



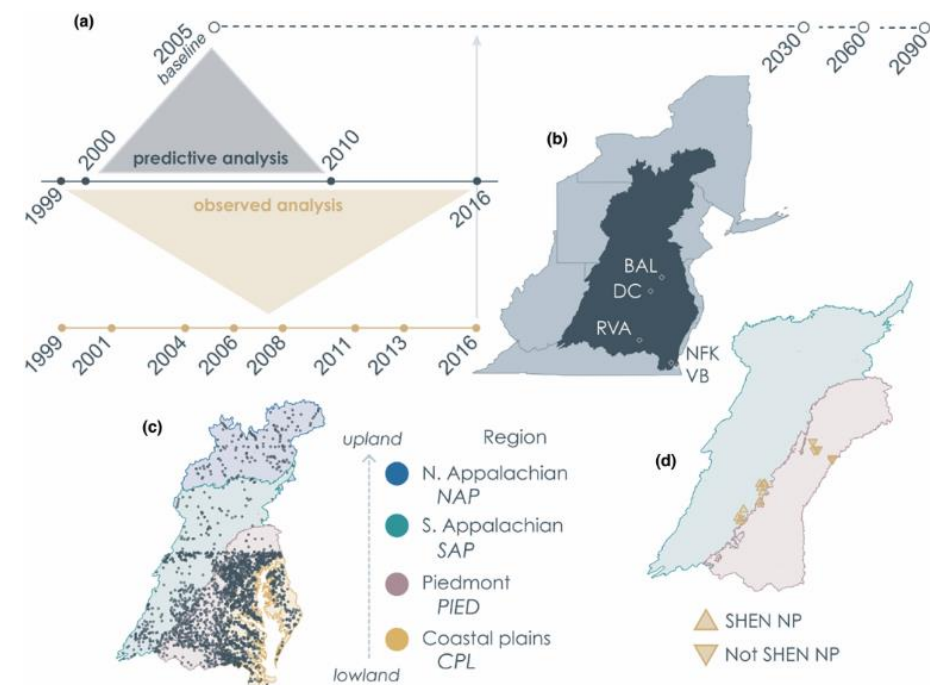
# Machine learning models applied to forecast ecology & flow under global change

Chesapeake Bay STAC: Leveraging Artificial Intelligence and Machine Learning to Advance  
Chesapeake Bay Research and Management: A review of status, challenges, and opportunities  
24-25 February 2025

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# Overview: 2 forecasting projects



Ecology



RESEARCH ARTICLE | [Open Access](#) |

**Observed and projected functional reorganization of riverine fish assemblages from global change**

Taylor Woods Mary C. Freeman, Kevin P. Krause, Kelly O. Maloney

First published: 06 April 2023 | <https://doi.org/10.1111/gcb.16707> | Citations: 1



Flow (ongoing)

**science objectives**

- **PREDICT STREAMFLOW ALTERATION AT ALL STREAMS 1980-2100 BASED ON CLIMATE & LAND-USE**
- **IDENTIFY THRESHOLDS IN FISH RESPONSES TO FLOW**
- **ASSESS VULNERABILITY OF FISH COMMUNITIES TO FUTURE FLOW ALTERATION**

**USGS**  
science for a changing world



# Questions/objectives

## *Ecology*

How will fish communities change in the future under different scenarios of climate & land-use change?

Which suites of traits are associated with 'winners' (habitat suitability gains) & 'losers' (habitat suitability losses)

## *Flow*

How will climate & land-use change affect flow regimes?

# Connection to Chesapeake goals/outcomes

Vital Habitats	Stream Health	Modeling, Monitoring, Research, Climate	Determine the effects of climate change on stream processes.
Vital Habitats	Stream Health	Analysis Additional text Additional text Additional text Additional text Additional text, Monitoring, Climate	Increase and improve the existing temperature monitoring network and standardize a methodology across the region, similar to the BIBI data, to assess important ecological thresholds and temperature criteria to protect fisheries.
Climate Resiliency	Climate Resiliency Monitoring and Assessment	Data Gathering, Monitoring, Climate, Indicator	Development of a flooding climate change indicators that links fine scale flooding data to community resilience.
Healthy Watersheds	Healthy Watersheds	Data Gathering, Synthesis, Climate	Use an integrative approach combining information on flows, groundwater, stream power, connectivity, and adaptive capacity to provide a more comprehensive approach for identifying climate refugia.
Climate Resiliency	Climate Resiliency Monitoring and Assessment	Analysis Additional text Additional text Additional text Additional text Additional text	Conduct climate vulnerability assessments to better understand both the exposure and sensitivity of species/habitats to rising temperatures, including indirect effects (e.g. invasive species), to better understand overall vulnerability.

# Rationale for method selection

Random forests

*General:*

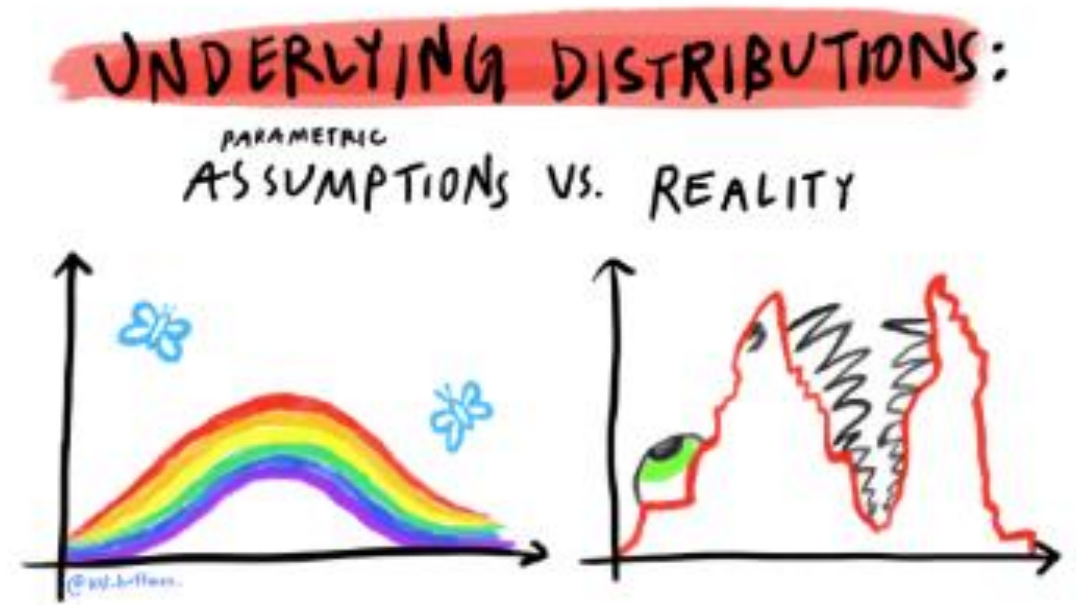
Non-linear, complex relationships

*Ecology (spatial):*

Predictive power for forecasting (classification)

*Flow (temporal):*

RF models with temporally lagged predictors performed similarly to or better than neural networks (LSTMs)



[https://www.khstats.com/art/illustrations\\_draw](https://www.khstats.com/art/illustrations_draw)

# Ecology: model methods

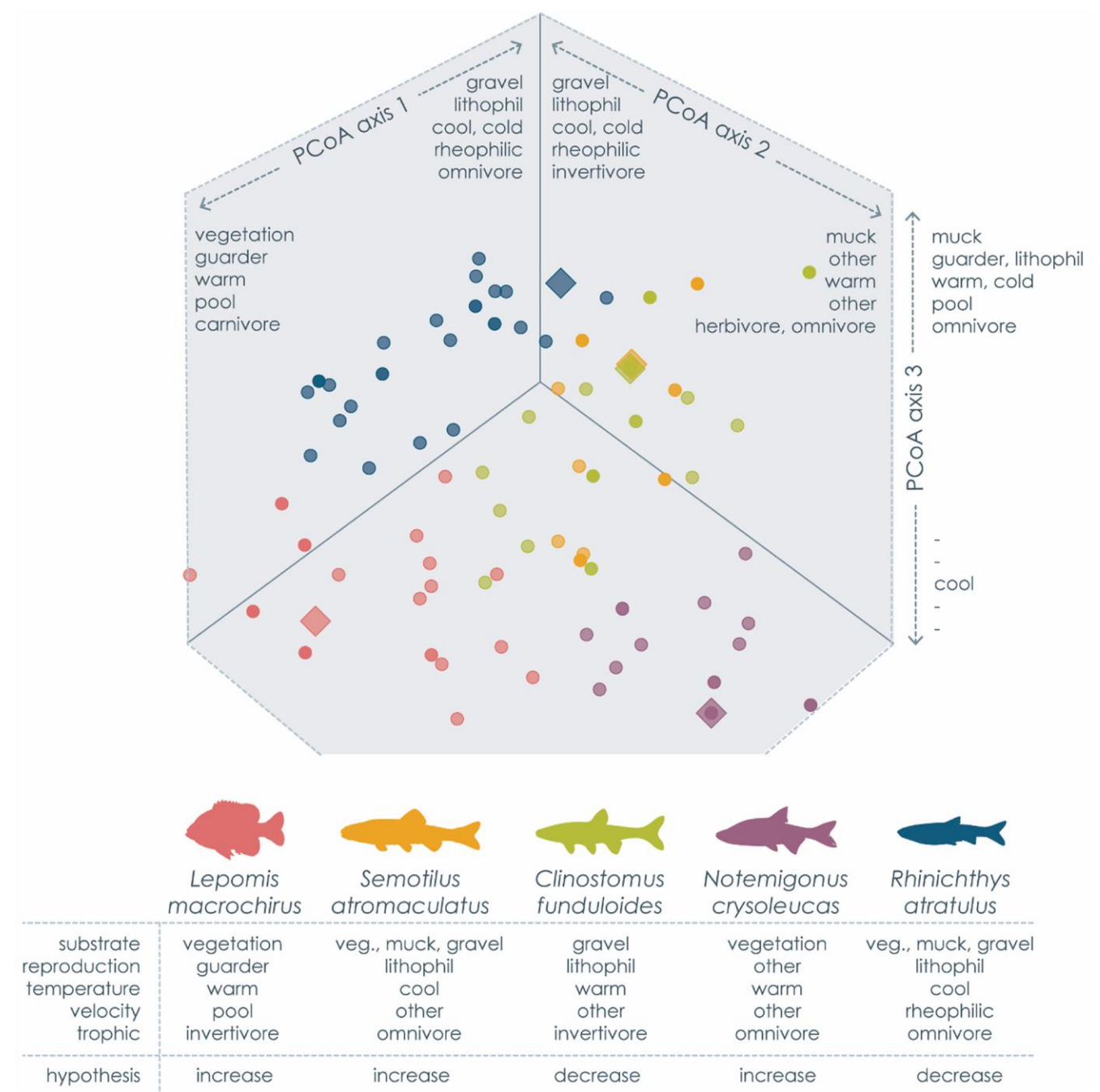
## Reponses

Habitat suitability (inferred by abundances as low, med, high) for different functional groups






## Predictors

Natural landscape

Climate & land-use



# Modeling framework

	 <i>Lepomis macrochirus</i>	 <i>Semotilus atromaculatus</i>	 <i>Clinostomus funduloides</i>	 <i>Notemigonus crysoleucas</i>	 <i>Rhinichthys atratulus</i>
substrate	vegetation	veg., muck, gravel	gravel	vegetation	veg., muck, gravel
reproduction	guarder	lithophil	lithophil	other	lithophil
temperature	warm	cool	warm	warm	cool
velocity	pool	other	other	other	rheophilic
trophic	invertivore	omnivore	invertivore	omnivore	omnivore
hypothesis	increase	increase	decrease	increase	decrease

*Abundance data*



*Low, medium, high* ~ *predictors*

"habitat suitability"

{multiple future scenarios}

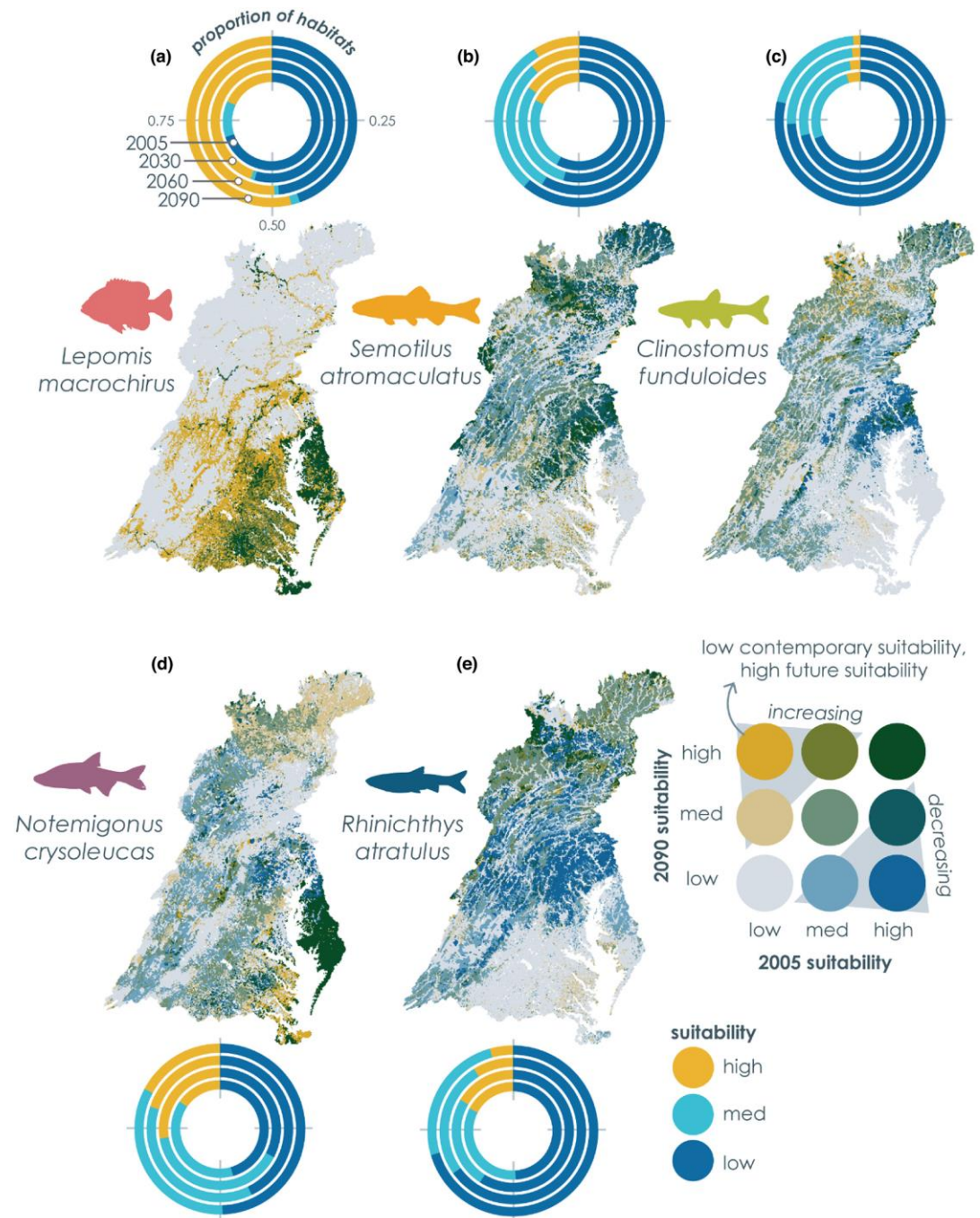
# Ecology: model results

## 'Winner' traits

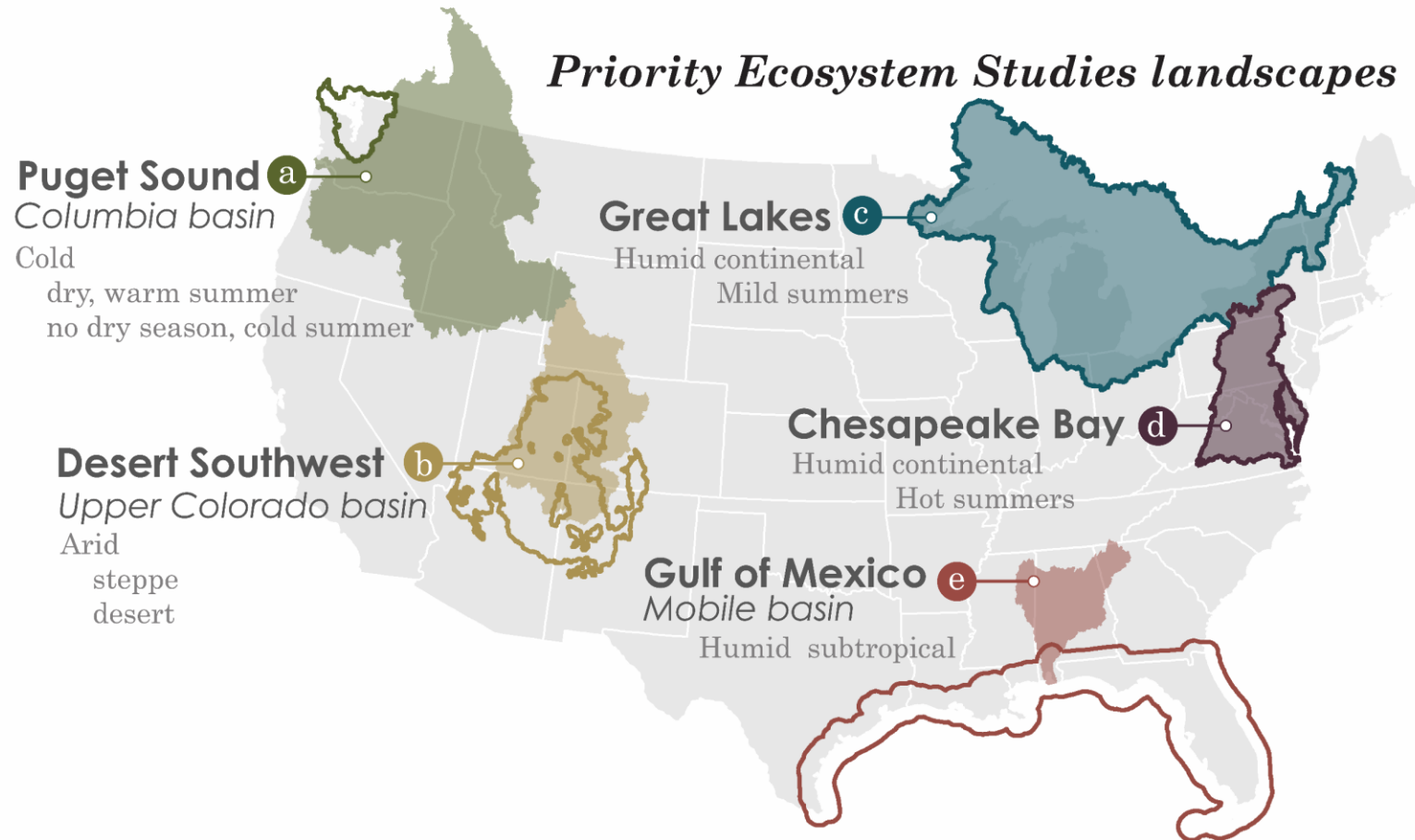
Generalist, warm-water, fine substrate, slow-water

## 'Loser' traits

Cold-water, clean substrate, fast-water



# Flow: model context

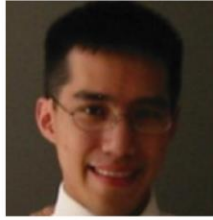


## science OBJECTIVES

- **PREDICT STREAMFLOW ALTERATION AT ALL STREAMS 1980-2100 BASED ON CLIMATE & LAND-USE**
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# hydrology team

- IDENTIFY PREDICTOR VARIABLES FOR FLOW MODELS
- PREDICT FLOW METRICS AT GAGED & UNGAGED REACHES 1980-NOW
- FORECAST FLOW METRICS NOW-2100



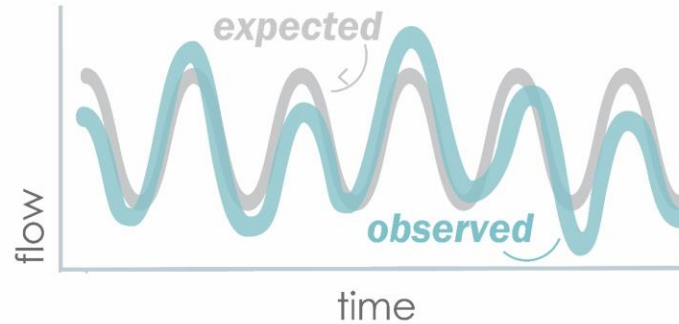
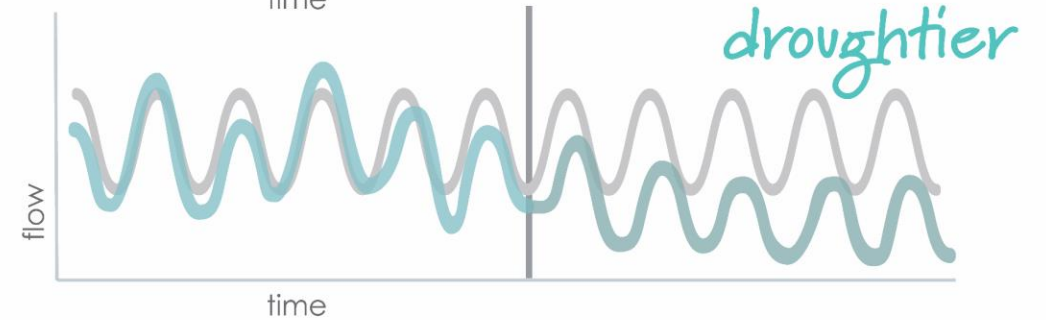
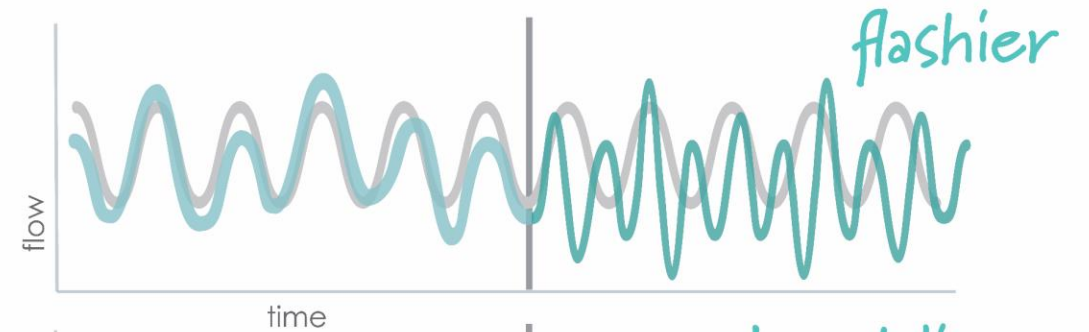
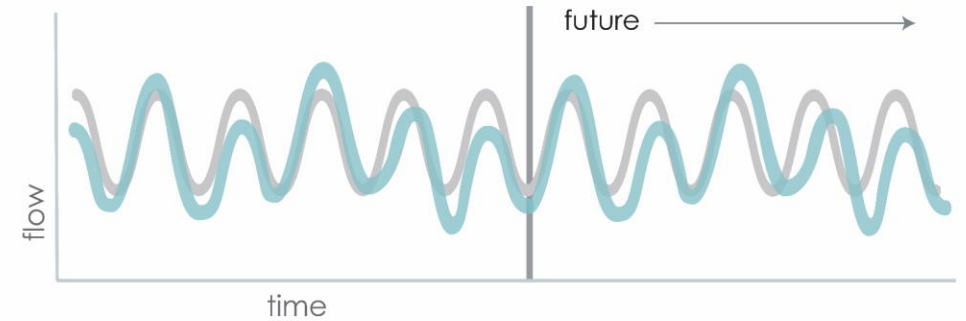
ken eng WMA



jared smith WMA

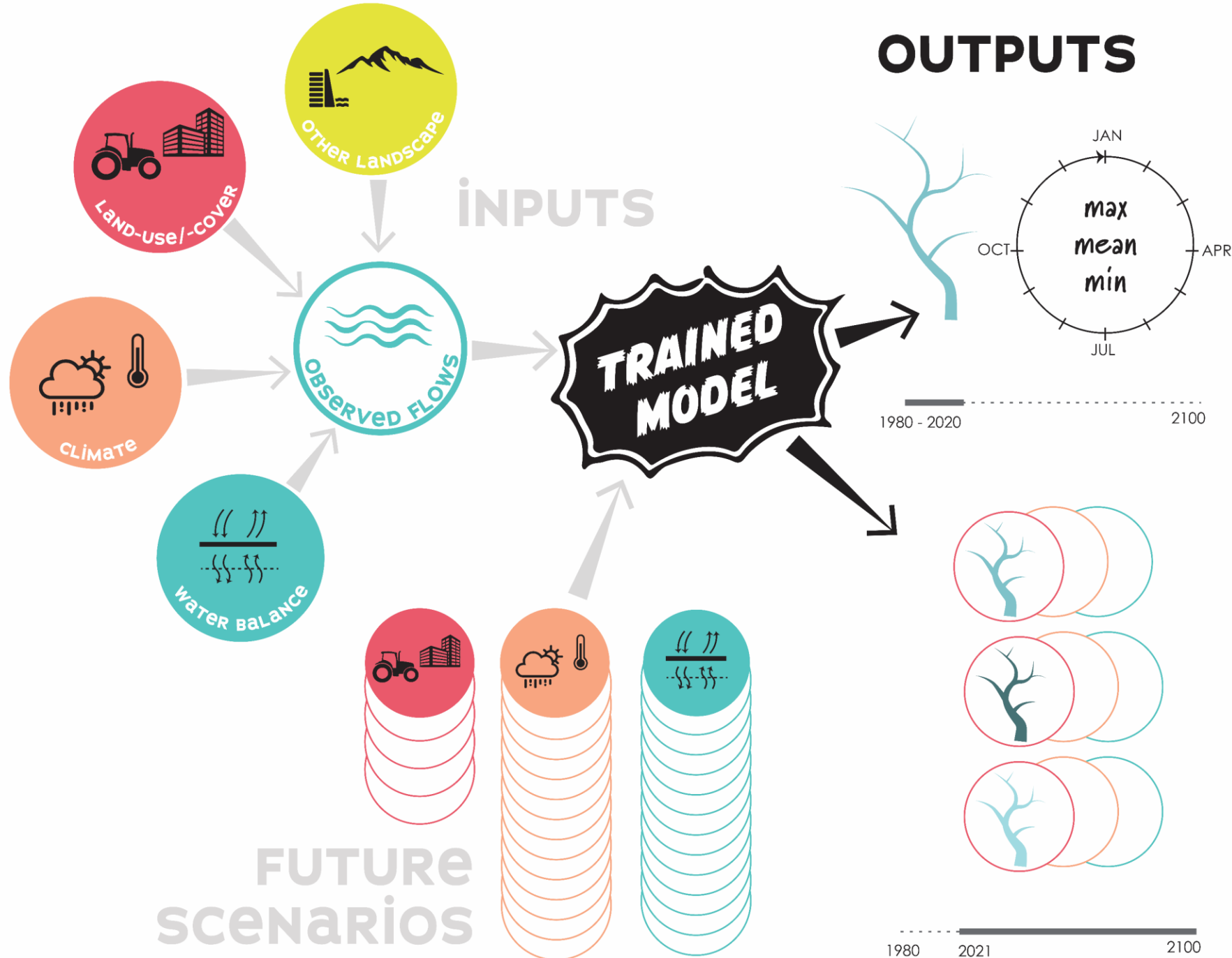


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# FLOW MODELS

- **MACHINE LEARNING MODELS TO PREDICT MONTHLY FLOWS 1980-2020 AT ALL NHDV2 REACHES**
- **OUTPUTS ARE MONTHLY MINIMUM, MEAN, MAXIMUM FLOW**
- **FORECAST MONTHLY FLOWS WITH FUTURE SCENARIOS 2021-2100**



# Flow: model results

REGION	HM_TYPE	NSE	PHASE
VPU02	MIN	0.899	0.948
VPU02	MEAN	0.943	0.973
VPU02	MAX	0.881	0.94
VPU03W	MIN	0.861	0.929
VPU03W	MEAN	0.926	0.966
VPU03W	MAX	0.851	0.926
VPU04	MIN	0.843	0.92
VPU04	MEAN	0.872	0.936
VPU04	MAX	0.741	0.876
VPU14	MIN	0.833	0.915
VPU14	MEAN	0.868	0.934
VPU14	MAX	0.857	0.927
VPU17	MIN	0.881	0.942
VPU17	MEAN	0.914	0.959
VPU17	MAX	0.864	0.932

# Challenges/gaps

*Data limitation:* small sample sizes for biology can be limiting for ML models

*Uncertainty:* how to handle uncertainty when using ML/AI outputs as ecological model inputs

