GIS Approaches for Channel Typing in the Columbia River Basin: **Carrying Fine Resolution Data to a Large Geographic Extent**

Hiroo Imaki, Tim Beechie

Northwest Fisheries Science Center, NOAA Fisheries, Seattle, Washington, USA

Introduction

Approach

We are developing a series of GIS and statistical techniques to predict 8 channel types based on geomorphic principles (Figure 1) and improving prediction accuracy in the Columba River basin (Figure 2). Our stream layer can be used as a geomorphic reference condition on a 50 ~ 100k scale. Four major steps are included:

(1) Reconstruct a historic stream layer based on current stream GIS layers, (2) Calculate reach attributes and construct channel prediction models, (3) Examine prediction errors, and (4) Develop GIS stream data with channel types and other attributes

Figure 1. Biophysical controls on channel pattern.





Figure 2. The Columbia River basin and the scale of channel typing. The total length of reaches in the GIS layer is 444,121,266 m and the number of reaches are 2,273,010. A blue area in the Walla Walla watershed (red area) includes 295 reaches all of which are 200 m long

Historic stream reconstruction We built our historic stream network based on current stream GIS layers. US

and Canadian stream lavers were merged and artificial channel types were removed from the network. To reconnect isolated natural channels, we restored the minimum number of artificial channels back to the network (Figure 3).



Figure 3. Historic channel reconstruction processes. Artificial channels (red lines) were removed, and isolated streams were reconnected with a minimum amount of artificial channels.

Reach Attributes

We started with a minimum reach length of 200 m and attached six attributes to each reach: 1) slope, 2) accumulated precipitation (surrogate of discharge), 3) relative shear stress to the above reach, 4) confinement, 5) % of fine sediment area in its drainage, and 6) % of alpine sediment supply area in its drainage (Figure 4). All 6 attributes were calculated based on a 10 ~ 30 m DEM (US and Canada). Where adjacent 200 m segments had similar slope and bankfull width, we aggregated multiple segments into longer geomorphically meaningful reaches. This also increased accuracy in slope calculations in low gradient floodplains.



Figure 3. GIS processes to calculate reach attributes

Channel Typing and Model Selection Our channel type classification is based on existing studies (Montgomery and Buffington 1997, Beechie et al. 2006, Hall et al. 2007) and Linear Discriminant Analysis (LDA, Figure 5). Reaches were first divided into either confined or floodplain channel types based on bankfull width and confinement. The four confined channel types were classified based on slope. The four floodplain channel types were classified based on LDA of reach attributes. We tested all combinations of six attributes and selected the model with the highest overall accuracy. We also tested three other statistical techniques: prior probabilities, random forest, and bagging (bootstrapping).





Figure 4. Channel

typing schema.

Reaches less than 8 m bankfull width were

classified into 4 confined

channel types based on

bankfull width > 8 m and unconfined were classified

as migrating (Hall et al.

2007) and subjected to

further classification with

I DA.

(1977), Reaches with

ntgomery & Buffingto

error matrices to examine prediction accuracy and errors. Then we further examined an error structure in our

Prediction accuracy and errors

prediction by conducting an individual perturbation analysis.

We constructed a series of classification

Results

We found that LDA with bagging showed the highest overall accuracy (80.8%, Table 1). However, the accuracy with a test dataset decreased to 60.3%. A model including all 6 parameters resulted in the highest accuracy among LDA (76.8%). We increased model accuracy about 20% compared to the traditional slope discharge model (Model 8). The prior probability of existing channel types increased overall accuracy up to 8%. Random forest resulted in relatively low overall accuracy.



		Table 2.	,					
		Braided	Island- braided	Meandering	Straight	Total	Commission error	classification error n of Model 1. We selected a training dat reflect a distribution of cha types in the basin.
ء ا	Braided	6	1	0	1	8	75.0	
5	Island-braided	3	39	6	-4	52	75.0	
adic	Meandering	0	3	26	3	32	81.3	
ĩ	Straight	1	3	1	15	20	75.0	
	Total	10	46	33	23	112		
	Omission error	60.0	84.8	78.8	65.2		76.8	



Conclusion

Accumulated Relative Confine- Fine

Stress

72.3

2.51

ment

74.2

1.67

Sediment

75.2

1.62

Precipitation Shear

Table 3. Individual perturbation analysis on channel

We found that major classification

confused these two types with the

island-braided type (omission error:

The most influential source on the

classification error was slope (Table 3:

60.0 and 65.2, respectively).

10.2% decrease) while other

decrease in accuracy.

parameters showed only slight

errors occurred in braided and straight

channel types (Table 2). Model 1 often

the model before adding errors was 76.0 % for this analysis

type classification errors. Errors were generated from known error

distributions based on field measurements and their estimations. For the

fine sediment, we used standard deviation of 0.25. An overall accuracy of

Slope

65.8 76.2

3.46

1.89

Mean

accuracy

(n=100)

SD

We predicted 8 channel types using multiple approaches and found that the bagging with LDA is the most promising approach to estimate channel types at the reach scale across an entire basin. Bagging resulted in increased overall accuracy and calculated a voting distribution which can then be used as an indicator of prediction certainty. Even with medium resolution DEM and stream layers, bagging allowed us to predict channel types with relatively high accuracy across the Columbia River basin in spite of its diverse geological environment. We also found that relatively lower accuracies with the test dataset were in large part due to observer's channel typing error. Upon cross examination of channel type calls with two independent observers, we roughly estimated that 10 ~ 15% of error can come from observer differences. The applicability of our prediction method is large and can be applied in many regions because it uses pre-existing GIS data.

Citations

Beechie, T.J., M. Liermann, M.M. Pollock, S. Baker, and J. Davies. 2006. Channel pattern and river-floo pattern and river-floodplain dynamics in forested mountain river system Geomorphology. 78(1-2): 124-141. Hall, J.E., D.M. Holzer, T.J. Beechie. 2007. Predicting river floodplain and lateral Train, J.E., U.M. Hotzer, I. J. Jeeche. 2007. Predicting river floodplain and lateral channel migration. To asalmon habita conservation. Journal of the American Water Resources Association. 43(3): 112. Montgomery, D.R. and J.M. Buffingion. 1997. Channel-reach morphology in mountain drainage basins. GSA Bulletin. 109(5): 596-611.

GIS	data	sources
-----	------	---------

olo data sources.							
	Canada	USA					
Stream layer	The Watershed Atlas http://www.env.gov.bc.cafish/watershed_atlas_map s/	National Hydrography Dataset Plus (NHDplus) http://www.horizon-systems.com/nhdplus/					
DEM	The Canadian Digital Elevation Data (CDED) http://www.geobase.ca/geobase	National Elevation Dataset (NED) http://ned.usgs.gov/					
Precipitation	ClimateBC http://www.genetics.forestry.ubc.ca/cfcg/climate- models.html	PRISM http://www.prism.oregonstate.edu/					
Geology	Digital Geology Map of British Columbia http://www.em.gov.bc.ca/Mining/Geolsurv/Publicatio ns/catalog/bcgeolmap.htm	Geological Survey from each state					
Land use / land cover		National Land Cover Data (NLCD) http://www.epa.gov/mfic/					