The N-EWN Knowledge Series

A Continuing Education Series about Engineering with Nature

Abel Porras
Supervising Engineer
City of Austin Watershed Department

Watershed Modeling Efforts in the City of Austin

The City of Austin Watershed Protection Department (WPD) is charged with protecting the lives and property of City of Austin residents from flooding, erosion, and water pollution. To that end, WPD has developed watershed models to answer a variety of questions related to erosion and water pollution. The impetus for these models was the Stream Functional Pyramid developed by Harman et al (2012), which linked hydrology with geomorphology, chemistry, and biology. WPD then adapted this framework to include the human/social component in watershed science. With this framework, they are able to examine how these components interact with each other using four modeling techniques: sociological modeling, superforecasting, physics-based watershed models, and deep learning algorithms. Mr. Porras will discuss sociological modeling and superforecasting briefly, but focus this presentation on physics-based modeling and deep learning algorithms. Using these models at a fine scale, WPD is able to identify problems and propose solutions.

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Presented by:

NETWORK FOR ENGINEERING WITH NATURE
LimnoTech
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Questions? Please contact:
Sage Paris, LimnoTech
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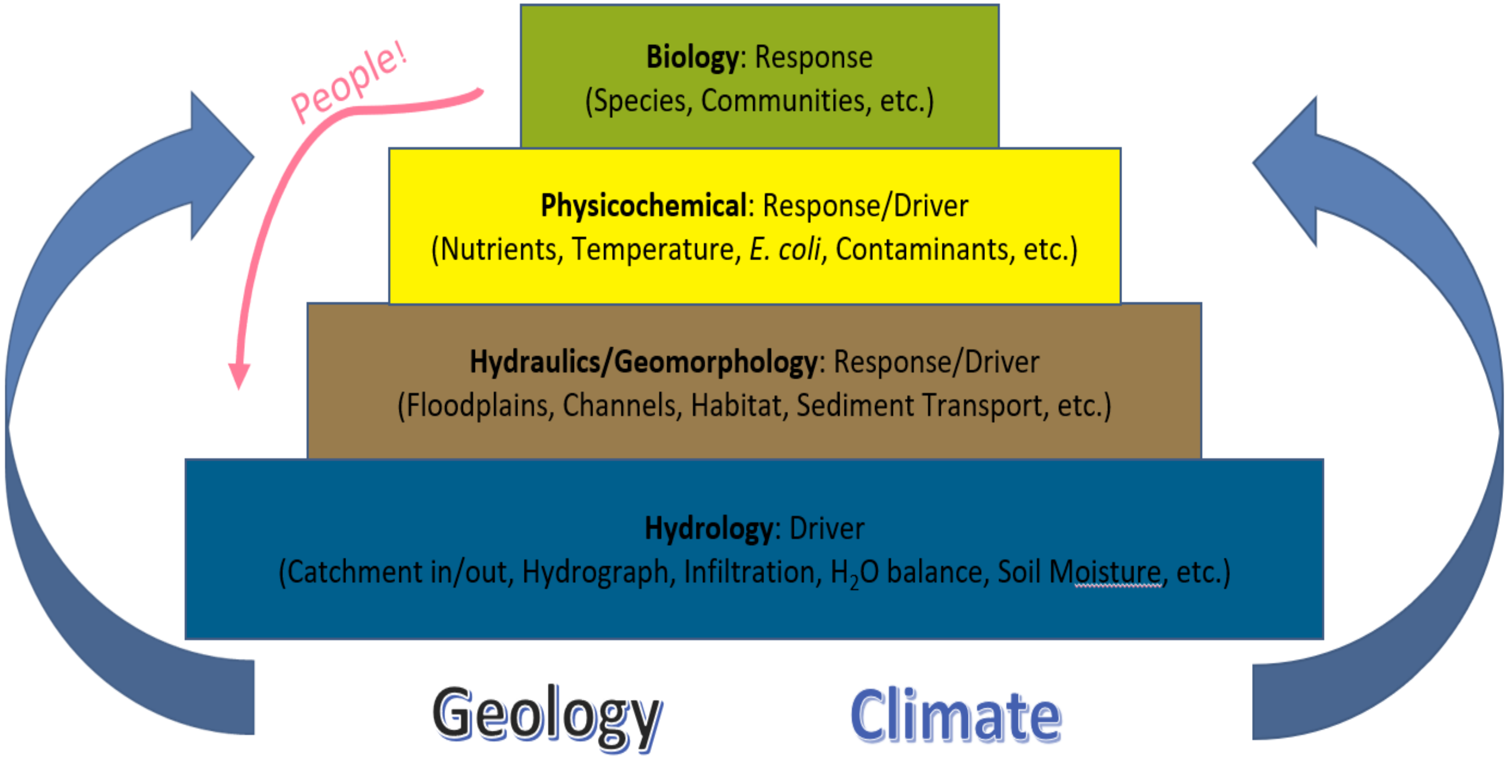
Watershed Modeling Efforts in the City of Austin

N-EWN Knowledge series

Abel Porras, PE
City of Austin
Watershed Protection Department

9/19/2024

How can we know what’s going on in our watersheds?



People!

Biology: Response
(Species, Communities, etc.)

Physicochemical: Response/Driver
(Nutrients, Temperature, *E. coli*, Contaminants, etc.)

Hydraulics/Geomorphology: Response/Driver
(Floodplains, Channels, Habitat, Sediment Transport, etc.)

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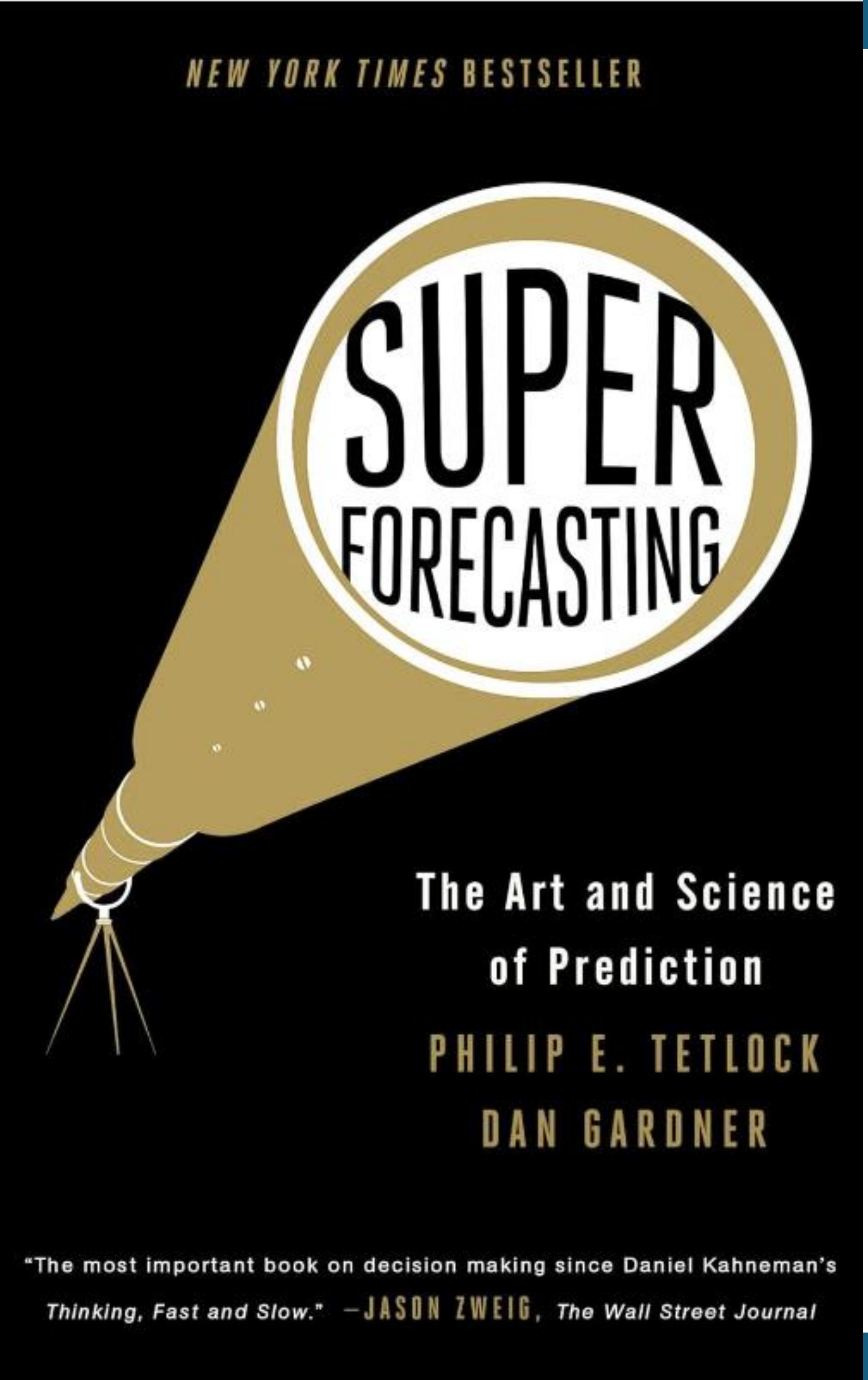
(Catchment in/out, Hydrograph, Infiltration, H_2O balance, Soil Moisture, etc.)

Geology

Climate

1. Superforecasting
2. Sociological modeling
3. Physics-based modeling
4. Deep learning

Superforecasting



How to know something with sparse data

- **Will (hopefully) answer questions related to nature-based policies, projects, programs, and practices. For example:**
- How effective are education outreach programs in mitigating over-fertilization?
- How do the life cycle costs compare between concrete channels and natural riparian areas?
- How effective are biofiltration ponds at removing nutrients from the system?

Our Plan for Superforecasting

1. SEND OUTREACH TO WATERSHED PROTECTION DEPT.
2. HAVE INTERESTED PERSONS TAKE AN ASSESSMENT
3. BASED ON THAT ASSESSMENT AND OTHER CRITERIA, SELECT TOP 10-15 PEOPLE
4. TRAIN THE SELECTED GROUP
5. START SUPERFORECASTING!

Sociological modeling

MEASURING PEOPLE'S BEHAVIORS TO AN ACTION/INCENTIVE

SOCIO-HYDROLOGY

Sociological modeling – measuring latent variables

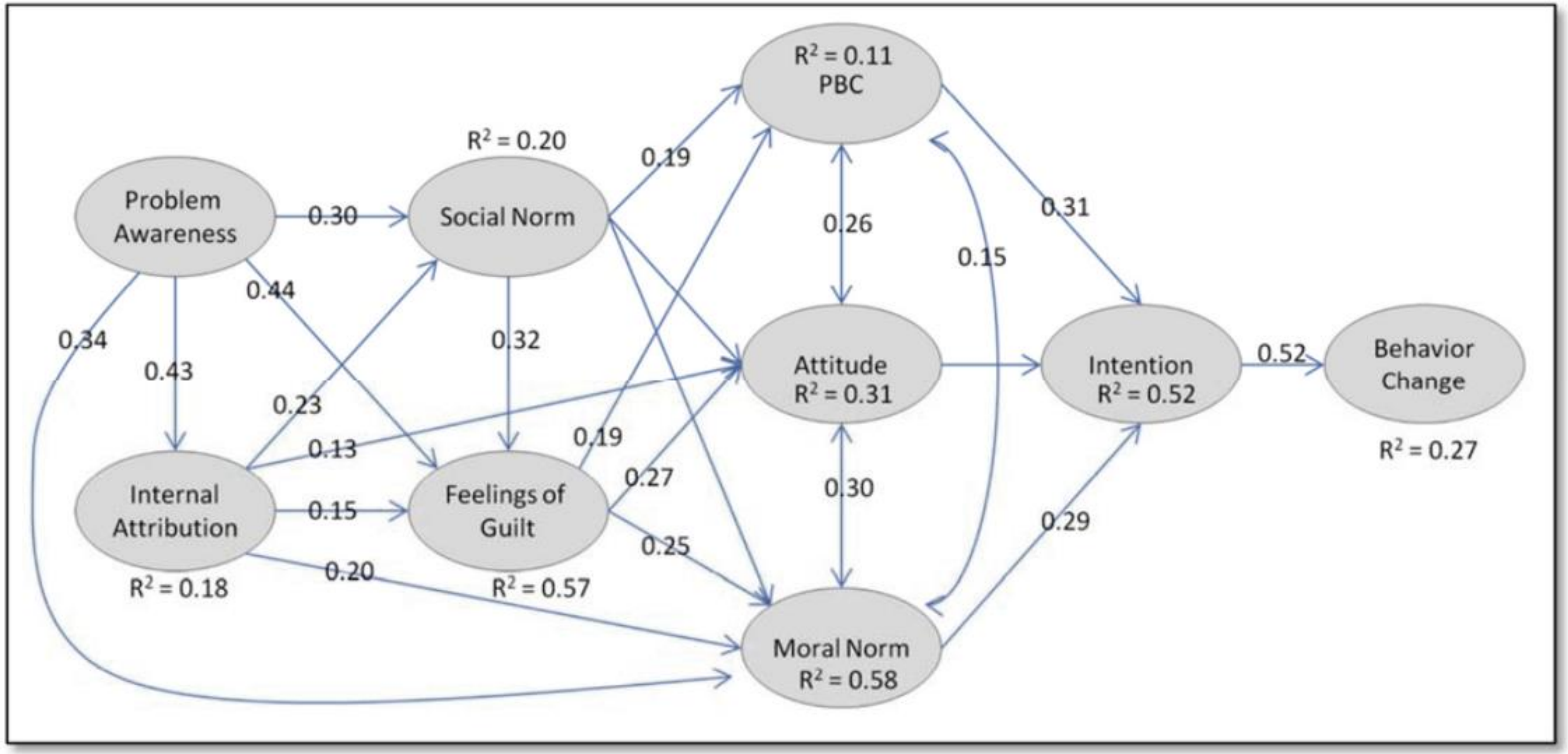
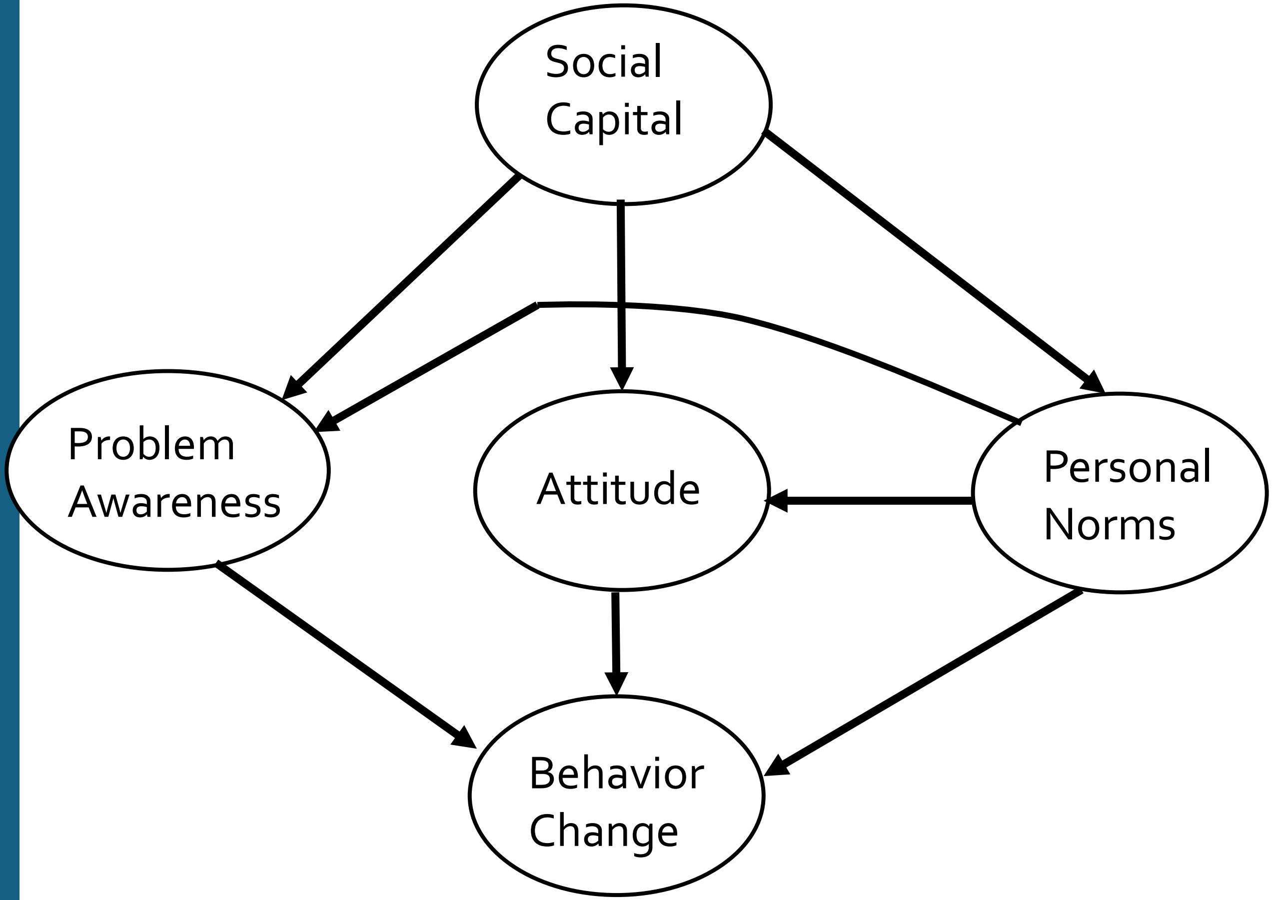
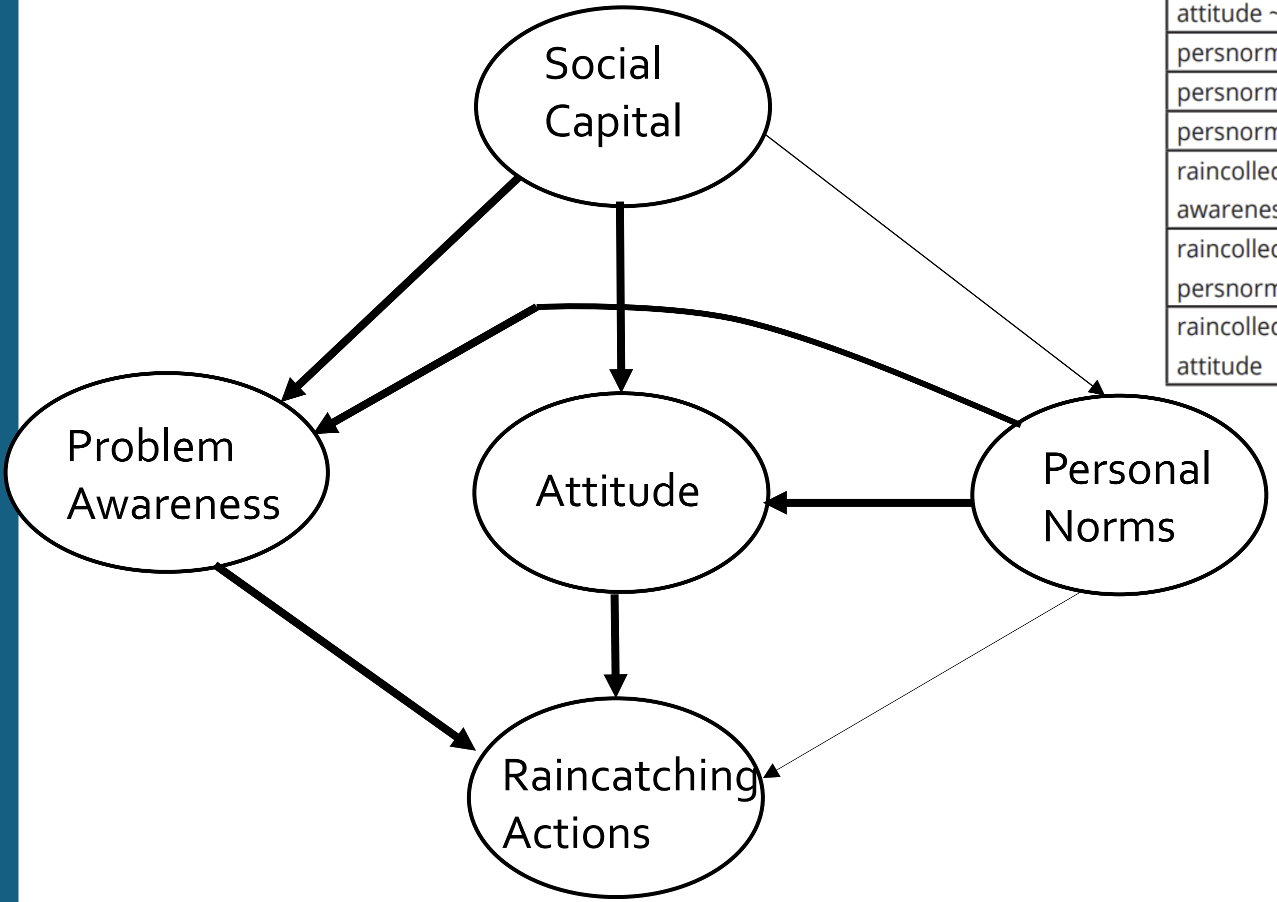


Figure 7. Bamberg and Moser (2007) Meta-Analysis Model of Pro-Environmental Behavior

Sociological modeling – for raincatching actions



Sociological modeling – raincatching actions



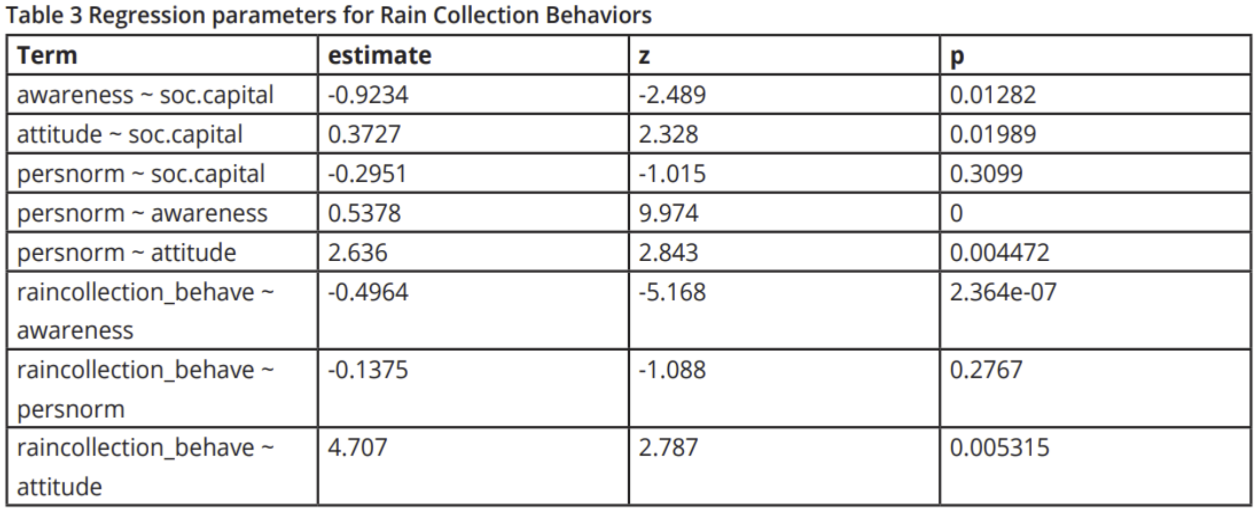
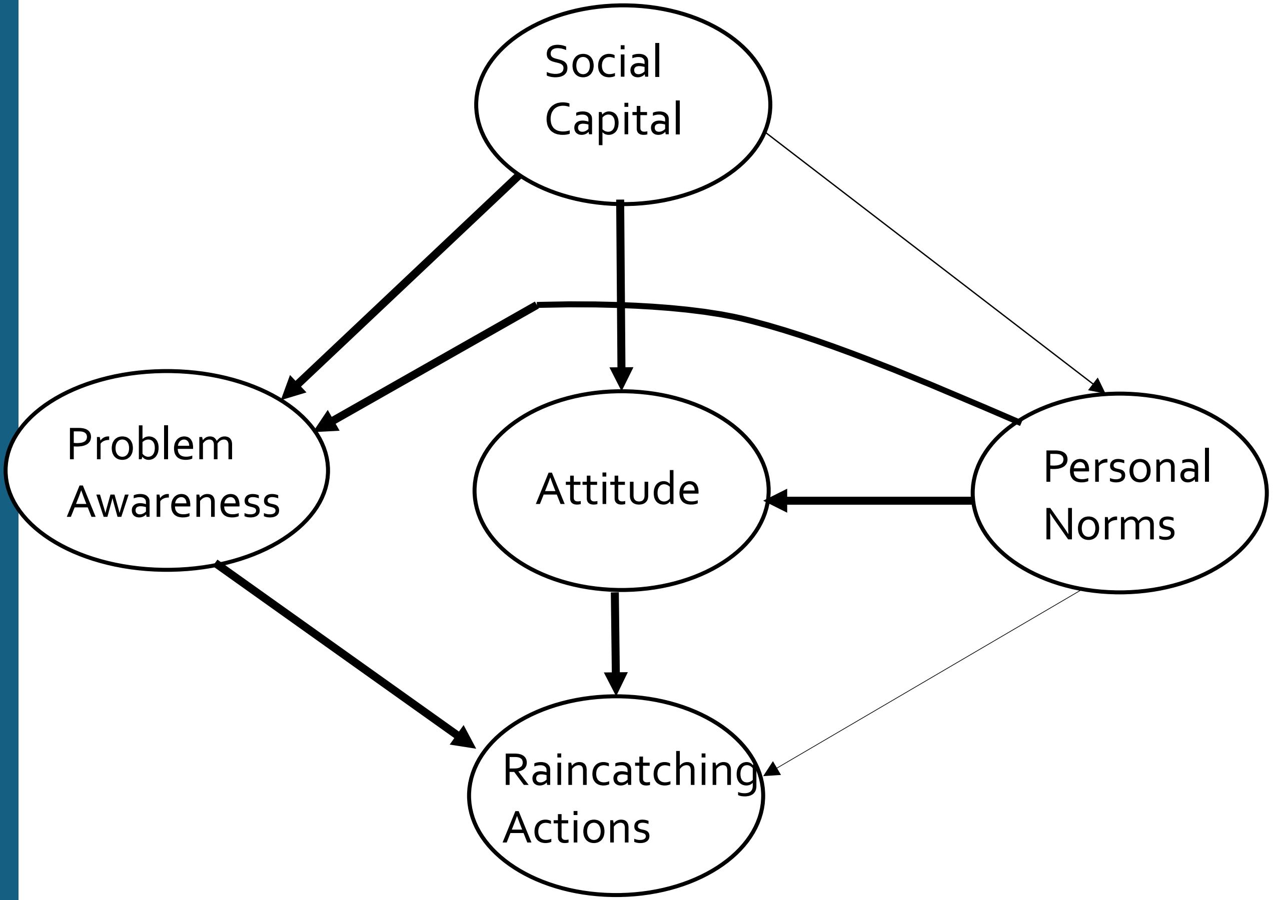


Table 3 Regression parameters for Rain Collection Behaviors

Term	estimate	z	p
awareness ~ soc.capital	-0.9234	-2.489	0.01282
attitude ~ soc.capital	0.3727	2.328	0.01989
persnorm ~ soc.capital	-0.2951	-1.015	0.3099
persnorm ~ awareness	0.5378	9.974	0
persnorm ~ attitude	2.636	2.843	0.004472
raincollection_behave ~ awareness	-0.4964	-5.168	2.364e-07
raincollection_behave ~ persnorm	-0.1375	-1.088	0.2767
raincollection_behave ~ attitude	4.707	2.787	0.005315

Sociological modeling – measuring latent variables



Social Capital

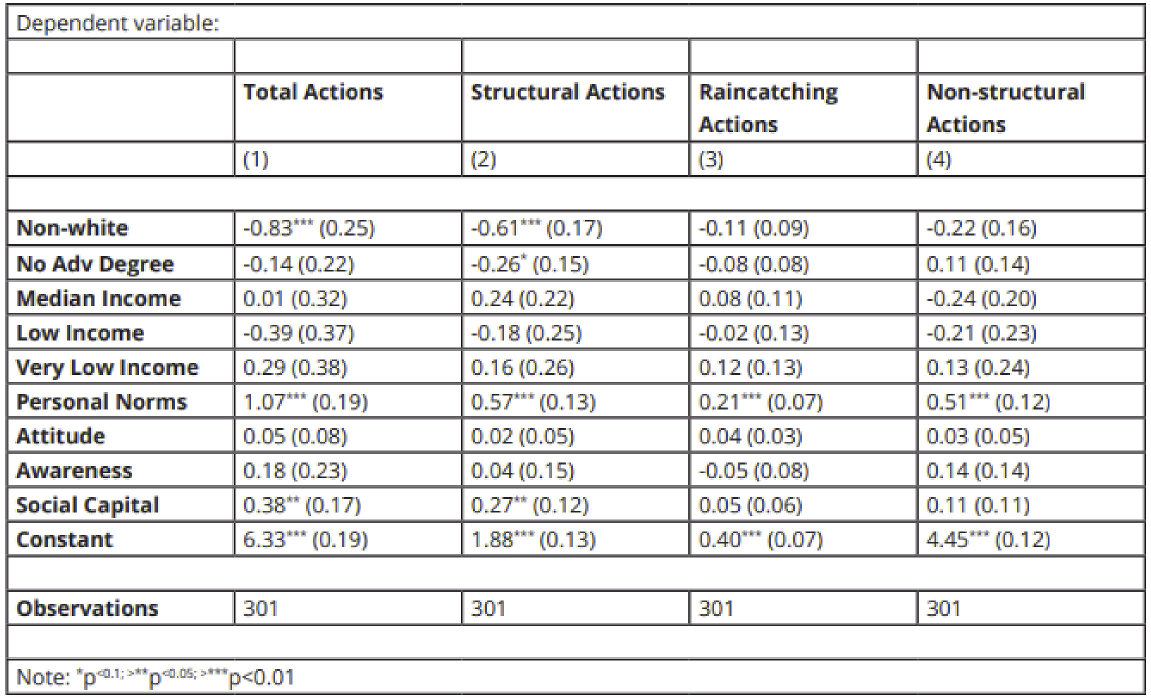
Problem Awareness

Attitude

Personal Norms

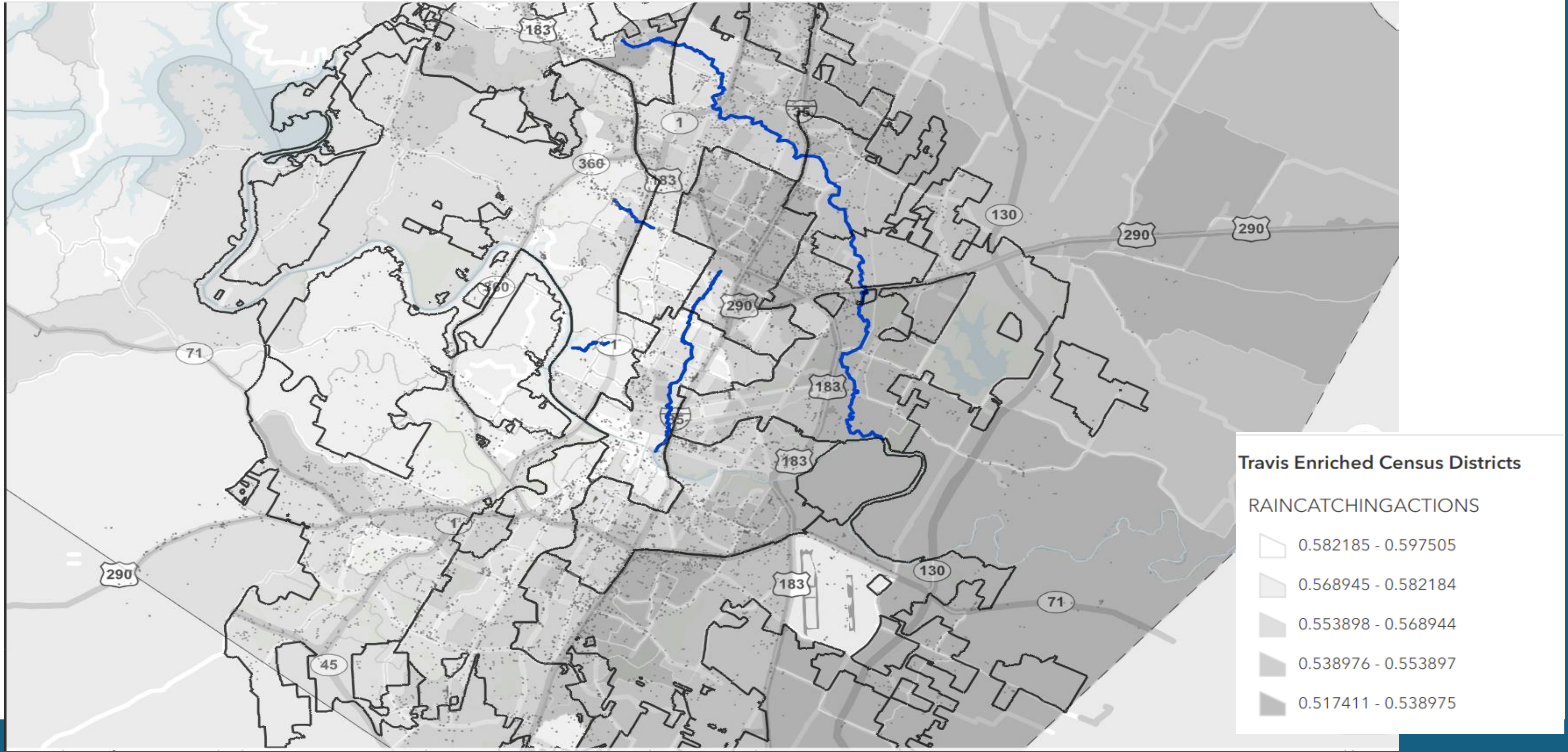
Raincatching Actions

Table 7: Regression Results for Combined Sample



Dependent variable:				
	Total Actions	**Structural Actions**	**Raincatching Actions**	**Non-structural Actions**
	(1)	(2)	(3)	(4)
Non-white	-0.83*** (0.25)	-0.61*** (0.17)	-0.11 (0.09)	-0.22 (0.16)
No Adv Degree	-0.14 (0.22)	-0.26* (0.15)	-0.08 (0.08)	0.11 (0.14)
Median Income	0.01 (0.32)	0.24 (0.22)	0.08 (0.11)	-0.24 (0.20)
Low Income	-0.39 (0.37)	-0.18 (0.25)	-0.02 (0.13)	-0.21 (0.23)
Very Low Income	0.29 (0.38)	0.16 (0.26)	0.12 (0.13)	0.13 (0.24)
Personal Norms	1.07*** (0.19)	0.57*** (0.13)	0.21*** (0.07)	0.51*** (0.12)
Attitude	0.05 (0.08)	0.02 (0.05)	0.04 (0.03)	0.03 (0.05)
Awareness	0.18 (0.23)	0.04 (0.15)	-0.05 (0.08)	0.14 (0.14)
Social Capital	0.38** (0.17)	0.27** (0.12)	0.05 (0.06)	0.11 (0.11)
Constant	6.33*** (0.19)	1.88*** (0.13)	0.40*** (0.07)	4.45*** (0.12)
Observations	301	301	301	301
Note: *p$^{<0.1; >**}$p$^{<0.05; >***}$p<0.01				

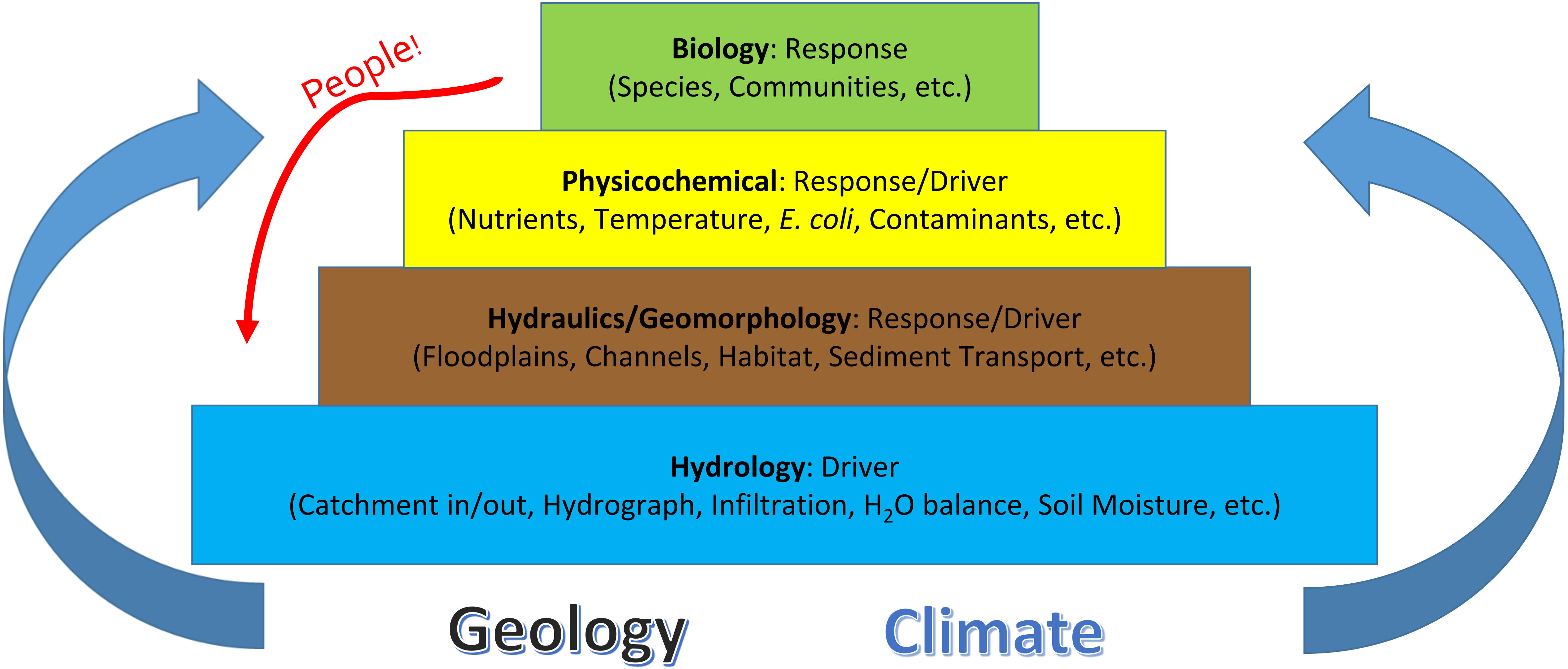
Results from sociological modeling raincatching actions



Physics-based modeling

GRIDDED SURFACE SUBSURFACE HYDROLOGIC ANALYSIS TOOL (GSSHA)

Urban Watershed Pyramid



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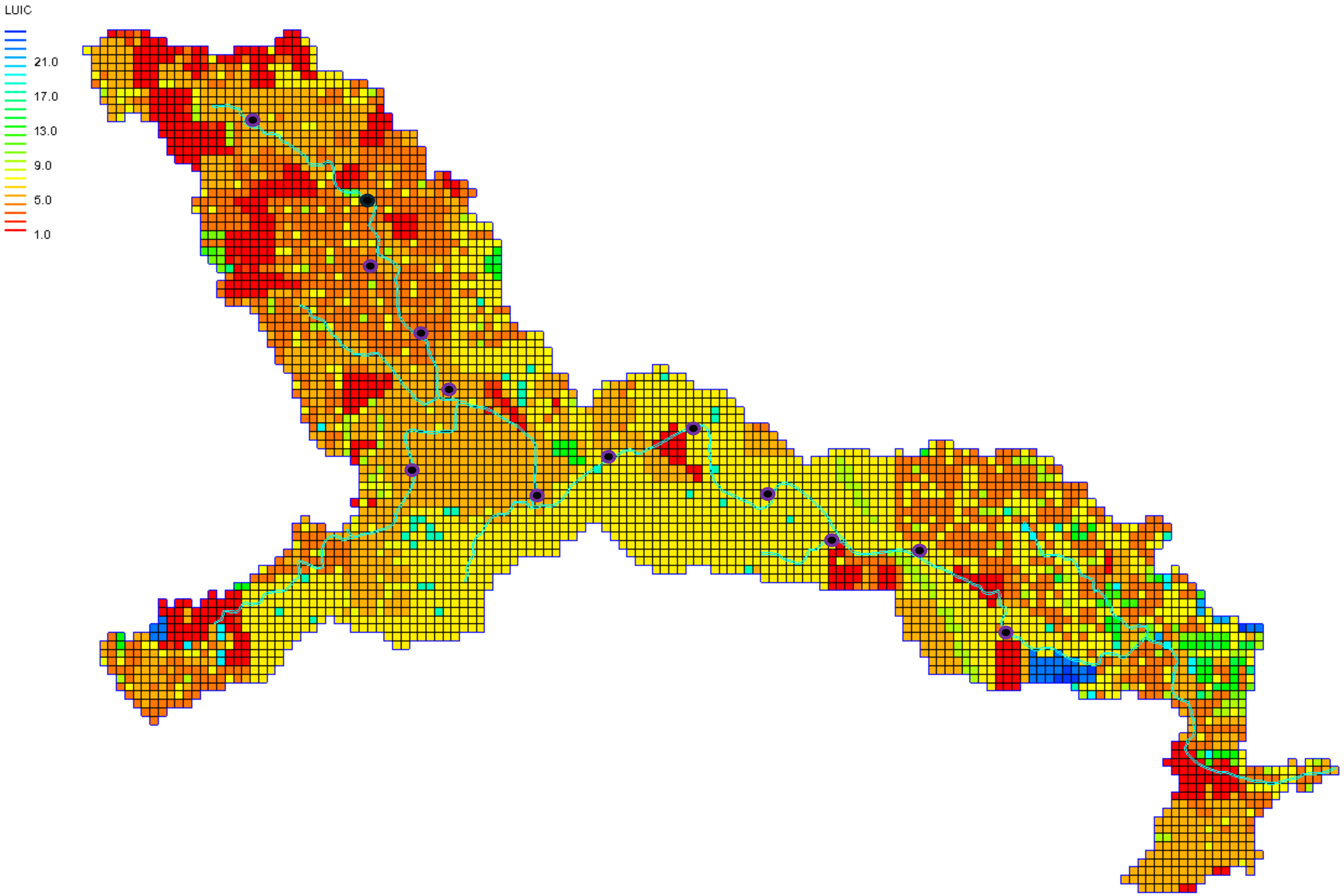
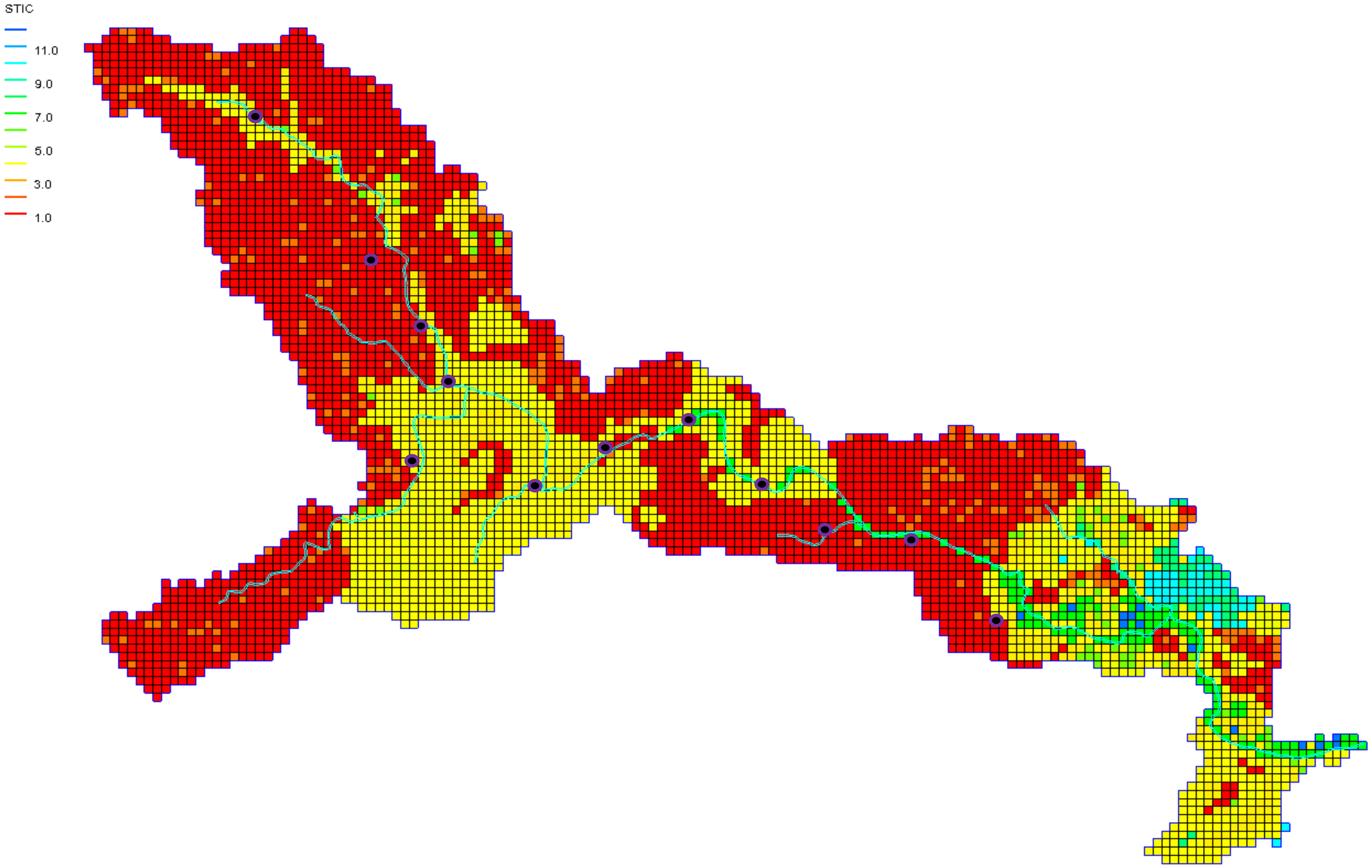
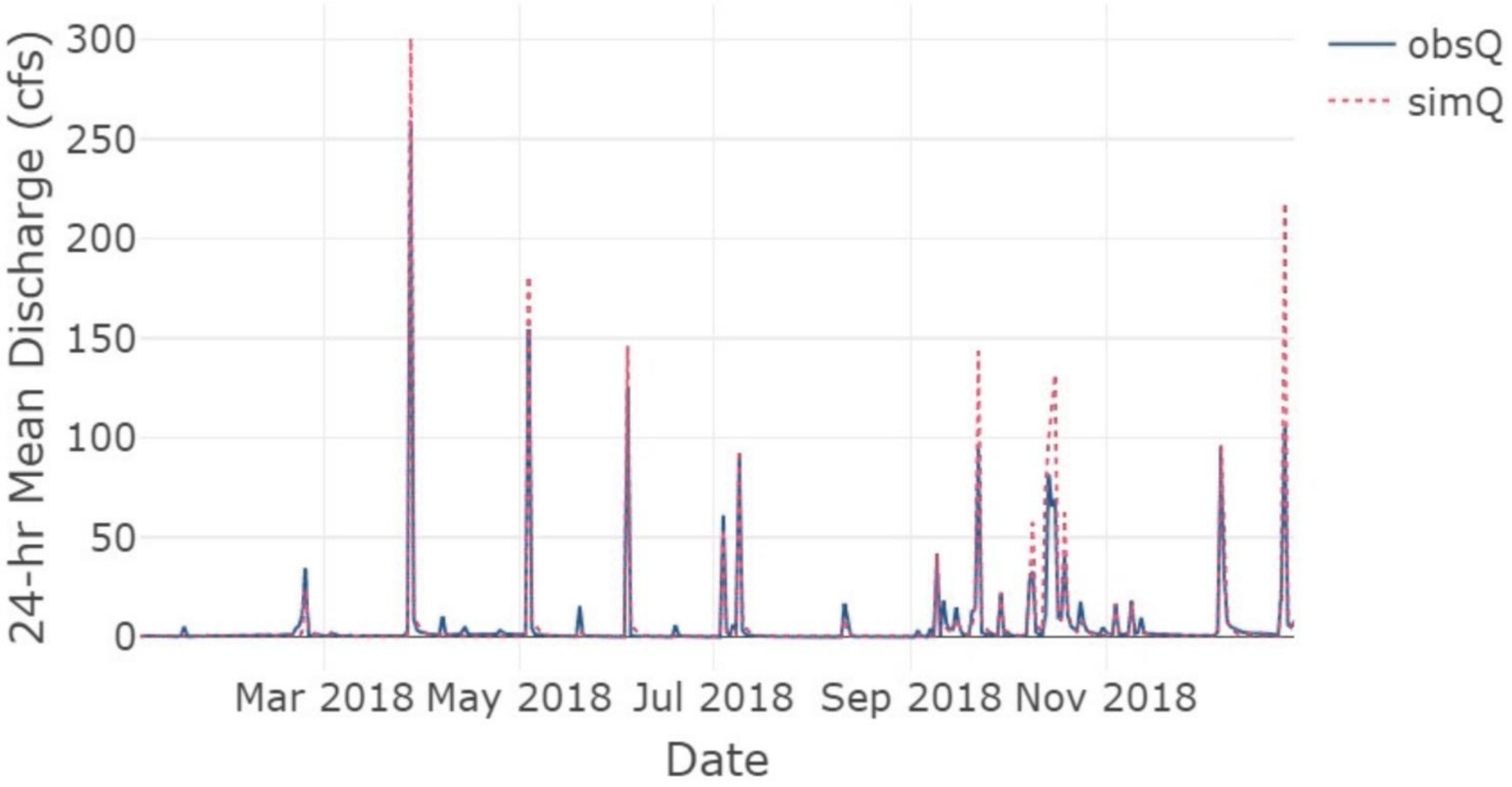
WMS – Land use

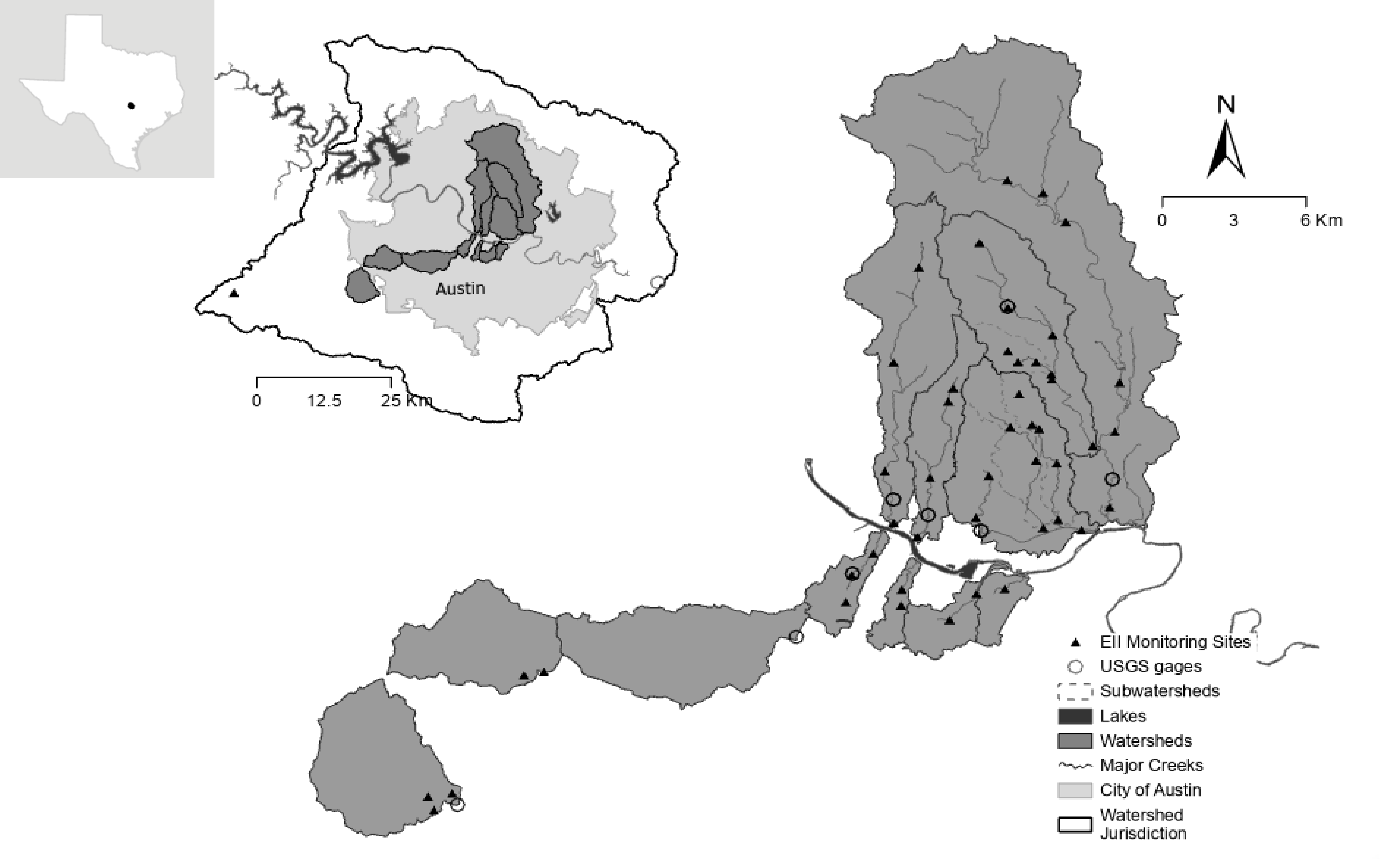


WMS – soil type

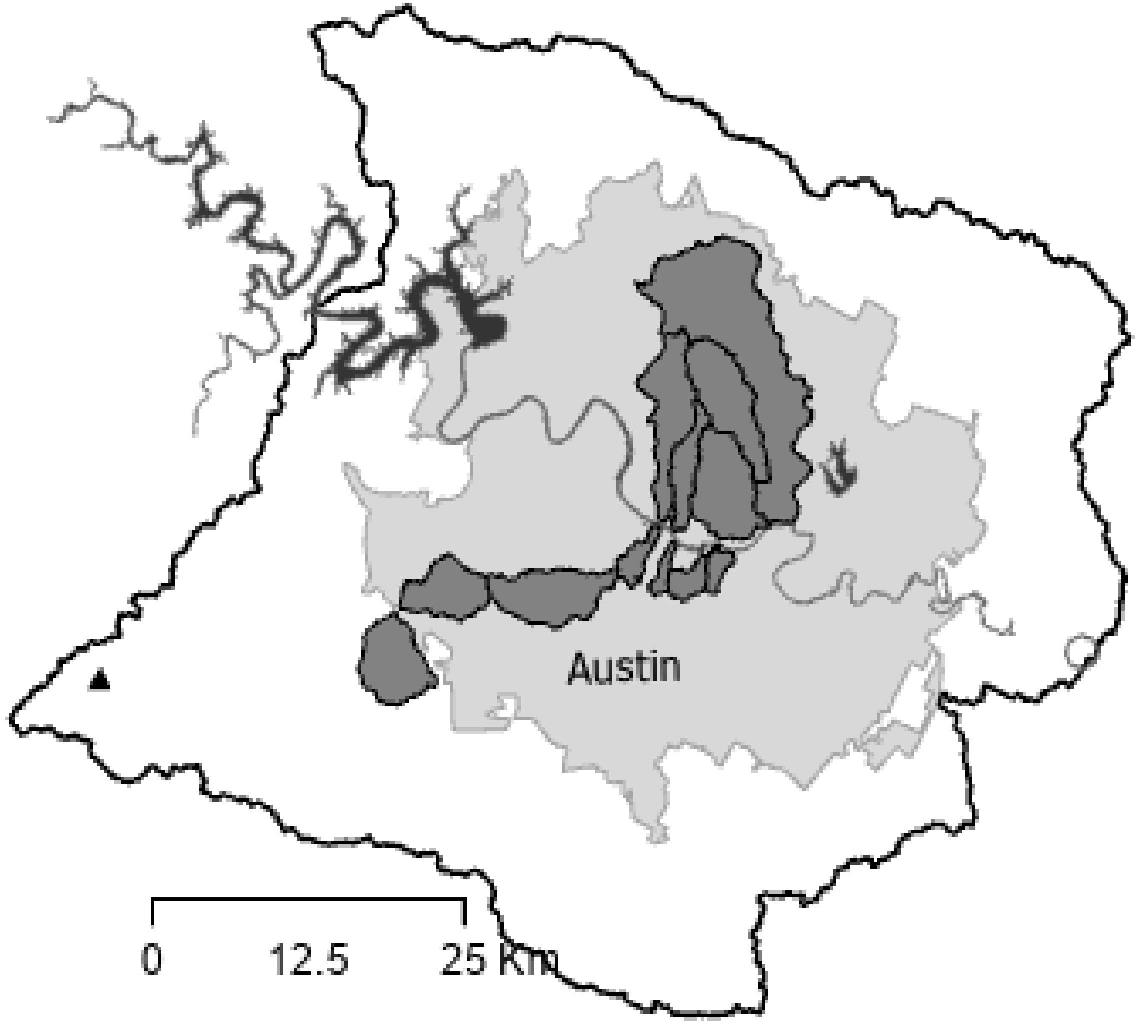


Hydrograph result

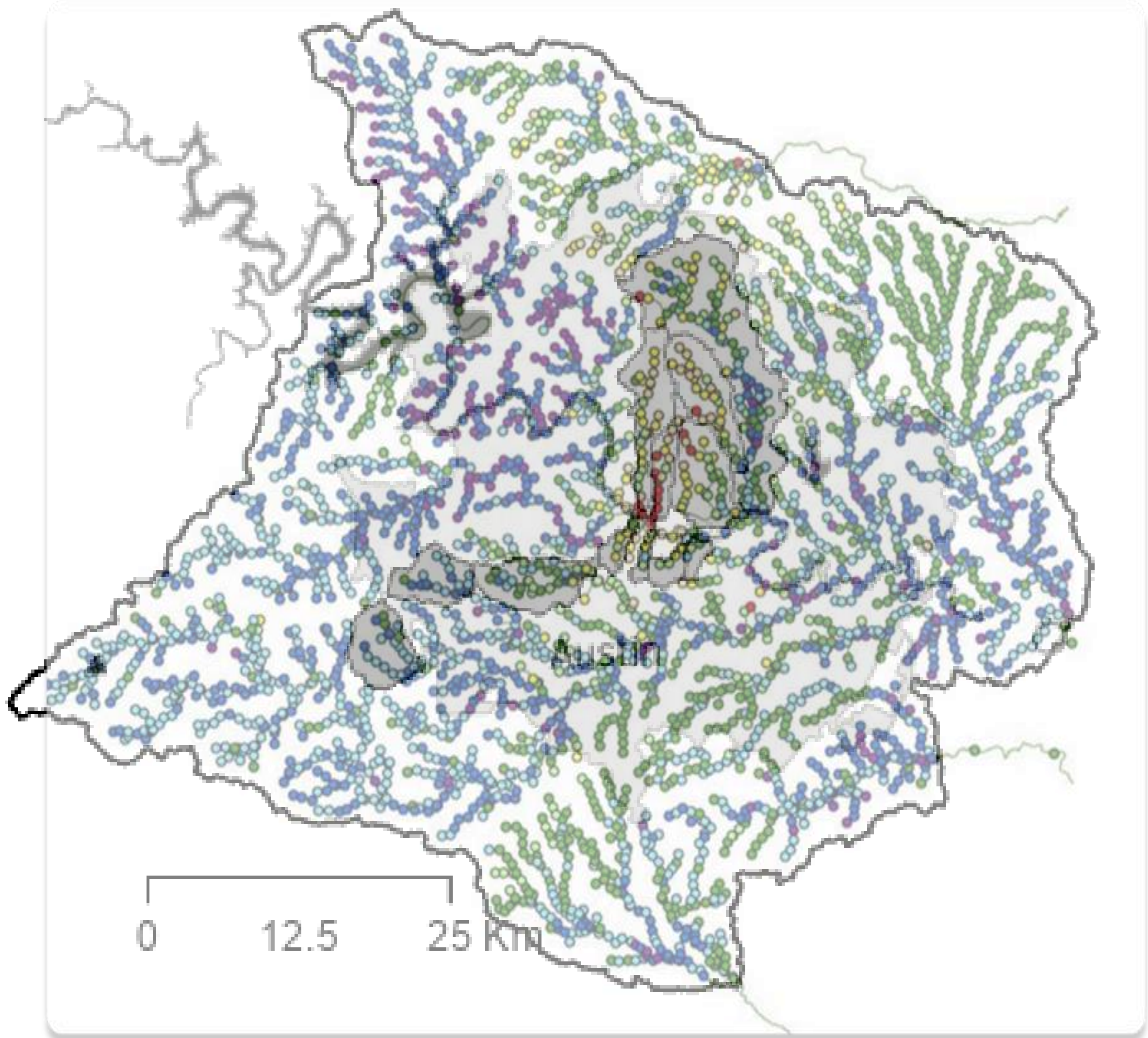



Austin
0
12.5
25 Km
N
0
3
6 Km
▲ EII Monitoring Sites
○ USGS gages
Subwatersheds
Lakes
Watersheds
Major Creeks
City of Austin
Watershed Jurisdiction

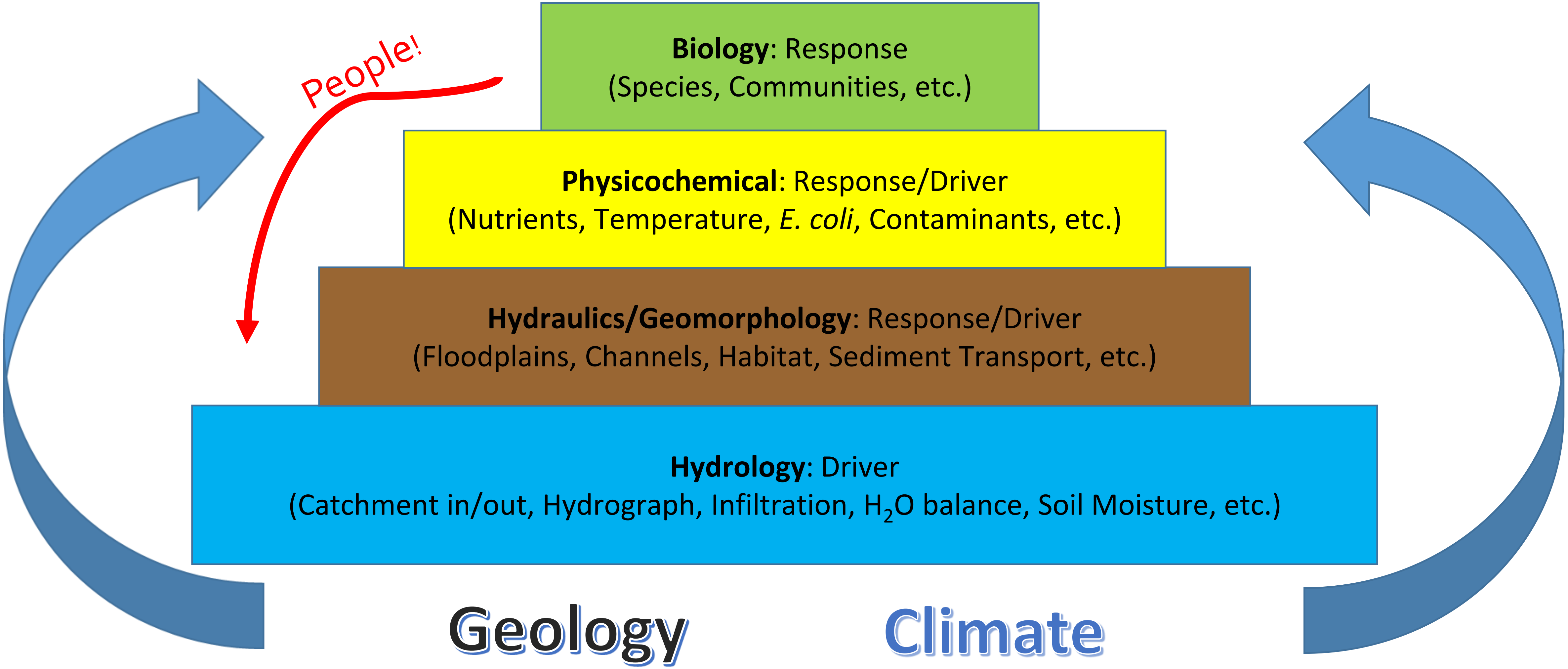
Study area



Study area-discretized



Urban Watershed Pyramid



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Geology

Climate

Deep learning algorithms

USING DEEP LEARNING

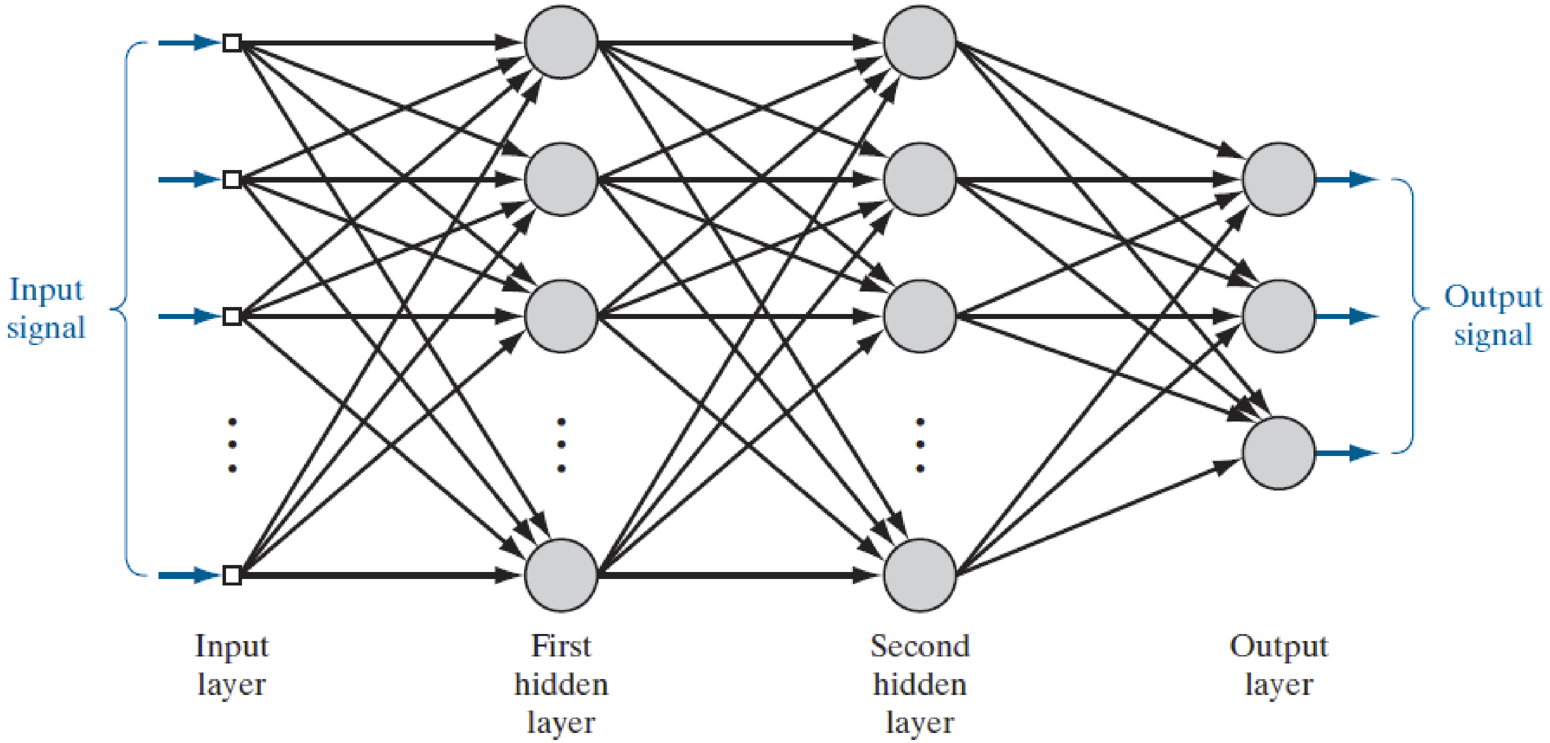
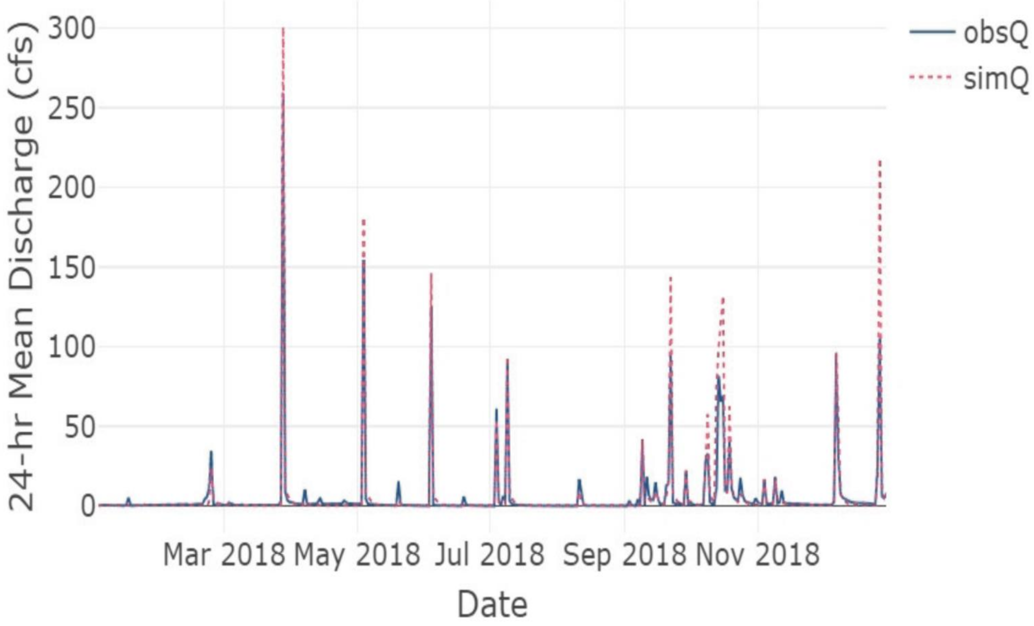
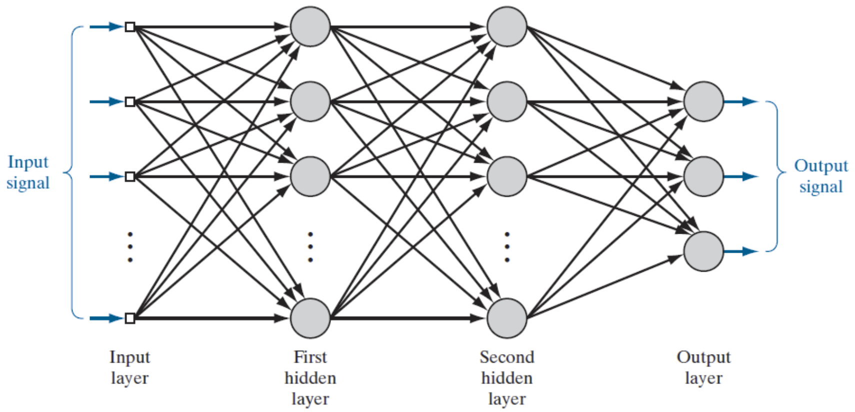


FIGURE 4.1 Architectural graph of a multilayer perceptron with two hidden layers.

Using Deep Learning with Hydrology





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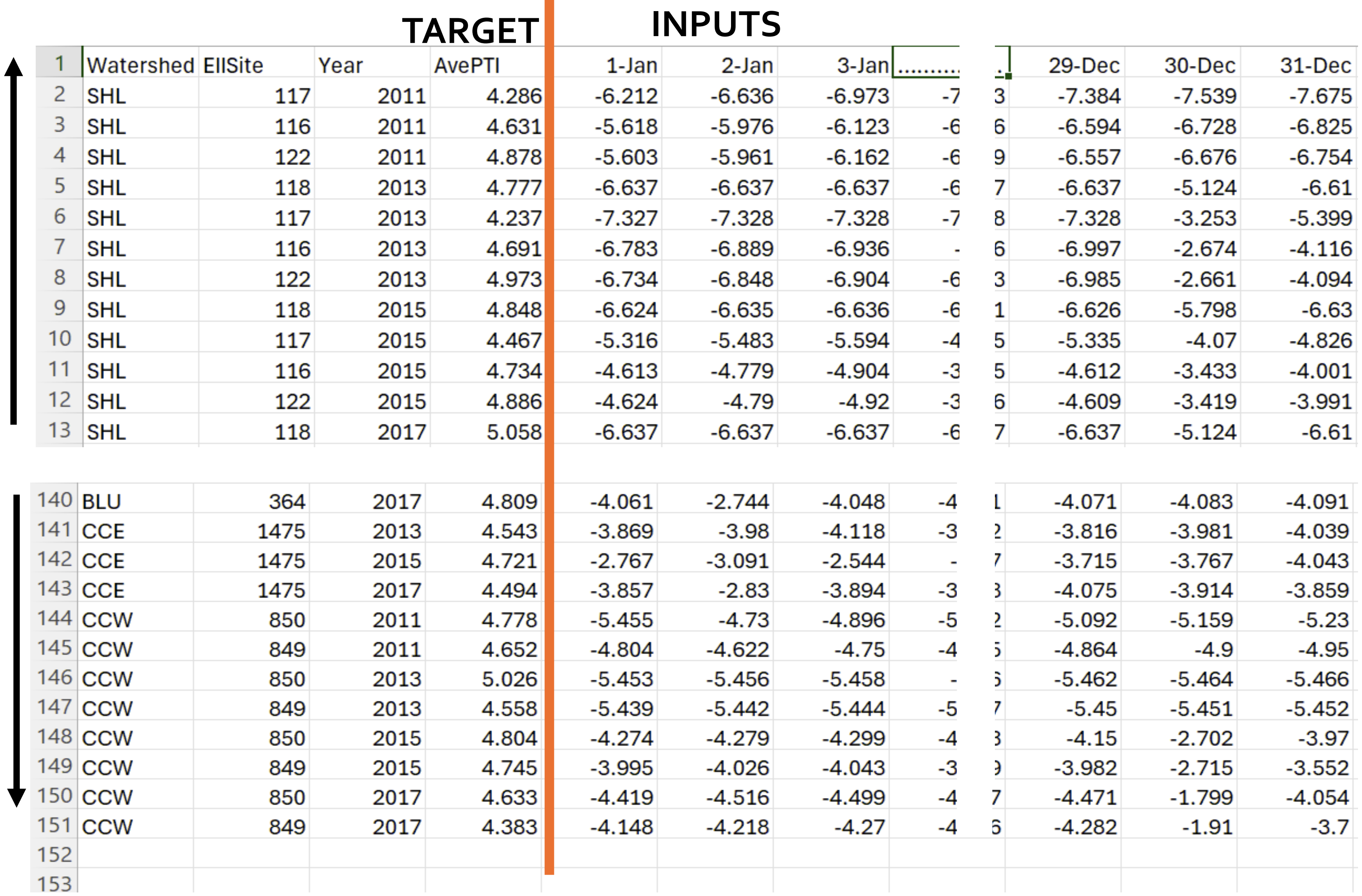
Observed Ecologic Community Metric

Using Deep Learning with Hydrology



TARGET

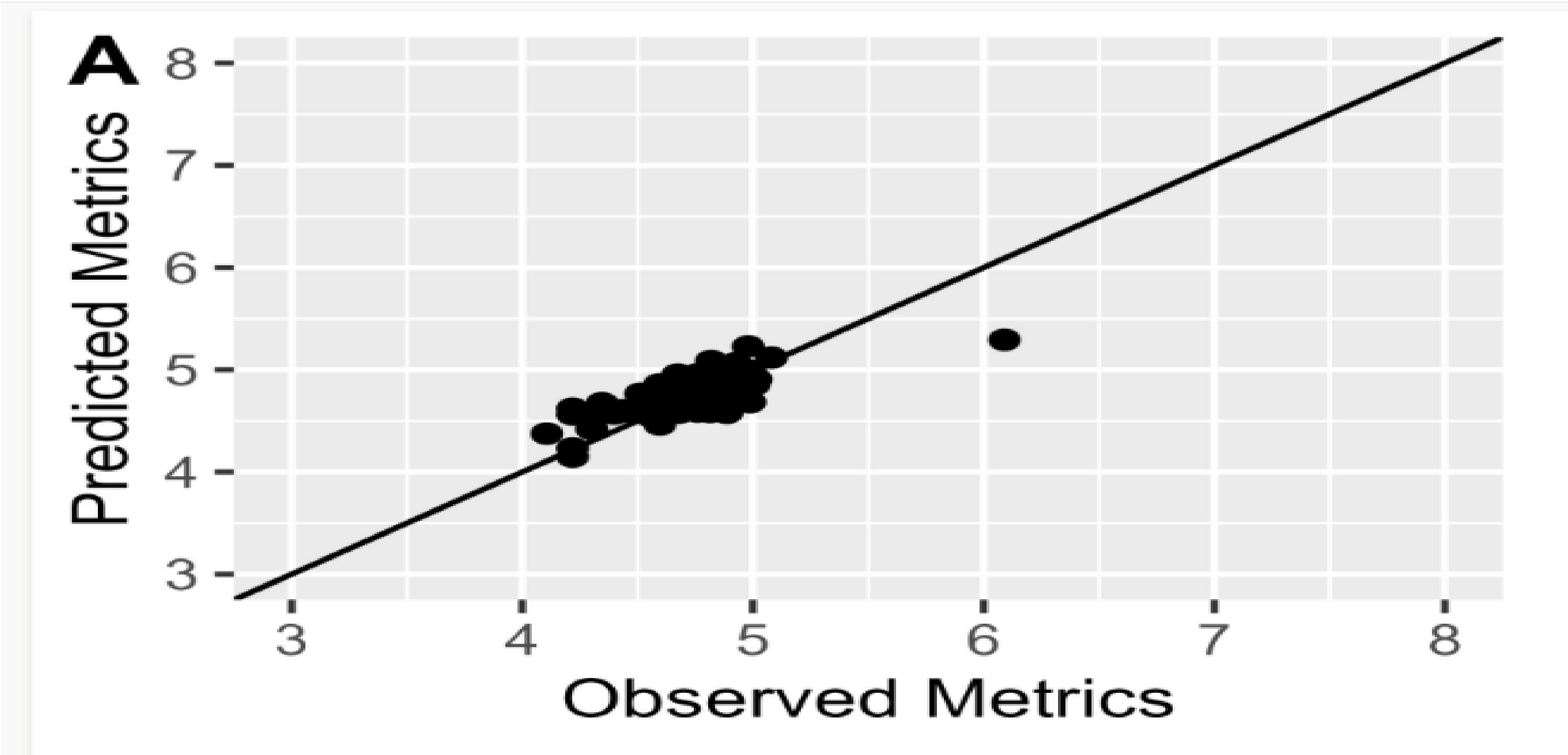
INPUTS

Training

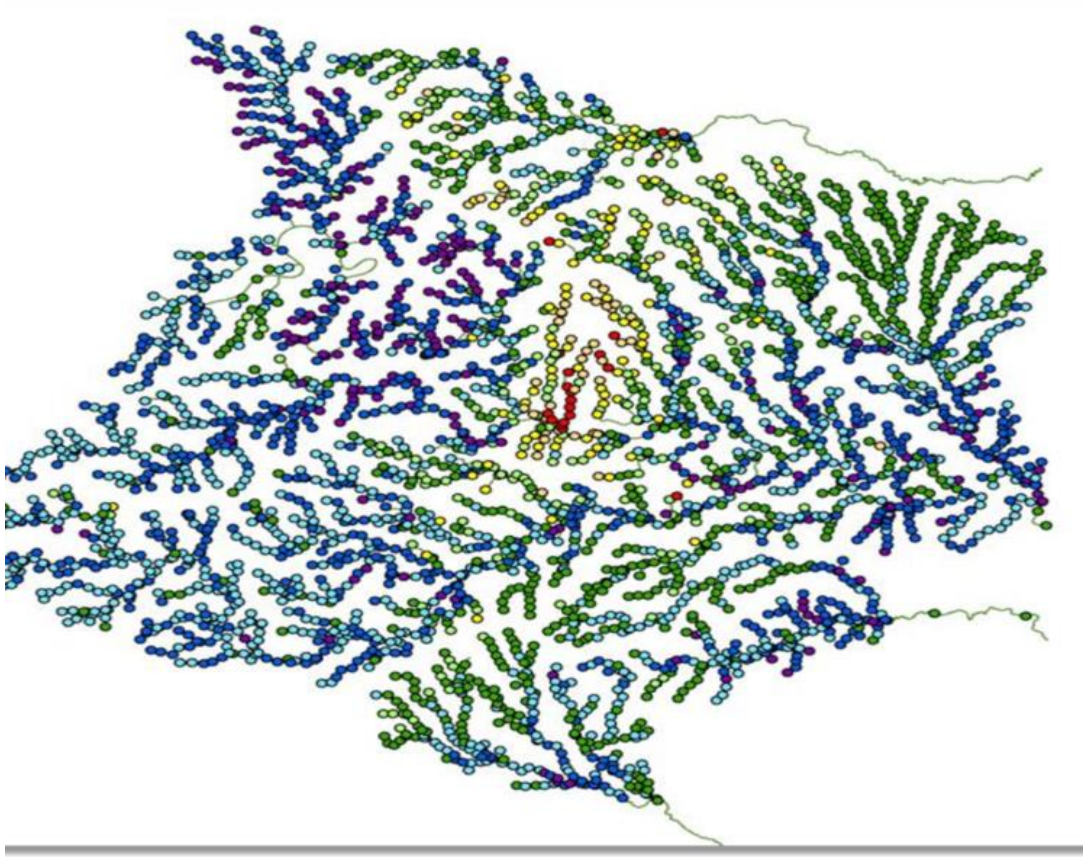
Testing

	Watershed	EllSite	Year	AvePTI	1-Jan	2-Jan	3-Jan	....	.	29-Dec	30-Dec	31-Dec
2	SHL	117	2011	4.286	-6.212	-6.636	-6.973	-7	3	-7.384	-7.539	-7.675
3	SHL	116	2011	4.631	-5.618	-5.976	-6.123	-6	6	-6.594	-6.728	-6.825
4	SHL	122	2011	4.878	-5.603	-5.961	-6.162	-6	9	-6.557	-6.676	-6.754
5	SHL	118	2013	4.777	-6.637	-6.637	-6.637	-6	7	-6.637	-5.124	-6.61
6	SHL	117	2013	4.237	-7.327	-7.328	-7.328	-7	8	-7.328	-3.253	-5.399
7	SHL	116	2013	4.691	-6.783	-6.889	-6.936	-	6	-6.997	-2.674	-4.116
8	SHL	122	2013	4.973	-6.734	-6.848	-6.904	-6	3	-6.985	-2.661	-4.094
9	SHL	118	2015	4.848	-6.624	-6.635	-6.636	-6	1	-6.626	-5.798	-6.63
10	SHL	117	2015	4.467	-5.316	-5.483	-5.594	-4	5	-5.335	-4.07	-4.826
11	SHL	116	2015	4.734	-4.613	-4.779	-4.904	-3	5	-4.612	-3.433	-4.001
12	SHL	122	2015	4.886	-4.624	-4.79	-4.92	-3	6	-4.609	-3.419	-3.991
13	SHL	118	2017	5.058	-6.637	-6.637	-6.637	-6	7	-6.637	-5.124	-6.61
140	BLU	364	2017	4.809	-4.061	-2.744	-4.048	-4	1	-4.071	-4.083	-4.091
141	CCE	1475	2013	4.543	-3.869	-3.98	-4.118	-3	2	-3.816	-3.981	-4.039
142	CCE	1475	2015	4.721	-2.767	-3.091	-2.544	-	7	-3.715	-3.767	-4.043
143	CCE	1475	2017	4.494	-3.857	-2.83	-3.894	-3	3	-4.075	-3.914	-3.859
144	CCW	850	2011	4.778	-5.455	-4.73	-4.896	-5	2	-5.092	-5.159	-5.23
145	CCW	849	2011	4.652	-4.804	-4.622	-4.75	-4	5	-4.864	-4.9	-4.95
146	CCW	850	2013	5.026	-5.453	-5.456	-5.458	-	5	-5.462	-5.464	-5.466
147	CCW	849	2013	4.558	-5.439	-5.442	-5.444	-5	7	-5.45	-5.451	-5.452
148	CCW	850	2015	4.804	-4.274	-4.279	-4.299	-4	3	-4.15	-2.702	-3.97
149	CCW	849	2015	4.745	-3.995	-4.026	-4.043	-3	9	-3.982	-2.715	-3.552
150	CCW	850	2017	4.633	-4.419	-4.516	-4.499	-4	7	-4.471	-1.799	-4.054
151	CCW	849	2017	4.383	-4.148	-4.218	-4.27	-4	6	-4.282	-1.91	-3.7
152												
153												

Evaluating Deep Learning



Predicting Benthic Macroinvertebrates Metrics



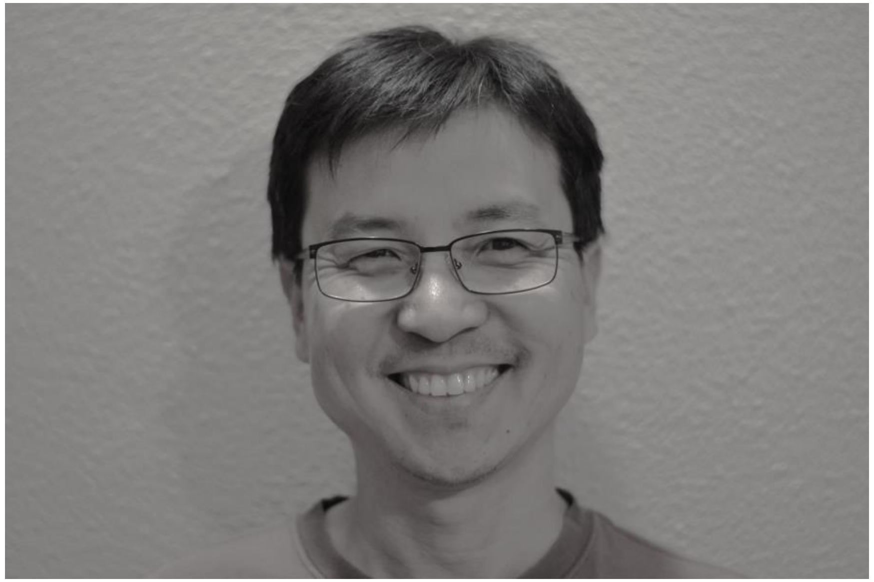
1. We can estimate the anthropogenic impact from land surfaces using literature values, Superforecasting, and sociological modeling
2. We can use GIS data and climate data to estimate hydrographs all around Austin using physics-based models
3. Then we can use the outputs of the physics-based models with empirical data collected on ecological community metrics to train a DL model
4. Finally, we can make predictions of the ecological community metrics using the trained DL model
5. We can use this framework to include other environmental data, such as

Meet the team

ANDREW CHU

HARSHITA MAHASETH

ANGEL SANTIAGO



YOUNG-HOON JIN

YAZMIN AVILA

THANK YOU

Questions?

Abel Porras
512-468-7095
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