General regression neural networks to estimate hydromodification response in semi-arid southern California streams

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Abstract

Changes in basin hydrology often result in geomorphic impacts to receiving channels, typically manifested as channel widening, deepening or both. Estimating these effects using traditional deterministic models is challenging due to the high number of factors that influence channel response and the highly stochastic nature of the responses. In this study we present General Regression Neural Network (GRNN) models as an additional tool to predict the effects of hydromodification in semi-arid streams of southern California. We developed GRNN models to predict the change in the stream channel cross section area using flows for 2, 10, 50, and 100-year return intervals as the primary independent variable, and compared the output to results of linear Multivariate Regression models (MVR) for the same region. Models were compared in terms of their predictive ability, sensitivity, and capacity to accommodate missing input data. Results show that the GRNN approach consistently outperforms the MVR by large margins as indicated by higher correlation with field validation data. GRNN analysis showed that the primary drivers of channel response to hydromodification vary depending on which flood return interval is included as the primary independent variable. Furthermore, variable-ranking properties of GRNN allowed us to reduce the number of predictor variables from 100 to the 29 to 40 most responsible for channel response (depending on the return interval). Our results suggest that GRNN predictions can be used in concert with other tools to help inform management decisions, such as the need for flow-duration based stormwater controls, and to tailor monitoring programs.

Introduction

Hydromodification is defined as the change in the channel form and hydraulic regime associated with change in the land use in a given watershed (Bledsoe *et al.* 2010). The semiarid systems of southern California are particularly susceptible to effects of hydromodification (Coleman *et al.* 2005, Hawley and Bledsoe 2011, Hawley *et al.* 2012), due to presence of channels that actively transport bedload sediment, historical overgrazing, lack of stabilizing vegetation, and relatively steep gradient channels with less resistant beds and banks than humid temperate settings, among other factors (Trimble 1997, Bull 1997, Bledsoe *et al.* 2012). This susceptibility can result in dramatic channel enlargement of up to 1,000% increase in cross-sectional area following small to moderate loss of pervious surfaces (Coleman *et al.* 2005, Hawley 2009). Other amplified stochastic responses, such as spasmodic sediment movements and extended aggradation/degradation phases are common in these systems (Bledsoe *et al.* 2002). As a result of these responses, most jurisdictions in

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California and many other states are now required to address the effects of hydromodification as conditions of either a municipal storm-water permit or a statewide general permit (Stein *et al.* 2012).

Controlling effects of hydromodification often involves management practices aimed at reducing runoff, retaining or detaining flows, and in rare cases controlling sediment flow to streams (Stein *et al.* 2012, Hawley 2012). Typical hydromodification control measures, such as flow control basins, may be quite large and can involve substantial cost to build and maintain. In order to optimize the size, location, and design of these facilities, it is important to understand their hydrologic/hydraulic performance and the resultant effect on the receiving streams. The former can be modeled through traditional tools such as HEC-RAS (Hydrologic Engineering Centers River Analysis System) or BASINS (Better Assessment Science Integrating point and Nonpoint Sources). However, modeling the effect of runoff retention/detention on the geomorphology of the streams to which they discharge is much more challenging (Novotny 2003, Yousef *et al.* 1986).

Traditional stormwater runoff models tend to inaccurately predict or ignore the effects of hydromodification because they are built on the tenet that most streams are in a state of dynamic equilibrium (Schumm 1977). These models mathematically simulate the sub-processes and physical mechanisms that govern the hydrological cycle. Processes included are non-linear, time-invariant, and deterministic, built with parameters representative of the watershed characteristics (Hsu *et al.* 1995, Zealand *et al.* 1999), and a predictable progression of responses is expected in a channel due to shift in equilibrium. However, when a channel is already unstable or not in a state of dynamic equilibrium prior to the disturbance of concern, the change in geomorphology of the channel is substantially more difficult to predict and traditional models may result in inaccurate representations of the system as they often do not account for mechanisms such as channel headcut migration about a downstream channel hardpoint such as bedrock or artificial grade control (e.g., Hawley 2009, Hawley *et al.* 2012). Given the spatially distributed, time varying, and stochastic responses of hydromodification, traditional models and concepts are particularly challenging for use in semi-arid systems of southern California.

To address the difficulty in using mechanistic models, the United States Geological Survey (USGS) and other agencies have adopted non-mechanistic, statistical models, such as multivariate power functions via regression analysis to quantify peak flows and durations, and the relationship with hydromodification (Hawley and Bledsoe 2011), as well as corresponding channel enlargement (Hawley 2009) and evolutionary trajectories (Hawley *et al.* 2012). These models have the advantage of providing empirically derived relationships, but typically depend on the strength of the calibration data set and provide only a single assessment endpoint (as opposed to mechanistic models which can better represent change at multiple points in time). Additionally, multivariate regression (MVR) is data-intensive--to model a process affected by multiple variables, a very large dataset quantifying all the relationships are required (Baker and Richards 1999).

Neural network (NN) models have the potential to improve performance over regression analysis for hydromodification assessment. NNs models can be superior to MVR because they perform better given limited datasets (Santos *et al.* 2005) and have a better ability to capture non-linearity and stochasticity (Maier and Dandy 2000). NN have the added advantage of being able to easily rank variable importance, thereby facilitating model optimization through elimination of variables with low predictive influence. NNs have been successfully used in hydrology-related areas such as rainfall-runoff modeling, stream flow forecasting, ground-water modeling, water quality, water management policy, precipitation forecasting, hydrologic time series, and reservoir operations (Hsu *et al.* 1995, Burrough and McDonnell 1998, Moradkhani *et al.* 2005, Govindraju and Rao 2000). Halff *et al.* (1993) designed three-layer feed-forward artificial neural networks using the observed rainfall hyetographs as inputs to predict hydrographs that were validated with the USGS flow data. Zhang and Govindraju (2000) used modular NNs for predicting rainfall-runoff over watersheds assigning probabilistic interpretation to the modular networks using Bayesian principles and found that the neural networks can serve as a good alternative to traditional methods of rainfall-runoff predictions. Though the application of NNs in various forms of hydrological issues is widespread, it has not been previously applied to predict the effects of hydromodification on channel cross-sectional geometry. Because stream channels are known to exhibit both discontinuous (e.g., geomorphic thresholds sensu Bledsoe and Watson 2001) and nonlinear behavior (Knighton 1998), NNs may have particular utility to hydromodification modeling.

Specific goals of this paper are as follows: 1) test the efficacy of NNs for predicting changes in stream channels due to hydromodification; 2) compare the NN model performance to an existing/optimized MVR model, and 3) identify and rank important variables with the greatest impact on hydromodification and change in channel cross-sectional area.

Methods

Study Domain

This study focuses on semi-arid to arid streams in the coastal region of southern California. The area has a typical Mediterranean climate; with average annual rainfall of 38 cm (15 in), occurring mostly between December and March. The proximity of high mountain peaks to the coast results in brief, high intensity runoff rainfall (Nezlin and Stein 2005) and runoff regimes with short-lived instantaneous peak flows that are much larger compared to corresponding mean daily flows (Hawley and Bledsoe 2011).

We selected thirty one sites (Figure 1), located in watersheds sized less than ~100 mi^2 to study the impact of hydromodification. The watersheds are in various stages of urbanization ranging from undeveloped, developing/recently-developed, to fully developed. Channels in these watersheds range from stable single-thread to incising, widening, and braiding stages of evolution. We excluded larger watersheds affected by dams and diversions or those with engineered channels in an attempt to isolate the effects of urbanization in relatively unhindered settings.

We collected physical data from 84 geomorphologically distinct sub-reaches spread over the 31 sites selected for model development. Channel cross-sections and measures of bank and bed stability were collected along 1- to 2-km reaches at each site according to the methods described in Hawley (2009), modeled after Harrelson *et al.* (1994) and Bunte and Abt (2001 a,b). Briefly, all grade breaks along the channel thalweg were captured

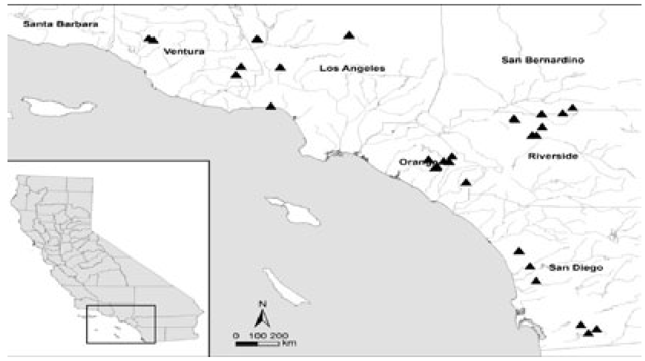

Figure 1. Study sites for hydromodification southern California.

including heads and toes of riffles, knickpoints, and other bedform features. Important lateral transitions were also measured such as bends, thalweg crossings, etc. The large number sub-reaches were included to capture the substantial differences in channel form that often occur over a 2 km channel segment. The additional cross-sectional measurements were used to improve model training and calibration. Historical and present-day aerial photography from the USGS and Google Earth were used to track changes through time, along with historical USGS quadrangle topographic maps.

Model Development

We used General Regression Neural Networks (GRNNs) embedded in the commercially available software, Decision Tree and Regression (DTREG; Sherrod 2003) for our simulations. Though, NNs models can be trained with a finite amount of data (significantly less than MVR) if the training data is fragmented or discontinuous, NNs models can become data intensive. GRNNs rely on one-pass learning algorithms and perform comparably to common multilayer perceptron based NNs using a smaller training dataset. The model structure and functionality are described in details in the DTREG manual (Sherrod 2003) and is briefly summarized here. There are four layers in the GRNNs model (Figure 2): input layer, training layer, pattern/summation layer, and decision layer. There is one neuron for each predictor variable that feeds the value to the associated neurons in the training layer. For the *x* vector of input values, the training neuron computes the Euclidean distance of the test case from the neuron's center point and then applies a radial basis function (RBF) kernel function using assigned sigma value(s) that is transmitted to the neurons in the pattern layer.

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{z\sigma^2}} g(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{z\sigma^2}} \quad \text{Eq. 1}$$

where g(x) is the Gaussian function, σ is sigma value that controls the radius of influence.

There are only two neurons in the pattern layer of GRNNs, a denominator summation unit and a numerator summation unit. The denominator summation unit adds up the weight values coming from each of the hidden neurons. The numerator summation unit adds up the weight values multiplied by the actual target value for each hidden neuron. The decision layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit to predict the target variable.

Target Variable Selection

There are many ways of quantifying hydromodification effects in a given channel or watershed. In this study, change in the channel cross-sectional area (i.e., $A_{post} - A_{pre}$) was selected as the most representative indicator of the extent of hydromodification, as a measure of both vertical incision and lateral widening. Pre-development area (A_{pre}) was estimated using historic aerial photographs and maps available from Seamless Data Warehouse of the US geological Survey (USGS), Cal-Atlas, Google Earth, the National Oceanic and Atmospheric Administration, and the Natural Resources Conservation Service, along with field indicators and testimony from local residents. Post Development area (A_{post}) was estimated based on current measurements of channel area and is the target variable in the GRNN model. The performance of the model was based on comparison of the actual change to the predicted change in the channel area (A_{post}-A_{pre}).

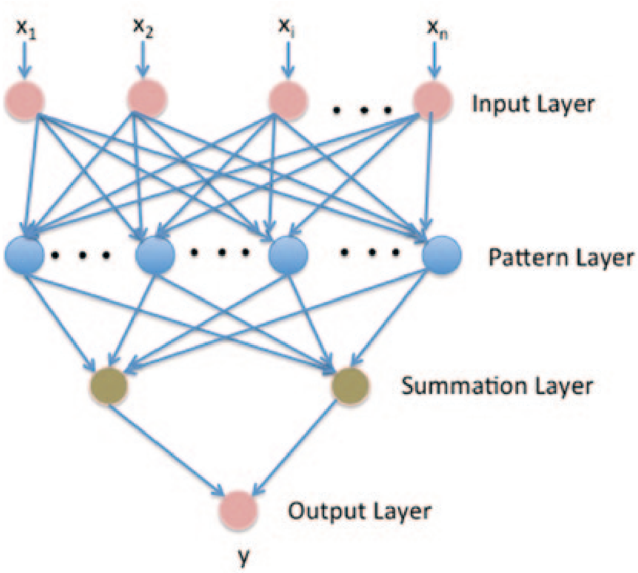

Figure 2. Layers in a general regression neural network.

Predictor Variable Selection

We used approximately 100 quantifiable hydrogeomorphic metrics measured or calculated across varying temporal and spatial scale as predictor variables. We classified the predictor variables in five broad categories: 1) watershed based parameters, 2) valley setting parameters, 3) stream based parameters, 4) climate based parameters, and 5) urbanization extent. For brevity, a truncated list of commonly used physical parameters for predicting hydromodification effects in channels from each of the categories is presented in Table 1 (see Hawley (2009) for a more expansive list).

Model Training

We trained the GRNN model iteratively with equal weights allocated to each predictor variable at the start of the simulation to eliminate bias. The network was pruned by removing the ten least important predictor variables at the end of each simulation. The model was then retrained with the pruned dataset until the GRNN achieves minimum absolute simulation error for the highest value of coefficient of determination, R^2. This process reduces the number of neurons, increases GRNN efficiency, and parses out the important variables.

An important sub-step of training the network is selecting a method to deal with missing predictor variable values. The easiest and perhaps the most accurate way is to exclude equations built on the rows with missing data. However, in the real world, complete datasets for all the predictor variables are a rarity and a reliable method of supplementing data is required to ensure successful model simulation convergence. We used surrogate variables to compute the missing predictor values. The surrogate variable is usually a different predictor variable that shows high collinearity/association with missing predictor variable. At each simulation step the collinearity/association between all the predictor variables are computed and assigned values between 0 and 100. In case of a missing data point the GRNN model is able to estimate a value

Table 1. Predictor variables by categories.

Watershed Based Parameters	Stream Based Parameters	Climate Based Parameters	Urbanization Extent	Valley Setting Parameters
Total Drainage Area	Flow	Watershed Area-Avg Annual Precipitation	Total Impervious Area	Valley Width
Total Stream Length	Stream Power, Shear Stress	NOAA 2YR 6HR Volume	Channelized or Artificial Length of Stream	Valley Expansion Ratio
Avg Surface Slope in Watershed (degrees)	Critical Flow for Sediment Transport	NOAA 2YR 24HR Volume	Local Road Length 2007	Width of Active Floodplain
Total %Burned in Last 5 Years	Distance to Downstream Hardpoint	NOAA 100YR 6HR Volume	Road Length of Major Roads	Sinuosity
	Median Bed Material			Valley Slope

using the strongest surrogate predictor, with at least >80 collinearity/association.

Calibration/Validation and Sensitivity

We built several GRNNs models to predict the change in the channel area resulting from watershed urbanization using alternative variables as the primary independent variable for each model. Because flow is the primary, process-based variable linking the watershed to channel form, representative flows were used as our primary independent variable for each model. Flows for 2-, 10-, 50-, and 100-yr recurrence-intervals that were calculated after Hawley and Bledsoe's (2011) models developed from 43 USGS gages in Southern California. The peak flows of these recurrence intervals correspond to combinations of frequency, duration, and magnitude of erosive energy that can correspond to a large proportion of the total cumulative work on semi-arid channels, especially the 2- to 10-year recurrence levels (Hawley 2009, Santa Clara 2004, San Diego 2011), and likely play an important role in shaping their morphologies (*sensu* Wolman and Miller 1960). Therefore we used similar GRNN setup for all recurrence interval flows to parse out the change in the influence of an individual term over different return periods, and to evaluate which recurrence interval flows had the greatest efficacy in explaining channel enlargement. There are countless model designs that could be tested in future studies, such as using the relative change in flow magnitude between post-developed and pre-developed states; however, because watershed imperviousness had decreasing levels of influence with increasing flow recurrence interval in the Hawley and Bledsoe (2011) models, designing the GRNNs in this way implicitly tested the influence of watershed urbanization on channel enlargement—a central objective to our regional hydromodification management program.

The number of sites and target variables are constant for the four GRNNs models, but the number of predictor variables is dependent on the interplay of individual variables with a given flow recurrence interval. We used a random 20% holdback method with a 67/17 split ($n_{calibration}/n_{validation}$) for most of the simulations. Additionally, we calibrated and validated the GRNNs against sets of selected channels ($n_{calibration} = 70$, $n_{validation} = 14$) at different stages of hydromodification as defined by the channel evolution model developed by Hawley *et al.* (2012).

Sensitivity analysis of the GRNNs networks is essentially an extension of the network training process described previously. For each set of GRNNs, we removed the predictor variables of least importance (significance 0.0-0.0001 in the parameter ranking) after each simulation until the model performance starts declining. Additionally, we tested the GRNNs sensitivity to the important predictor variables by removing them from optimized simulations.

Multivariate Regression Model (MVR)

We built four comparable linear MVR models based on same return intervals: MVR Q2, MVR

Q10, MVR Q50, and MVR Q100, using the DTREG software. The target variable for MVR models is the same as the GRNNs models: change in channel area ($A_{post} - A_{pre}$). Similar to the GRNNs, we used a random 20% holdback method with a 67/17 split ($n_{calibration}/n_{validation}$) for the MVR simulations. MVR lacks the ability to find and replace missing values with surrogates and excludes the watershed subsegment with any missing predictor variable. Therefore, we removed columns for predictor variables with >10 missing data points, and rows for watersheds subsegments with >5 missing predictor variable values. This preprocessing is important since there are only 84 datapoints (watershed subsegments) and approximately 100 predictor variables resulting in convergence error. Beyond excluding variables with missing data, no other distinctions between input datasets existed between the GRNNs and the MVR models. That is, no variable transformations were undertaken in either model, underscoring the ability of the GRNNs to implicitly account for non-normal distributions in variables such as flow and drainage area (variables that are typically log-transformed in MVR models.

Model Comparison

The GRNN and the MVR model were compared based on the ability of the model to predict the change in the stream channel area for each given recurrence interval flow, using the absolute error of prediction and R^2 values for calibration and validation runs. Although the structure of the models, i.e., the target variable and predictor variable data set, are identical for GRNNs and MVR, there are some differences, such as, the number of predictor variables in the final simulation. The goal was to compare the simulation results for the best fit and the least error, and both the GRNNs and MVR were allowed to reach that state with respective number of predictor variable.

Results

Model Performance

The GRNN models performed relatively well for all return intervals evaluated; however, the number of predictor variables required for the most optimized validation run are different for each of the four GRNNs models. The validation R^2 values for the four return interval GRNN models range from 0.60 to 0.73 (Table 2). The GRNN Q2 optimized with a 29 predictor variable network with a mean absolute error (MAE) of 13.75 and R^2 of 0.70, whereas, the GRNN Q10, Q50, and Q100 reach an optimized minimum error state with approximately 40 predictor variables (Table 2) and absolute error values ranging between 7.0 and15.0. The GRNNs performance measured in terms of R^2 remains stable even when the networks are further pruned though the absolute error increases until the number of predictor variables is <10, at which point the performance sharply decreases (R^2 approximately~0.01 - 0.06; Table 2; Figure 3).

Linear MVR models require larger number of predictor variables and data points to converge, although power MVR models built from log-transformed variables would have likely been more robust. The most optimized MVR Q2 run is observed with a network built on 42 variables with a R^2 value of 0.24. The higher MVRs-Q10, Q50, and

Table 2. Calibration/validation and pruning results for GRNN and MVR model.

	Model Type	Number of Predictor Variables	Calibration (R^2)	Validation (R^2)
Q2	GRNN	100	0.99	0.72
	GRNN	29	0.83	0.70
	GRNN	5	0.54	0.06
	MVR	42	0.96	0.24
Q10	GRNN	71	0.94	0.73
	GRNN	44	0.86	0.70
	GRNN	5	0.60	0.02
	MVR	15	0.9	0.00
Q50	GRNN	82	0.99	0.71
	GRNN	42	0.88	0.63
	GRNN	5	0.60	0.01
	MVR	32	0.94	0.20
Q100	GRNN	92	0.99	0.70
	GRNN	38	0.90	0.71
	GRNN	5	0.64	0.02
	MVR	20	0.94	0.20

*GRNN- General Regression Neural Network, MVR-MultiVariate Regression
**Optimized Neural Network Model marked in grey

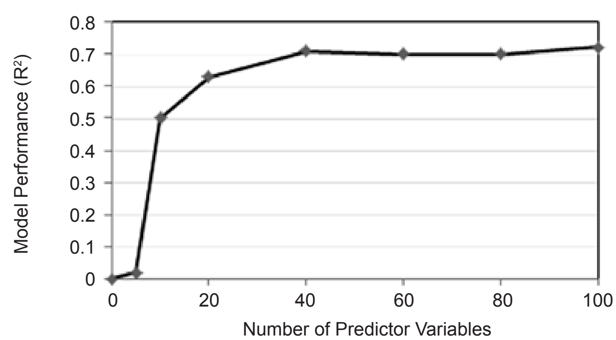

Figure 3. Sigmoidal performance of the GRNN Q2.

Q100 reach an optimized minimum error state with 15-30 predictor variables, with R^2 values comparable to MVR Q2 at 0.20, except for Q10, which has a high calibration R^2, but fails to converge during the validation runs ($R^2 = 0.0$).

Model Comparison

Comparing the GRNN model predictions for change in the channel area associated with flow for Q2, Q10, Q50, and Q100 to change in area predicted by MVR for the same flow intervals (Q2, Q10, Q50, and Q100, respectively) shows that the GRNN models are comparable to the MVR models during calibration but perform significantly better than the MVR models during the validation runs, with lower absolute error (Table 2). The GRNNs had fewer convergence issues compared to the MVR models (R^2 for Q10 validation = 0.0). Due to GRNN's ability to use surrogate variables for missing datapoints for some important predictor variables, more predictor variables could be used in the network and ranked accordingly. In contrast, any predictor variable with missing data point was not used in the MVR. Because one of the goals of the study was to rank predictor variables, results are skewed in the MVR due to lesser number of predictor variables used even in the preliminary runs.

Missing Variables

GRNN models inform selection of surrogate relationships between predictor variables. For example, the variable "*elevation at outlet*" shows high association with the variable "*elevation at 10% of the total flow path*", allowing us to replace missing data points with an estimated value based on the surrogate. A list of predictor associations for variables with missing values is shown in Table 3. Because MVR does not provide a mechanism for assigning surrogate variables, the predictor variables with missing values were omitted during the calibration and validation runs for the MVR models.

Model Validation

In addition to the random 20% holdback validation runs discussed below, we validated the model using 14 pre-selected watersheds with channel responses at three stages of hydromodification based on the Channel Evolution Model (CEM) developed specifically for these sites by Hawley *et al.* (2012): stable and/or the very early stages of incision (CEM I), substantial incision at or nearing the critical bank height for mass wasting bank failure (CEM II), and active bank failure with geotechnically unstable banks and continued incision (CEM III). The model prediction error is less for the stream reaches with active responses to hydromodification (CEM II, III) compared to the stable reaches (CEM I; Table 4), much of which can be explained by the fact that the dataset included reaches that were just upstream of substantial headcuts (e.g., Acton G, upstream of a 2-meter headcut), where hydromodification responses were inevitable, but not captured at the time of the field surveys.

Table 3. Relationship between the primary and surrogate predictor variables defined by association constant.

Predictor	Surrogate	Association (%)
Total Stream Length	Watershed Area	93
Precipitation (USGS)	NOAA (avg.)	78
Median Bed Material (d_{50})	2-yr Shear Stress	88
2-yr Stream Power	Median Bed Material (d_{50})	77
2-yr Shear Stress	2-yr Valley Specific Stream Power	88
2-yr Hydraulic Radius	Total Stream Length	64

* Association constant is estimated based on a fitted linear or a polynomial function between the predictor and surrogate variables.

Variable Importance and Ranking

Seven variables consistently ranked among the strongest predictor variables for all four GRNN models; however, the order of importance varies with recurrence interval (Table 5). For example, predictor variables, such as, representative geotechnical stability of the stream cross-section (i.e., poorest bank stability of either bank after Hawley (2009)), bed material, and bed load capacity ranked high for all four GRNN models. However, other variables, such as total impervious area and calculated flow, ranked high for the lower recurrence flows Q2 and were insignificant for GRNN Q100. The distance to the hardpoint variable responds in the opposite way, with its rank increasing with recurrence interval (GRNN Q100 rank ~3 and insignificant for GRNN Q2). Although there were numerous differences in predictor variables, all GRNN models included at least some measure or surrogate measure of urbanization such as Composite NRCS Curve Number and Composite C for the Rational Method (both are directly dependent on watershed imperviousness), or the length of channelized/

Table 4. Validation on a selected sample of watersheds.

Site	Hydromodification Stage	Channel Area$_{pre}$ (m^2)	Channel Area$_{post}$ (m^2)	Channel Area$_{modeledpost}$ (m^2)	DA$_{observed}$ (post-pre)	DA$_{modeled}$ (post-pre)	Relative Error for CEM Bin
Acton G	CEM 1	1.71	1.71	3.67	0.00	1.96	0.48
Hick's Canyon		1.60	4.27	3.78	2.67	2.18	
Proctor Tributary		1.91	1.91	4.31	0.00	2.40	
Dulzura Creek		13.52	22.30	20.02	8.78	6.50	
AltPerris_B		3.97	3.97	4.35	0.00	0.38	
Challenger Creek B		2.37	3.67	3.07	1.30	0.70	
Lk Perris Site 1 A	CEM 2	3.53	5.35	4.11	1.82	0.58	0.21
Lk Perris Site 1 C		3.99	5.29	4.19	1.30	0.20	
Agua Hedionda B	CEM 3	10.44	19.54	16.98	9.10	6.54	0.39
Agua Hedionda C		14.04	24.43	18.52	10.39	4.48	
Dry Acton A		9.66	21.17	21.55	11.52	11.90	
Borrego Canyon C		23.94	104.86	93.59	80.92	69.65	
Challenger Creek B		2.37	3.67	3.07	1.30	0.70	
Yucaipa B		26.30	66.07	31.24	39.84	5.01	

*Channel evolution model (CEM) classification described for semi-arid streams of southern California in Hawley *et al.* (2012)

Table 5. Ranking and variable importance for GRNN models based on flows for four-recurrence interval optimized for multiple runs for each flow interval.

Predictor Variable	Q 2	Q10	Q 50	Q 100
Calculated Flow	1	3	9	0
Bedload Capacity	2	5	5	7
Geotechnical Stability of Cross-section	3	3	3	4
Total Impervious Area	4	9	15	0
Stream Power	6	6	NA	NA
Bed material	8	7	10	5
Distance to Hardpoint	0	15	7	3

artificial stream length (which is likely to increase in urban areas).

The GRNNs also tested a host of variables that are independent of urbanization allowing for an evaluation of the relative importance of factors that affect the intrinsic susceptibility of a site to hydromodification. These factors include bed material composition (d_{16}, d_{50}, d_{84}), soil composition at the site (percent sand, silt, k_f factor, and k_w factor in soil at site), valley width, valley slope, sinuosity, and drainage density.

Sensitivity Analysis

We tested the sensitivity of the GRNN models using two different approaches to network pruning. When the least significant variables were removed after each simulation, the four GRNNs models were found to be relatively stable as indicated by the consistent ranking of the important predictor variables (Table 6 for GRNN Q2). We tested GRNN Q2 for decreasing number of predictor variables and observed a sharp sigmoidal decrease in performance when the network has less than seven predictor variables (Figure 3).

The ranking of variable importance was confirmed by the fact that when we removed highly ranked predictor variables, model performance substantially declined. For example, removal of calculated flow, from the Q2 GRNN network the model R^2 value dropped from 0.84 to 0.68, and dropped to 0.50 when we removed three highly ranked predictor variables (calculated 2-yr flow, total impervious area, and geotechnical stability of the cross section).

Table 6. Predictor variables ranked for Q2 during pruning.

Rank	n = 100	n = 80	n = 60	n = 40	n = 20	n = 10
1	Calculated 2 Year Flow	Calculated 2 Year Flow	Calculated 2 Year Flow	Calculated 2 Year Flow	Calculated 2 Year Flow	Calculated 2 Year Flow
2	Valley Expansion Ratio	Total Impervious Area	Geotechnical Stability of Cross-Section	Geotechnical Stability of Cross-Section	Geotechnical Stability of Cross-Section	Geotechnical Stability of Cross-Section
3	Total Impervious Area	Geotechnical Stability of Cross-Section	Total Impervious Area	Total Impervious Area	Valley Expansion	Valley Expansion
4	Geotechnical Stability of Cross-Section	Total Road Length in Watershed	Valley Expansion	Valley Expansion	Total Impervious Area	Valley Width
5	Total Road Length in Watershed	Stream Power	Bed Material	Total Road Length in Watershed	Total Road Length in Watershed	Total Impervious Area
6	Bed Material	Bed Material	Stream Power	Bed Material	Valley Width	Bed Material
7	Stream Power	Total Burned in Last 5 Years	Total Road Length in Watershed	Bankfull Width	Bed Material	Soil Composition
8	Total Burned in Last 5 Years	Bankfull Width	Total Burned in Last 5 Years	Stream Power	Bankfull Width	Bankfull Width
9	Valley Expansion	Channel Slope	Stream Power	Hydraulic Radius for Sediment Transport	Hydraulic Radius for Sediment Transport	Channel Area Pre-Hydromodification
10	Area for Sediment Transport	Area for Sediment Transport	Soil Composition	Area for Sediment Transport	Channel Area Pre-Hydromodification	Distance to DS Hardpoint

Discussion

GRNNs are a relatively easy to use, flexible method to analyze and link a large number of potential predictor variables to observed hydromodification responses in channels, and rank the predictor variables according to importance. Our work demonstrates that GRNN models can be used to help identify the dominant watershed processes necessary to predict anticipated changes in channel morphology associated with hydromodification. Once validated, GRNN predictions can be used in concert with other tools to help inform management decisions, such as the need for flow-duration based stormwater controls, and to tailor monitoring programs. In particular, GRNNs expand the utility of traditional deterministic models by allowing for more explicit consideration of uncertainties, and accounting for discontinuous, threshold-type behavior. GRNNs allow identification of variables that have the greatest influence on model uncertainty allowing for targeted calibration efforts to improve model parameterization.

Our analysis documented a broad range in the performance of the recurrence interval flows in explaining channel enlargement—findings which ultimately support our underlying hypothesis that improperly mitigated urban development is a primary driver of stream channel instability in Southern California. Total impervious area is a commonly used surrogate for urbanization extent across numerous disciplines (Fitzpatrick *et al.* 2005, McBride and Booth 2005). It is also widely documented as being an important variable for predicting peak flow during lower return interval storms, such as Q2, but is less significant for flows resulting from larger storms (Hawley and Bledsoe 2011, Hollis 1975). Because the Hawley and Bledsoe (2011) flow models are highly dependent on watershed imperviousness for lower flows (e.g., exponential imperviousness coefficient of 12 for Q1.5, 9 for Q2, and 3 for Q5) and are independent of the influence of urbanization for higher flows (≥Q10), it follows that the GRNNs would show different levels of influence on flow if urbanization is a primary driver of channel enlargement. Indeed, the optimized GRNN Q2 model requires 25% fewer predictor variables than the other recurrence interval flows to arrive at similar performance, and the Hawley and Bledsoe (2011) Q2 consistently ranked as the most important predictor variable at every pruning stage (i.e., "importance" of 100 compared to importance of 22 for the second highest ranked variable). Because the Hawley and Bledsoe (2011) 10-, 50-, and 100-year recurrence interval flows did not carry an urban signature it is not surprising that they did not perform as well in predicting channel enlargement, ranking number 3, 9, and insignificant in their respective models (Table 5; i.e., "importance" of 0.000 in the GRNN Q100 model). It follows that GRNNs built on a process-based driver of hydromodification such as the urban-amplified two-year peak flow, would require less total variables to explain similar amounts of variance in channel enlargement than GRNNs built on higher recurrence interval flows that did not convey an urban signature.

Unlike the Q2 GRNN, the Q10, Q50, and Q100 GRNNs required scale dependent variables, such as, size of the watershed, stream length, and annual precipitation, and were much more dependent on runoff characteristics that incorporated watershed imperviousness such as the composite NRCS Curve Number and the composite C for the Rational Method ("importance" of 23 and 11, respectively, for the Q100 GRNN, compared to 0.18 and 0.13, respectively, for the Q2 GRNN). All models included predictor variables describing geomorphic context and valley confinement, such as, Valley Width and Valley Expansion Ratio that are not related to watershed development, but characterize the relative susceptibility of the valley setting (*sensu* Bledsoe *et al.* 2012) in that enlargement is much more likely/severe in wider valleys (i.e., streams have more room to become wider).

GRNN can also able to incorporate variables that are difficult to include in traditional deterministic models, such as distance to a downstream hardpoint. Particularly evident in fine-grained (i.e., sandy) systems with less capacity to self-armor, hard points can serve as energy dissipaters and thus distance to hardpoint can be a good predictor of channel response (Hawley 2009). Larger responses are observed with increasing distance upstream from hardpoints as channels adjust their slopes to dissipate erosive energy. The relatively high GRNN ranking of the distance to hardpoint variable is consistent with empirical observations of Bledsoe *et al.* (2012) who note that this factor is influential in predicting the susceptibility of a channel to hydromodification responses. On the whole, all of the variables used in the Bledsoe *et al.* (2012) screening tool for hydromodification susceptibility had high amounts of explanatory power in the GRNNs, relative to variables that were not included in the screening tool.

A final advantage of using GRNN models is the ability to replace missing datapoints with values estimated using surrogate variables. Because data collection is an extremely expensive process and it is often not possible to collect the entire suite of data, important variables data might not be available at some locations. For example, in this study data on total area burned in the last five years was unavailable for several watersheds resulting in variable exclusion in the MVR models. However, an active fire regime exacerbates the sediment yields in inherently dynamic channels (Lave and Burbank 2004, Hawley *et al.* 2012) making it an important variable in predicting hydromodification. The ability to use surrogate variables means that this factor can be included in the GRNN models.

Few attempts have been made to comprehensively model a broad set of parameters that influence hydromodification response in southern California streams, mostly due to the computational limitations of deterministic models and the relative simplicity of regression models. Existing empirical tools can predict general response, but typically produce qualitative output, such as high, medium, low rankings (Booth 2010, Bledsoe *et al.* 2012). GRNNs can capture many of the non-linear relationships that cause hydromodification response in channels of southern California and provide quantitative estimates of change and the uncertainty associated with those estimates. GRNN provides a flexible modeling approach for identifying the important parameters that connect land use change to channel response in a given watershed and in a defined geomorphic setting.

Like all models, GRNNs comes with caveats and inherent weaknesses, such as, the choice of model inputs, network structures and internal model parameters; and method of preprocessing of model inputs (Maier and Dandy 2000). Because most ANN models are data driven (Chakraborty *et al.* 1992), and are able to determine critical parameters, users tend to pay little attention to the selection of appropriate model inputs (Faraway and Chatfield 1998). It is important to ensure that the model includes process-based surrogate measures of response drivers and mechanisms that can accurately represent the real system, and are not just built on available data. GRNNs rely on associations between target and predictor variables; therefore, the more process-based the predictor variables used, the less complex a GRNN will need to be. For example, in this study the GRNN that was developed with the urban-amplified Q2 required 25% fewer variables to match the performance of the higher recurrence interval flow models, which did not inherently reflect watershed imperviousness. Pre-processing for GRNN networks includes standardization to ensure all variables are treated equally (Maeir and Dandy 2000). Scaling the variables to fall within the limits of activation functions used in the outer layer is also recommended as a pre-processing step (Maeir and Dandy 2000, Minns and Halls 1996).

Finally, GRNNs can also quickly and efficiently verify the stochastic importance of variables (especially those with discontinuous/non-linear behavior such as valley expansion from confined to unconfined, valley width, and current channel stability), in support of rating channel susceptibility to hydromodification and identifying target variables for detailed data collection (sensu Bledsoe *et al.* 2012). In this way GRNN can be used to support not only predictive modeling, but also to inform effective field monitoring and assessment programs.

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