Interpretable Transformer Neural Network Prediction of Diverse Environmental Time Series Using Weather Forecasts

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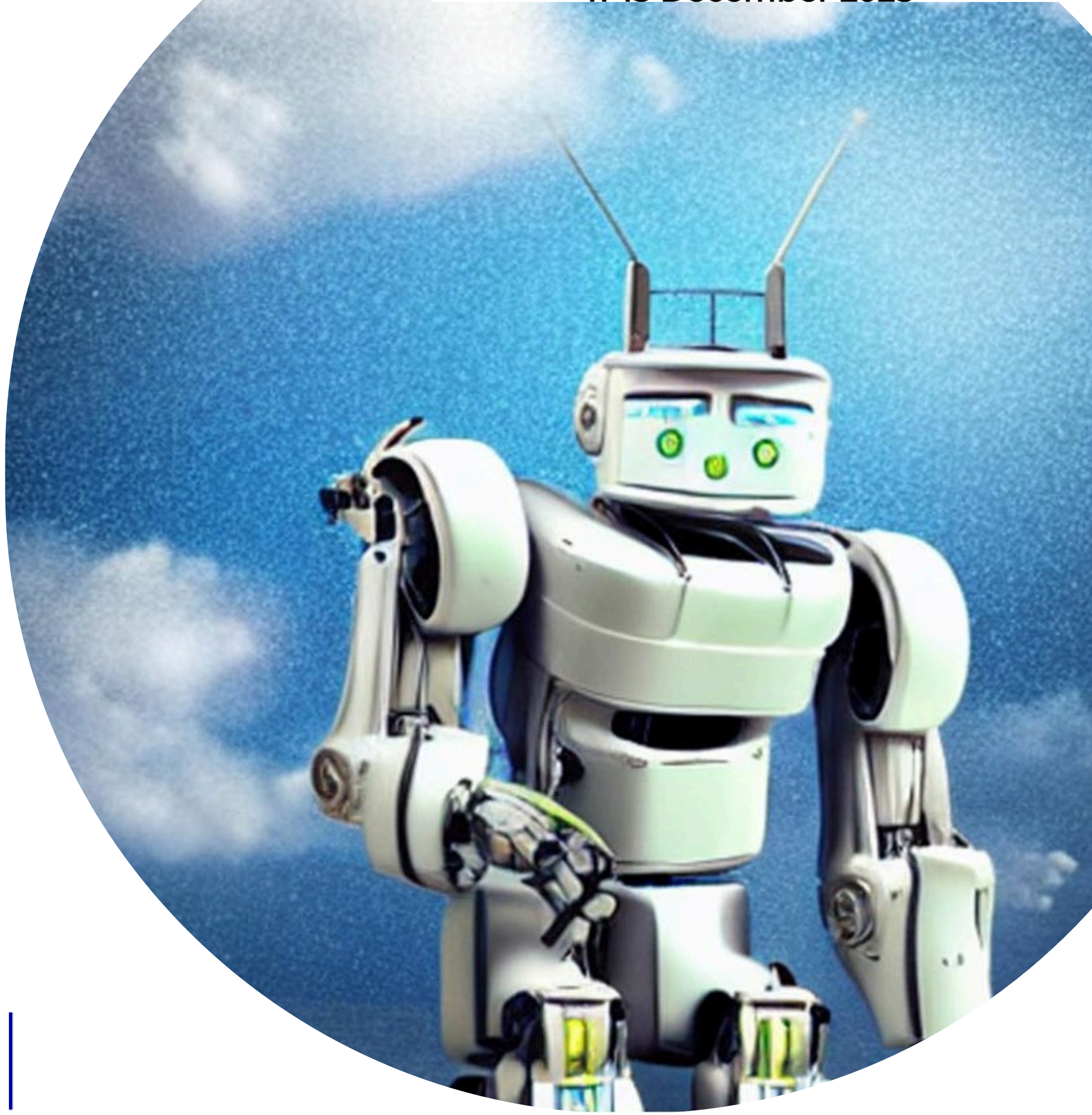

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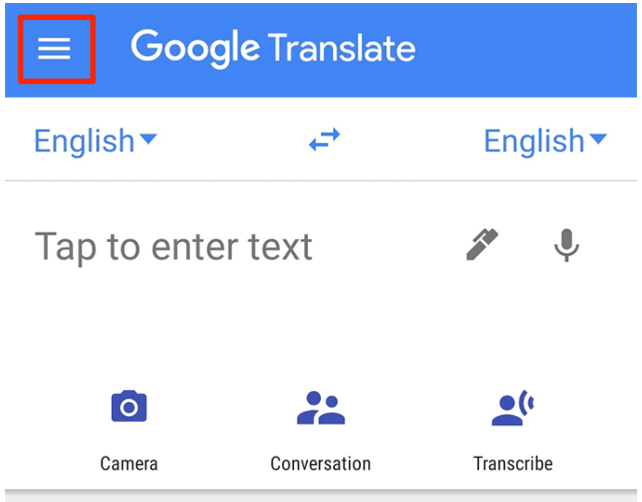
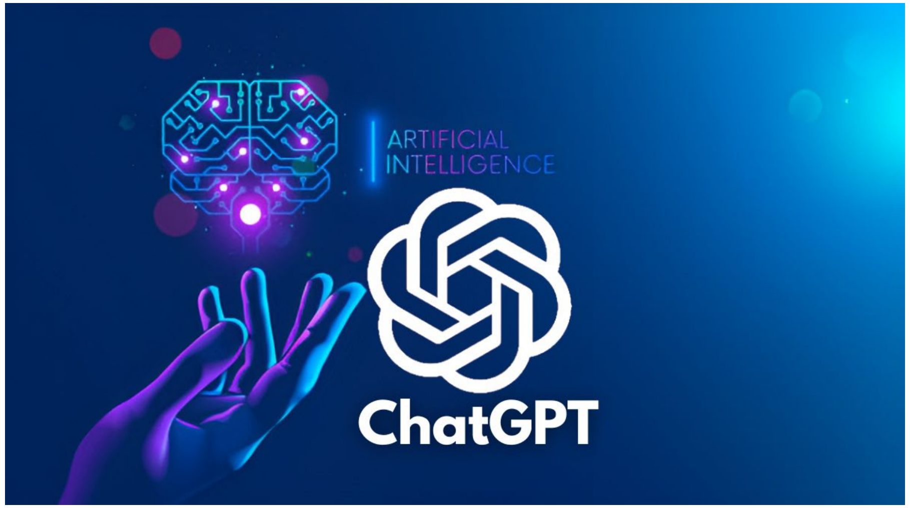
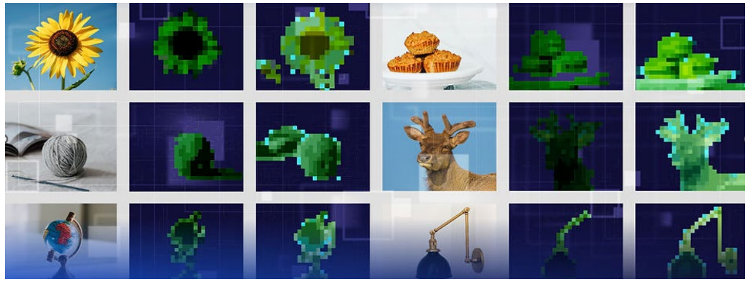
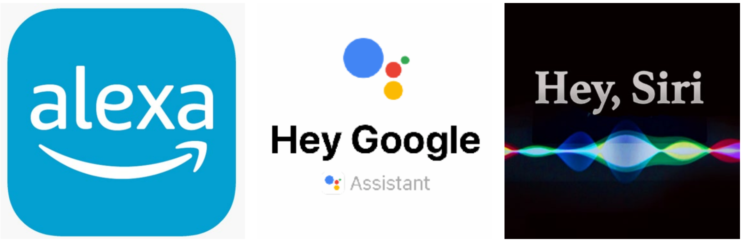
Transformers







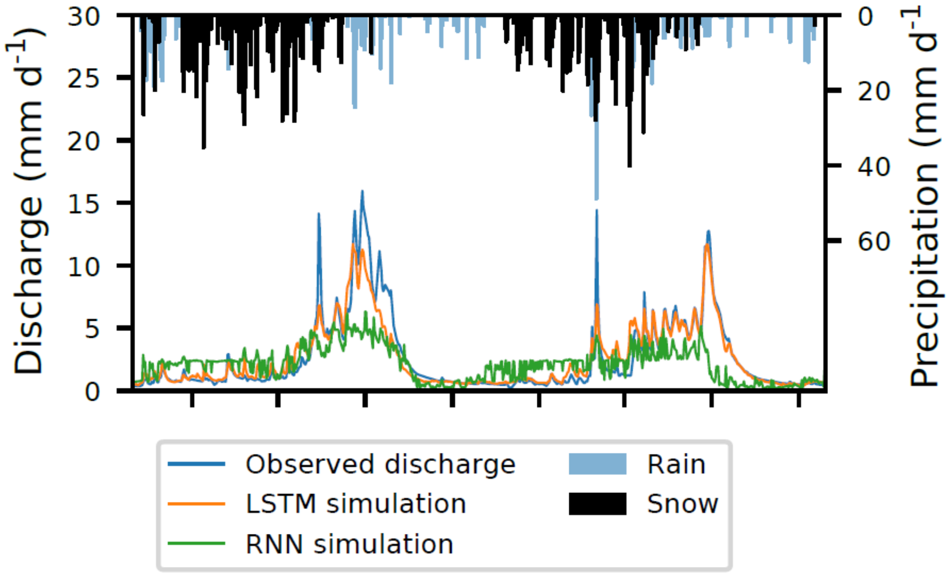


Vaswani et al., 2017. Attention Is All You Need

Motivation

- Increasing climate variability → flash extreme system responses (floods, droughts, extreme salinity fluctuations, etc).
- Transformer neural networks (TNNs) focus and model the most relevant interdependencies in complex datasets
- How to measure the impact of individual variables in the model output across different environmental conditions?

Flooded neighborhood in the aftermath of Hurrican Ian. Sep 2022, Orlando, FL (AP photo/Phelan M. Ebenhack)

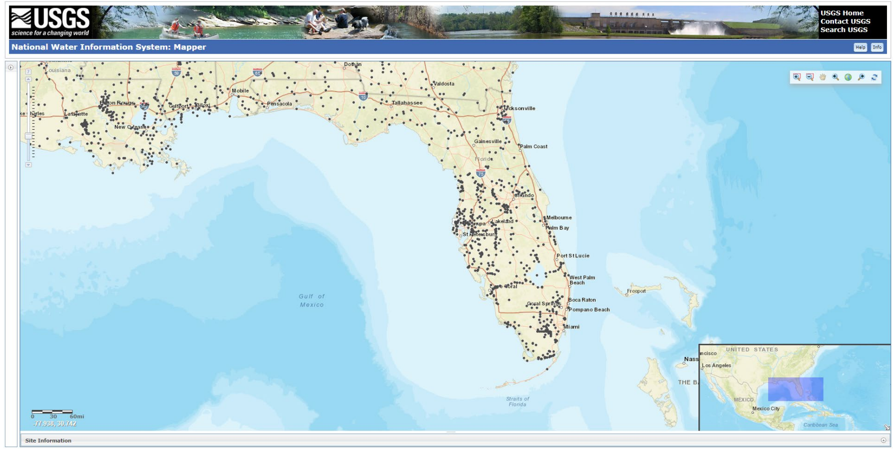


Rainfall–runoff modelling using LSTM networks. Kratzert et al. (2019)

Objectives

- TNN for environmental time series forecasting:
  - Middle-range daily forecasts (up to 14 days) of different environmental variables + prediction uncertainty
  - Use past gauged values and weather forecasts
- Analyze models’ sensitivities to identify the most influential input variables across environmental conditions

Impacted ecology in salty lagoon after freshwater flash flood. Nov 2019, Mar Menor in Murcia, Spain

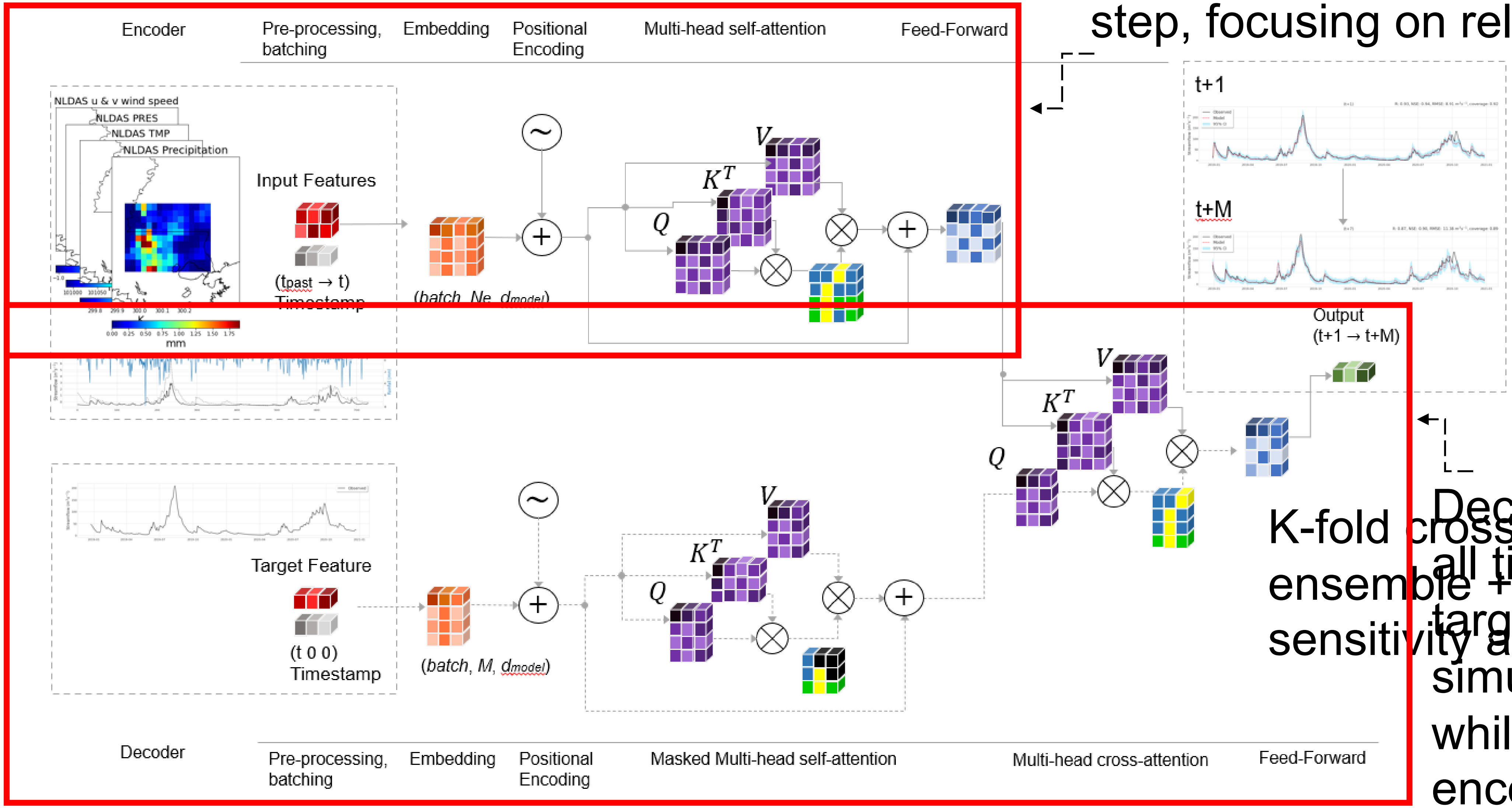


National water information system mapper. United states geological survey

Transformer Model

NLP-based encoder-decoder architecture

Encoder reads input and generates a representation for each time step, focusing on relevant steps



Decoder forecasts all time-steps of the target variable simultaneously while consulting encoder output

K-fold cross-validation: ensemble + uncertainty + sensitivity analysis

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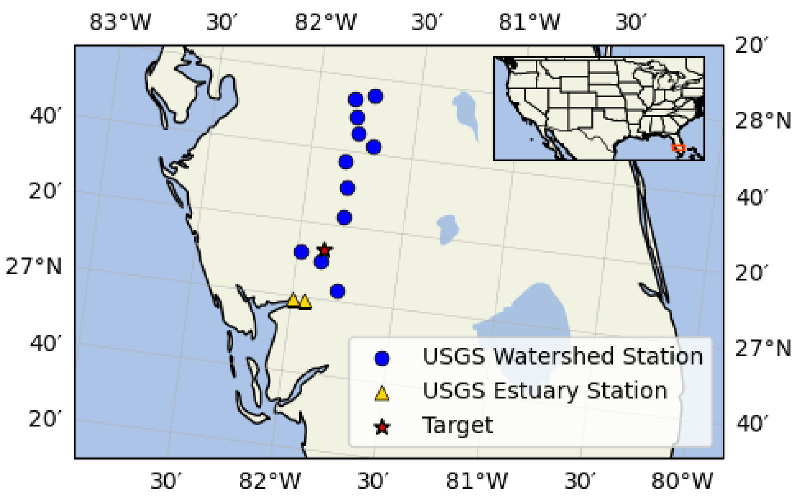
Scenarios and Input Data

Input Variables

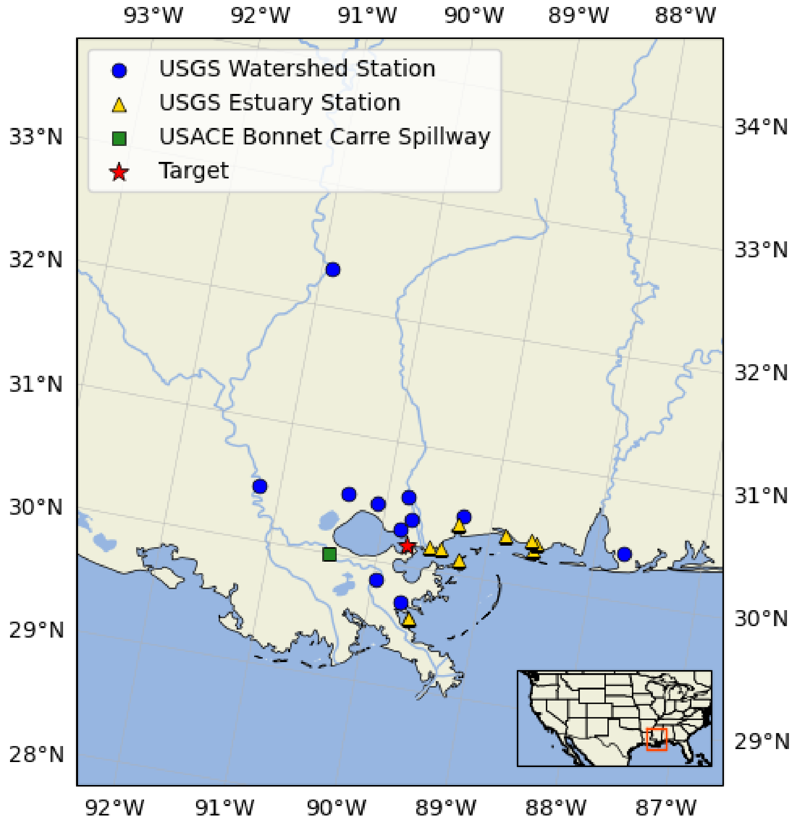
	Dataset 1 Variable	Unit	Source	Quantity
past	Streamflow (Q)	$m^3\ s^{-1}$	USGS	12
	Gage height (GH)	m	USGS	12
	Soil Moisture (Θ)	m^3/m^3	Copernicus	13
forecast	Precipitation (r)	mm	NLDAS	45
	2-m above ground specific humidity (h)	kg/kg	NLDAS	45
	2-m above ground temperature (T_a)	C	NLDAS	36
	10-m above ground zonal wind speed (u)	m/s	NLDAS	36
	10-m above ground meridional wind speed (v)	m/s	NLDAS	36
	Solar radiation flux downwards (s)	W/m^2	NLDAS	36

	Dataset 2 Variable	Unit	Source	Quantity
past	Discharge (Q)	$m^3\ s^{-1}$	USGS	11
	Gage height (GH)	m	USGS	49
	Salinity at Lake Pontchartrain with Northern Gulf	ppt	USGS	1
	Discharge from Bonnet Carre Spillway	$m^3\ s^{-1}$	USACE	1
forecast	Precipitation (r)	mm	NLDAS	204
	Surface pressure (P)	Pa	NLDAS	60
	2-m above ground temperature (T_a)	C	NLDAS	60
	10-m above ground zonal wind speed (u)	m/s	NLDAS	103
	10-m above ground meridional wind speed (v)	m/s	NLDAS	103

*NLDAS (National Land Data Assimilation Service)



$\hat{Y}$ = Peace River (FL) Flow and Stage



$\hat{Y}$ = Gulf of Mexico (LA) Temperature and Salinity

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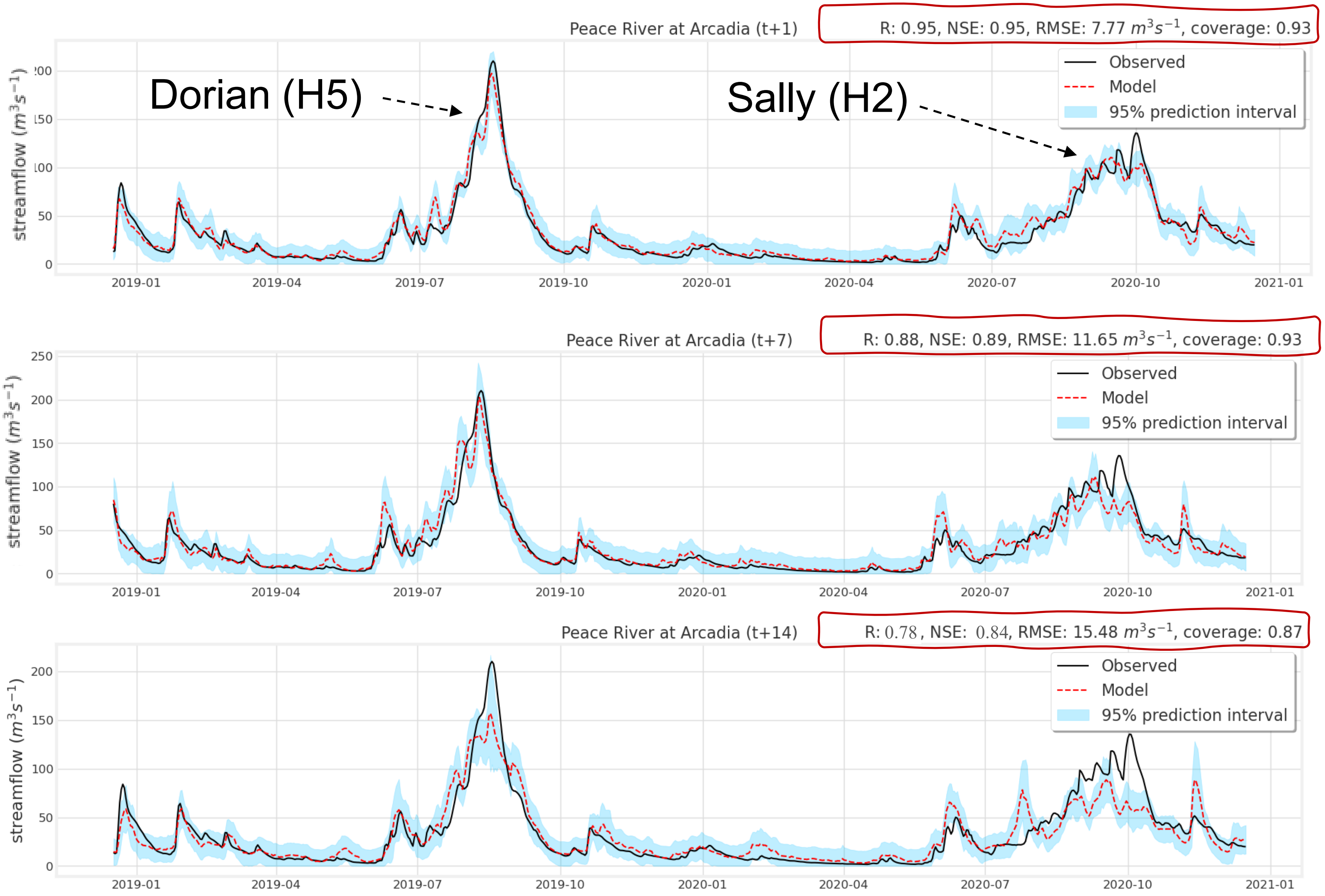
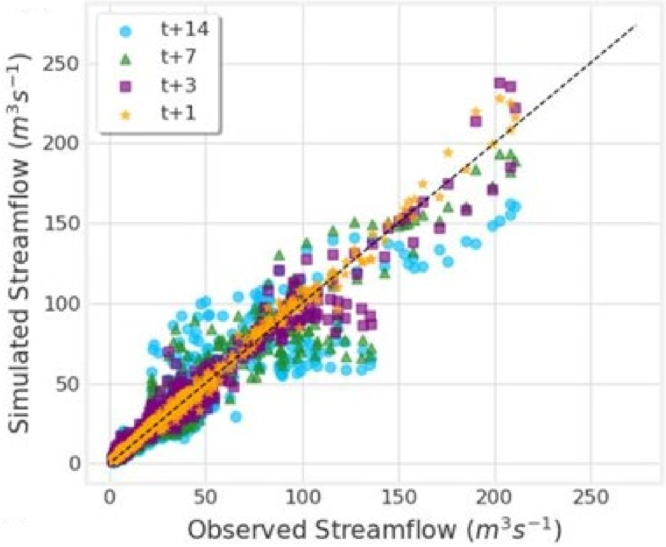
Streamflow Forecasting Results



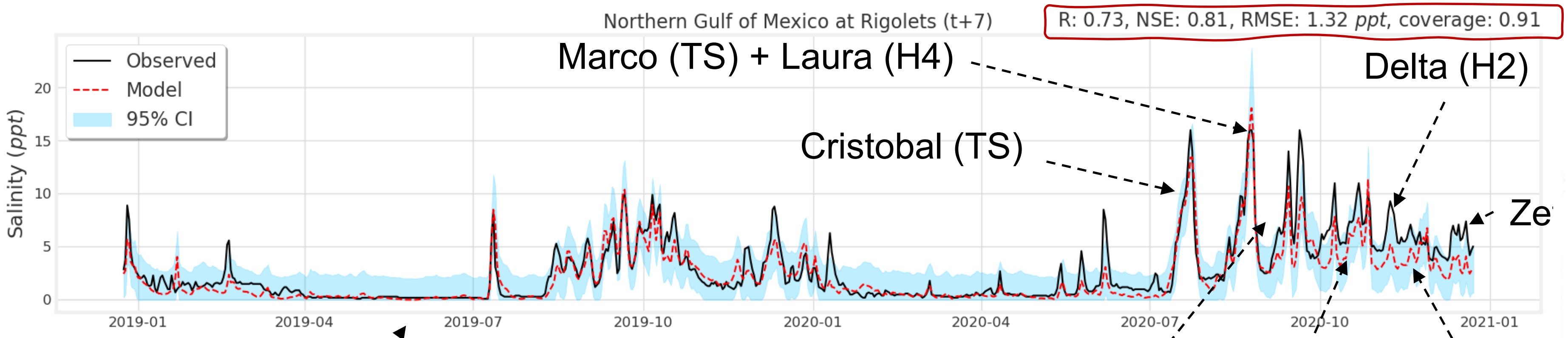


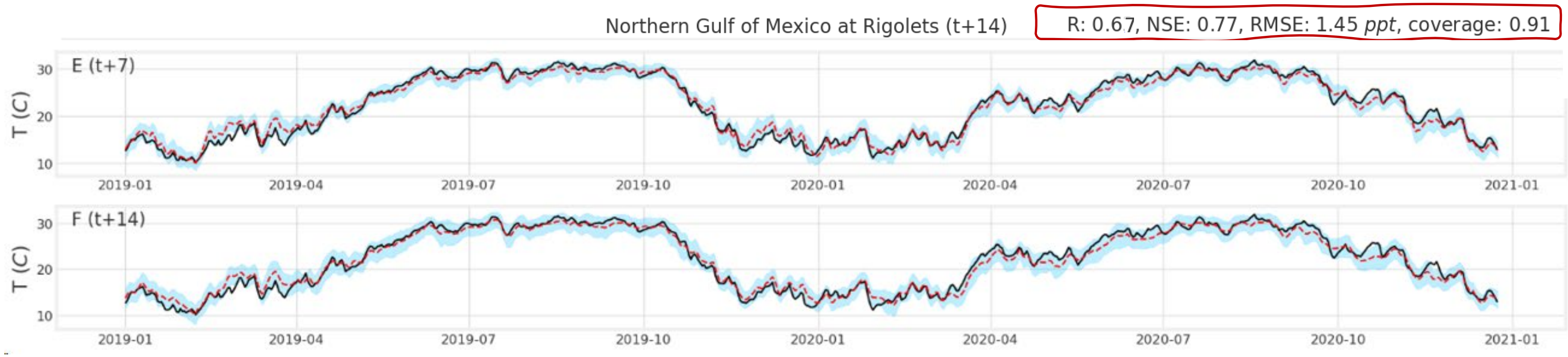
7-day lead time: very good performance; uncertainties ~15-25 cms

14-day lead time: good performance; uncertainties ~35-40 cms

Figure. Results from 1-,7-, and 14-day streamflow forecasting model

Salinity and Temperature Forecasting Results





Figures. 7- and 14-day lead time salinity/temperature forecasts

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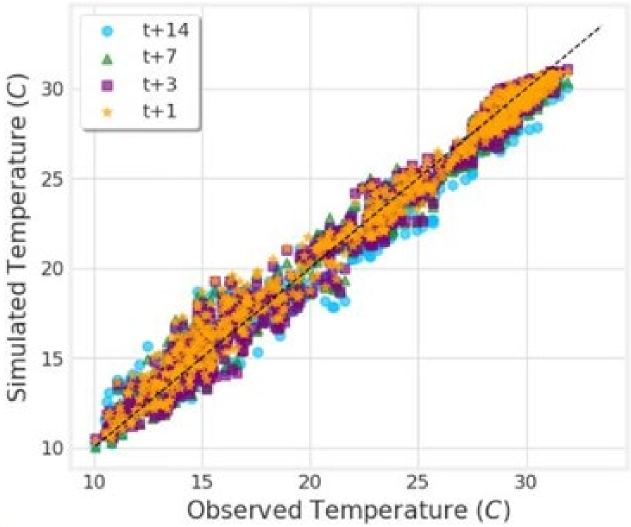
TS: Tropical Storm
H: Hurricane (category)

7-day lead time: good performance; uncertainty ~2-2.5 ppt

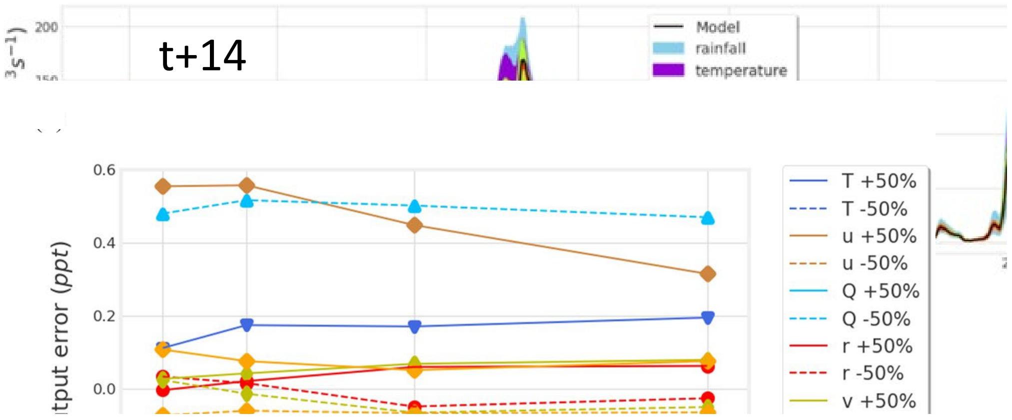


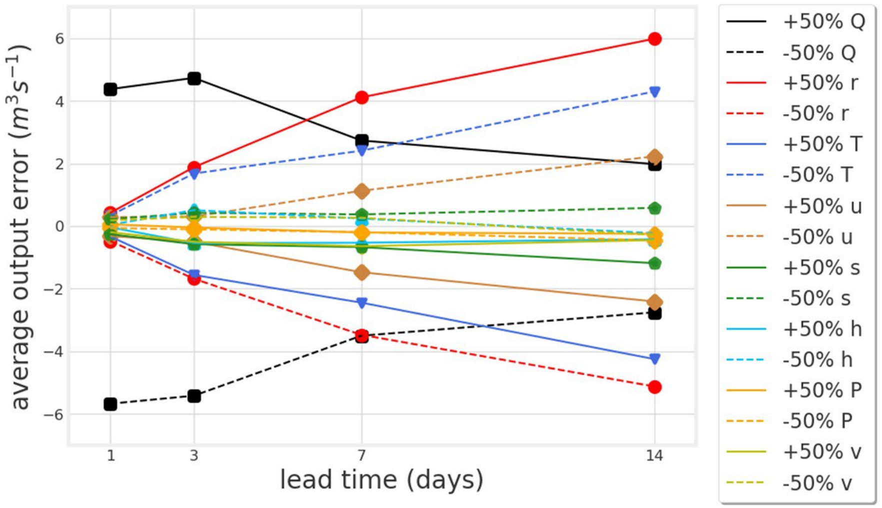
14-day lead time: slightly lower performance; uncertainty ~2.5 ppt.

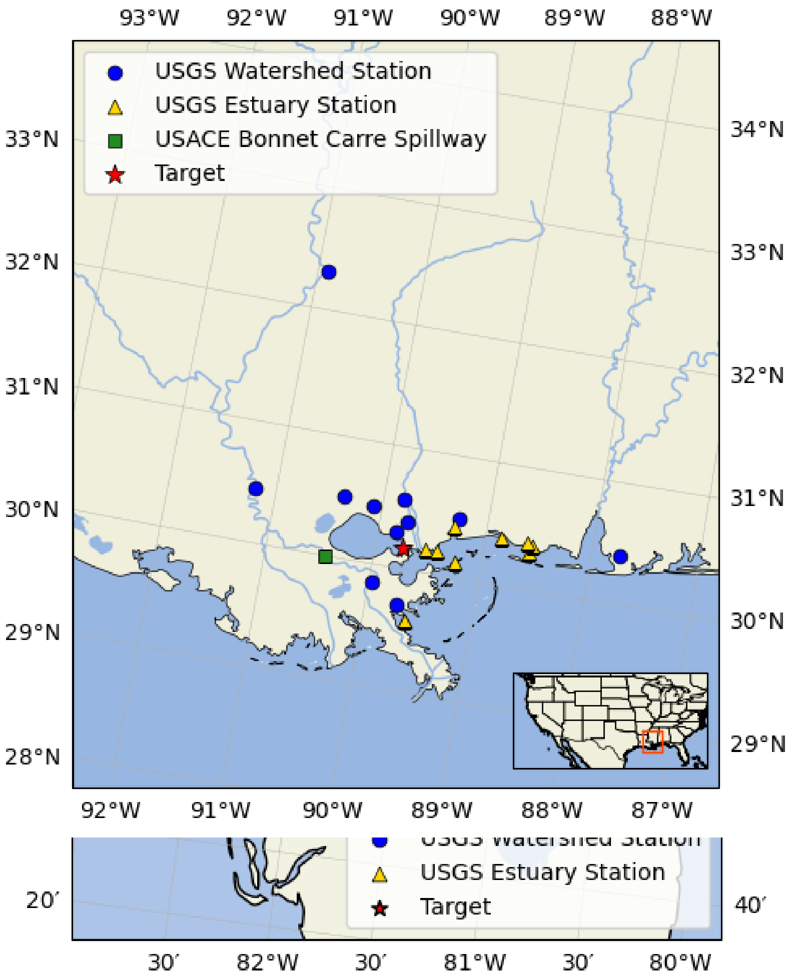
R&NSE>0.97;
RMSE<1.12

Predictions seem to be driven mostly by weather forecasts

Sensitivity Analysis







nalysis can also be used
nost influential input
ross different
tal conditions

and **temperature**
portant on hydrograph
antecedent **streamflow**
n falling limb

nity + streamflow + tide
tant during low-flow
ecasted **temperatures**,
l **v-winds** important
during hurricanes and tropical
storms.

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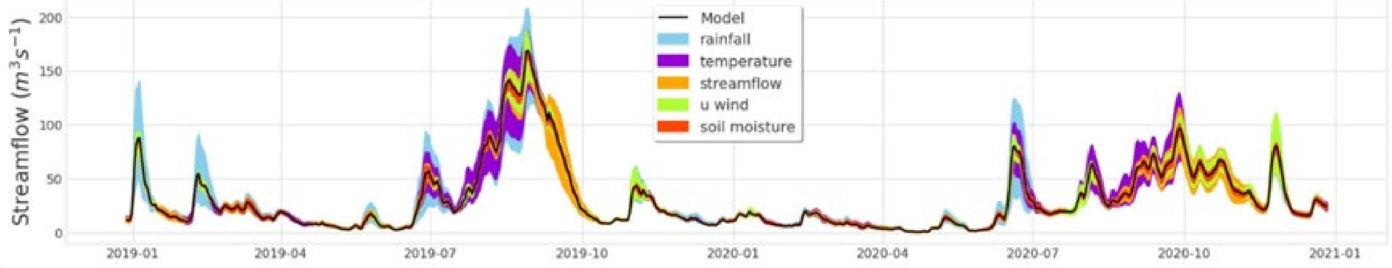
Take-aways

- Transformers:
  - Very good performance for middle-range environmental forecasting
  - Non-iterative inference: no accumulation of error
- Sensitivity analysis highlights:
  - Interpretability of the TNN models' temporal sensitivity to hydroclimatic input factors
  - As forecasting lead time increases, models' decisions move from past data to forecasts
  - The TNN evidence flexibility to adapt and ability to learn physical patterns directly from data.



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