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PREDICTING THE LIKELIHOOD OF ALTERED STREAMFLOWS AT UNGAUGED RIVERS ACROSS THE CONTERMINOUS UNITED STATES

K. ENG[a]*, D. M. CARLISLE[b], D. M. WOLOCK[c] and J. A. FALCONE[d]

[a] *National Research Program, U.S. Geological Survey, Reston, Virginia USA*
[b] *National Water-Quality Assessment Program, US Geological Survey, Reston, Virginia USA*
[c] *National Water-Quality Assessment Program, US Geological Survey, Lawrence, Kansas USA*
[d] *National Water-Quality Assessment Program, US Geological Survey, Reston, Virginia USA*

ABSTRACT

An approach is presented in this study to aid water-resource managers in characterizing streamflow alteration at ungauged rivers. Such approaches can be used to take advantage of the substantial amounts of biological data collected at ungauged rivers to evaluate the potential ecological consequences of altered streamflows. National-scale random forest statistical models are developed to predict the likelihood that ungauged rivers have altered streamflows (relative to expected natural condition) for five hydrologic metrics (HMs) representing different aspects of the streamflow regime. The models use human disturbance variables, such as number of dams and road density, to predict the likelihood of streamflow alteration. For each HM, separate models are derived to predict the likelihood that the observed metric is greater than ('inflated') or less than ('diminished') natural conditions. The utility of these models is demonstrated by applying them to all river segments in the South Platte River in Colorado, USA, and for all 10-digit hydrologic units in the conterminous United States. In general, the models successfully predicted the likelihood of alteration to the five HMs at the national scale as well as in the South Platte River basin. However, the models predicting the likelihood of diminished HMs consistently outperformed models predicting inflated HMs, possibly because of fewer sites across the conterminous United States where HMs are inflated. The results of these analyses suggest that the primary predictors of altered streamflow regimes across the Nation are (i) the residence time of annual runoff held in storage in reservoirs, (ii) the degree of urbanization measured by road density and (iii) the extent of agricultural land cover in the river basin. Published 2012. This article is a U.S. Government work and is in the public domain in the USA.

KEY WORDS: human alterations; land use; urbanization; dams; altered flows

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INTRODUCTION

State and local resource managers must often balance the water needs of humans with those required to maintain ecosystem resources such as fisheries and recreation. One of the key controls on riverine ecosystem integrity is the streamflow regime (e.g. Power *et al.*, 1995; Walker *et al.*, 1995; Poff *et al.*, 1997). It is well documented that alterations to the natural streamflow regime are associated with ecosystem degradation (Bunn and Arthington, 2002; Konrad *et al.*, 2008; Carlisle *et al.*, 2010b; Poff and Zimmerman, 2010). Thus, sound management decisions about water allocations require an understanding of how streamflow (henceforth referred to as flow) alteration influences river biological communities (e.g. Poff *et al.*, 2010). Flow monitoring networks, such as those operated and maintained by the US Geological Survey (USGS), aid these management decisions but are limited to a small fraction of all river reaches in a given geographic area. To aid managers in understanding the pervasiveness of alterations to the flow regime beyond the limited networks, methods are needed to extend information from gauged to ungauged rivers. Because substantial amounts of biological data are already collected at ungauged rivers (e.g. USEPA, 2007), the ability to estimate flow information at ungauged rivers would allow these biological data to be used in evaluating the potential ecological consequences of altered flows (Poff *et al.*, 2010).

There are different approaches of varying complexity for deriving flow information for ungauged river segments. Watershed models (e.g. Kennen *et al.*, 2008; Poff *et al.*, 2010) are used to construct synthetic daily-time series of flow values, including both altered flows and expected natural flows. These synthetic time series can then be summarized by an array of statistics, or hydrologic metrics (HMs) (Poff *et al.*, 2010), that describe various characteristics of the flow regime. A major disadvantage of using watershed models to generate synthetic time series are that these models are often complex; they require many ancillary variables at a high temporal and spatial resolution, which are often difficult or costly to obtain.

*Correspondence to: Ken Eng, Research Hydrologist, National Research Program, US Geological Survey, 12201 Sunrise Valley Drive, Mail Stop 430, Reston, Virginia 20192, USA.
E-mail: keng@usgs.gov

Statistical approaches also are commonly used to estimate flow alteration. Unlike watershed models, statistical approaches, such as spatial interpolation or multiple-linear regression, are generally used to estimate HMs (natural and altered) directly rather than to synthesize daily-flow records (e.g. Thomas and Benson, 1970; Yuan, 2004; Eng and Milly, 2007; Carlisle *et al*., 2010a; Eng *et al*., 2011). Statistical approaches generally are simpler than watershed modelling, particularly if the statistical models are based on readily available data sources such as geospatial features of the catchment. Statistical models can be used to predict both expected natural and altered HMs if the natural features and human disturbance variables, such as climate, land use and water management features, can sufficiently describe the spatial variation and seasonal patterns in these metrics.

There are two general approaches in computing natural and altered HMs. First, a model is developed that includes both natural and human disturbance variables to predict observed, or altered, conditions. Predictions of natural HMs are then made by setting the human variables in these models to 'zero'. The use of statistical methods to estimate altered HMs and then deriving natural HM values from these models (or vice versa) is not novel (e.g. Sauer *et al*., 1983; McCuen, 1998; Fitzhugh and Vogel, 2010; Suen, 2011). An alternative to the aforementioned approach is to construct statistical models that estimate the *deviation* from natural conditions within a single model structure. Such an approach requires a consistent and objective method to describe deviations in HMs from natural conditions across large regions.

Our objective is to develop a statistical modelling approach that uses human disturbance of the watershed for a given river segment to predict the likelihood that it is hydrologically altered from its natural condition. We select five HMs that represent various aspects of the perennial flow regime. Predictive models for measures of the deviation of each HM from its natural condition are formed using human disturbance variables at 4196 gauged rivers across the United States. From these models, we are able to identify the important regional human disturbance variables to the flow regime and their general relation to the HMs. Two example applications of the models are presented: (i) for all river reaches within a single river basin (the South Platte River, Colorado) and (ii) for all 15 406 10-digit hydrologic units (HUC 10, USDA, 2010) in the conterminous United States.

STUDY AREA, HYDROLOGIC METRICS AND HUMAN DISTURBANCE VARIABLES

The 4196 gauged rivers used in this study are located throughout the conterminous United States (Figure 1). These rivers represent a wide range of climatic conditions and human disturbance, particularly with respect to hydrologic modification (Falcone *et al*., 2010). Gauged river locations that have a daily-flow record of at least 10 years in length during the period 1990–2009 are selected. The drainage areas of the gauged rivers range from 0.80 to 49 802 km^2 with a median of 718 km^2.

We select five HMs to represent different aspects of the flow regime: the annual (calendar year) 1-day maximum

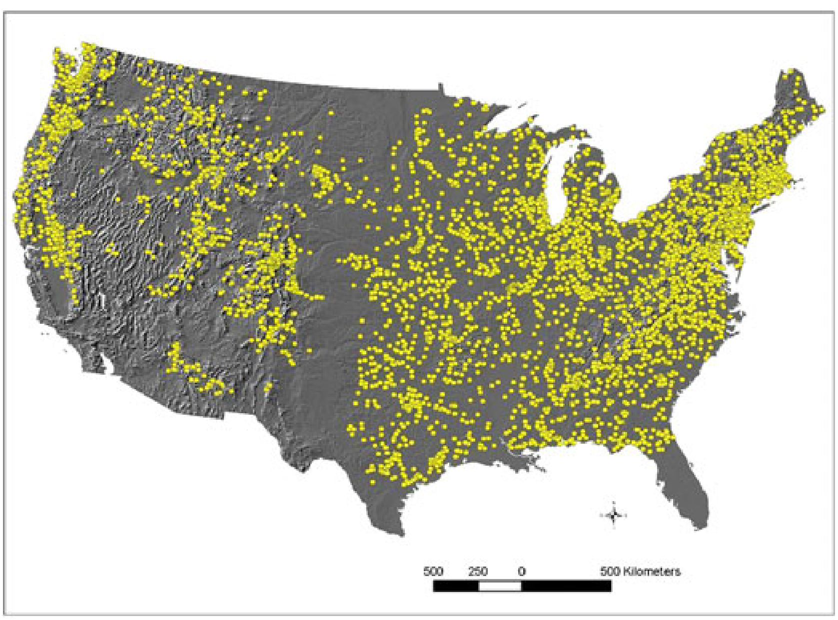

Figure 1. Circles represent US Geological Survey gauges on the 4196 gauged rivers used in this study. This figure is available in colour online at wileyonlinelibrary.com/journal/rra.

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daily flow (henceforth referred to as annual maximum), skew of daily flows in May (henceforth referred to as May skew) and average May, July and November flows. This selection is subjective and based on a review of HMs used in other studies of human disturbance on flows (e.g. Zhang and Schilling, 2006), as well as our desire to maintain a tractable yet illustrative analysis. One important criterion, however, is that we only consider HMs for which natural conditions can be accurately and precisely estimated. The five chosen HMs are calculated from the observed daily-flow values from the USGS National Water Information System website (http://waterdata.usgs.gov/nwis) using software that allows batch-mode retrieval and data formatting (GNWISQ version 1.0) (Granato, 2008).

Eighteen human disturbance variables are selected as potential predictors of altered flow (Table 1); these explanatory variables are described by Falcone (2011) and are available at http://water.usgs.gov/GIS/metadata/usgswrd/XML/gagesII_Sept2011.xml. The disturbance variables include the impacts of dams (reservoir storage and dam density), land-use intensity (land cover, impervious surfaces, population density, agricultural fertilizer application) and waste-water discharge points as identified in the National Pollutant Discharge Elimination System by the United States Environmental Protection Agency (http://cfpub.epa.gov/npdes/). A simple reservoir storage index (total reservoir storage, in volume/year, divided by estimated annual runoff, in volume/year) is used because detailed storage operations information is not available for most of the gauged sites.

PREDICTION OF THE LIKELIHOOD OF ALTERED FLOWS

The overall procedure of our modelling process is depicted in Figure 2. In general, the modelling effort is tiered because models for predicting flow alteration at ungauged rivers are first developed at gauged rivers, which requires estimates of the site-specific expectations of natural flows. Great care is taken in this two-phased approach to rigorously evaluate model performance at each step and minimize the effects of compounding error throughout the modelling process. Specific details of each step are described in the succeeding text.

Quantifying altered flows at gauged rivers

For each of the five HMs, the deviation of observed from expected natural conditions is quantified at each gauged river by dividing the observed (from 1990 to 2009) HM (O_{HM}) value by its expected natural (E_{HM}) value. The E_{HM} value is estimated with statistical models (e.g. Carlisle *et al*., 2010a) developed at 1035 gauged natural rivers. These models use a large number of natural features such as climate and topography to make predictions of E_{HM}. Independent validation of these random forest (RF) models revealed that, for the five HMs in this study, E_{HM} estimates are within 10% of observed values at gauged natural rivers, which indicates relatively low prediction error and minimal potential to increase the error in subsequent models.

Models for each E_{HM} are applied to 4196 gauged rivers that spanned a wide range of human disturbance (Falcone *et al*., 2010). The $O_{\mathrm{HM}}/E_{\mathrm{HM}}$ values quantify the average deviation from expected natural conditions at each gauged river and are used to then classify each gauge site as ‘diminished’ ($O_{\mathrm{HM}}/E_{\mathrm{HM}} <$ that of 90% of gauged natural rivers), ‘inflated’ ($O_{\mathrm{HM}}/E_{\mathrm{HM}} >$ that of 90% of gauged natural rivers) or ‘unaltered’ if $O_{\mathrm{HM}}/E_{\mathrm{HM}}$ is any other value. Although errors in the prediction of E_{HM} are <10%, some misclassification of gauged rivers is possible, especially for sites with $O_{\mathrm{HM}}/E_{\mathrm{HM}}$ values near the percentile (10% and 90%) cutoff values, which could add to error in the subsequent modelling. Independent validation of subsequent classification models is therefore critical and is undertaken as described in later sections.

Classification models for predicting likelihood of altered flows

In a second tier of modelling, RF classification models are formed to predict the diminished and inflated classes of flow alteration at gauged rivers by using a set of human disturbance variables (Table 1). The first step in building these models is to group highly correlated human disturbance variables. The predictions of RF classification models are not affected by high correlations among the human disturbance variables (Cutler *et al*., 2007), but high correlations do affect the evaluation of the relative importance of disturbance variables. Two groups of human disturbance variables are highly correlated (Spearman rank correlation, $|r| > 0.9$). The first group is associated with urban development and includes population density, road density, percentage of impervious cover and percentage of basin that is urbanized. The second group is associated with agricultural activities and includes percentage of basin used for agriculture, nitrogen fertilizer application rates and phosphorous fertilizer application rates. To minimize the effect of large correlations on the relative importance of the human disturbance variables, each model is formed using a set of 13 variables from a pool of 18:1 from the urban group, 1 from the agriculture group and 11 human disturbance variables that are not correlated with either group. All 12 possible combinations of sets of human disturbance variables (four urban variables multiplied by three agricultural variables) are tested in this study. The final set of human disturbance variables for each HM is identified by the set of variables that had the largest mean Gini index value across all RF (see *Performance*

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Table I. List of 18 human disturbance variables from Falcone (2011)

Human disturbance variable	Units	Abbreviation	Description
CHANGE_PCT	%	CHP	Per cent of land cover in watershed that changed between early 1990s and early 2000s (regardless of type of change), according to NLCD01 'Change Product'.
PDEN_2000_BLOCK[1]	persons/km^2	PDN	Population density in the watershed, persons per sq km, from 2000 Census block data regridded to 100 m.
NDAMS_2006	no. of dams	NDM	Number of dams in watershed, from our enhanced version of the 2006 National Inventory of Dams (NID).
DDENS_2006	no. of dams/100 km^2	DDS	Dam density.
STOR_2006	megaliters/km^2	STO	Dam storage in watershed (1 megaliters = 1 000 000 litres = 1000 cubic metres).
MAJ_NDAMS_2006	no. of dams	MDM	Number of 'major' dams in watershed. Major dams defined as being ≥ 50 ft in height (15 m) or having storage ≥ 5000 acre feet (617 hectare meter, National Atlas definition).
MAJ_DDENS_2006	no. of dams/100 km^2	MDS	Major dam density.
NPDES_MAJ_DENS	no. of sites/100 km^2	NPD	Density of National Pollutant Discharge Elimination System (NPDES) 'major' point locations in watershed. Major locations are defined by an EPA-assigned major flag. From download of NPDES national database summer 2006.
ROADS_KM_SQ_KM[1]	km/km^2	RDS	Road density from Census 2000 TIGER roads.
NLCD01_IMPERV_PCT[1]	%	IMP	Per cent impervious surfaces from 30-m resolution NLCD01 data.
BAS01_URBAN[1]	%	URB	Watershed percent 'urban', 2001 era.
BAS01_AG[2]	%	AGR	Watershed per cent 'agriculture', 2001 era.
NITR_APP_KG_SQKM[2]	kg/km^2	NIT	Estimate of nitrogen from fertilizer and manure, from Census of Ag 1997, on the basis of county-wide sales and percent agricultural land cover in watershed.
PHOS_APP_KG_SQKM[2]	kg/km^2	PHO	Estimate of phosphorus from fertilizer and manure, from Census of Ag 1997, on the basis of county-wide sales and percent agricultural land cover in watershed.
PESTAPP_KG_SQKM	kg/km^2	PES	Estimate of agricultural pesticide application (219 types), from Census of Ag 1997, on the basis of county-wide sales and percent agricultural land cover in watershed.
PADCAT1_PCT_BASIN	%	PC1	Per cent watershed in Protected Areas Database (PAD) Category 1 (GAP status 1): 'most protected lands': areas managed to maintain a natural state and within which natural disturbance events are allowed to proceed without interference. Primarily: National Park, National Monument, Wilderness Area, Nature Reserve/Preserve, Research Natural Area.
PADCAT2_PCT_BASIN	%	PC2	Per cent watershed in PAD Category 2 (GAP status 2): (somewhat less protected than Cat 1). Areas generally managed for natural values but which may receive uses that degrade the quality of existing natural communities. Primarily: State Parks, State Recreation Areas, National Wildlife Refuge, National Recreation Area, Area of Critical Environmental Concern, Wilderness Study Area, Conservation Easement, Private Conservation Land, National Seashore.
STOR_INDEX	yrs	STI	Average residence time of annual runoff held in storage behind dams.

[1]Indicates highly correlated variable (Spearman rank correlation > 0.90) for group 1 (urban).
[2]Indicates highly correlated variable (Spearman rank correlation > 0.90) for group 2 (agriculture).

metrics for classification models section), which measures the relative importance of the variables in the RF classification models.

RF classification models (Prasad *et al*., 2006; Cutler *et al*., 2007) are developed using the Matlab application (by Jaiantilal, 2009, available at http://code.google.com/p/

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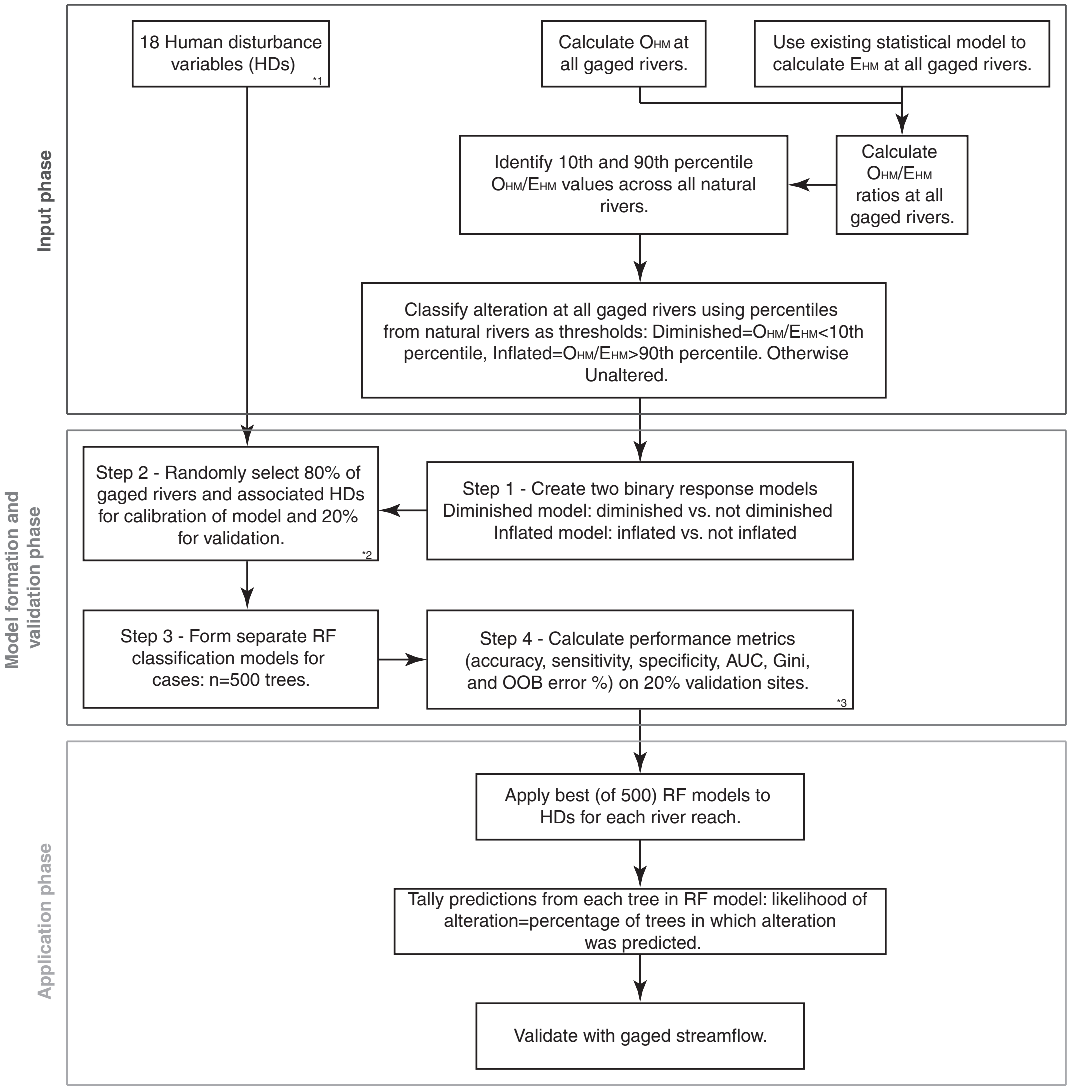

*1 Identify correlated groups of HDs. Use 12 different sets of HDs to form models. Each set contains all independent disturbance variables (=11) and 1 each from the urban and agriculture correlated groups.

*2 Formation of RF classification models (steps 2 to 4) is repeated 500 times for all sets of HDs for each HM.

*3 After steps 2 to 4 repeated 500 times, calculate average of all performance metrics. The largest AUC value is used to identify the best RF model. The best set of HDs is identified by the largest average Gini value.

Figure 2. Generalized flow diagram of modelling approach. HDs indicates human disturbance variables, O_{HM} indicates observed hydrologic metric, E_{HM} indicates estimated hydrologic metric at a natural river, RF indicates random forest, AUC indicates area under the curve and OOB indicates out-of-bag

randomforest-matlab/). Two binary RF classification models for each HM are developed: one model predicting diminished versus not diminished (which includes all unaltered and inflated sites) HM conditions henceforth called the 'diminished' model, and another model predicting inflated versus not inflated (which includes all unaltered and diminished observations) HM conditions henceforth called the 'inflated' model. In all cases, the binary classification is predicted using the sets of 13 human disturbance variables described previously.

For each binary RF classification model, 12 different versions of the model are produced because of the different pools of human disturbance variables. These different versions are formed to discern which combination of urbanization and agricultural variables, when combined with the remaining 11 human disturbance variables, yield the best predictive model. For each combination of variables, 500 RF classification models are formed using a randomly selected set of 80% of the 4196 gauged rivers to calibrate the model, and the remaining 20% of sites are used

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for model validation. This is performed so that the predictions from the models are not dependent on any particular configuration of the network of gauged rivers. Within each RF model, 500 individual trees are grown, and four human disturbance variables [(total number of human disturbance variables in set)$^{0.5}$ and rounded up to nearest whole number] are randomly selected at each split (Cutler *et al*., 2007).

Performance metrics for classification models

The performance of binary RF classification models is assessed with metrics (i.e. sensitivity, specificity, accuracy) calculated from confusion matrices on the basis of results of applying models to validation sites. Sensitivity is the percentage of correctly classified positive cases out of all positive cases, specificity is the percentage of correctly classified negative cases out of all negative cases and accuracy is the percentage of the correctly classified positive and negative cases out of all positive and negative cases. A positive case is defined as either the diminished or an inflated condition, and a negative case is defined as the not diminished or not inflated condition. Arithmetic averages of the accuracy, sensitivity and specificity values are also calculated across the 500 RF models.

An additional performance metric is the area under the curve (AUC) metric associated with the receiver operator curve approach (e.g. Hand and Till, 2001). The AUC metric is similar to the test statistic from the Mann–Whitney–Wilcoxon two sample test. Its value varies from 0 (low accuracy) to 1 (high accuracy), where a value of 0.5 indicates a model that predicts either class equally. A mean AUC value is calculated from the 500 RF classification models. The RF classification model with the largest AUC value is considered the best model and is the one applied to the South Platte River Basin and the HUC 10 units in the conterminous United States.

The mean out-of-bag (OOB) error percentages are also reported for every RF classification model constructed with the calibration data. For each individual classification tree in each RF, two-thirds of the observations are used to estimate the parameters of the tree, and the remaining third are placed OOB and classified through the tree as test cases. This procedure is repeated for all trees in the forest, and the per cent of cases incorrectly classified is calculated for each observation that is OOB. The mean OOB value for an RF classification model is calculated as the mean of all of the percentages of incorrectly classified observations.

The relative importance of human disturbance variables in the RF classification models is evaluated by measuring the loss of overall predictive accuracy when each disturbance variable in the model is randomized (Cutler *et al*., 2007). Loss of predictive accuracy is measured as the Gini index (Cutler *et al*., 2007), where increasing values of the index indicate increasing loss of predictive accuracy. The human disturbance variables are ranked in decreasing order of their Gini index values and generally produce one of two possible patterns. One common pattern is a significant decrease in Gini index values after one, or a few, of the top ranked human disturbance variables. In this case, the most important human disturbance variables are those listed prior to the substantial drop (subjectively defined as a decrease of at least 30% in the Gini index value). The second is a gradual decrease of the Gini index value across all human disturbance variables. In this case, the most important human disturbance variables cannot be identified.

Applications to the South Platte River Basin and HUC 10 units

We illustrate how models of flow alteration can be applied to ungauged rivers by generating predictions at two scales: a single river basin and the conterminous United States. The best RF classification model for the annual maximum flow is applied to every 30-m river reach in the South Platte River Basin, Colorado, to predict the likelihood that each reach has, on average, diminished annual maximum flows. The likelihood is defined as the fraction (0 to 1) of classification trees within the RF model that classified the river reach as having diminished maximum flows. The likelihood values are plotted using ArcMap version 9.2. Model performance in the South Platte for all HMs is evaluated by comparing model predictions with HMs calculated from actual daily flow data at 28 USGS gauged rivers that had been excluded from model development. Predictions of flow alteration across the conterminous United States are derived by calculating the human disturbance variables (Table 1) for every HUC 10 unit in the conterminous United States. The inflated model of average July flows is then applied to all HUC 10 units, and the likelihood of alteration are computed as just described.

RESULTS AND DISCUSSION

Model performance

In general, all inflated and diminished models perform substantially better (on the basis of average AUC values) than models that predicts either class equally (AUC = 0.5), but the diminished models performed consistently better than the inflated ones (Table 2). The best diminished models are annual maximum flow and average May flow, followed by average November and July flows and the May skew. The best inflated models are average July flow followed by average May flow, annual maximum flow, average November flow and the May skew. The relatively poorer

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Table II. Performance of the random forest (RF) classification models for five hydrologic metrics

Hydrologic metric (HM)	Number of cases: diminished/not diminished or inflated/not inflated	Average accuracy	Average sensitivity	Average specificity	Average area under the curve (AUC)	AUC of best RF model	Most significant human disturbance variables	Mean out-of-bag (OOB) % errors
RF classification model for diminished versus not diminished (unaltered & inflated) conditions								
May skew	1192/3004	0.81	0.75	0.82	0.72	0.75	NA	18.82
Annual maximum flow (DA)	1673/2523	0.83	0.81	0.84	0.81	0.86	STI^{+}	15.69
Average May flow (DA)	812/3384	0.90	0.83	0.90	0.77	0.82	STI^{+}, RDS^{-}, & AGR^{-}	10.33
Average July flow (DA)	674/3522	0.89	0.77	0.90	0.71	0.77	RDS^{-} & STI^{+}	11.29
Average November flow (DA)	678/3518	0.91	0.84	0.91	0.75	0.81	STI^{+} & RDS^{-}	9.54
RF classification model for inflated versus not inflated (unaltered & diminished) conditions								
May skew	564/3632	0.88	0.66	0.89	0.61	0.64	RDS^{+}	13.01
Annual maximum flow (DA)	370/3826	0.93	0.67	0.94	0.65	0.72	RDS^{+}	7.75
Average May flow (DA)	592/3604	0.89	0.70	0.90	0.66	0.74	AGR^{+}, RDS^{+}, & PES^{+}	11.52
Average July flow (DA)	986/3210	0.83	0.74	0.84	0.69	0.75	RDS^{+} & AGR^{+}	16.36
Average November flow (DA)	599/3597	0.88	0.70	0.89	0.62	0.68	RDS^{+} & CHP^{+}	12.28

NA indicates that there was no substantial decrease in the Gini index among the top ranked predictors.
(DA) indicates that the hydrologic metric is normalized by drainage area.
STI indicates storage intensity, RDS indicates road density, AGR indicates percent of basin used for agriculture, PES indicates the agricultural pesticide applications and CHP indicates per cent of land cover in watershed that changed between early 1990s and early 2000s (regardless of type of change).
'+' indicates a general positive relation and a '−' indicates a general negative relation.

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performance of the inflated models may have been caused by having so few sites in the data set where HMs are inflated (Table 2).

Predictors of altered flows

Three primary factors—storage index (STI), road density (RDS) and percentage of basin used for agriculture (AGR)—are consistently influential in predicting flow alteration across the conterminous United States (Table 2). Increased reservoir storage intensity is associated with increased likelihood of diminished annual maximum flow and diminished May, July and November average flows. In contrast, reservoir storage intensity is not a significant predictor of inflated flows for any of the flow metrics considered.

The significant effect of reservoir storage intensity on diminished annual maximum flow is consistent with other studies showing that dams reduce peak flows (Ye *et al*., 2003; Yang *et al*., 2004; Poff *et al*., 2007). This result is not surprising given that one of the primary functions of reservoir storage is flood control. The finding that increased reservoir storage is a predictor of diminished average flows for May, July and November may be related to reservoir effects on peaks as average flows are often correlated with peak flows. In addition, the relation between reservoir storage and diminished average flows may be due to the use of water stored in reservoirs for consumptive uses such as irrigated agriculture.

Road density is associated with streamflow alteration in two ways. First, the likelihood of diminished annual maximum flow and diminished May, July, and November average flows declines as RDS increases. Second, the likelihood of inflated flows for all of the metrics considered (May skew, annual maximum flow and average May, July and November flows) increases as RDS increases. Other studies (e.g. Burns *et al*., 2005; Konrad *et al*., 2005; Poff *et al*., 2006) have also reported that RDS, which is related to the extent of impervious cover in a watershed, increases the likelihood of inflated flows primarily by increasing the amount of direct runoff to rivers and by decreasing the amount of recharge to aquifers.

The likelihood of inflated summer flows (represented by the average July flow) increases in basins with a larger extent of agricultural land cover. One explanation for this result is the hydrological changes associated with the transition from perennial vegetative cover to crop production during the summer growing season. Crop lands generally increase recharge to groundwater and decrease evapotranspiration compared with perennial vegetation, and these increases in baseflow are associated with increases in mean

Table III. Observed alteration of hydrologic metrics (HMs) and their correct classification by statistical models at 28 gauged rivers in the South Platte River, Colorado, USA. This table is available in colour online at wileyonlinelibrary.com/journal/rra.

USGS Streamgage No.	Name	LATITUDE	LONGITUDE	Years of Record (1990-2009)	Observed Altered Hydrologic Metric: May skew	Annual maximum flow (DA)	Average May flow (DA)	Average July flow (DA)	Average November flow (DA)
06701500	SOUTH PLATTE RIVER BELOW CHEESMAN LAKE, CO.	39.209	-105.268	14	Unaltered	Diminished	Diminished	Diminished	Diminished
06709530	PLUM CREEK AT TITAN RD NR LOUVIERS, CO	39.507	-105.024	19	Diminished	Diminished	Diminished	Diminished	Diminished
06710385	BEAR CREEK ABOVE EVERGREEN	39.633	-105.337	19	Unaltered	Diminished	Diminished	Diminished	Unaltered
06710500	BEAR CREEK AT MORRISON, CO.	39.653	-105.196	17	Unaltered	Diminished	Diminished	Diminished	Unaltered
06710605	BEAR CREEK ABOVE BEAR CREEK LAKE NEAR MORRISON, CO	39.652	-105.174	19	Unaltered	Diminished	Diminished	Diminished	Diminished
06711500	BEAR CREEK AT MOUTH, AT SHERIDAN, CO.	39.652	-105.033	17	Unaltered	Diminished	Diminished	Diminished	Diminished
06711565	SOUTH PLATTE RIVER AT ENGLEWOOD, CO.	39.665	-105.004	19	Inflated	Diminished	Diminished	Diminished	Diminished
06714000	SOUTH PLATTE RIVER AT DENVER, CO.	39.760	-105.003	17	Inflated	Diminished	Diminished	Diminished	Diminished
06714215	SOUTH PLATTE R AT 64TH AVE. COMMERCE CITY, CO.	39.812	-104.958	19	Inflated	Diminished	Diminished	Diminished	Diminished
06716500	CLEAR CREEK NEAR LAWSON, CO.	39.766	-105.626	14	Diminished	Diminished	Diminished	Unaltered	Unaltered
06719505	CLEAR CREEK AT GOLDEN, CO.	39.753	-105.235	19	Unaltered	Diminished	Diminished	Unaltered	Unaltered
06720500	SOUTH PLATTE RIVER AT HENDERSON, CO.	39.922	-104.868	17	Inflated	Diminished	Diminished	Diminished	Diminished
06725450	ST. VRAIN CREEK BELOW LONGMONT, CO.	40.158	-105.014	19	Inflated	Diminished	Diminished	Unaltered	Unaltered
06730200	BOULDER CR AT NORTH 75TH ST NR BOULDER	40.052	-105.179	19	Inflated	Diminished	Diminished	Unaltered	Unaltered
06730500	BOULDER CREEK AT MOUTH, NEAR LONGMONT, CO.	40.152	-105.015	18	Inflated	Diminished	Diminished	Diminished	Unaltered
06738000	BIG THOMPSON R AT MOUTH OF CANYON, NR DRAKE, CO.	40.422	-105.227	17	Inflated	Diminished	Diminished	Diminished	Unaltered
06741510	BIG THOMPSON RIVER AT LOVELAND, CO.	40.379	-105.061	19	Inflated	Diminished	Diminished	Diminished	Diminished
06746095	JOE WRIGHT CREEK ABOVE JOE WRIGHT RESERVOIR, CO.	40.540	-105.883	19	Unaltered	Inflated	Unaltered	Inflated	Unaltered
06746110	JOE WRIGHT CREEK BELOW JOE WRIGHT RESERVOIR, CO.	40.562	-105.864	19	Inflated	Unaltered	Diminished	Inflated	Inflated
06751490	NORTH FORK CACHE LA POUDRE R. AT LIVERMORE, CO	40.787	-105.252	19	Inflated	Diminished	Diminished	Diminished	Diminished
06752000	CACHE LA POUDRE R A MO OF CN, NR FT COLLINS, CO.	40.664	-105.224	17	Unaltered	Diminished	Diminished	Unaltered	Diminished
06752260	CACHE LA POUDRE RIVER AT FORT COLLINS, CO.	40.589	-105.070	19	Inflated	Diminished	Diminished	Diminished	Diminished
06752280	CACHE LA POUDRE R AB BOXELDER C, NR TIMNATH, CO.	40.552	-105.011	19	Inflated	Diminished	Diminished	Diminished	Diminished
06754000	SOUTH PLATTE RIVER NEAR KERSEY, CO.	40.412	-104.563	17	Inflated	Diminished	Diminished	Diminished	Diminished
06712000	CHERRY CREEK NEAR FRANKTOWN, CO.	39.356	-104.763	20	Inflated	Diminished	Diminished	Diminished	Diminished
06713000	CHERRY CREEK BELOW CHERRY CREEK LAKE, CO.	39.654	-104.863	15	Inflated	Diminished	Diminished	Diminished	Diminished
06713500	CHERRY CREEK AT DENVER, CO.	39.742	-105.000	20	Inflated	Diminished	Diminished	Diminished	Diminished
06720820	BIG DRY CREEK AT WESTMINSTER, CO	39.906	-105.035	18	Unaltered	Unaltered	Unaltered	Inflat/correct	Unaltered
	Mean Out-of-Bag % Error from RF Classification Models for 28 gaged rivers (Diminished vs. Not Diminished)				14.9	5.1	4.4	18.6	14.3
	Mean Out-of-Bag % Error from RF Classification Models for 28 gaged rivers (Inflated vs. Not Inflated)				33.8	16.1	10.1	25.2	21.3

(DA) indicates that the hydrologic metric is normalized by drainage area.
Indicates both estimates from diminished and inflated RF models agree with observed condition.
Indicates one estimate from either diminished or inflated RF models agree with observed condition.
Indicates neither estimates from diminished and inflated RF models agree with observed condition.

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flows (Zhang and Schilling, 2006). In addition, the presence of tile drains used in agriculture, such as those throughout the corn belt, also would increase the amount of runoff to rivers.

Predicted flow alteration in the South Platte Basin

In general, predictions for the South Platte River Basin are most accurate for the diminished models (Table 3). Performance of the models for May skew and the average July and November flows are poorer than models of annual maximum and average May flows. The inflated flow conditions are not predicted as well as diminished conditions in this basin because of the scarcity of inflated conditions throughout the model calibration data set. Out of the 140 observed HM values (28 gauges multiplied by 5 HMs), 23% are misclassified by either the diminished or the inflated model, and 3% are misclassified by both models. The remaining cases (74%) are correctly classified.

Overall, nearly one-third (28%) of river reaches in the South Platte River Basin are predicted to have diminished annual maximum flows (likelihood > 50%, Figure 3). There appears to be a greater prevalence of diminished annual maximum flows in the larger downstream segments than in the smaller headwater segments. One exception to this pattern is the southernmost headwater portions of the basin, which include many high-elevation agricultural areas and associated impoundments that likely reduce maximum flows.

Predicted flow alteration in HUC 10 units

The likelihood of inflated average July flows shows strong geographic patterns across 10-digit HUCs of the conterminous United States (Figure 4). In general, inflated July flows are predicted to occur in geographic areas with intensive agricultural activity such as the central United States or in urban settings. Both of these human impacts are associated with increasing the average flow in summer as noted earlier. Our predictions for hydrologic units are based on coarse generalizations of the land uses within them, and unlike the South Platte example, do not pertain to any single river segment. Nevertheless, maps such as Figure 4 can be developed for a variety of HMs and used to identify broad geographic patterns in various types of flow alteration. In addition, broad-scale patterns in altered flows could be juxtaposed with maps for key ecological indicators such as distributions of imperilled aquatic species, which may show substantial spatial overlap and potential causal associations. Maps would also be useful for designing regional studies targeted at specific types of altered flows.

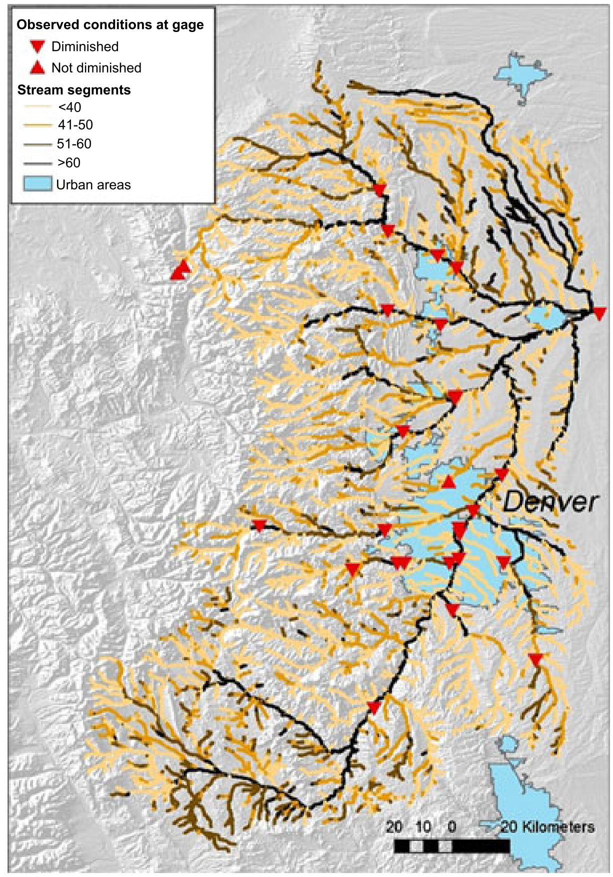

Figure 3. Likelihood (defined as the percentage of votes from the best random forest classification model) of diminished annual maximum flow for each 30-m stream reach in the South Platte River Basin, Colorado. This figure is available in colour online at wileyonlinelibrary.com/journal/rra.

CONCLUSIONS

Flow is widely recognized as a key factor in river health but is not measured in the vast majority of rivers. This information gap hinders the ability of scientists and resource managers to determine where and when altered flows are a potential cause of poor river health. We found that statistical models predicting flow alteration can be developed within the river gauging network and applied with relatively high confidence to ungauged river segments across broad geographic areas. Applied in this way, statistical models can be used to identify where the likelihood of flow alteration is high--from the scale of specific river segment within a river basin or across a continent. Our study examines only a few aspects of the flow regime, but the modelling approach may be applicable to the plethora of HMs cited in various investigations.

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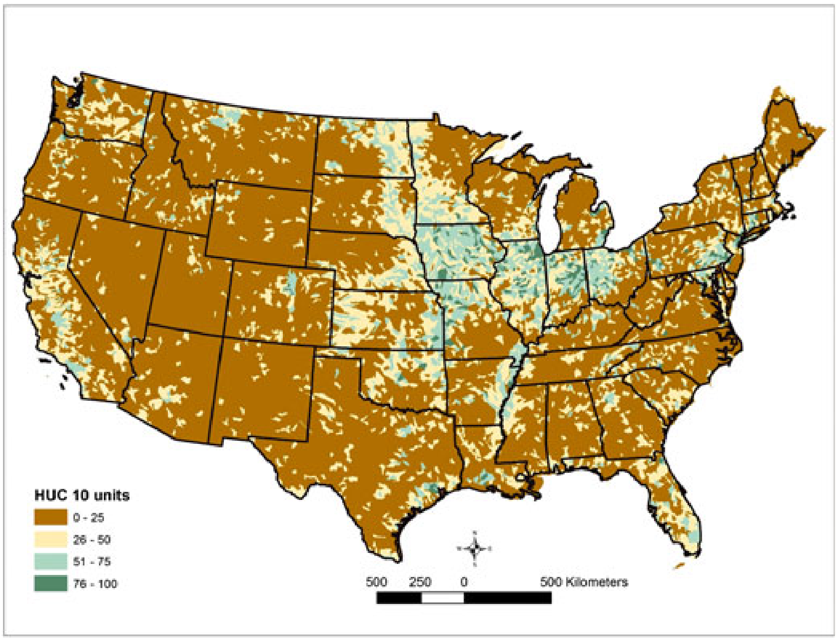

Figure 4. Likelihood (defined as the percentage of votes from the best random forest classification model) of inflated average July flow for 15 406 10-digit hydrologic units in the conterminous United States. This figure is available in colour online at wileyonlinelibrary.com/journal/rra.

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