Understanding the Dynamic Nature of Catchment Response Time in UK Streams through Machine Learning Analysis

Mistaya Langridge, Rachel Walton, Bahram Gharabaghi, Hossein Bonakdari

School of Engineering, University of Guelph, Guelph, Ontario, Canada

Objectives

- Previous works into understanding the influencing factors of Time to Peak (Tp) have been static in nature, dependent upon constant catchment characteristics alone.
- This does not allow for consideration into the variability in Tp between storms or antecedent conditions
- Identifying this gap in current perceptual understanding, this study looks to perform

Introduction

- The 1975 UK Flood Studies Report (FSR), and the subsequent Flood Estimation Handbook (FEH)[1] are comprehensive guides to understanding flood prediction in the UK.
- This method is dependent solely upon static catchment descriptors; therefore predicting the same Tp value for any given storm within a catchment.

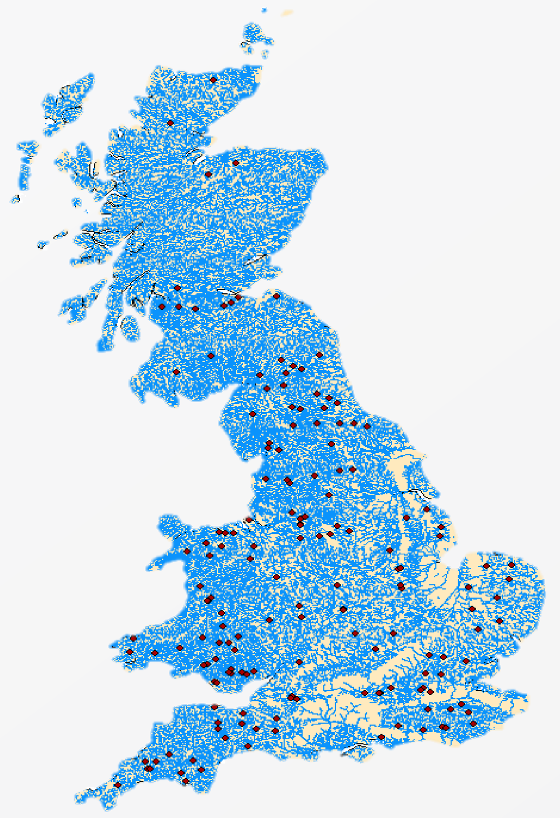

Figure 1: Location of Stream Gauges on Map of Great Britain

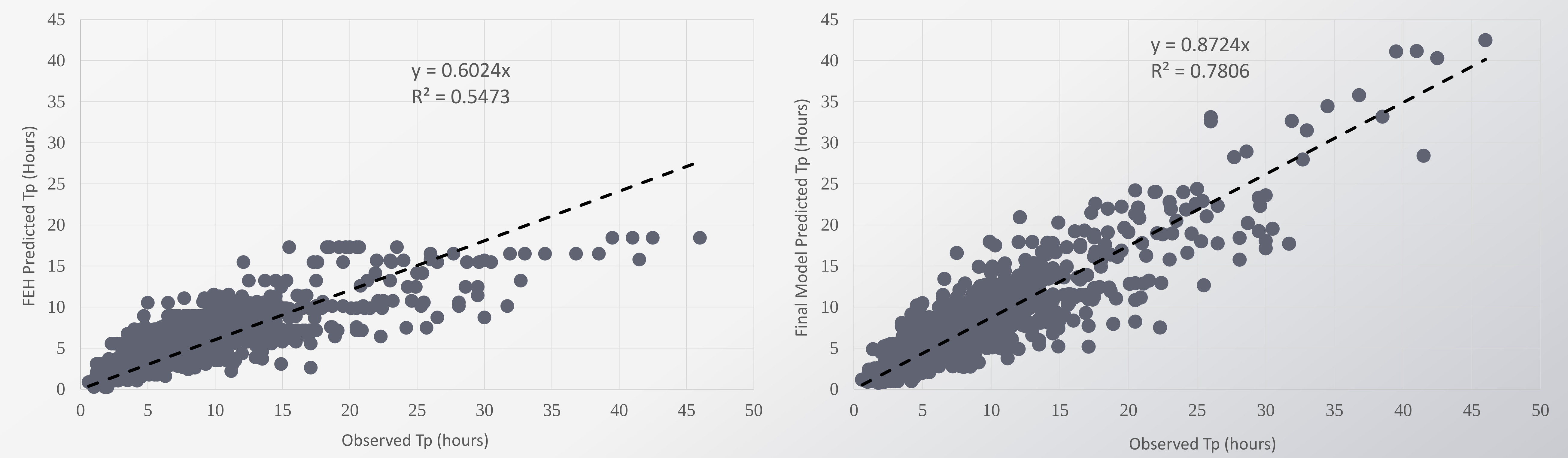

Figure 3: Plot of Model Results against Observed Values a) Original FEH Equation b) Final Model

Methods

- An extensive data set was collected from the UK National River Flow Archive (NRFA) and FEH, including more than 1400 storms and the corresponding catchment characteristics of 153 stream gauges across Great Britain
- The extent of urban area in these watersheds range from 0-25%, with an average of 2%, allowing us to enhance the process understanding of these rural watersheds in this study.
- Using data and literature analyses the data set was narrowed from 43 variables to apply only the key inputs to machine learning.
- An iterative model was employed, to demonstrate improved predictive capability with each additional input parameter.
- Application of seasonal soil moisture trends in conjunction with land cover to encompass antecedent soil moisture.

Results

Model	Inputs	R^2	NASH	MAPE (%)	Relative Bias
Original FEH Equation	L, S, PROPWET, $URBEXT_{1990}$	0.54	0.42	4.37	-0.31
ANN Model 1	L, S, PROPWET, URB	0.68	0.49	4.11	-0.32
ANN Model 2	L, S, PROPWET, URB, DA	0.69	0.68	3.25	-0.09
ANN Model 3	L, S, PROPWET, URB, DA, Qp	0.71	0.58	3.06	-0.11
Final Model	L, S, PROPWET, URB, DA, Qp, LCM	0.78	0.77	2.77	-0.11

Table 1: Statistical Results of Iterative ANN Models

Peak Flow

- Incorporating the peak flow (Qp) allows for the magnitude of the storm to be considered
- A negative correlation between Tp and Qp has been found and supported, where increasing Qp corresponded to a reduction in Tp[3,4]

Drainage Area

- Drainage Area (DA) was included as an additional static catchment descriptor, after extensive literature review demonstrated the necessity for DA in catchment response prediction
- Review further discovered that time parameter models that did not include DA overestimated Qp[2, 5, 6, 7, 8]

ANN

- Machine learning and Artificial Neural Networks (ANN) have been applied with great success to the prediction of stream flows, and are lauded for their ability to understand the complex nature of hydrologic systems[9, 10]
- ANN is applied as a simple tool to evaluate the effect of different input combinations

Land Cover Moisture (LCM) Factor

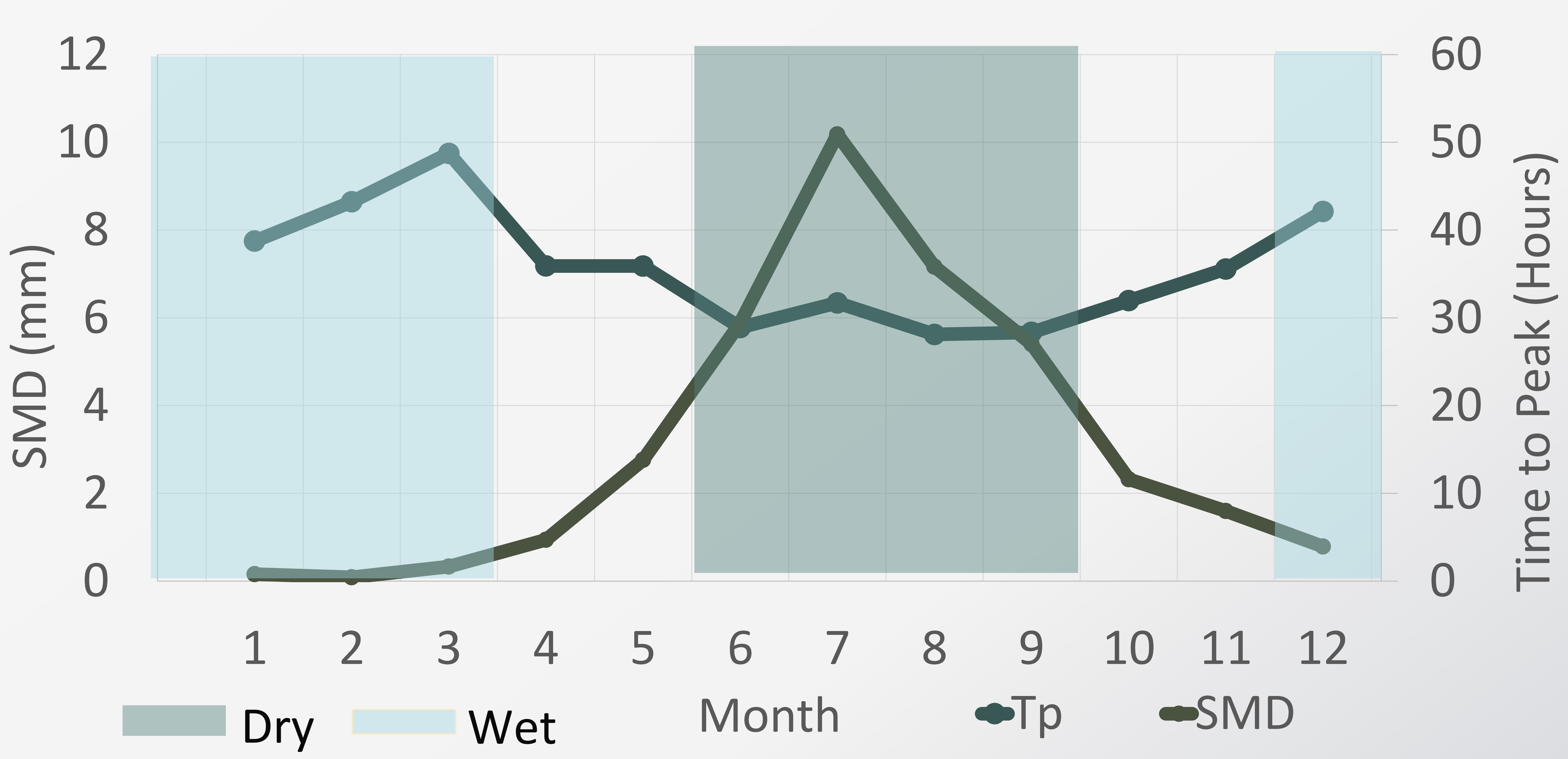

Figure 2: Mean Monthly Soil Moisture Deficit (mm) and Time to Peak (Hours)

- As in Figure 2, seasonal trends in soil moisture correspond to trends in Tp
- This seasonal response was encapsulated by introducing a new LCM factor
- Three seasons were identified by average Soil Moisture Deficit (SMD)
- Each catchment was classified by its dominant land coverage (woodland, arable, grass or mountain)
- The average SMD for each season and land cover was utilized to create the LCM

Conclusions

- Dynamic prediction provides dynamic variability, rather than providing a single value for a given catchment, by using three key variable types:
  - Storm specific- encompassing the magnitude of the storm (Qp)
  - Static catchment-encompassing the variability between each catchment (L, S, DA, PROPWET, URBEXT),
  - Dynamic catchment- encompassing the variability within a catchment due to antecedent conditions (LCM)
- Identification and application of seasonal trends in soil moisture applied to hydrologic modelling and introduction of LCM factor
- Application of machine learning and ANNs to a large data set spanning Great Britain
- Next Steps: Apply this improved perceptual understanding of the processes dominating these study areas to other locations (data in Canada and the US being collected), and improve ease of application of the model by using other machine learning methods like GEP to create a simplified empirical equation

Contact

Mistaya Langridge
University of Guelph
50 Stone Rd E, Guelph, Ontario, Canada
langridm@uoguelph.ca
001 (519) 323-7033

References

1. Kjeldsen, T.R., 2007. The revitalised FSR/FEH rainfall-runoff method 1–64.
2. Gericke, O.J., Smithers, J.C., 2017. Direct estimation of catchment response time parameters in medium to large catchments using observed streamflow data. Hydrol. Process. 31, 1125–1143. https://doi.org/10.1002/hyp.11102
3. Costache, R., 2014. Using GIS Techniques for Assessing Lag Time and Concentration Time in Small River Basins. Geogr. Tech. 9, 31–38.
4. Nagy, E.D., Torma, P., Bene, K., 2016. Comparing Methods for Computing the Time of Concentration in a Medium-Sized Hungarian Catchment. Slovak J. Civ. Eng. 24, 8–14. https://doi.org/10.1515/sjce-2016-0017
5. Pegram, G., Parak, M., 2004. A review of the regional maximum flood and rational formula using geomorphological information and observed floods. Water SA 30. https://doi.org/10.4314/wsa.v30i3.5087
6. Simas, M.J., Hawkins, R.H., 1998. Lag Time Characteristics for Small Watersheds in the U. S. ASCE, pp. 1290–1296.
7. Williams, G.B., 1922. Flood discharges and the dimensions of spillways in India. Engineering 134, 321–322.
8. Salimi, E.T., Nohegar, A., Malekian, A., Hoseini, M., Holisaz, A., 2017. Estimating time of concentration in large watersheds. Paddy Water Environ. 15, 123–132. https://doi.org/10.1007/s10333-016-0534-2
9. Besaw, L.E., Rizzo, D.M., Bierman, P.R., Hackett, W.R., 2010. Advances in ungauged streamflow prediction using artificial neural networks. J. Hydrol. 386, 27–37. https://doi.org/10.1016/j.jhydrol.2010.02.037
10. Sudheer, K.P., Nayak, P.C., Ramasastri, K.S., 2003. Improving peak flow estimates in artificial neural network river flow models. Hydrol. Process. 17, 677–686. https://doi.org/10.1002/hyp.5103
11. Tiberius Data Mining Software