as inputs to a hydraulic inundation model, enabling rapid flood extent mapping when elevated flows are predicted. Figure 2 shows real-time probabilistic discharge forecasts generated by the TFT-based prediction system alongside Mattagami River high-flow event thresholds.

2.2.2 Flood Frequency Analysis

Within ISWMS™, flow forecast analysis is implemented as a dedicated function that provides design flows for regulatory and planning applications. This functionality was used to derive return-period discharges for the Mattagami River. The analysis was based on annual maximum series extracted from long-term daily discharge records. These annual maxima were fitted to a Generalized Extreme Value (GEV) distribution using the L-moments method, which offers stable parameter estimation for extreme value distributions commonly applied in hydrologic studies. To quantify uncertainty in the estimated flood quantiles, ISWMS™ employs a bootstrap resampling procedure that repeatedly samples the annual maxima to approximate the sampling distribution of return-period flows.

This approach yields robust 95% confidence intervals for each return period. Flood quantiles were subsequently derived for the 25-, 50-, and 100-year return periods, with three values reported for each: the lower confidence bound, the median estimate, and the upper confidence bound. By integrating L-moments-based GEV fitting with bootstrap uncertainty analysis, the ISWMS™ flood-frequency function provides both point estimates and confidence ranges, enabling a reliable characterization of flood risk at the station. These design flows served as the hydraulic inputs for evaluating the Blackbird model in this study, complementing the broader ISWMS™ framework including flow forecasting.

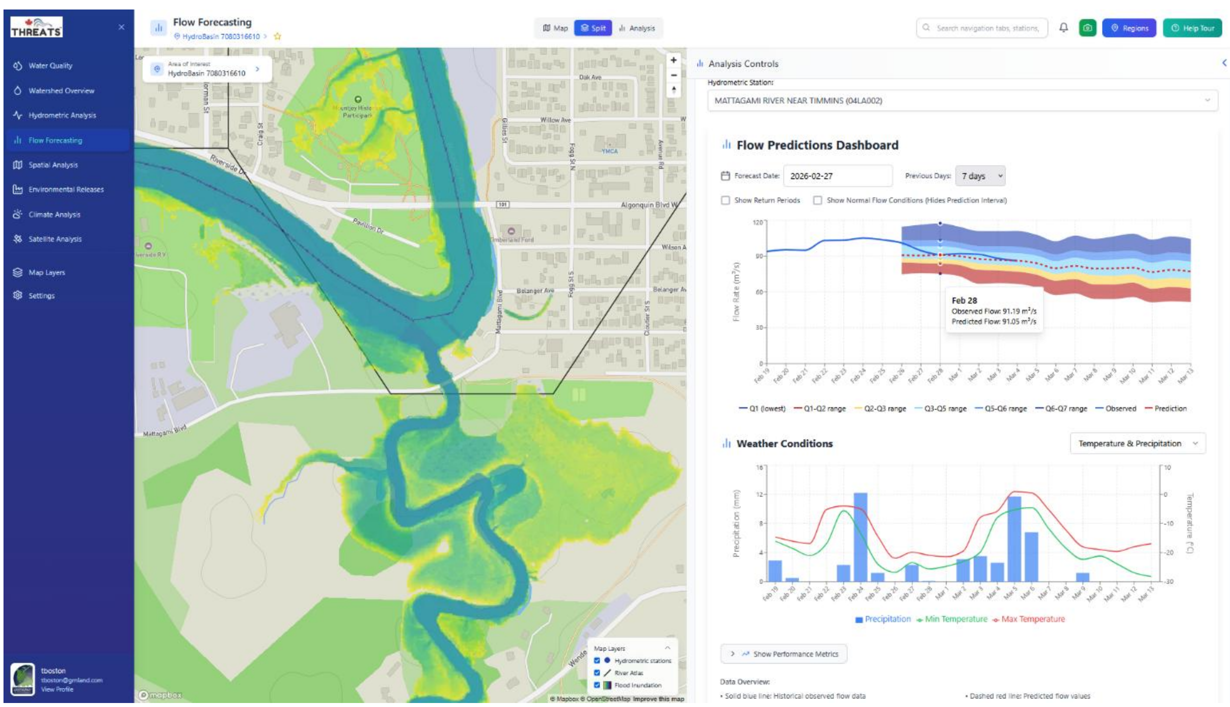

Figure 2: ISWMS™ flow prediction interface showing probabilistic discharge forecasts for the Mattagami River. The right panel displays predicted flows and confidence bands with meteorological forecast data, while the left panel shows locations of any flood inundation for forecast flows or return period events.

2.2.3 HEC-RAS 1D model development

The HEC-RAS hydraulic model for the Mattagami River was developed using high-resolution digital elevation data and detailed field survey information to construct river geometry, cross-sections, culverts, and bridge structures. All hydraulic structures such as bridge decks were incorporated based on direct field verification. The model was run under steady-state conditions using flow values for selected return period floods derived from Flood Frequency Analysis (FFA) of the long-term record at hydrometric station 04LA002. The resulting flood extents were then used as references for validation of the Blackbird model simulations.

2.2.4 Blackbird model description

Blackbird applies the Geospatially Augmented Standard Step (GASS) method, which integrates geospatial data directly into hydraulic calculations. A central concept is conveyance, representing the ability of a river reach to carry flow under a given stage. Unlike traditional cross-sectional models, Blackbird computes conveyance by aggregating contributions from raster cells across the reach, ensuring hydraulic capacity is calculated consistently across the terrain.

The hydraulic solver is based on the standard step method, which balances energy between successive stream nodes:

$$z_j + d_j + \alpha_2 \frac{\overline{u}_j^2}{2g} = z_{j-1} + d_{j-1} + \alpha_1 \frac{\overline{u}_{j-1}^2}{2g} + \Delta h_j \tag{1}$$

where z is channel invert, d is depth, α is the velocity coefficient, $\overline{u}$ is mean velocity, g is acceleration due to gravity, and Δh_j is head loss.

Head loss is expressed as:

$$\Delta h_j = L_{e_j} S_{f_j} + C_j \left(\frac{\alpha_j \overline{u}_j^2}{2g} - \frac{\alpha_{j-1} \overline{u}_{j-1}^2}{2g} \right) \tag{2}$$

with L_{e_j} the effective reach length, S_{f_j} the friction slope, and C_j contraction or expansion coefficients. The friction slope is linked to conveyance:

$$S_{f_j} = \left(\frac{Q_j}{K_j} \right)^2 \tag{3}$$

where Q_j is discharge and K_j is conveyance.

Flood depths are mapped using the Height Above Nearest Drainage (HAND) algorithm, which preserves terrain connectivity. Cell depth is determined by:

$$d_i = \max(d_j - H_i, 0) \tag{4}$$

where H_i is the HAND value for cell i.

Together, these formulations allow Blackbird to compute flood extents rapidly while maintaining hydraulic realism, with outputs provided as spatially distributed flood depth rasters.

2.2.5 Accuracy assessment

To evaluate the accuracy of Blackbird in flood inundation mapping, we applied nine statistical performance measures, namely the Critical Success Index (CSI), Probability of Detection (POD), False Alarm Ratio (FAR), True Positive Rate (TPR), F1 score (F1), Overall Accuracy (ACC), Hit Rate (HR), Cohen's Kappa (Kappa), and Bias using results from previous modelling using HEC-RAS as a standard. The application of Blackbird was an out-of-the-box application on a single length of the Mattagami River. There was no calibration and no adjustments were made to address constrictions at bridges or the influence of tributaries joining the main reach.

3 RESULTS

3.1 ISWMS™ machine-learning flow forecasting model

The performance of the TFT model integrated into ISWMS™ was evaluated extensively by French (2023). Across approximately 8,500 North American catchments, the model demonstrated strong hindcasting skill and reliable short-term forecasting performance through cross-validation.

Forecast accuracy was highest within the first several days of prediction, decreasing toward the 14-day horizon due to increasing meteorological forecast uncertainty. Table 1 summarizes the forecasting performance metrics, including NSE, R^2, and PBIAS across the full validation dataset. These results show that the TFT model consistently achieved high predictive skill for short-term flow forecasting across approximately 8,500 hydrometric stations, with reasonable performance in capturing peak flows, an essential requirement for operational flood forecasting. Results showed regional variation in performance with regulated watersheds being harder to predict reliably. These findings support the informed use of the TFT model as the real-time forecasting engine within ISWMS™ and justify its integration with a hydraulic mapping tool for rapid flood extent prediction during forecast flow events.

Table 1 Quantification of prediction performance and thresholds (hindcasting) (French (2023)).

R^2 Median	NSE Median	PBias Median	KGE Median
0.86	0.81	-3.25	0.78

Statistic	Unsatisfactory	Satisfactory	Good	Very Good
R^2	12%	13%	22%	53%
NSE	15%	14%	17%	54%
PBias	35%	15%	22%	28%

Thresholds used

Metric	Not satisfactory	Satisfactory	Good	Very Good
R^2	$\leq$0.60	(0.6,0.75]	(0.75,0.85]	>0.85
NSE	$\leq$0.50	(0.5,0.7]	(0.7,0.8]	>0.8
PBIAS	$(-\infty, -15] \cup [15, \infty)$	$(-15,-10] \cup [10, 15)$	$(-10,-5] \cup [5, 10)$	(-5,5)

3.2 Flood Frequency Analysis

Design flow conditions estimated from the fitted GEV distribution yielded peak flow values of 396.1 m^3/s, 426.5 m^3/s, and 450.46 m^3/s for the 25-, 50-, and 100-year return periods, respectively. These values represent the expected magnitude of flow events based on statistical extrapolation of annual maxima. The Timmins Storm, an observed extreme event, produced a peak discharge of 707.92 m^3/s, as reported by the Mattagami Region Conservation Authority. This observed flow substantially exceeds the 100-year estimate, underscoring the severity of the event and its relevance for model validation. Both Blackbird and HEC-RAS 1D were executed using the four design flows. Results from Blackbird were evaluated against HEC-RAS 1D, which served as the reference model for validation.

3.3 Blackbird Hydraulic Model Assessment

Table 2 presents the performance metrics derived from spatial intersection between Blackbird and HEC-RAS 1D flood inundation maps across four flood scenarios: 25-year, 50-year, 100-year, and the Timmins Storm. These metrics quantify Blackbird's ability to replicate HEC-RAS predictions using statistical measures. From Table 2, Blackbird demonstrates consistently high performance for the 25-, 50-, and 100-year flood events. CSI ranged narrowly from 0.85 to 0.87, and POD and TPR remained stable at 0.95 across these three scenarios. F1 scores were similarly strong (0.92–0.93), and ACC was exceptionally high at 0.99. Cohen's Kappa values (0.91–0.93) indicated substantial agreement with HEC-RAS, and Bias values close to 1 (1.08, 1.06, 1.03) suggested minimal overprediction.

Performance declined under the Timmins Storm. CSI dropped to 0.73, and POD/TPR fell to 0.74, indicating reduced detection of flooded areas. The F1 score decreased to 0.85, and Kappa dropped to 0.83, reflecting weaker agreement. Notably, Bias fell to 0.75, suggesting underprediction of flood extent. Despite this, HR increased to 0.99, indicating that Blackbird correctly identified most of the areas flagged by HEC-RAS as flooded, but with reduced precision.

Table 2 Performance metrics of Blackbird flood inundation mapping under multiple flood events.

Performance metrics	25-year Flood	50-year Flood	100-year Flood	Timmins Storm	Average
CSI	0.85	0.86	0.87	0.73	0.83
POD	0.95	0.95	0.95	0.74	0.90
FAR	0.12	0.10	0.08	0.01	0.08
TPR	0.95	0.95	0.95	0.74	0.90
F1 Score	0.92	0.93	0.93	0.85	0.91
ACC	0.99	0.99	0.99	0.97	0.98
HR	0.88	0.90	0.92	0.99	0.92
Kappa	0.91	0.92	0.93	0.83	0.90
Bias	1.08	1.06	1.03	0.75	0.98

Figure 3 illustrates the spatial agreement between Blackbird and HEC-RAS flood extents across four flood scenarios. For the 25-, 50-, and 100-year floods, True Positive areas dominate, with minimal False Positives and False Negatives, indicating strong spatial accuracy.

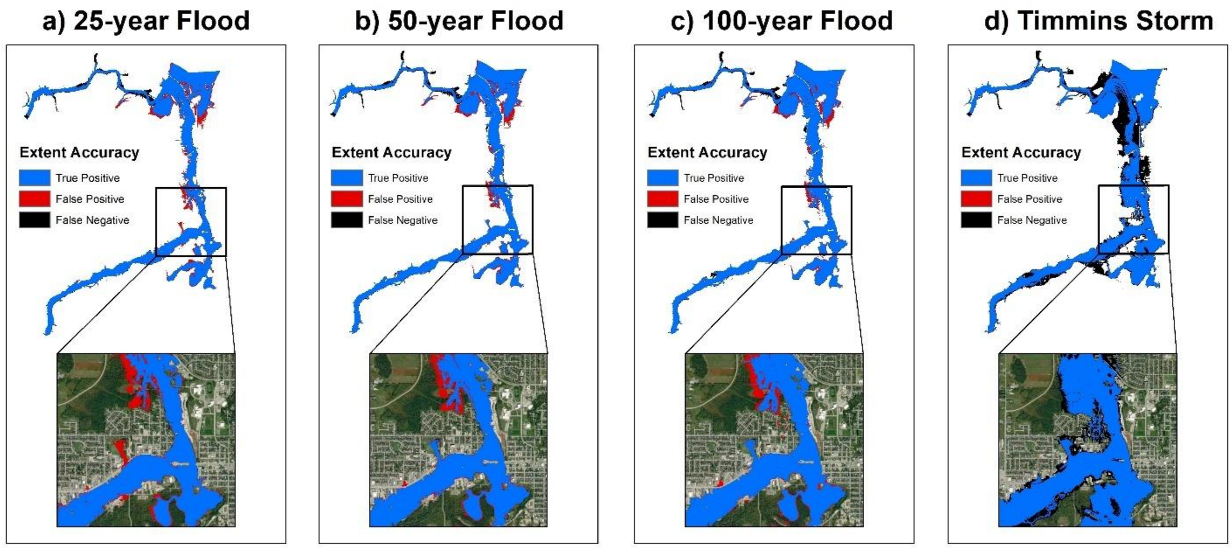

Figure 3: Spatial distribution of flood extent accuracy for four flood scenarios: (a) 25-year, (b) 50-year, (c) 100-year, and (d) Timmins Storm. Each panel shows areas correctly predicted as flooded (True Positives, blue), areas incorrectly predicted as flooded (False Positives, red), and areas that flooded but were not predicted (False Negatives, black).

4 DISCUSSION

Blackbird achieved strong agreement with HEC-RAS for the 25-, 50-, and 100-year floods, with consistently high CSI, POD, F1, and accuracy values. Its performance declined under the Timmins Storm, where detection rates dropped and false negatives increased. The reasons for this divergence are likely tied to the structural and hydraulic complexities of extreme events that were not adequately addressed in the model setup. Blackbird does not explicitly simulate bridges, culverts, or other hydraulic controls, which play a critical role in shaping flow patterns during high-magnitude floods. When discharge levels rise substantially, as in the Timmins Storm (≈707 m^3/s compared to ≈450.46 m^3/s for the 100-year flood), these structures and other tributaries influence backwater effects, channel conveyance, and localized inundation to a greater degree. Without their representation, Blackbird tends to underestimate flood extent, as reflected in the lower Bias and higher false negative rate. Similar limitations of simplified flood models have been documented in prior studies, which emphasize that neglecting urban features and hydraulic structures can reduce predictive skill in complex scenarios (Fewtrell et al., 2008; Neal et al., 2012; Schubert and Sanders, 2012).

An import distinction is that the Blackbird model was uncalibrated. Several adjustments could have been made to improve its performance for the Timmins Storm, but this would have deviated from the study goal of doing an “out-of-the-box” comparison to see how it might perform without additional information being coded into the model.

While the flow inputs used in this study were derived from flood frequency analysis rather than machine learning forecasts, they represent the types of high-flow conditions that ISWMS™ aims to predict operationally. The machine learning algorithms within ISWMS™ can forecast discharge up to 14 days ahead, enabling early detection of potential flood events. By validating Blackbird against benchmark flood extents using design flows and a historical storm, we demonstrated its capability to rapidly generate inundation maps under conditions consistent to those forecasted by ISWMS™ algorithms. This confirms Blackbird’s suitability for integration into the ISWMS™ workflow, where it will support real-time flood mapping triggered by TFT model flow predictions. The consistently high accuracy for design floods demonstrates that Blackbird is reliable for typical hazard assessment. Its computational efficiency makes it particularly valuable in remote regions, where developing detailed hydraulic models like HEC-RAS 1D or 2D may be impractical. Thus, while refinement in model approach and application technique is needed to improve performance under extreme events, Blackbird already offers a practical balance between accuracy and speed for operational flood mapping.

5 CONCLUSION

The TFT based algorithms used in ISWMS™ provides access to stream flow forecasting across North America at approximately 8,500 hydrometric stations. The wide availability of forecasting data creates a strong potential for wide-spread, cost effective adoption of the system for extreme event prediction. The model was found to perform well in cross-validation across thousands of hydrometric stations where weather forcing data was accurate and there was limited influence on flows due to regulation.

The Blackbird hydraulic mapping model using flood frequency analysis derived flows and a regulatory storm event, demonstrated strong agreement with HEC-RAS 1D for return period flood events with strong agreement across statistical metrics and very low misclassification rates. It struggled with the Regional Timmins storm event likely due to inadequate handling of bridge constrictions and tributary inflows.

Since ISWMS™ can forecast discharge, integrating Blackbird offers a practical solution for rapidly rendering forecasted flows into flood extent maps in real-time. Scenario flows can be used for planning and mitigation purposes. The result will be a fully operational deployment of ISWMS™ within the THREATS web platform, supporting its broader goal of scalable, efficient, real-time flood risk assessment. Future applications could include:

- Flood and drought forecasting to protect vulnerable floodplain communities.
- Flow predictions to reduce risks in operating hydropower and other utility facilities.
- Flow predictions to protect the operations of resource industry (mining) projects.
- Flow predictions for infrastructure assets at risk from flooding or accelerated erosion processes, including: 1) Wastewater Treatment Plants (with or without CSO storage or overflow capabilities) affected by floodplains; 2) stream/river road crossing structures monitoring; 3) road/highway construction & community servicing retrofit projects susceptible to "flash flood" events; and, 4) oil/gas pipeline and telecommunication underground floodplain crossings impacted by severe flow - erosion induced events.

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