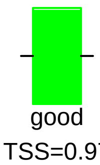
Ictinia mississippiensis

Habitat Suitability Model (HSM) assessment metrics and metadata
Common name: Mississippi Kite
Grank: G5 - Secure
Date: 02 Sep 2021; Code: ictimiss-br (EGT_ID: 104468)



validation success

This model was developed for the Arizona Game and Fish Department. This HSM was modeled using the algorithms in Table 1 using R[4], incorporating the number of known and background locations indicated in Table 2. We validated the model by jackknifing[5,6,7] by spatial grouping and testing 42 groups. Table 3 reports the validation statistics for these jackknifing runs.

Expert reviewers indicated these algorithms performed the best: rf, xgb. The reported TSS (above and Table 3b) is based on the reviewer-defined threshold for these models. Some data are provided for all models run, but the focus of this metadata report will be on these models chosen by expert review.

Table 1. These algorithms were created for review. If multiple passed review, those were ensembled. The specific implementations are listed in the package column.

Name	Code	R package
Random Forest	rf	randomForest
Extreme Gradient Boosting	xgb	xgboost

Table 2. Input statistics. Presence locations may be based on point observations buffered by their spatial accuracy and polygons with nearby locations grouped together. Environmental conditions are randomly subsampled within each of these groups as noted to generate the number of presence inputs (by tree for rf; for entire model for others). Background points are placed throughout model except for presence locations.

Sample	Count
Presence locations (groups)	42
Subsamples within groups	4.81
Total presence inputs	202
Background inputs - rf	202
Background inputs - xgb	202

Table 3. Mean validation statistics for jackknife trials (+/- standard deviation). AUC = area under the ROC curve, Sens = sensitivity, Spec = specificity, TSS = True Skill Statistic[8,9,6].

alg	AUC	Sens	Spec	TSS
rf	0.97(0.09)	0.74(0.41)	0.97(0.04)	0.71(0.41)
xgb	0.95(0.12)	0.95(0.09)	0.84(0.32)	0.78(NA)

Table 3b. Validation statistics for expert-chosen algorithms and thresholds. TSS = True Skill Statistic[8].

alg	thresh	TSS
rf	0.60	0.94
xgb	0.64	1.00

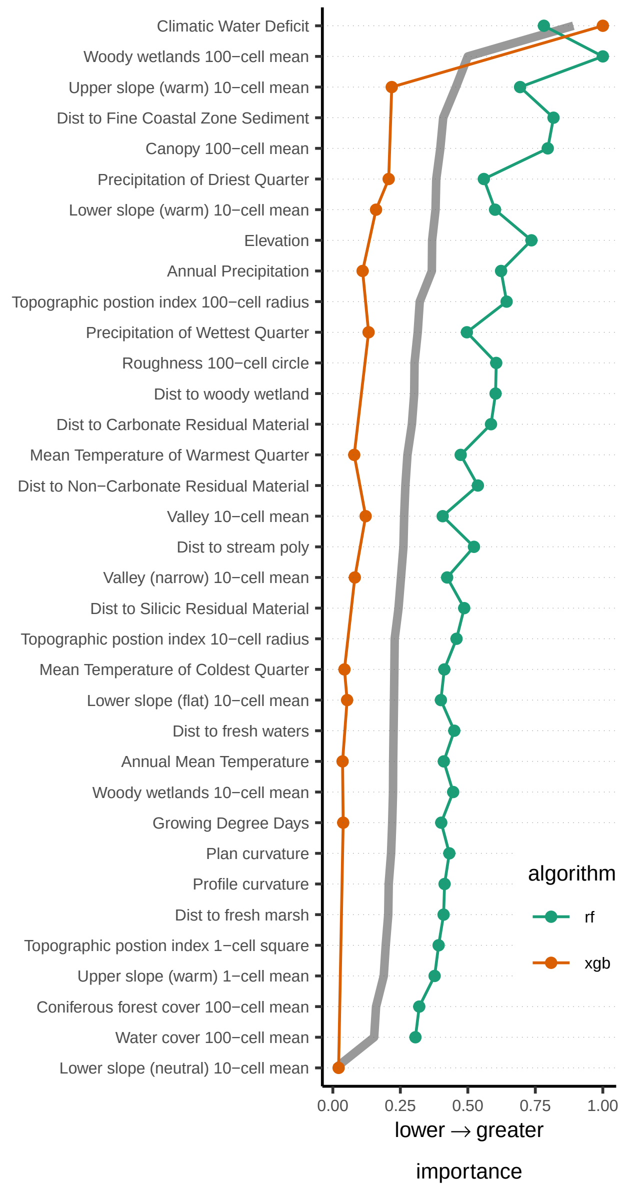


Figure 1. Relative importance of environmental variables based on the full model. Importance values are extracted from each algorithm and plotted in descending order based on an average of all algorithms (grey line). Note each algorithm has variable removal rules (see Appendix 2); a missing point indicates the variable was not used by that algorithm. See Appendix 1 for variable descriptions.

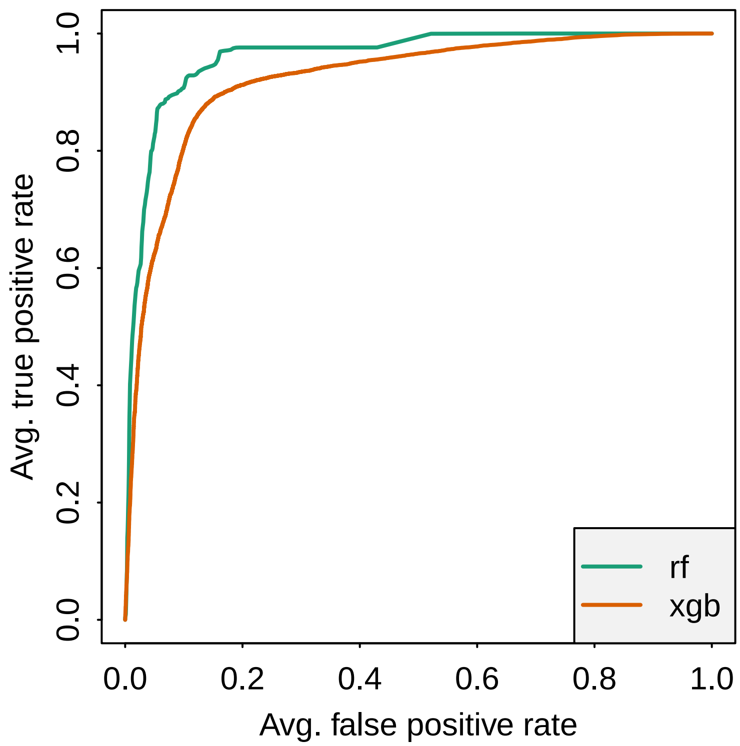


Figure 2. ROC plot for all 42 validation runs, averaged along cutoffs, for each modeling algorithm.

Species distribution model outputs display the probability (0-1) of a location (i.e. stream reach or raster cell) having similar environmental conditions in comparison to known presence locations. No model will ever depict sites where a targeted element will occur with certainty, it can *only* depict locations it interprets as appropriate habitat for the targeted element. The delineation of suitable habitats is made by the selection of a threshold value, where locations with values above the threshold are designated as likely suitable habitat, and those with values below the threshold may be unsuitable. Threshold values are often statistically calculated. SDMs can be used in many ways and the depiction of appropriate habitat should be varied depending on intended use. For targeting field surveys, an SDM may be used to refine the search area; users should always employ additional GIS tools to further direct search efforts. A lower threshold depicting more area may be appropriate to use in this case. For a more conservative depiction of suitable habitat that shows less area, a higher threshold may be more appropriate. Different thresholds for this model (full model) are described in Table 4.

Table 4. Thresholds[11,12] calculated from the final model. The Value column reports the threshold; Groups indicates the percentage (number in brackets) of groups within which at least one point was predicted as suitable habitat; Pts indicates the percentage of PR points predicted having suitable habitat. Total numbers of groups and presence points used in the final model are reported in Table 1.

Code	Value	Groups	Points
Algorithm = rf			
eqSS	0.822	100(42)	99
maxSSS	0.763	100(42)	100
MTP	0.658	100(42)	100
MTPGP	0.966	100(42)	77
TenPctile	0.940	100(42)	90
ROC	0.776	100(42)	99
Algorithm = xgb			
eqSS	0.896	100(42)	100
maxSSS	0.896	100(42)	100
MTP	0.896	100(42)	100
MTPGP	0.969	100(42)	88
TenPctile	0.965	100(42)	90
ROC	0.896	100(42)	100

Code	Threshold full name	Threshold description
eqSS	Equal sensitivity and specificity	The probability at which the absolute value of the difference between sensitivity and specificity is minimized.
maxSSS	Maximum of sensitivity plus specificity	The probability at which the sum of sensitivity and specificity is maximized.
MTP	Minimum Training Presence	The highest probability value at which 100% of input presence points remain classified as suitable habitat.
MTPGP	Minimum Training Presence by Group	The highest probability value at which 100% of input groups have at least one presence point classified as suitable habitat.
TenPctile	Tenth percentile of training presence	The probability at which 90% of the input presence points are classified as suitable habitat.
ROC	ROC plot upper left corner	The point on the ROC curve with the shortest distance to the top-left corner (0,1) of the ROC plot.

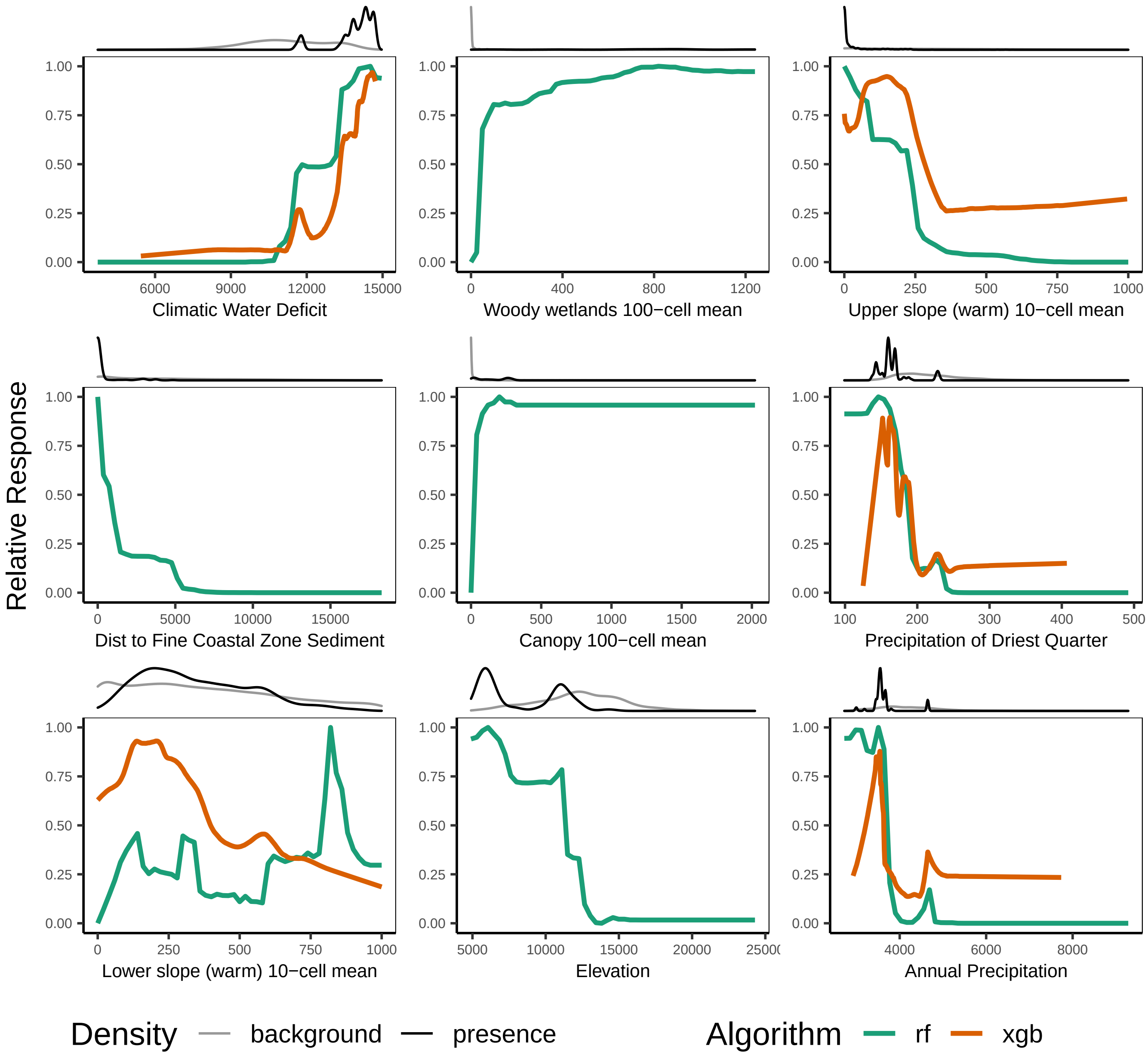


Figure 3. Partial dependence plots for the 9 environmental variables with the most influence on the models (averaged). Each plot shows the effect of the variable on the probability of appropriate habitat with the effects of the other variables removed [3]. The x-axis covers the range of values for the variable assessed; the y-axis represents the effect between the variable and model response. Peaks in the line indicate where this variable had the strongest influence on predicting appropriate habitat. Decreasing lines from left to right show a negative relationship overall; increasing lines, positive. The distribution of each category (thin red = Background points, thick blue = Presence points) is depicted at the top margin. See Appendix 1 for variable descriptions.

Model Evaluation and Intended Use

All SDMs are sensitive to data inputs and methodological choices. Table 5 presents scoring of modeling factors based on the model evaluation rubric presented in Sofaer et al. 2019[13].

Table 5. Model evaluation results based on Sofaer et al. (2019). Scores can be attributed as ideal, acceptable, or interpret with caution.

Category	Metric	Score	Notes
Species Data	Presence data quality	Acceptable	Heritage Network data augmented with outside data which may or may not be vetted for accuracy or weighted for spatial representation.
	Absence/Background Data	Acceptable	Background points randomly placed throughout modeling area excluding species locations.
	Evaluation Data	Acceptable	Models are validated by jackknifing (i.e. leave-one-out).
Environmental Predictors	Ecological and predictive relevance	Acceptable	Selection of predictor variables were based on previous modeling experience by the Natural Heritage Network and subsetted using variable importance.
	Spatial and temporal alignment	Acceptable	Reasonable attempts to align predictor and presence data were made.
Modeling Process	Algorithm choice	Acceptable	Algorithms were carefully chosen for modeling rare species.
	Sensitivity	Acceptable	Ensemble used to minimize algorithm sensitivity.
	Statistical rigor	Acceptable	Collinearity of predictors recognized and addressed; presence points grouped to minimize sample bias and minimize spatial autocorrelation boost during validation; other assumptions recognized and considered.
	Performance	Acceptable	Mean TSS for expert-derived thresholds ≥ 0.6.
	Model review	Acceptable	Model was reviewed by regional, taxonomic experts.
Model Products	Mapped products	Acceptable	Continuous models plus thresholded models available to users.
	Interpretation support products	Ideal	All standards met.
	Reproducibility	Ideal	All standards met.
	Iterative	Interpret with Caution	Model not re-run with new or modified data.

Model Comments

The standard variables (nlcdopn1, nlcdopn10, nlcdopn100, impsur1, impsur10, impsur100, ntm_1_01, ntm_1_02, ntm_1_06, ntm_1_08, ntm_1_09, ntm_2_01, ntm_2_02, ntm_2_05, ntm_2_06, ntm_3_01, ntm_3_03, ntm_3_09, ntm_3_12, ntm_4_01, ntm_4_02, ntm_4_03, ntm_4_05, ntm_4_06, ntm_5_01, ntm_6_01, ntm_6_02, ntm_6_03, ntm_6_04, nlcdshb1, nlcdshb10, nlcdshb100, soil_ph, poresize, clay, bulkdens) were excluded from this model.

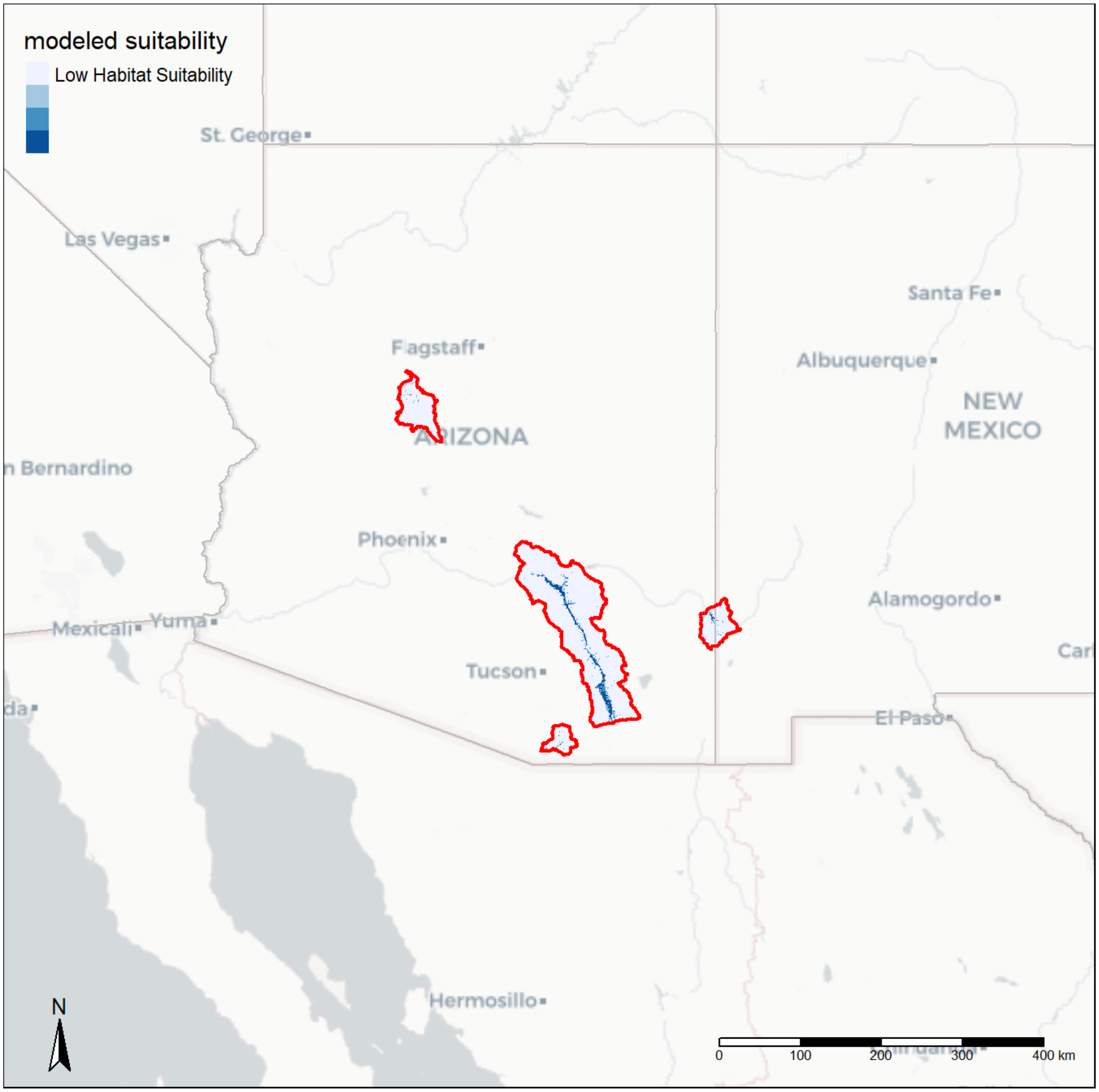


Figure 4. A generalized view of the model predictions throughout the modeled area. If an ensemble was created this map shows simply an average of all model predictions. State boundaries are depicted as a thin gray line. The modeled area is outlined in red. Basemap: CartoDB.Positron (©OpenStreetMap, contributors: ©CARTO).

This distribution model would not have been possible without data sharing among organizations. Other data sets and sources may have been evaluated, but this final model includes data from these sources:

- Arizona Game and Fish Department

This model was built using a methodology developed through collaboration among the Florida Natural Areas Inventory, the New York Natural Heritage Program, the Pennsylvania Natural Heritage Program, and the Virginia Natural Heritage Program, all member programs of the NatureServe Network. It is one of a suite of species distribution models developed using the same methods, scripts, and environmental data sets. Our goal was to be consistent and transparent in our methodology, validation, and output.

Please cite this document and its associated SDM as:
NatureServe and Heritage Network Partners. 2021. Species distribution model for Mississippi Kite (*Ictinia mississippiensis*). Created on 02 Sep 2021. Arlington, VA with Network partners from VA, PA, and NY.

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Appendix 1. Descriptions for environmental variables included in model.

Variable Name	Variable Description
Annual Mean Temperature	Annual Mean Temperature
Annual Precipitation	Annual Precipitation
Canopy 100-cell mean	mean percent canopy cover in 100-cell radius (30 meter cells)
Climatic Water Deficit	Climatic Water Deficit
Coniferous forest cover 100-cell mean	mean coniferous forest cover within 100 cell radius
Dist to Carbonate Residual Material	Euclidean distance to surficial geology type: Carbonate Residual Material
Dist to Fine Coastal Zone Sediment	Euclidean distance to surficial geology type: Alluvium and Fine-Textured Coastal Zone Sediment
Dist to Non-Carbonate Residual Material	Euclidean distance to surficial geology type: Non-Carbonate Residual Material
Dist to Silicic Residual Material	Euclidean distance to surficial geology type: Silicic Residual Material
Dist to fresh marsh	Distance to freshwater emergent wetland
Dist to fresh waters	Euclidean distance to nearest stream, river, or other inland waterbody (excluding estuaries)
Dist to stream poly	Euclidean distance to nearest stream (features represented by polygons)
Dist to woody wetland	Distance to forested palustrine wetland
Elevation	Elevation in decimeters (originally in meters)
Growing Degree Days	Growing Degree Days
Lower slope (flat) 10-cell mean	mean percent Lower slope (flat) in 10-cell mean (30 meter cells)
Lower slope (neutral) 10-cell mean	mean percent Lower slope (neutral) in 10-cell mean (30 meter cells)
Lower slope (warm) 10-cell mean	mean percent Lower slope (warm) in 10-cell mean (30 meter cells)
Mean Temperature of Coldest Quarter	Mean Temperature of Coldest Quarter
Mean Temperature of Warmest Quarter	Mean Temperature of Warmest Quarter
Plan curvature	The curvature of a cell perpendicular to the direction of the maximum slope. Influences convergence and divergence of flow
Precipitation of Driest Quarter	Precipitation of Driest Quarter
Precipitation of Wettest Quarter	Precipitation of Wettest Quarter
Profile curvature	The curvature of a cell in the direction of the maximum slope. Affects the acceleration and deceleration of flow and, therefore, influences erosion and deposition
Roughness 100-cell circle	The standard deviation of elevation values within a circular neighborhood with a radius of 100 cells.
Topographic postion index 1-cell square	Topographic position index using elevation values within the neighborhood immediately surrounding the center cell
Topographic postion index 10-cell radius	Topographic position index using elevation values within a circular neighborhood with a radius of 10 cells.
Topographic postion index 100-cell radius	Topographic position index using elevation values within a circular neighborhood with a radius of 100 cells.
Upper slope (warm) 1-cell mean	mean percent Upper slope (warm) in 1-cell mean (30 meter cells)
Upper slope (warm) 10-cell mean	mean percent Upper slope (warm) in 10-cell mean (30 meter cells)
Valley (narrow) 10-cell mean	mean percent Valley (narrow) in 10-cell mean (30 meter cells)
Valley 10-cell mean	mean percent Valley in 10-cell mean (30 meter cells)
Water cover 100-cell mean	mean open water cover within 100 cell radius
Woody wetlands 10-cell mean	mean woody wetland cover within 10 cell radius
Woody wetlands 100-cell mean	mean woody wetland cover within 100 cell radius

Appendix 2. Model details for reproducibility

- All R Scripts are available at github
- The repository version (repo head) used for this run was: e64daa9979d4eb0a3f7dd907c78173b2b87a3c8c
- The model run name was: ictimiss-br_20210811_130642
- R version: R version 4.1.0 (2021-05-18)
- Random seed for each model: 811130642

Table 1. Algorithm-specific details.

Name	value
Algorithm = rf	
number of predictors used	34
mtry	4
number of trees	2000
type of trees	classification
Algorithm = xgb	
number of predictors used	14
iterations	99
eta	0.3
max depth	3
gamma	0
colsample by tree	0.6
min child weight	1
subsample	0.75
objective	binary:logistic

Table 2. Reviewer star ratings for all model outputs of the accepted model version. More than one row for an algorithm indicates more than one reviewer. Average star ratings of 3 or more triggered the use of that algorithm in the final output.

model version	algorithm	star rating
ictimiss-br_20210811_130642	rf	4
ictimiss-br_20210811_130642	xgb	4