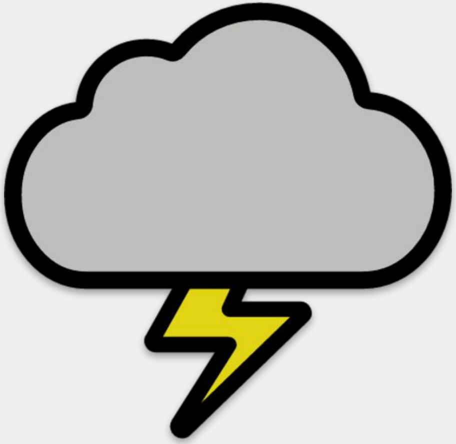


Forecasting the weather with deep learning

A predictive analysis of daily temperature and precipitation in 21 United States cities

Gabriel Patron, Jaylin Lowe, and Tim White

STATS 604 - Project 4

Outline

Main tasks

1. **Find data**
    a. METAR or something else?

2. **Specify, train, and evaluate models**
    a. What class of models? How many models?

3. **Make our workflow reproducible**
    a. How does Docker work?

Data

Data considerations

	Advantages	Disadvantages
METAR	Ground truth dataset Access to weather condition codes for snow	Slow to pull
Meteostat	Fast to pull Contains similar weather variables	Many weather condition codes missing; only snow depth and precipitation available

Approach

Pull data dating back to January 1st, 2014

Use METAR for **precipitation covariates**

Use Meteostat for **all other covariates**, such as temperature, humidity, atmospheric pressure, and others

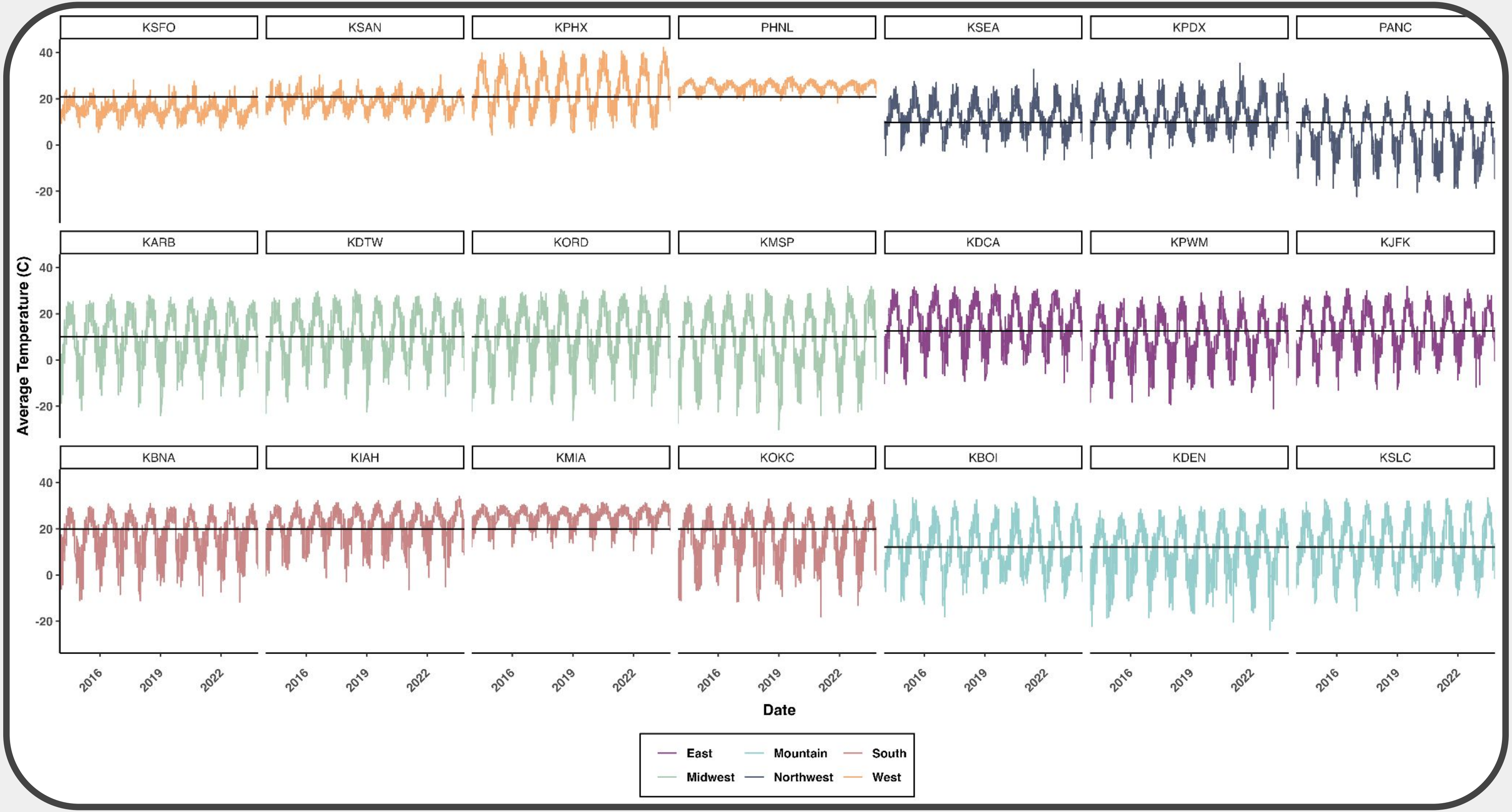
Use Meteostat for **all neighboring airport covariates** for three closest airports to each station

Preprocessing

1. Impute missing values using values of previous hour and next hour
2. Calculate min/avg/max temp and precip/snow for each day
3. Save temperatures and other weather covariates at hours 0, 12, and 23

Final covariates:

- Basic date and airport information
- Five response variables
- Weather conditions for hours 0, 12, 23
- Information for three nearest airports


KSFO
KSAN
KPHX
PHNL
KSEA
KPDX
PANC
KARB
KDTW
KORD
KMSP
KDCA
KPWM
KJFK
KBNA
KIAH
KMIA
KOKC
KBOI
KDEN
KSLC
Average Temperature (C)
40
20
0
-20
2016
2019
2022
Date
East
Mountain
South
Midwest
Northwest
West

Models

Decisions

Five models:

Daily temperature (continuous)

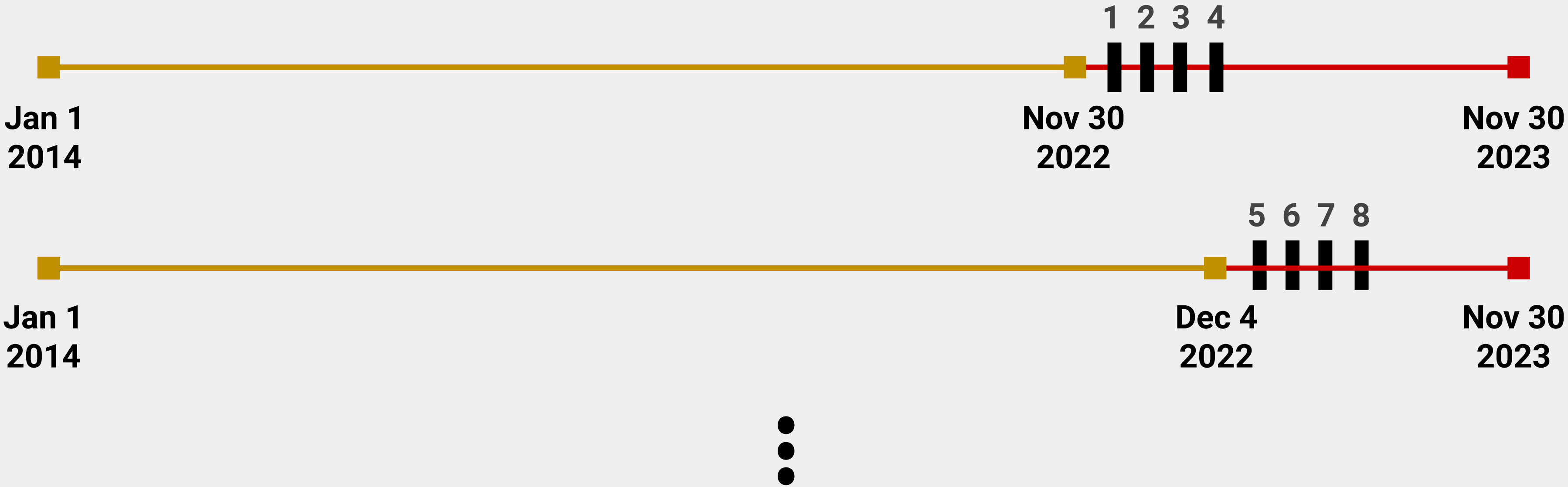
1. Minimum
2. Average
3. Maximum

Daily precipitation (binary)

1. Any precipitation
2. Snow

~~One model for temperature~~	or	Three models for temperature
~~One model for precipitation~~	or	Two models for precipitation
One model per target	or	~~21 models per target~~

Evaluation strategy



NeuralForecast model architectures

Long short-term memory (LSTM)	Neural hierarchical interpolation (NHITS)
Used for temperature	**Used for precipitation**
Tuned and trained with **AutoLSTM**	Tuned and trained with **AutoNHITS**
20 hyperparameter configurations	10 hyperparameter configurations
80 minutes per model	160 minutes per model

Performance metrics

Temperature	Precipitation
RMSE, MAE	Accuracy, AUC, Brier

Baselines

1. **`Naive`** today ← yesterday
2. **`SeasonalNaive`** today ← one year ago
3. **`HistoricAverage`** today ← moving average of (train + appended test)

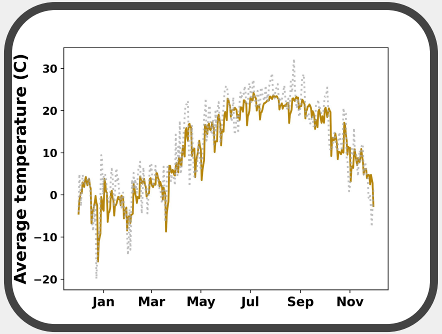
Results for temperature

	Minimum temp		Average temp		Maximum temp	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
LSTM (ours)	3.39	2.47	3.50	2.57	3.91	2.87
Naive	4.32	3.09	3.95	2.77	4.62	3.31
SeasonalNaive	5.54	4.08	5.32	3.92	6.13	4.57
HistoricAverage	8.14	6.62	8.52	6.97	9.22	7.56

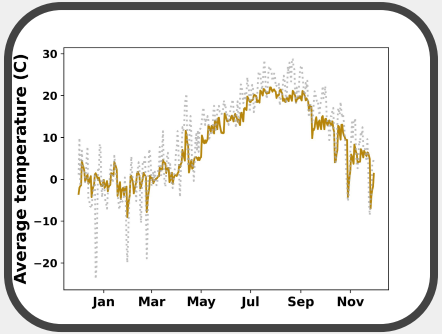
Results for precipitation

	Any precipitation			Snow		
	Accuracy	AUC	Brier	Accuracy	AUC	Brier
NHITS (ours)	0.62	0.66	0.23	0.92	0.90	0.06
Naive	0.59	0.59	0.41	0.90	0.69	0.10
SeasonalNaive	0.56	0.55	0.44	0.88	0.63	0.12
HistoricAverage	0.58	0.60	0.24	0.92	0.78	0.07

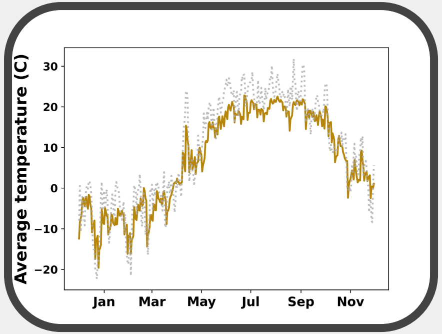
City-specific results



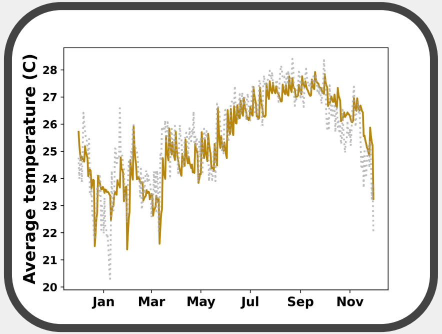
Chicago



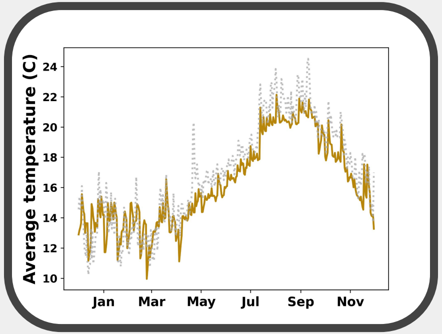
Denver



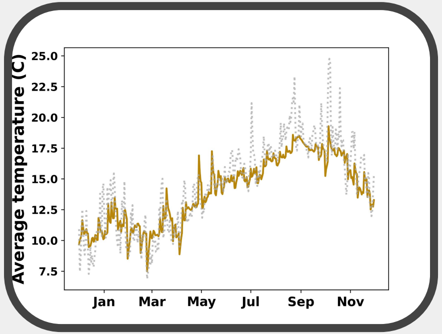
Minneapolis



Honolulu



San Diego



San Francisco

City-specific results

	Min temp		Avg temp		Max temp		Any precip		Snow	
	$\bar{\hat{y}}$	RMSE	$\bar{\hat{y}}$	RMSE	$\bar{\hat{y}}$	RMSE	$\hat{p}$	Accuracy	$\hat{p}$	Accuracy
Ann Arbor (KARB)	3.7	4.5	8.6	4.0	14.3	4.5	0.40	0.58	0.16	0.86
Anchorage (PANC)	0.5	3.2	2.3	2.9	5.7	3.1	0.53	0.59	0.22	0.78
Boise (KBOI)	6.6	3.4	10.5	4.1	17.5	4.4	0.34	0.64	0.12	0.87
Chicago (KORD)	7.5	4.1	10.7	4.3	15.8	4.7	0.52	0.56	0.12	0.86
Denver (KDEN)	3.2	4.3	8.4	4.9	18.1	5.5	0.36	0.66	0.15	0.85
Detroit (KDTW)	7.0	3.7	10.9	3.8	15.8	4.2	0.51	0.57	0.14	0.83
Honolulu (PHNL)	22.9	1.4	25.4	0.9	29.2	1.0	0.53	0.61	0.00	1.00
Houston (KIAH)	17.2	4.0	21.0	3.8	27.6	4.1	0.43	0.62	0.00	1.00
Miami (KMIA)	23.3	2.0	25.8	1.7	29.5	1.8	0.49	0.62	0.00	1.00
Minneapolis (KMSP)	4.5	4.4	7.1	4.8	12.1	4.5	0.47	0.50	0.20	0.79
Oklahoma City (KOKC)	10.2	4.1	16.9	4.3	22.7	4.7	0.33	0.66	0.05	0.97
Nashville (KBNA)	11.9	4.2	16.9	4.0	22.2	4.4	0.46	0.52	0.03	0.97
New York (KJFK)	10.1	3.0	12.6	3.1	16.5	3.9	0.44	0.52	0.04	0.95
Phoenix (KPHX)	18.6	2.7	22.9	3.4	30.4	3.1	0.18	0.86	0.01	1.00
Portland (ME) (KPWM)	5.9	3.9	8.2	3.9	13.0	4.5	0.47	0.52	0.12	0.86
Portland (OR) (KPDX)	9.4	2.8	12.4	2.8	18.4	3.6	0.43	0.69	0.03	0.96
Salt Lake City (KSLC)	7.3	3.5	10.5	4.2	17.2	4.7	0.35	0.63	0.14	0.82
San Diego (KSAN)	14.1	2.0	16.2	1.4	19.8	2.3	0.22	0.75	0.00	1.00
San Francisco (KSFO)	11.5	1.8	14.0	1.7	18.1	2.6	0.21	0.74	0.00	1.00
Seattle (KSEA)	8.4	2.4	11.6	2.5	16.1	3.3	0.47	0.70	0.03	0.95
Washington DC (KDCA)	12.0	3.1	14.9	3.3	20.0	4.1	0.41	0.55	0.02	0.98

Docker

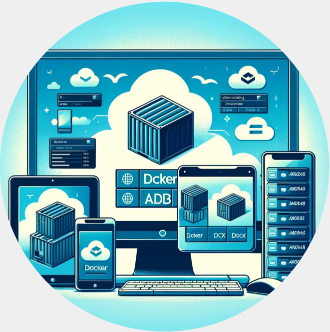
Specifications

Docker

Ubuntu

R

Python



Multiplatform

Consistent across time zones

Train

- fetch_meteostat.py
- fetch_metar.R
- clean_meteostat_and_metar.R
- train.py

Predict

- fetch_updated_meteostat.py
- fetch_updated_metar.R
- clean_meteostat_and_metar.R
- predict.py

Discussion

Data limitations

- Omitted information: additional hours, other weather conditions, intensity of weather conditions, more historical data
- Differences in report times between `pmetar` (R) and `Metar` (Python)

Modeling limitations

- Separate models ⇒ Predictions not always logical when evaluated together
- Did not consider classical models (e.g., ARIMA)

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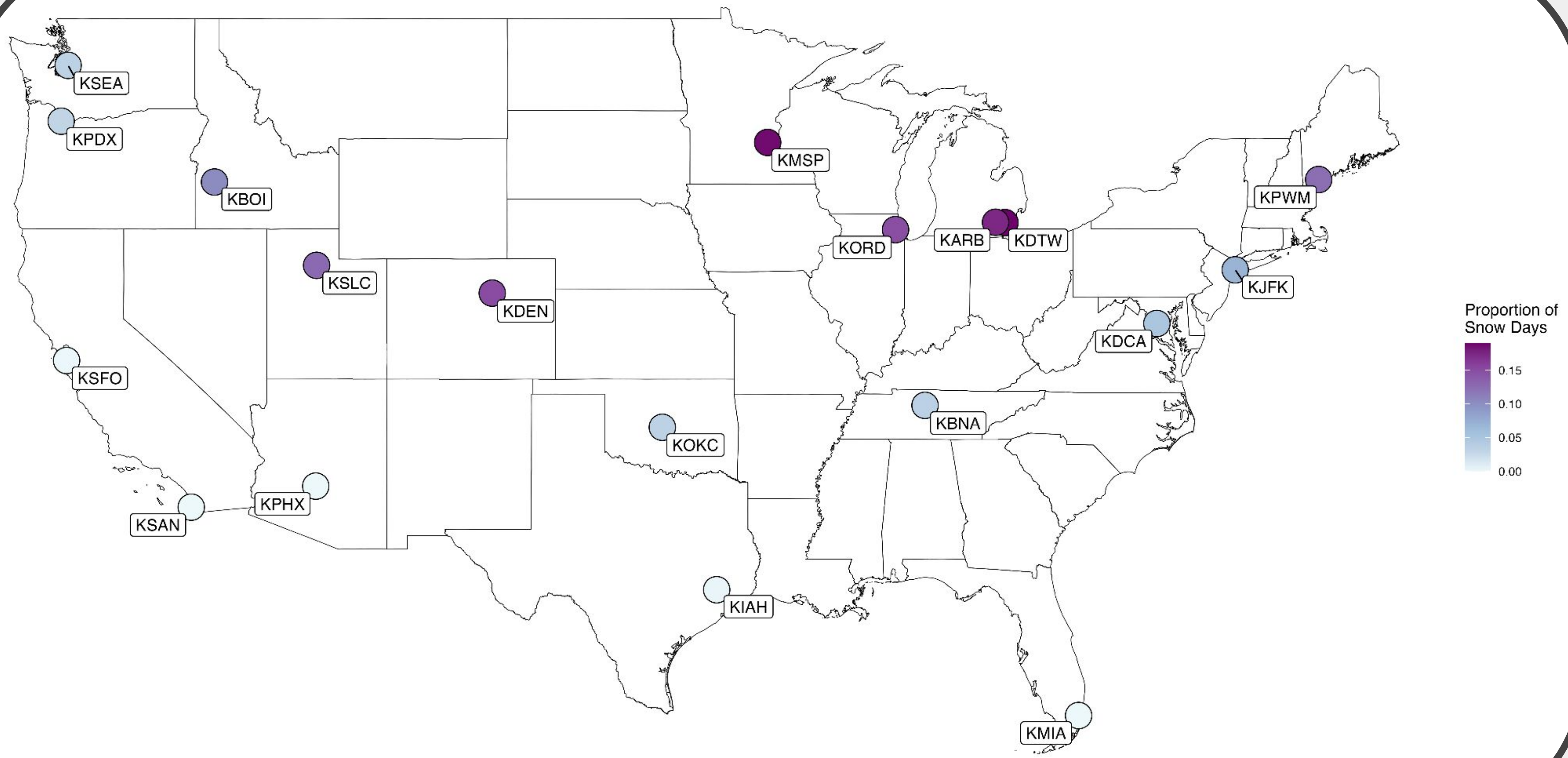
KSEA
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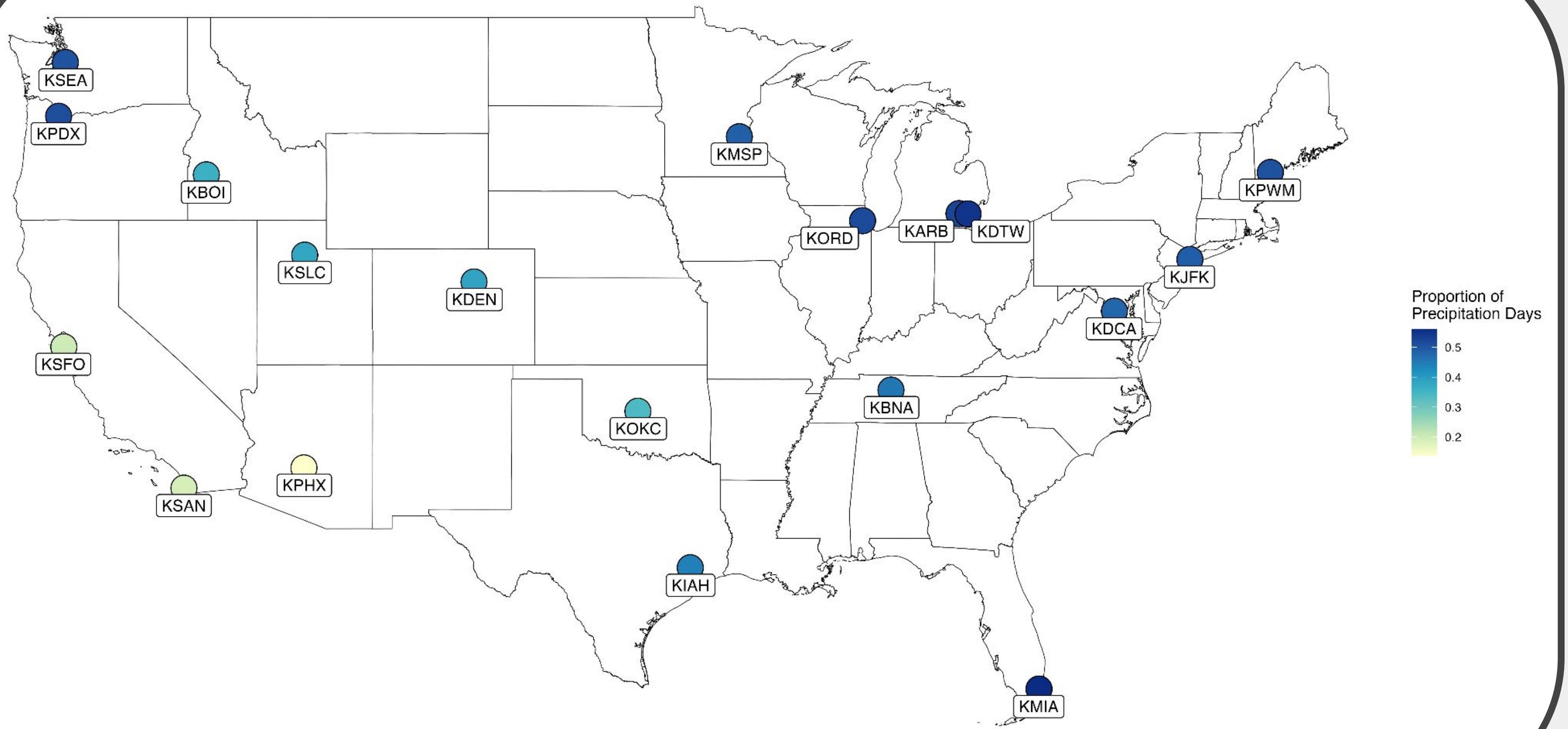
KDTW
KSLC
KDEN
KJFK
KDCA
KSFO
KBNA
KOKC
KPHX
KSAN
KIAH
KMIA
Proportion of Snow Days
0.15
0.10
0.05
0.00


KSEA
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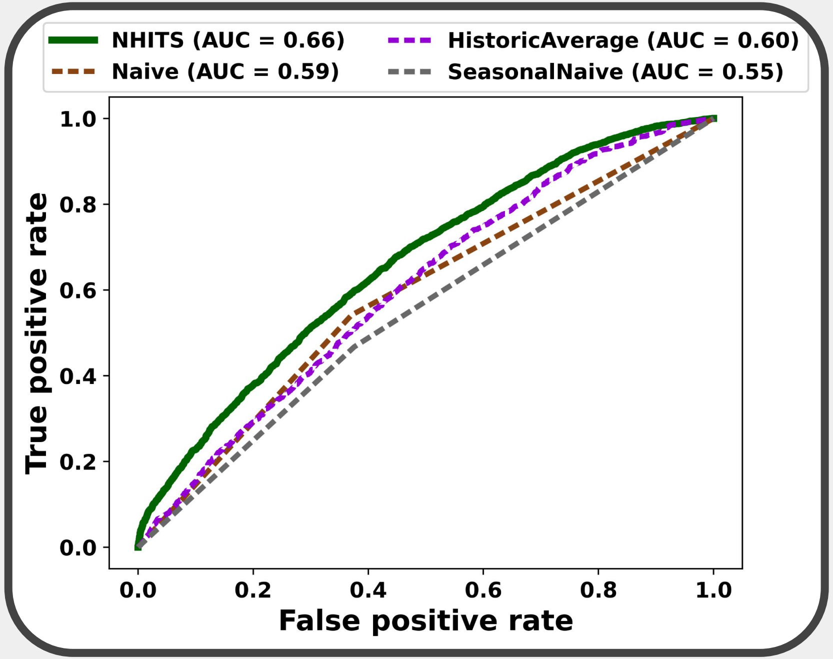
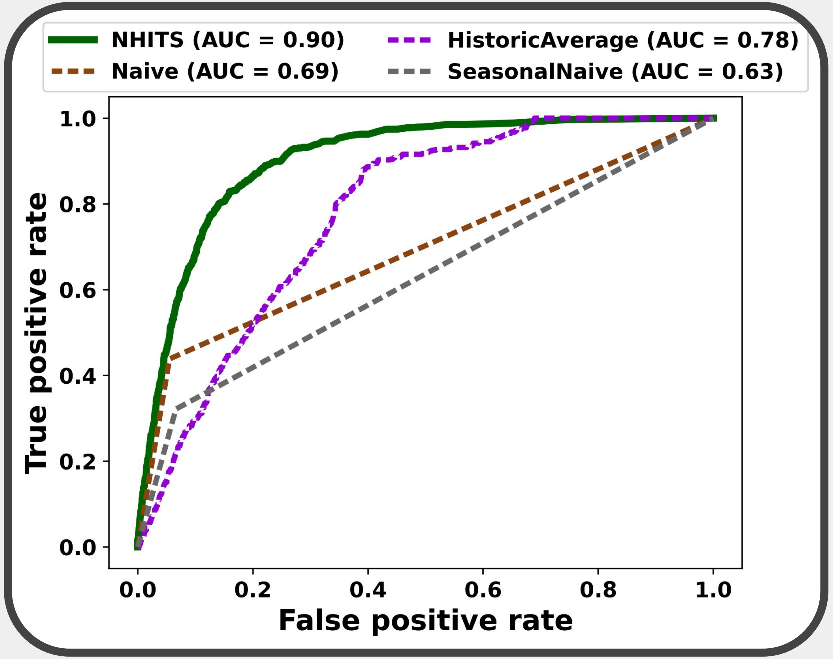
KSLC
KDEN
KJFK
KDCA
KSFO
KBNA
KOKC
KPHX
KSAN
KIAH
KMIA
Proportion of
Precipitation Days
0.5
0.4
0.3
0.2

Results for precipitation



Any precipitation



Snow