Lecture 5
Introduction of WRF-HRRR and Mesonet Data

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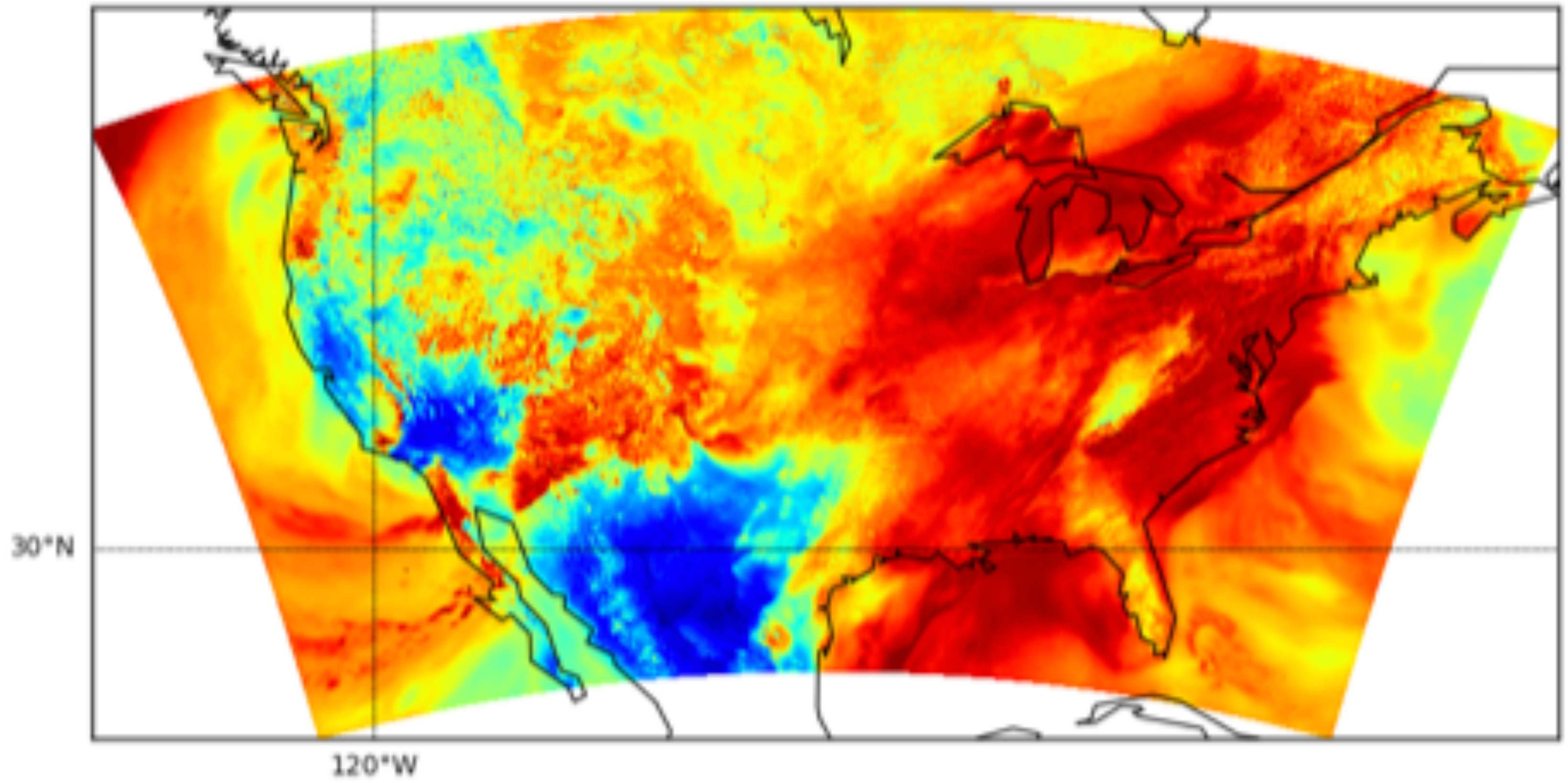
WRF-The Weather Research and Forecasting

- **Next generation mesoscale numerical weather prediction system**
- **It can produce simulations based on actual atmospheric conditions (i.e., from observations and analysis)**
- **It has been developed since the later of 1990's**

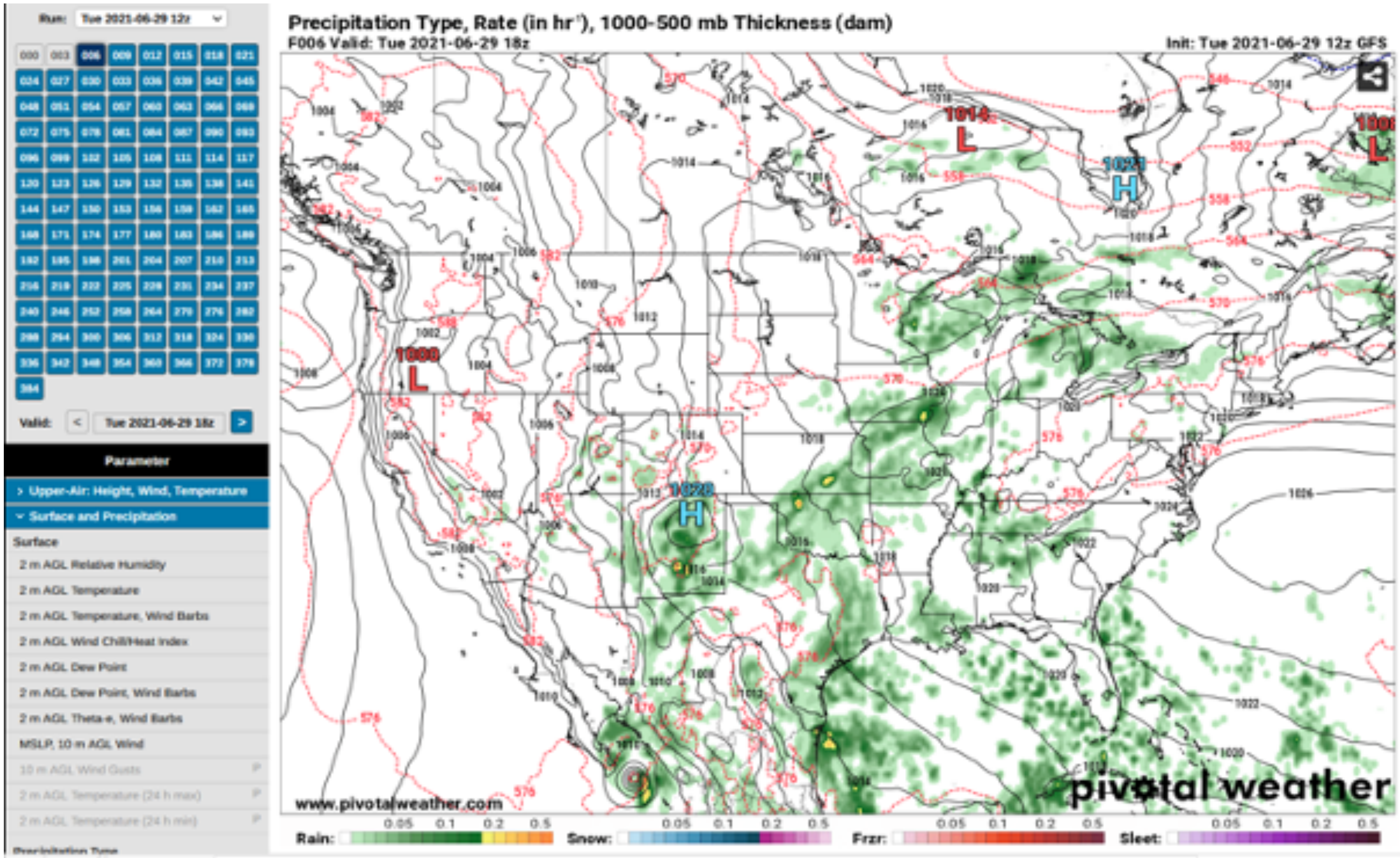
WRF-HRRR

The Weather Research and Forecasting Model with
High-resolution Rapid Refresh



Predict hourly weather parameters covering US continent

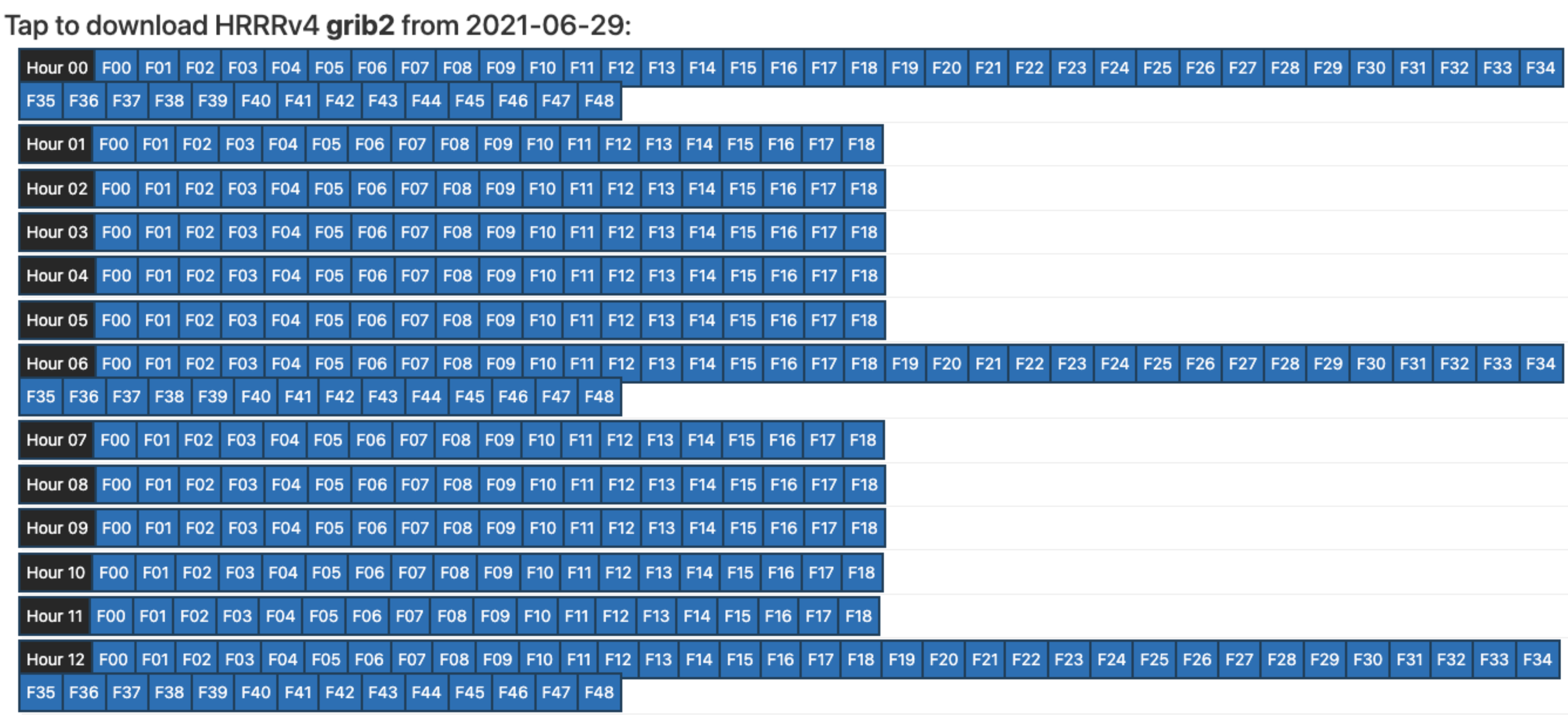
WRF-HRRR: High-resolution Rapid Refresh



Source: https://www.pivotalweather.com/model.php

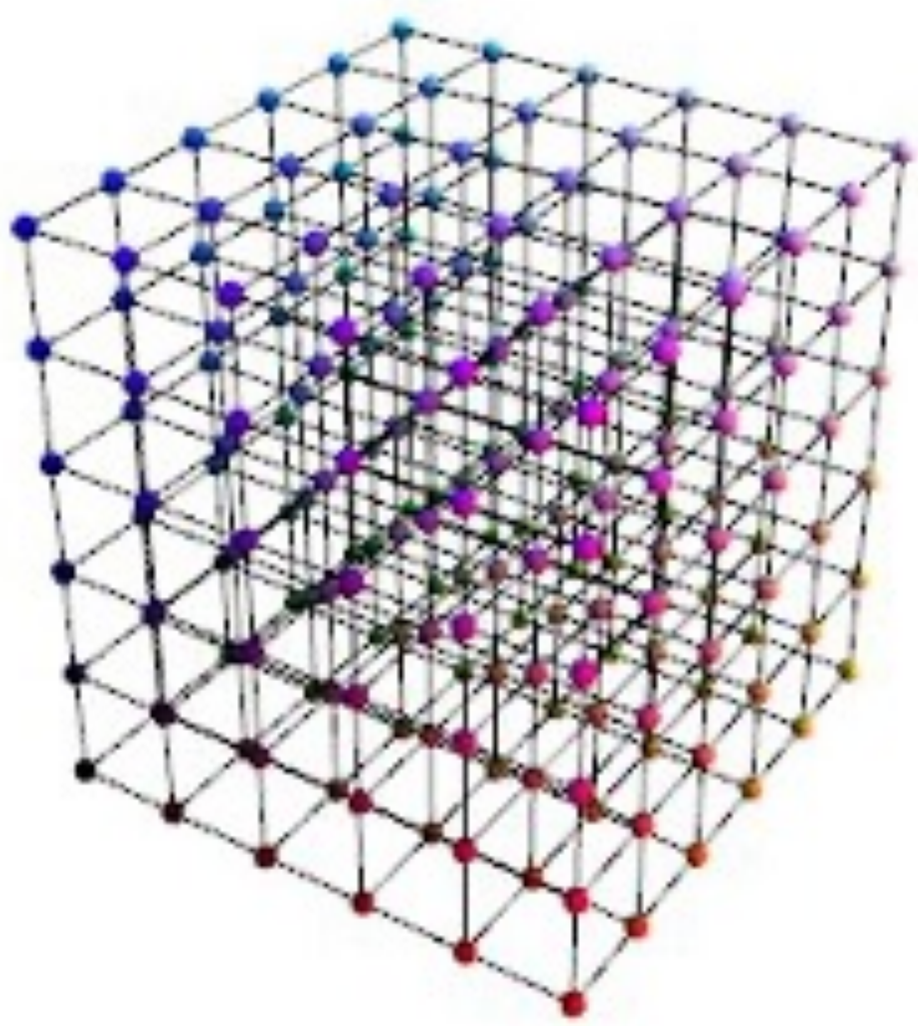
WRF-HRRR Data Source

- **Source: https://home.chpc.utah.edu/~u0553130/Brian_Blaylock/cgi-bin/hrrr_download.cgi**



WRF-HRRR Data Format

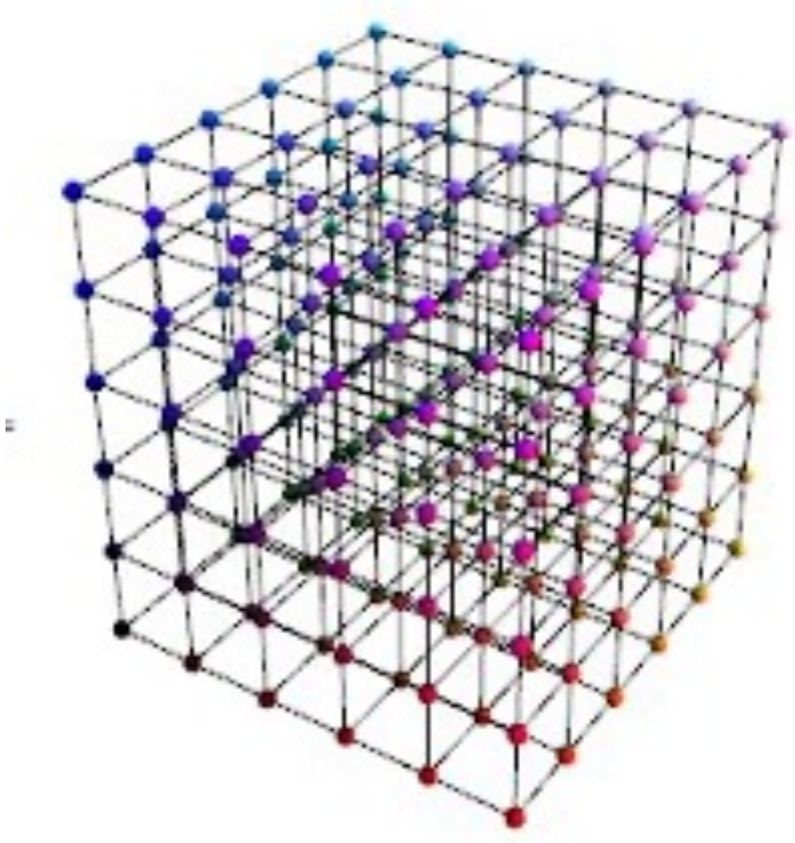
- **HRRR models store data in GRIB format (i.e., 3-D grid), which is a compressed format**
- **Each Grid is of fixed size, 3km x 3km**
  - Covering the United States continent: 1059 x1799 geo-grids



WRF-HRRR Data Format

- **Each layer in a GRIB file represents one feature (e.g., temperature), spanning throughput United States**
  - Horizon represents locations and vertical represents features

- **So all vertically aligned grid points represents the set of features for a particular location**
  - The latitude and longitude information are encoded in the GRIB file



148 Parameters = 148 Layers

Examples for Features at Some Layers

Layer	Feature
1	Maximum/Composite radar reflectivity
8	Wind speed (gust)
11	U component of wind
12	V component of wind
13	Geopotential Height
14	Temperature
15	Dew point temperature
57	Surface pressure
66	2 meter temperature
71	10 meter U wind component
72	10 meter V wind component
73	10 meter wind speed

Extracting Weather Conditions at A Location

- **The latitude and longitude of the UL Lafayette (ULL) is 30.2126 and -92.0193, respectively**
  - How to get the weather conditions at ULL?

- **We can fetch the latitude and longitude matrix from GRIB file**
  - Find the grid point that has the closest distance to ULL

Extracting Weather Conditions at ULL

```
lt_ULL = 30.2126
ln_ULL = -92.0193
gr = pygrib.open('path/to/grib/file')              # open file
msg = gr [1]                                        # get layer-1 message (any layer no. works here).
lt, ln = msg.latlons()                              # extract GPS coordinate
dis_mat = (lt-l_lt_ULL)**2+(ln-l_ln_ULL)**2         # compute distance between each grid point and ULL
p_lt, p_ln = numpy.unravel_index(dis_mat.argmin(), dis_mat.shape) # pick smallest distance index
data = msg.values
feature_ULL = data[p_lt,p_ln]
```

Mesonet

- **Comprising a set of automated weather stations located at some specific area in the USA**
  - Each station monitors tens of of atmospheric measurements, like temperature, rainfall, wind speed, etc., once per minute
  - South Alabama Mesonet includes a network of 26 weather stations, maintained by Dr. Sytske Kimball, Co-PI of our project
  - Kentucky Mesonet is led by Dr. Eric Rappin, Co-PIs of our project

South Alabama Mesonet

- **Data is publicly available at: http://chiliweb.southalabama.edu/archived_data.php**
  - A combination of selectable features for a given range of date is available for downloading
  - Dataset includes 60 features, excluding time, date, and location
  - Data are in CSV format

South Alabama Mesonet

South Alabama Mesonet

South Alabama Mesonet

Temperature (soil - 5 depths and above the surface at 1.5, 2, 9.5, and 10 m).

Relative Humidity (above the surface at 2 and 10 m).

Horizontal Wind Speed and Direction (2 and 10 m).

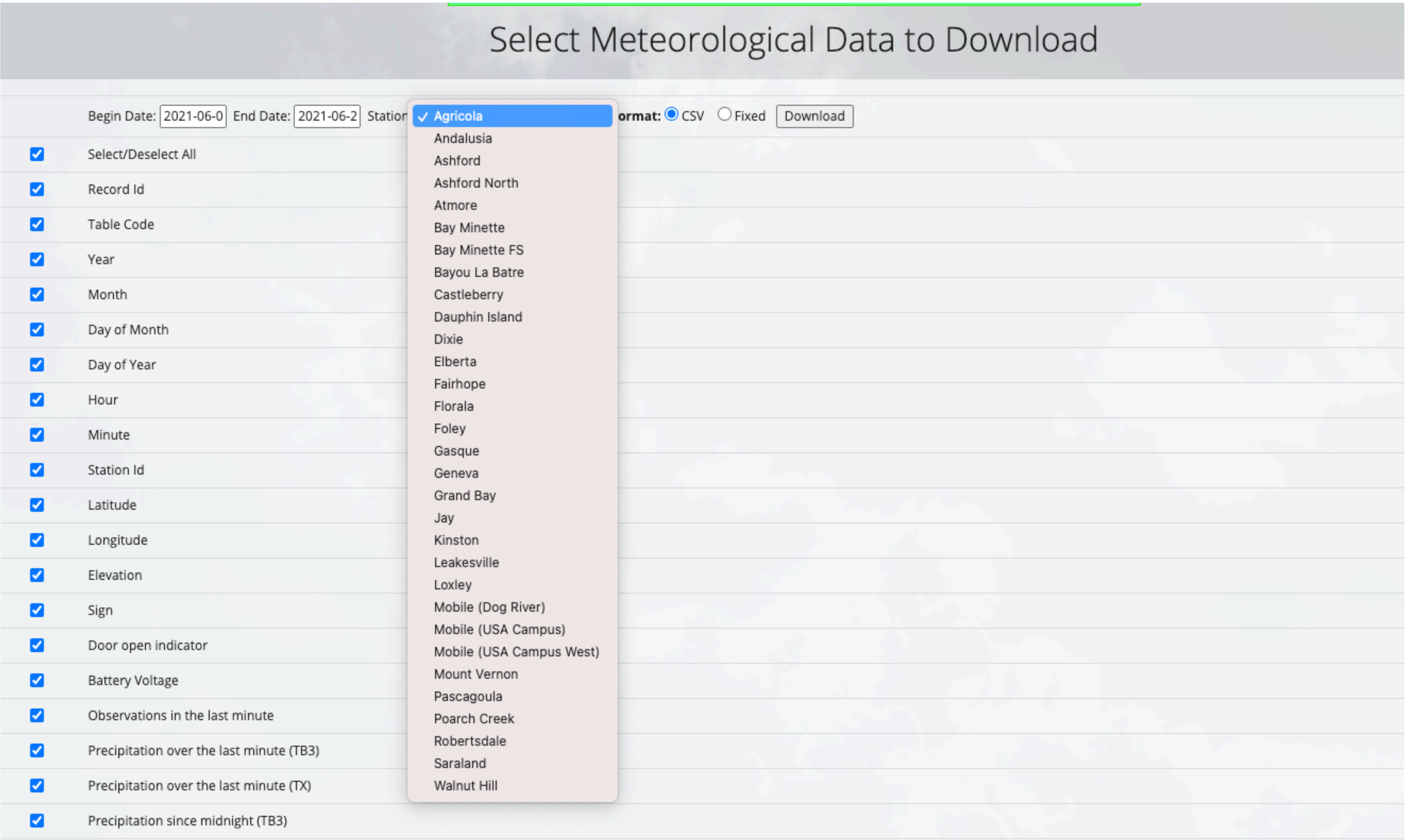
Vertical Wind Speed (10 m).

Atmospheric Pressure.

Rainfall.

Solar Radiation (Total Radiation and PAR).

Example



Source: http://chiliweb.southalabama.edu/archived_data.php

WRF-HRRR verus Mesonet

	Parameters	Resolution	Frequency	Height	Accuracy	Future Prediction
WRF with HRRR	148	3 km * 3 km	1 hour	Upper air	Low	Yes
Mesonet	60	single point	1 minute	Near-surface	High	No

We would like to …

By incorporating the two datasets, we develop Deep Learning approach to predict the future weather conditions.

The good thing here is that you don't need to label the data.

Comparing to Twitter Data

- **Twitter Data**
  - Unstructured
  - Classification on purpose
  - Classification based on spam patterns: feature extraction
  - No ground truth
  - Binary classification

- **Weather Data**
  - Structured
  - Prediction on purpose
  - All features (weather parameters) have been provided
  - No ground truth
  - Time-series Prediction

Machine Learning Modelets for Weather Forecasting

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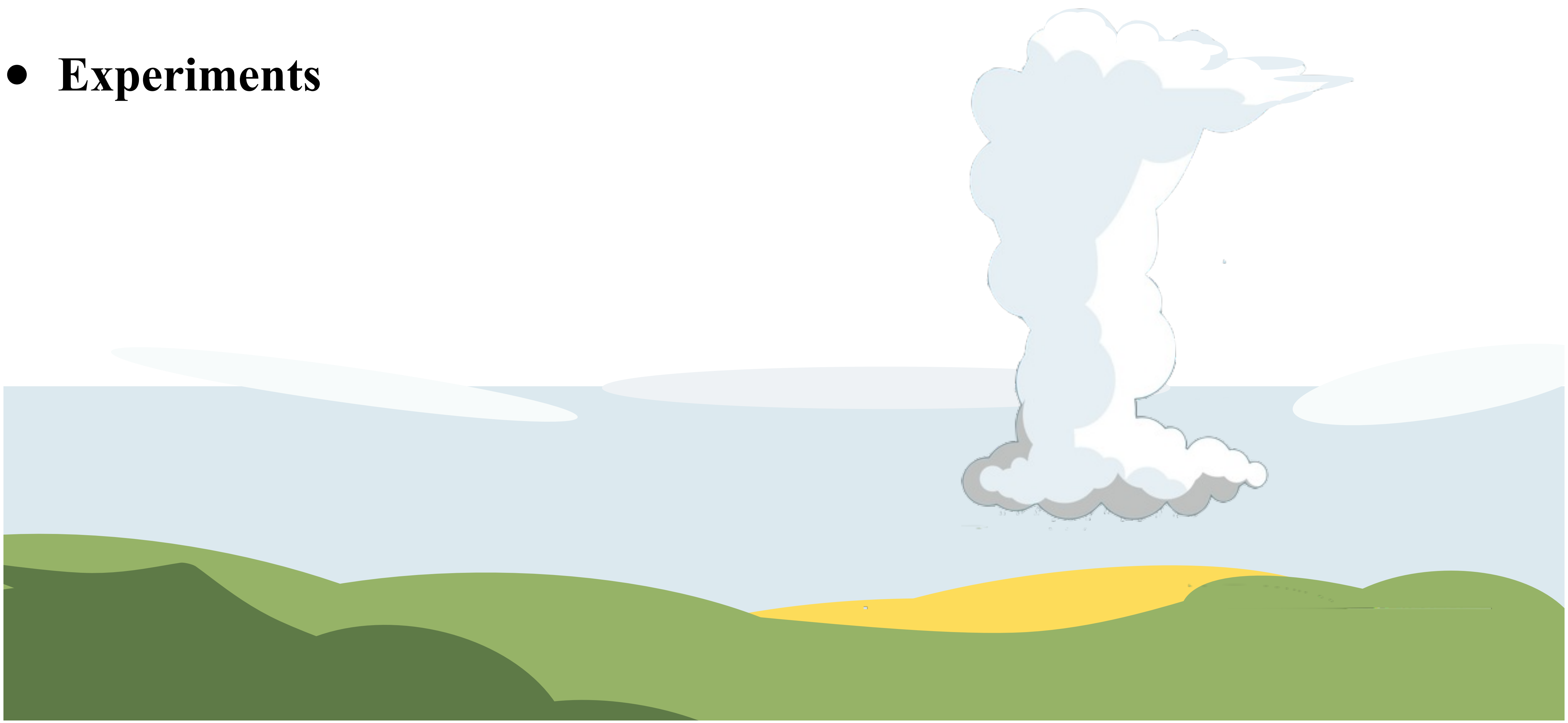
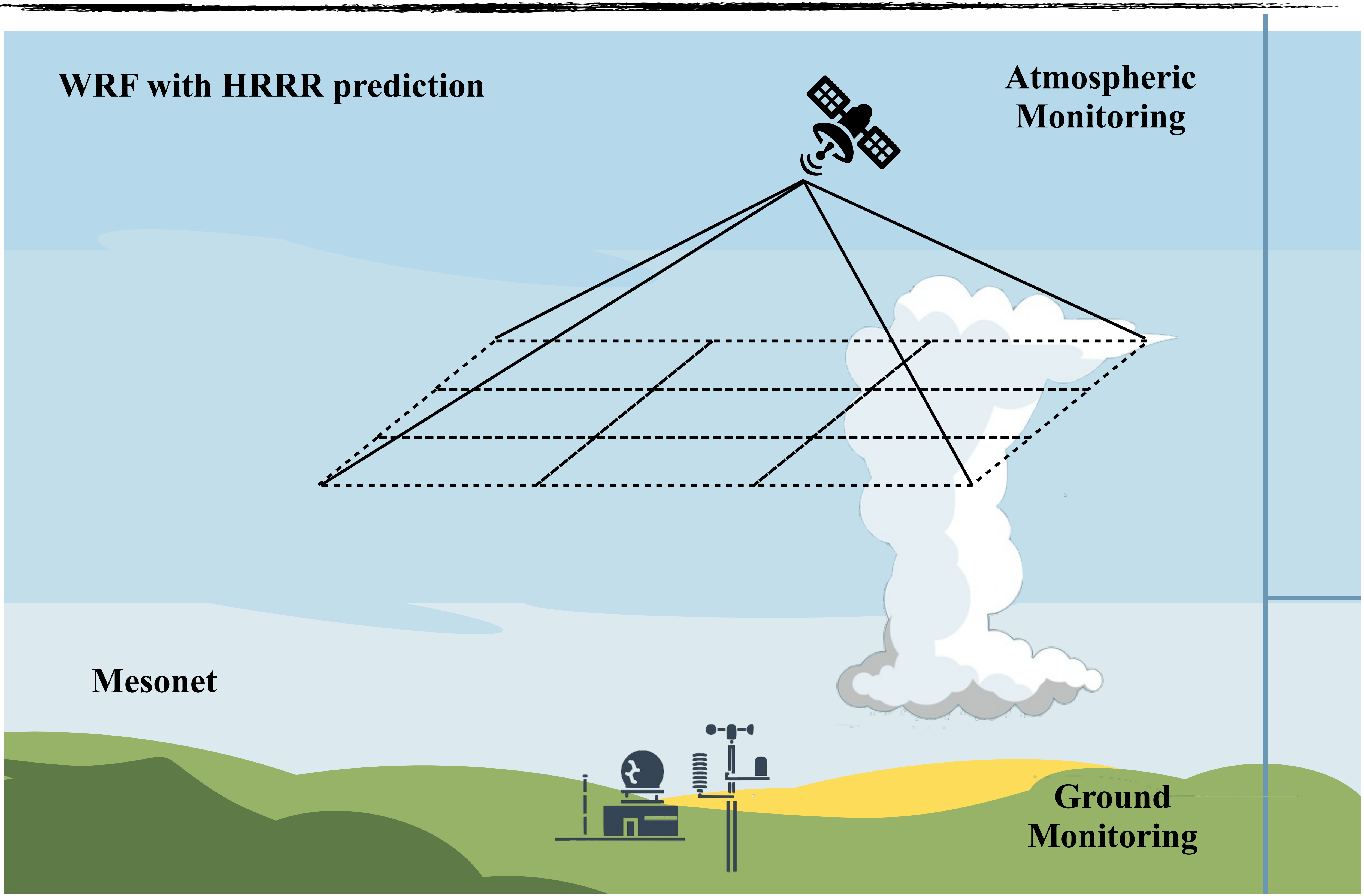
Outline

- **Background**
- **Micro Model**
- **Micro-Macro Model**
- **Experiments**



Background


WRF with HRRR prediction
Atmospheric Monitoring
Mesonet
Ground Monitoring

Background

Only for hourly prediction and its prediction accuracy is far from satisfaction

	Parameters	Resolution	Frequency	Height	Accuracy	Future Prediction
WRF with HRRR	148	3 km * 3 km	1 hour	Upper air	Low	Yes
Mesonet	60	single point	1 minute	Near-surface	High	No

Gathering the current near-surface measurements, unable to predict future values

Weather Forecasting Problem

- *Suppose a Mesonet station monitors the weather conditions for the past several years, then based on this information, a computer program can learn and predict the weather conditions in next several days.*

Past several years' observation

Weather Forecasting Problem

- *Suppose a Mesonet station monitors the weather conditions for the past several years, then based on this information, a computer program can learn and predict the weather conditions in next several days.*

Past several years' observation

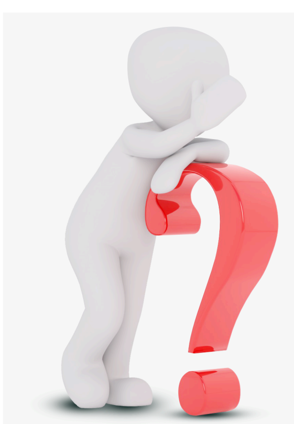
Last one week's observation

Tasks

Next week

Our Goal: Fine-grained Weather Predication

- **Flexible Fine-grained Temporal Domain Prediction**
  - Extracting the temporal variation features from the past measurements
  - Making precise prediction in the next few time horizons
  - Enabling flexible temporal resolution as desired, say 5 minutes, 10 minutes …



Weather Conditions

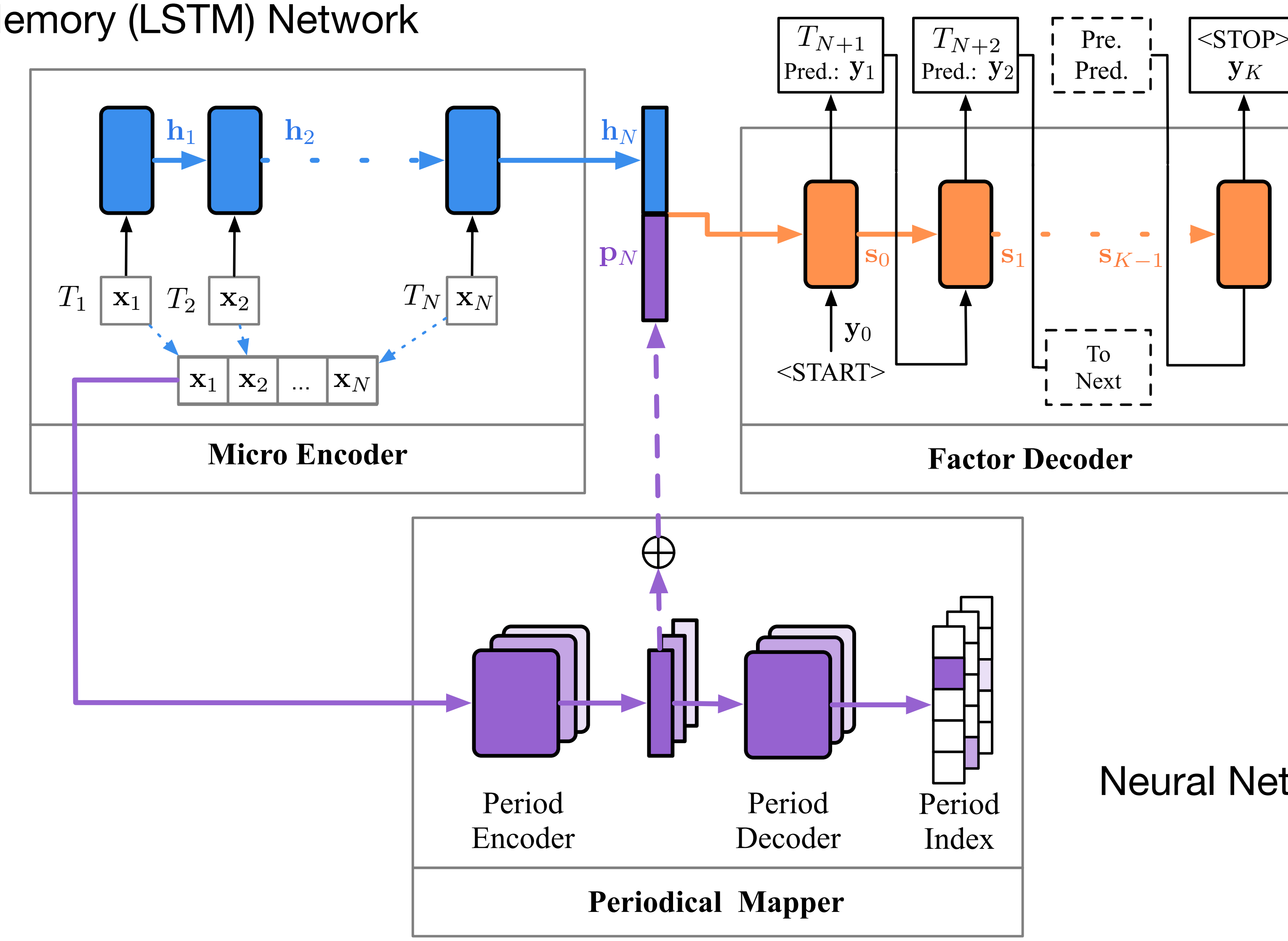
- **Continuous changes with time**
  - Having the time sequential patterns
  - Periodical patterns

- **Different from twitter data, whereas**
  - All tweets are independent
  - Less temporal domain relations

Micro Model

- **Micro Model**
  - Micro Encoder: capturing the sequential temporal patterns
  - Periodical Mapper: extracting the periodical patterns
  - Factor Decoder: Forecasting a set of weather parameters in the next few short time horizons

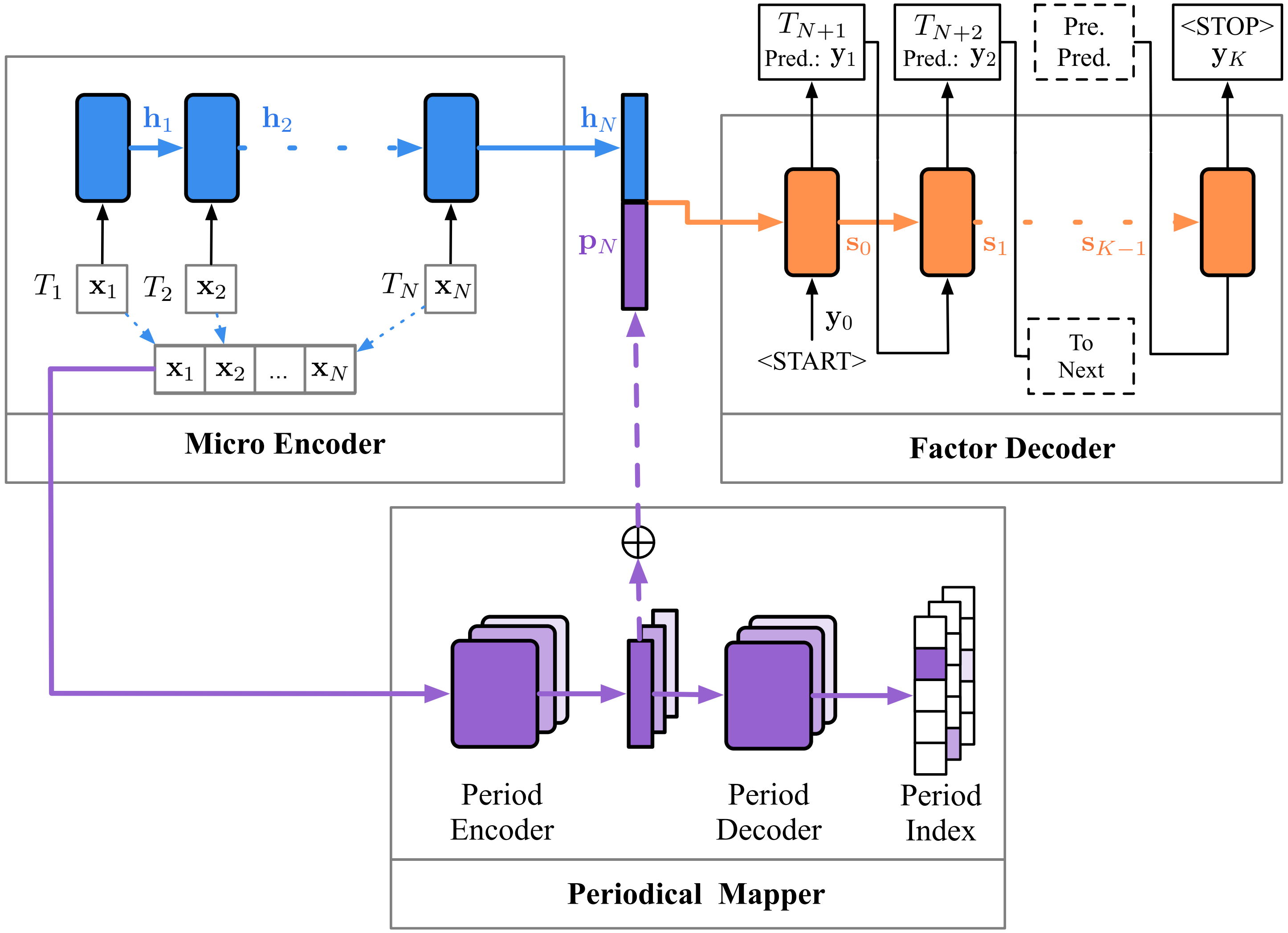
Long Short-term Memory (LSTM) Network



Neural Networks

Micro Model

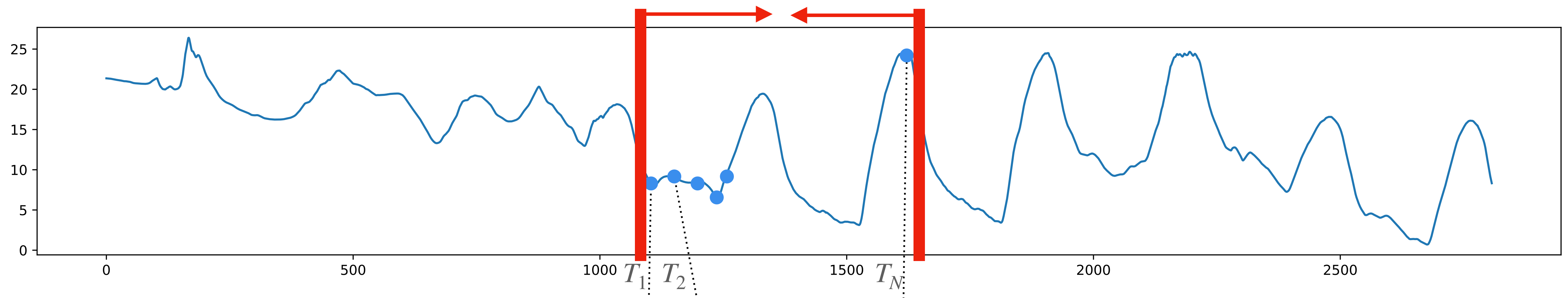
- **Micro Model**
  - Micro Encoder
  - Periodical Mapper
  - Factor Decoder

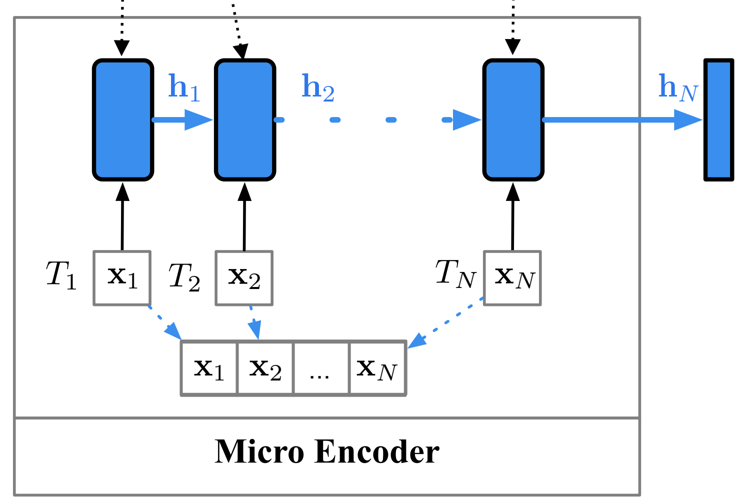


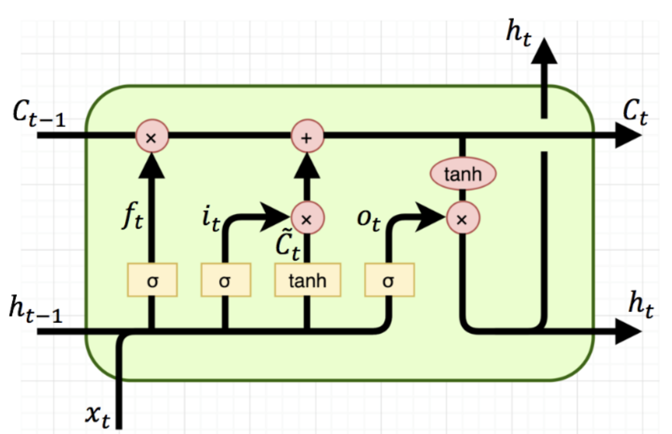
Micro Model

- **Micro Encoder**

Encode the temporal sequence data in a certain period into one single dense vector.





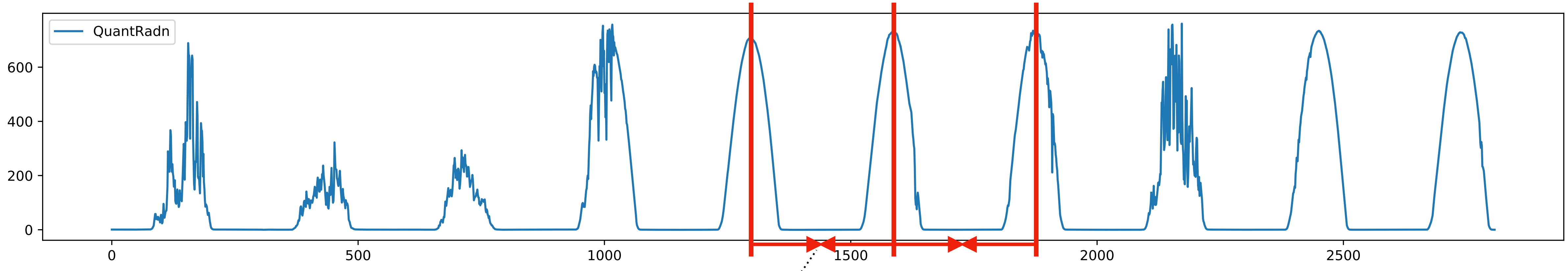


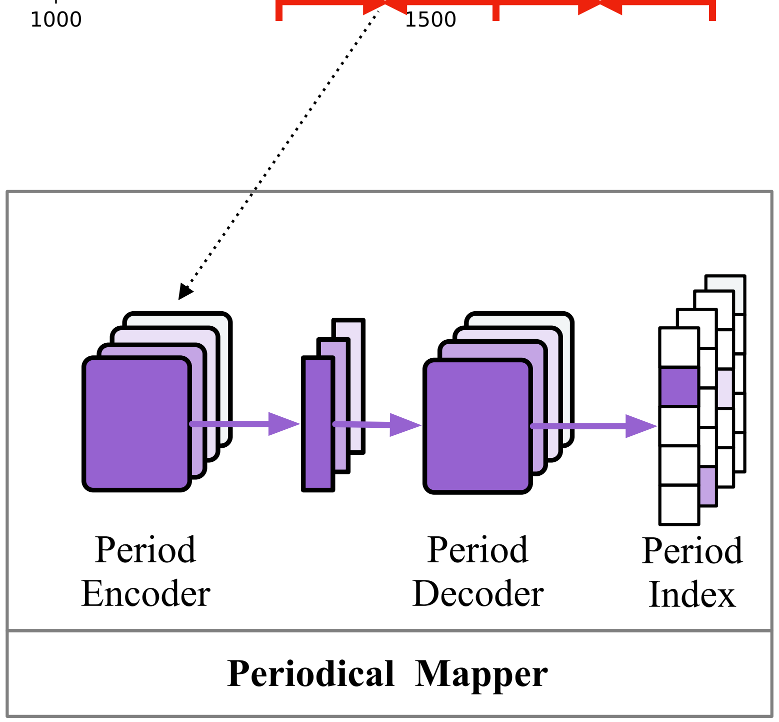
LSTM structure

Micro Model

- **Periodical Mapper (1)**

  Extracting the periodical patterns

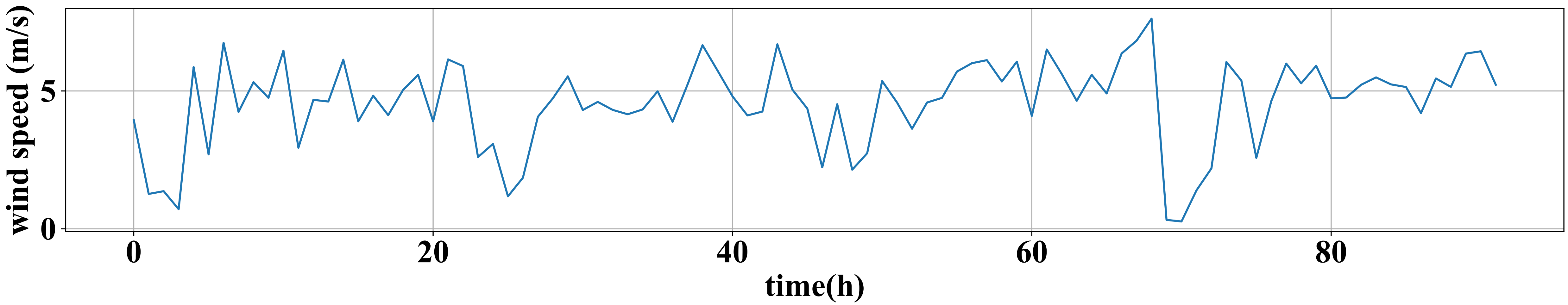




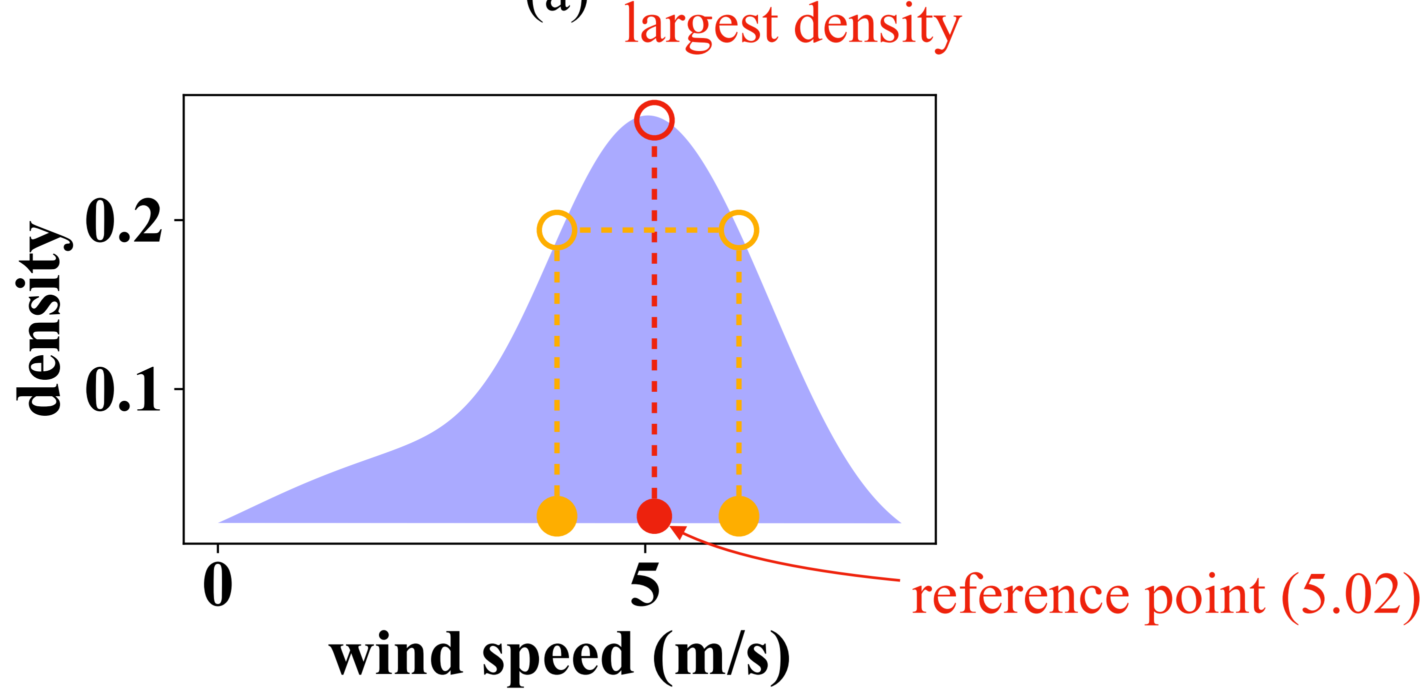
Micro Model

- **Periodical Mapper (2)**

  Reference points and reference area.



(a)

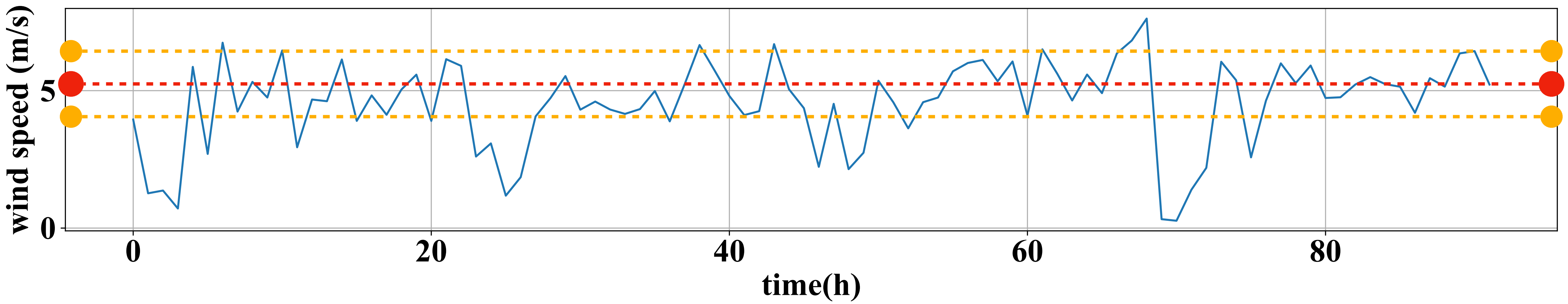


(b)

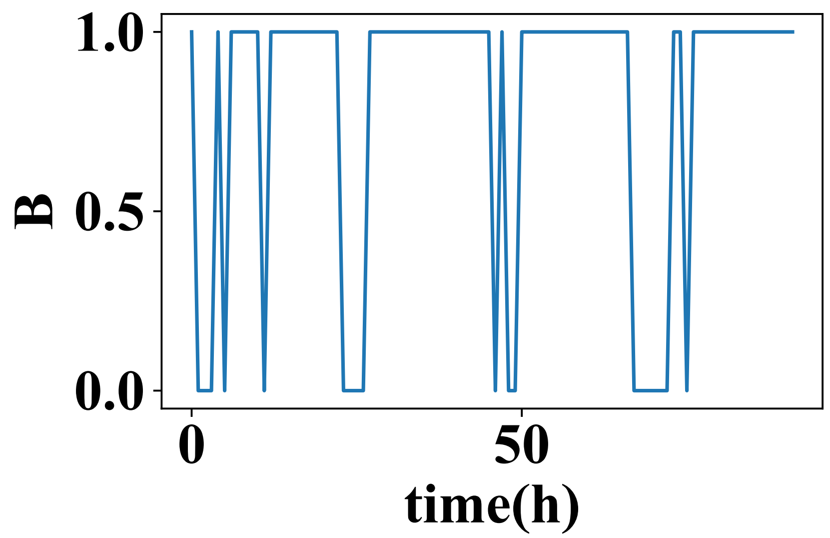
Micro Model

- **Periodical Mapper (3)**

  Binarization and Periodic Correlation.



(a)



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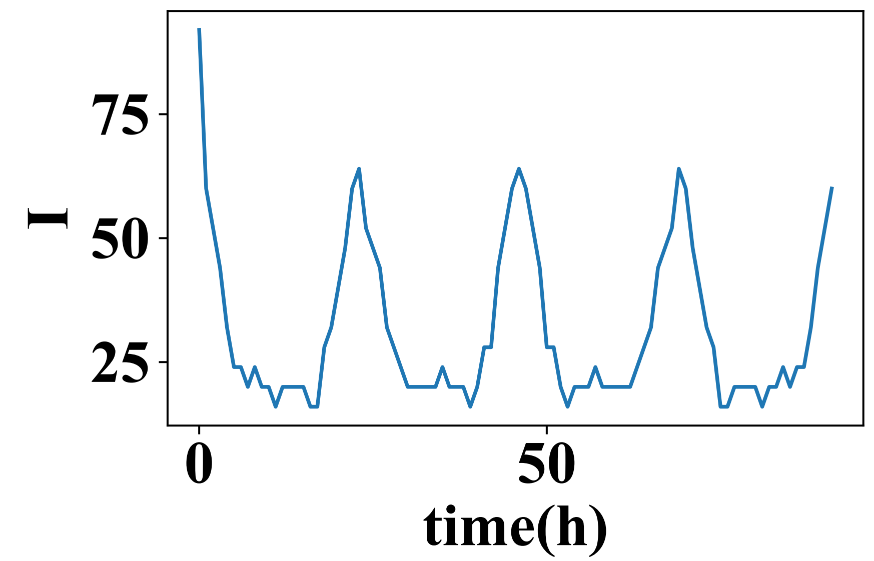
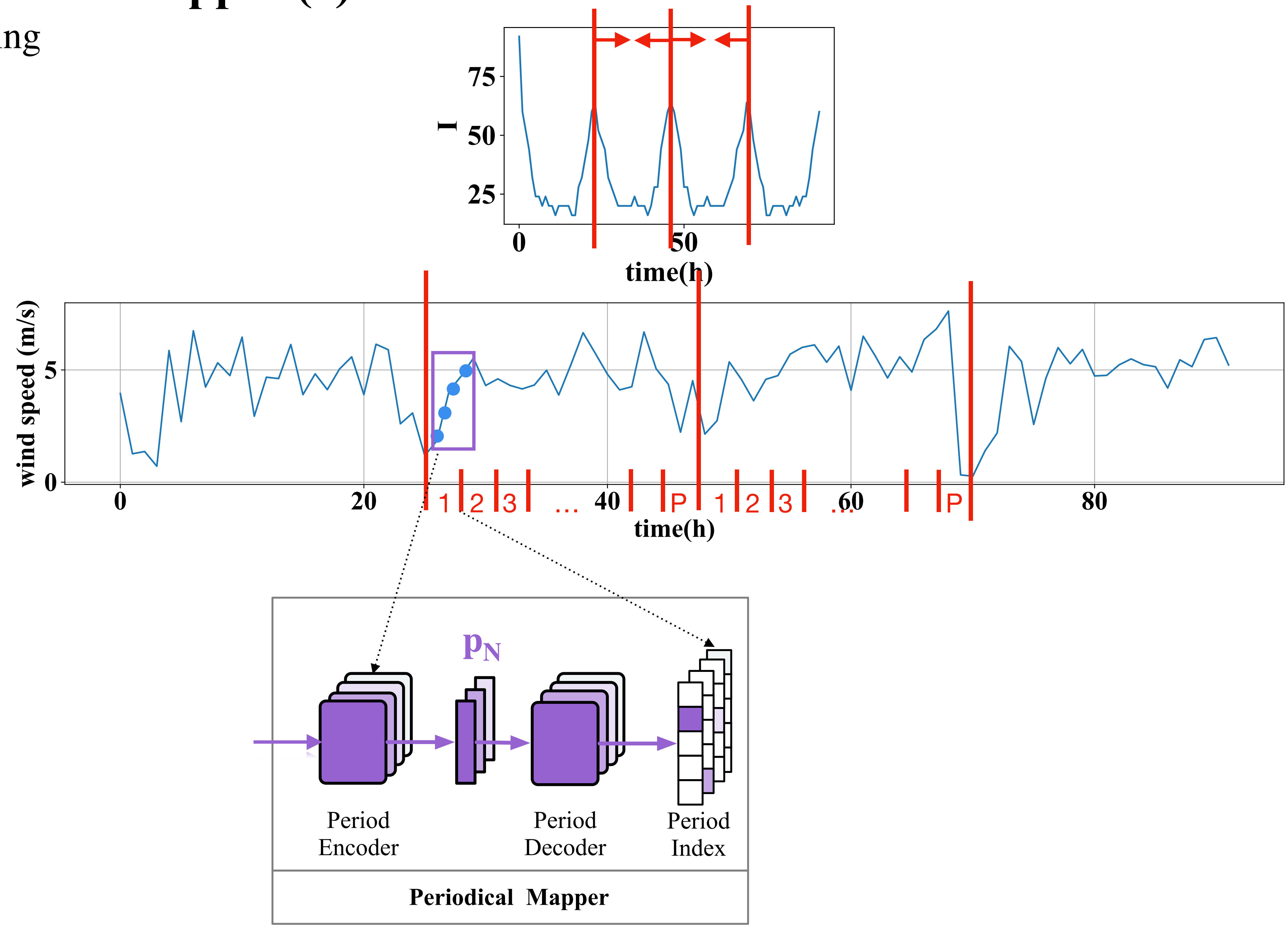


(c)

Micro Model

- **Periodical Mapper (4)**

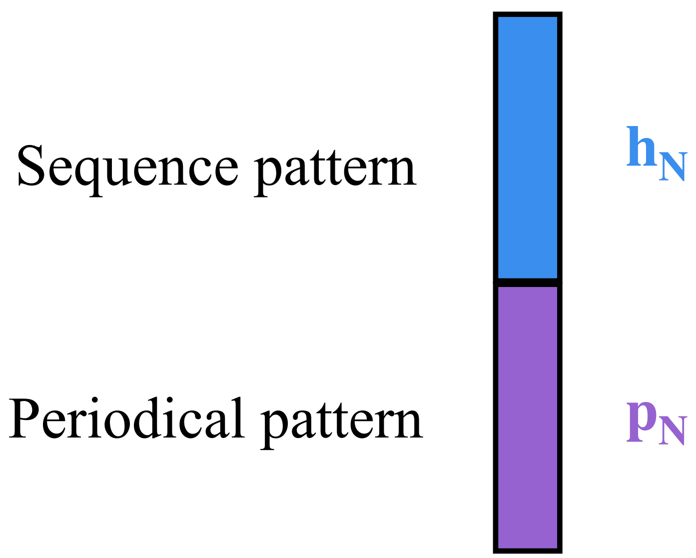
  Indexing



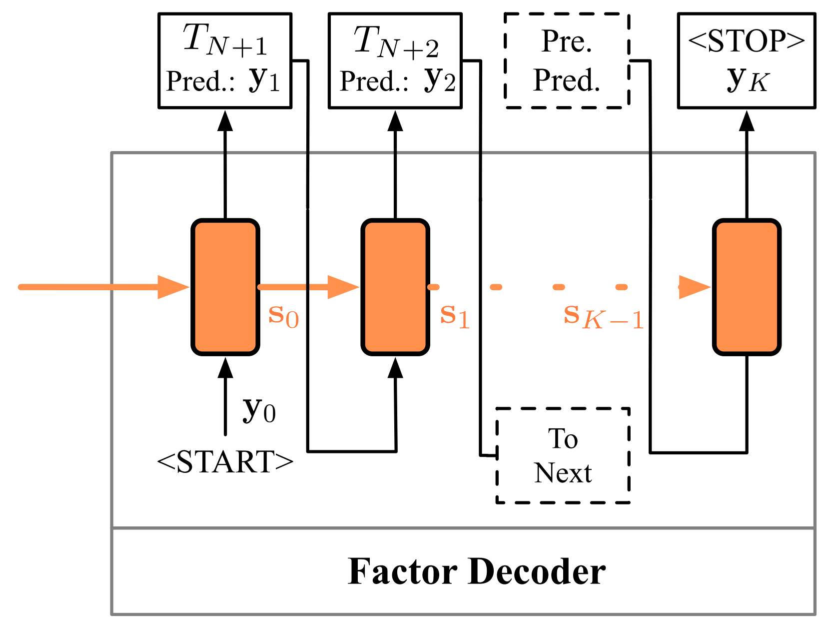
Micro Model

- **Micro Decoder**

  Predict weather parameters.

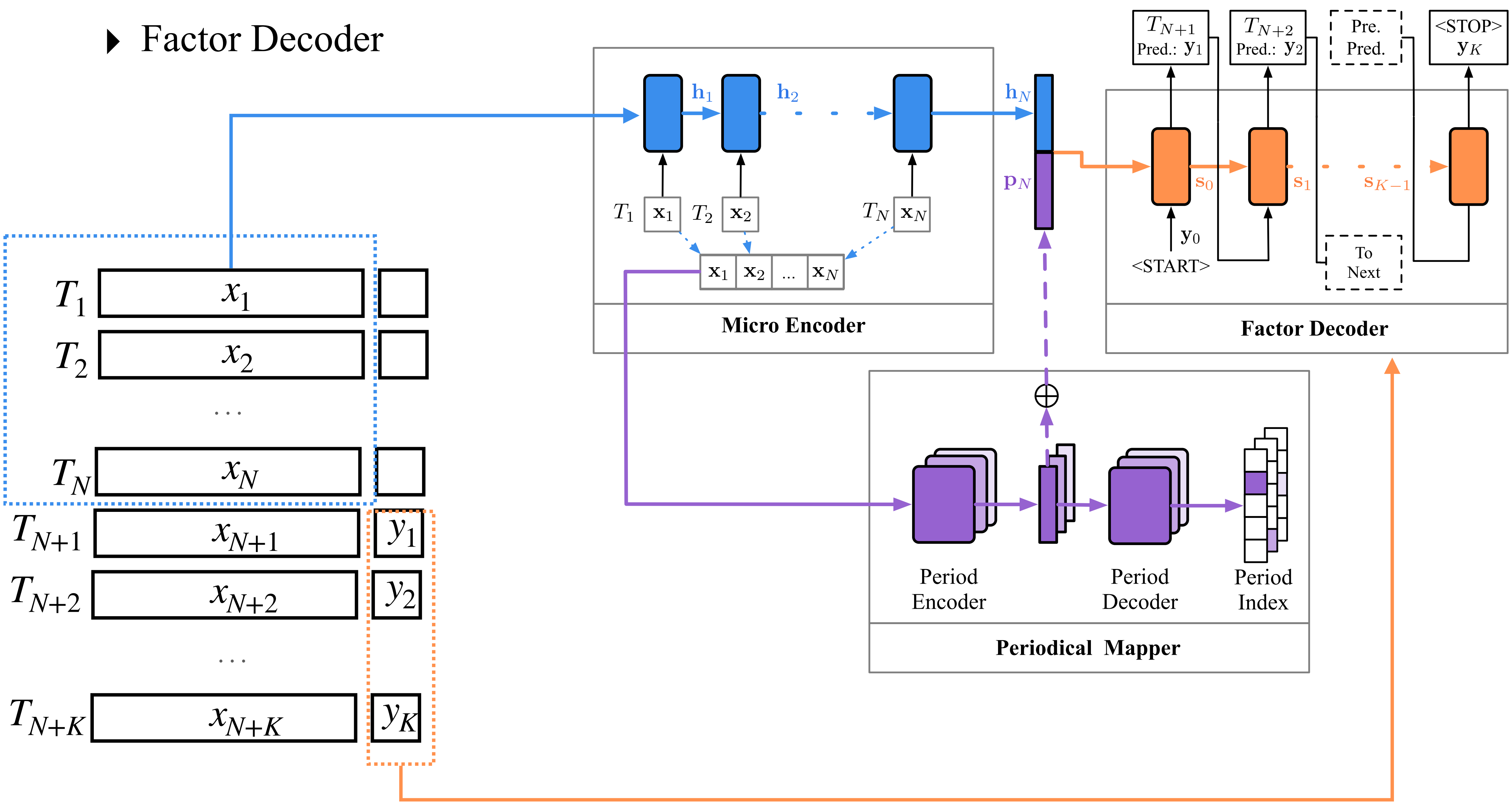


Encoder hidden vector



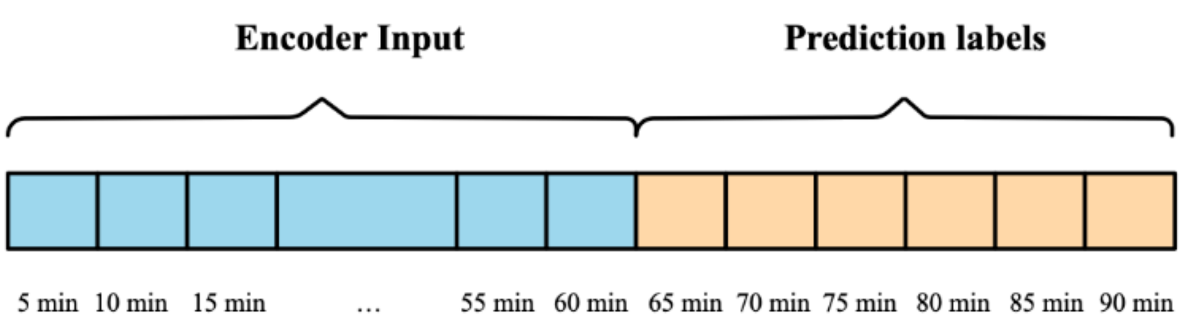
Micro Model

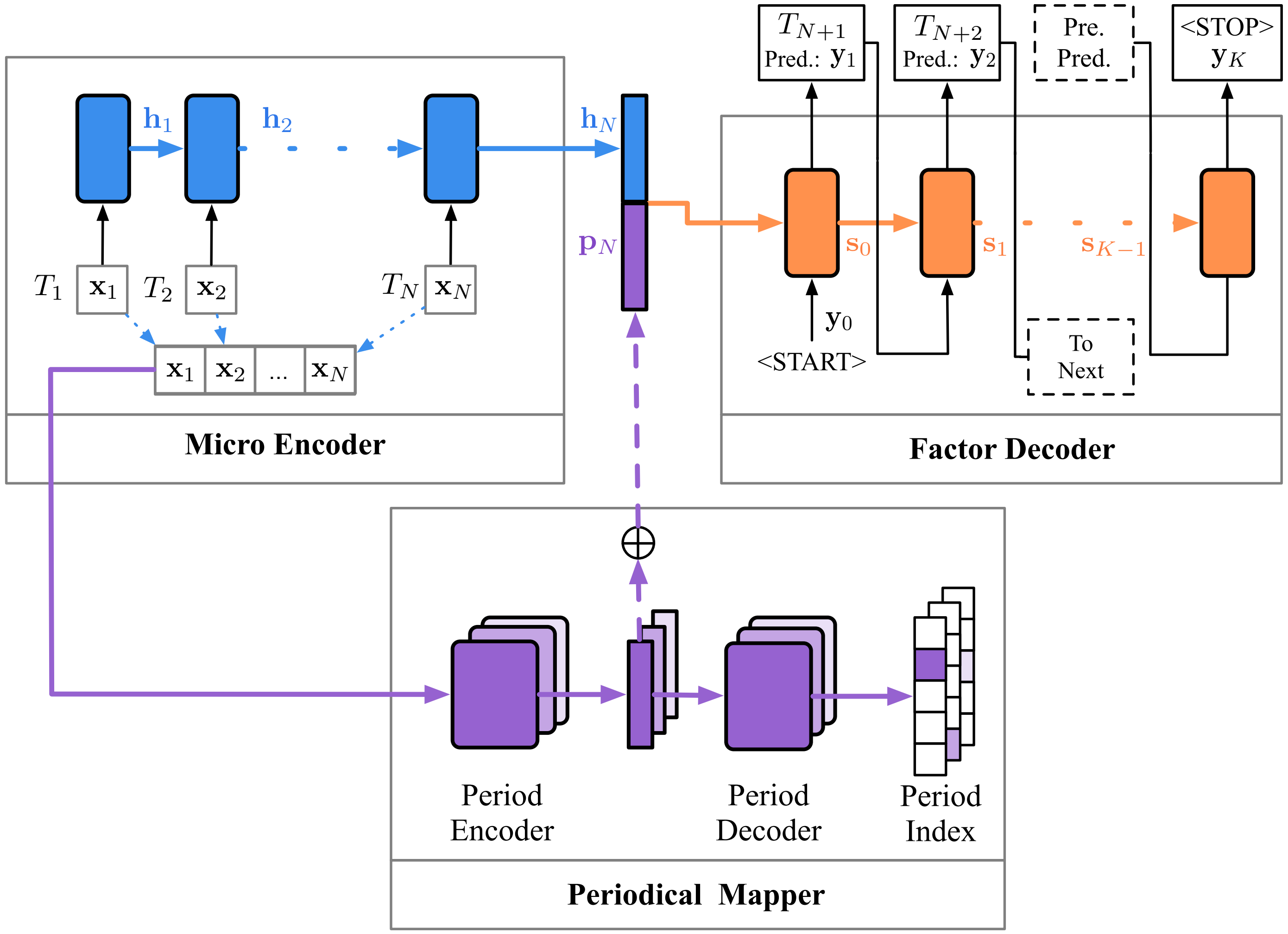
- **Micro Model**
  - Micro Encoder
  - Periodical Mapper
  - Factor Decoder



Micro — Training Phase

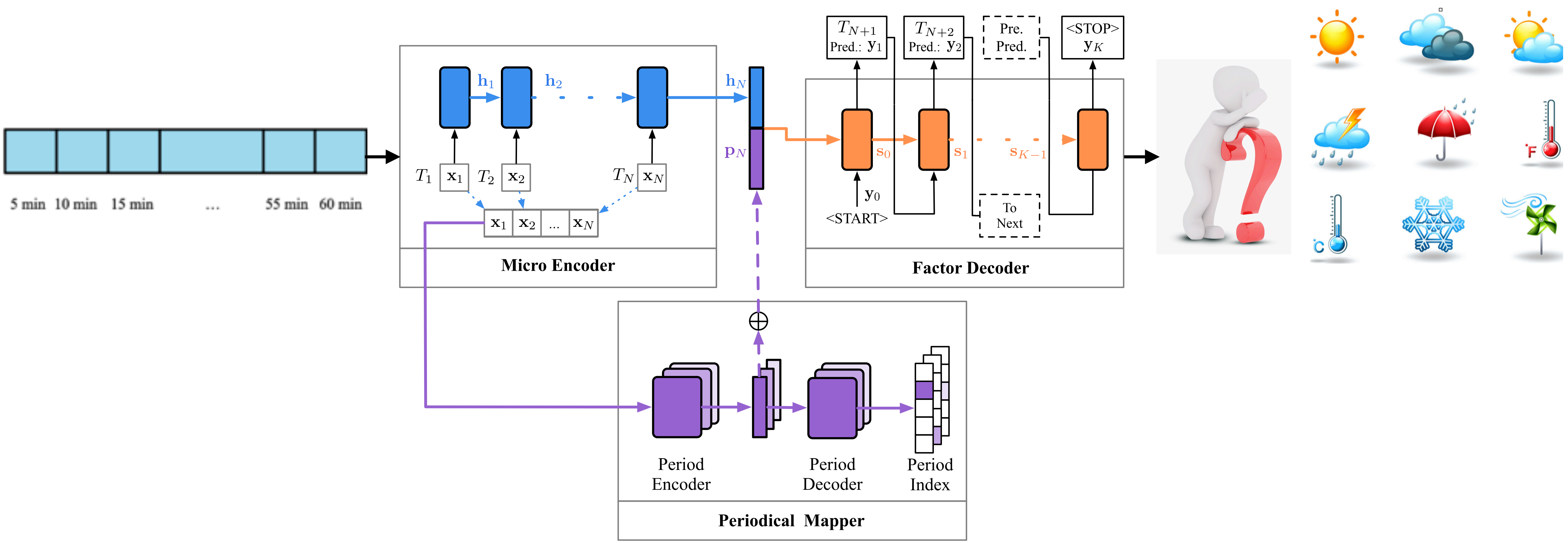
- **Data Labeling**
  - Select the most relevant parameters for predicting each specific weather parameter
  - Take previous years' measurements as the ground truth
  - Take each (N x T)-minute data as inputs and label the data in the subsequent M time interval





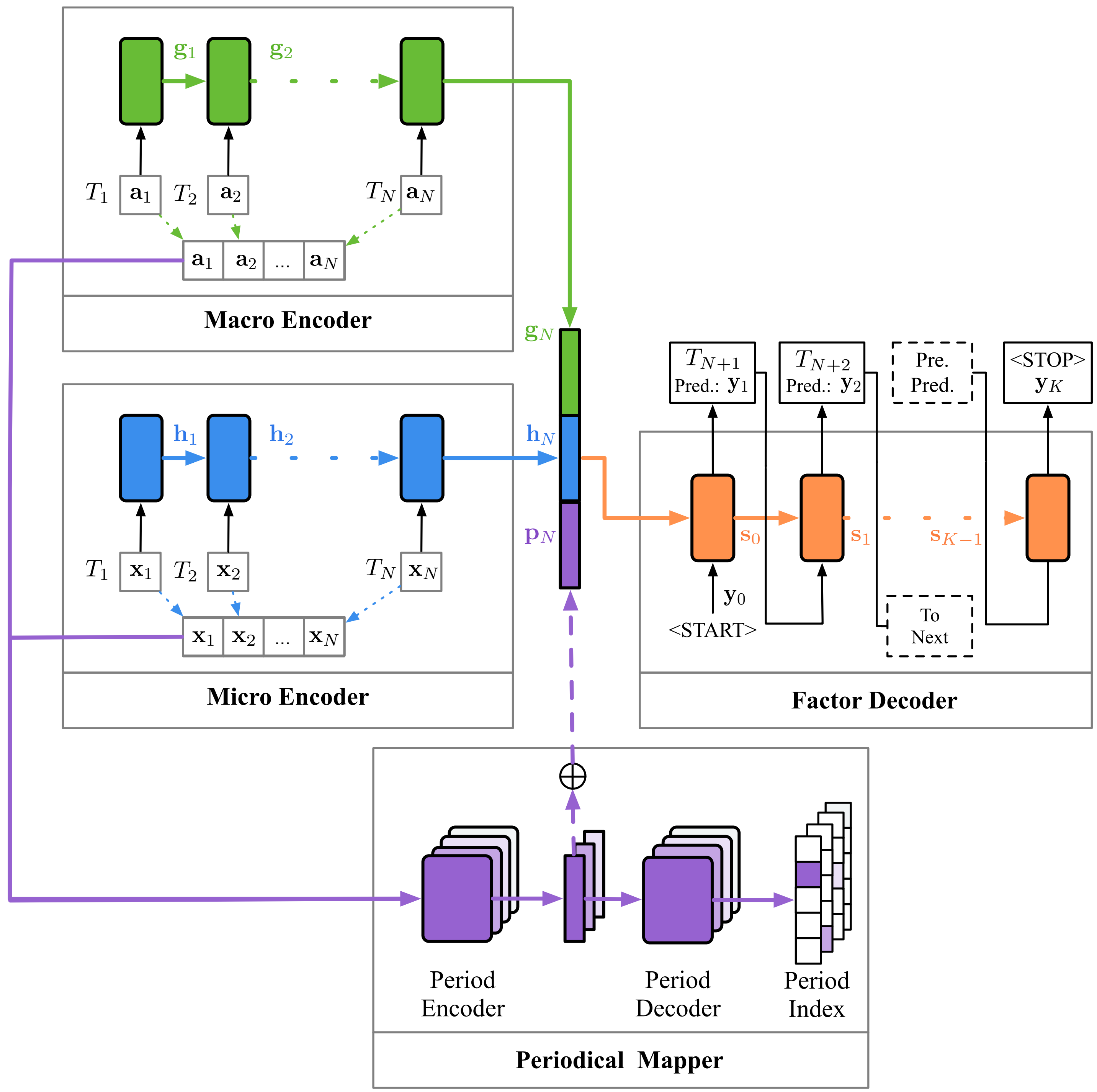
Micro — Prediction Phase

- **Data Processing**
  - Take the previous (N x T)-minute data, as input
  - Prediction: 



Micro-Macro Model

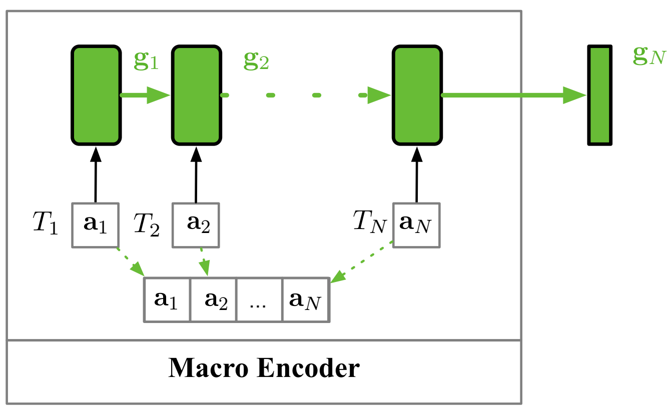
- **Micro-Macro Model**
  - Micro Encoder
  - Macro Encoder
  - Periodical Mapper
  - Factor Decoder

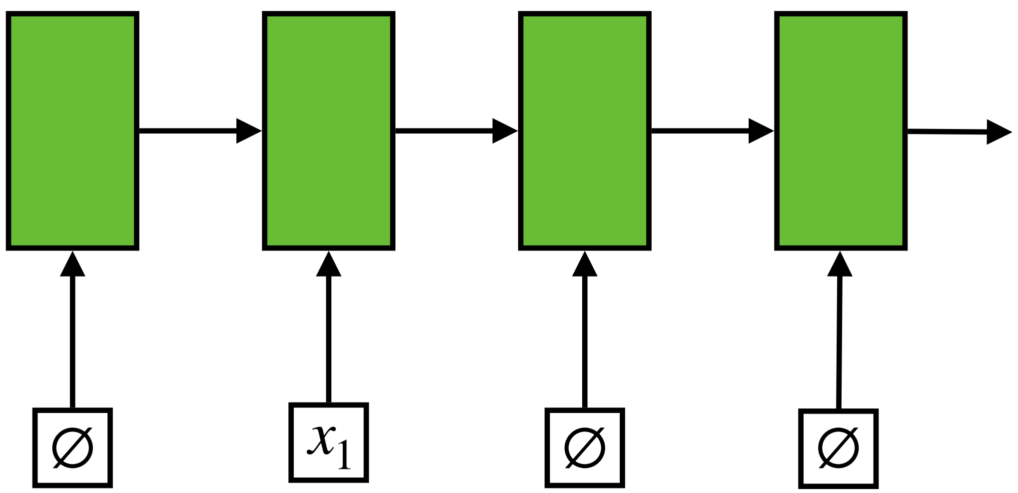


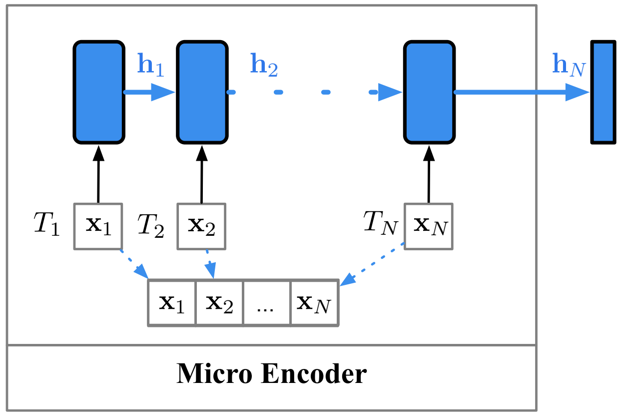
Micro-Macro Model

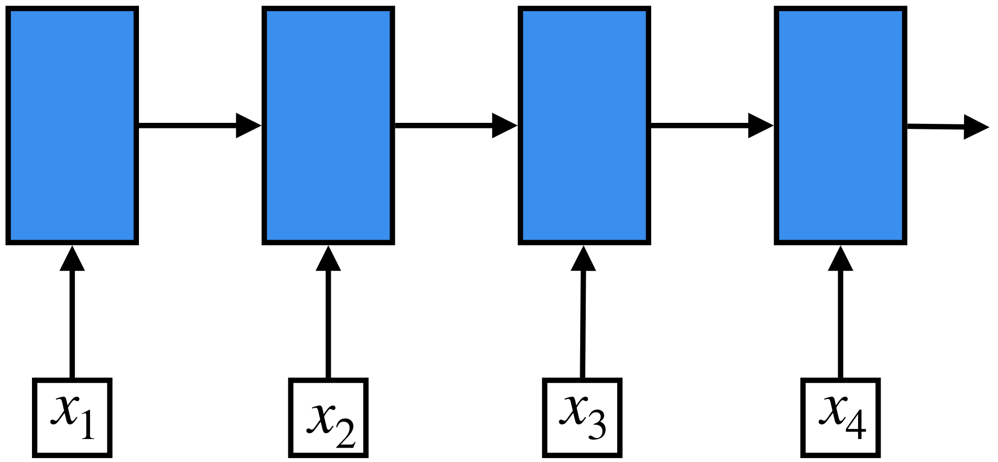
- **Macro Encoder**

  Downscaling



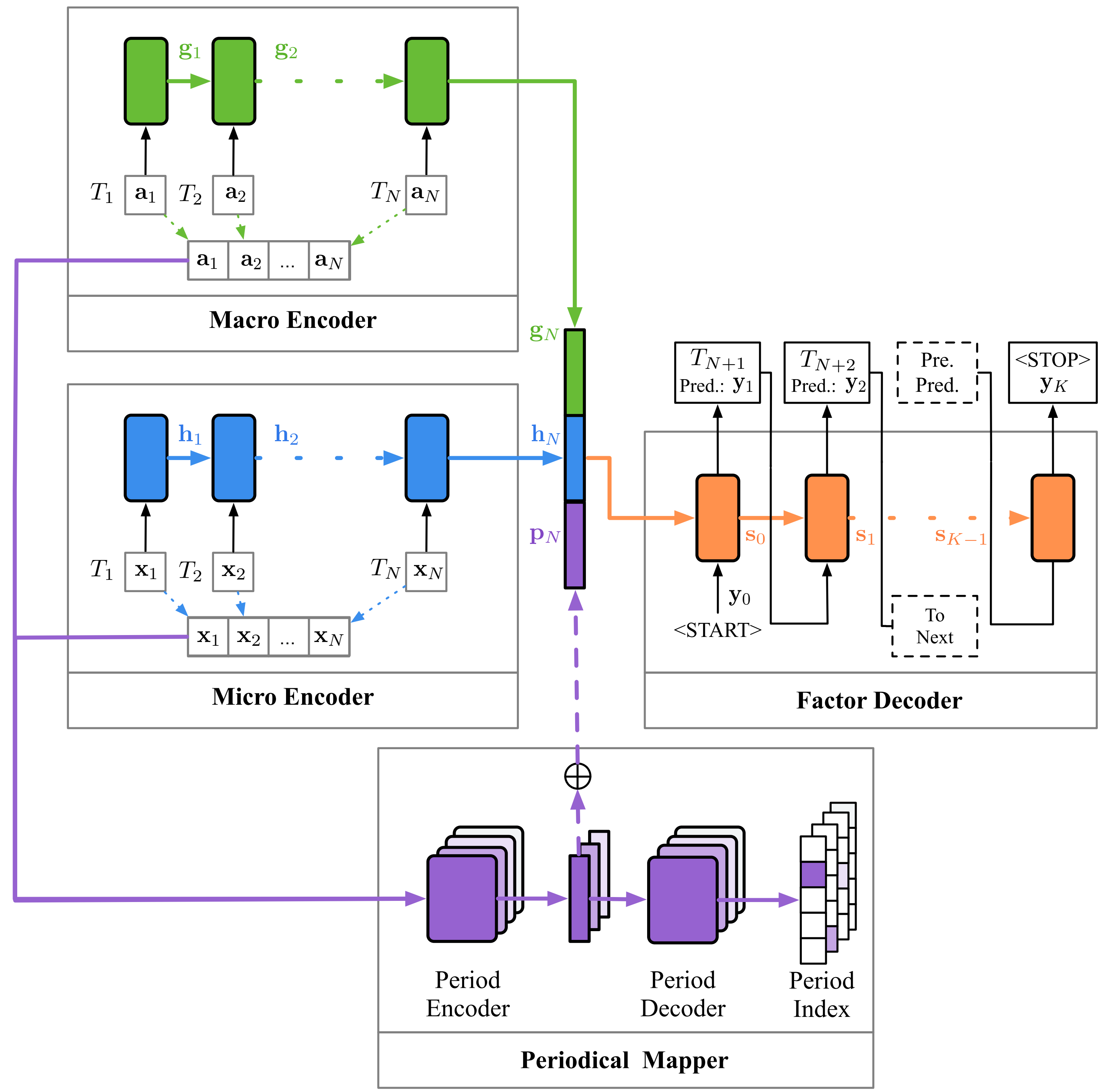






Micro-Macro Model

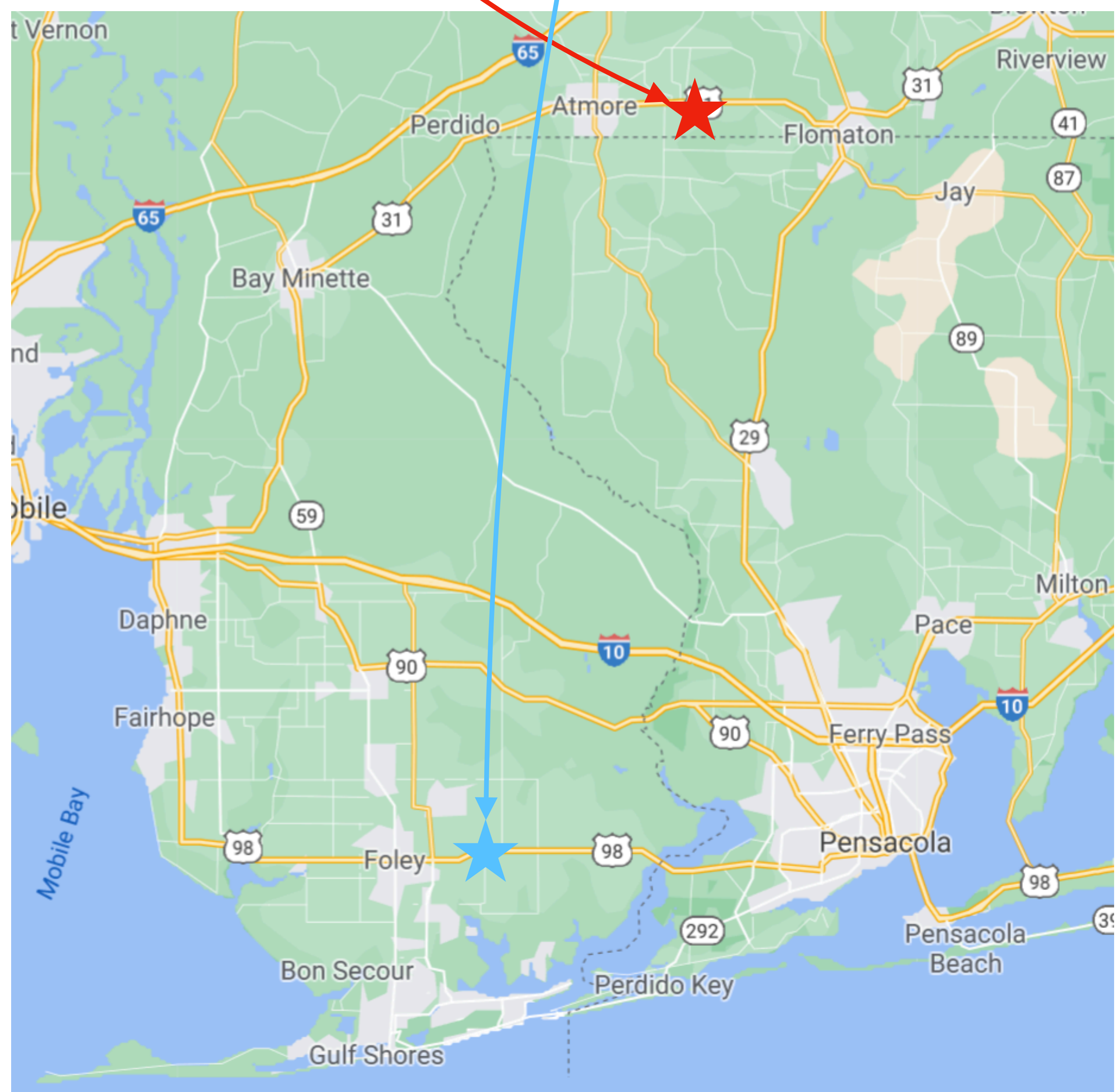
- **Micro-Macro Model**
  - Micro Encoder
  - Macro Encoder
  - Periodical Mapper
  - Factor Decoder



Experiments

- **Dataset**
  - SA Mesonet (26 automated weather stations, Atmore and Elberta in this experiment)
  - WRF-HRRR
  - Training: 2017, 2018
  - Test: 2019

Temperature,
Humidity,
Pressure,
Wind speed



Relevant Parameters

Predictions	Measurement parameters
TEMP	Vitel_100cm_d, IRTS_Body, SoilCond, SoilWaCond_tc, Vitel_100cm_b, eR, wfv, Vitel_100cm_a, SoilCond_tc, RH_10m
HUMI	Temp_C, Vitel_100cm_d, Vitel_100cm_a, Vitel_100cm_b, AirT_2m, AirT_10m WndSpd_Vert_Min, SoilT_5cm,Pressure_1, PTemp, IRTS
PRES	RH_10m, SoilCond, Temp_C, Vitel_100cm_d, AirT_1pt5m, IRTS_Trgt, PTemp, Vitel_100cm_b, SoilSfcT, AirT_10m
WSPD	WndSpd_2m_WVc_1, WndSpd_10m, WndSpd_2m_Max, WndSpd_Vert_Tot, WndSpd_2m_Std, QuantRadn, WndSpd_2m_WVc_2, WndSpd_Vert, WndSpd_10m_Max, WndDir_2m

From Mesonet Observation

Feature ID	Description
9	250hpa U-component of wind (m/s)
10	250hpa V-component of wind (m/s)
55	80 meters U-component of wind (m/s)
56	80 meters V-component of wind (m/s)
61	Ground moisture (%)
71	10 meters U-component of wind (m/s)
72	10 meters V-component of wind (m/s)
102	Cloud base pressure (Pa)
105	Cloud top pressure (Pa)
116	1000m storm relative helicity (%)

From WRF-HRRR Output

Overall Performance

		0 to 5 min	5 to 10 min	10 to 15 min	15 to 20 min	20 to 25 min	25 to 30 min
	TEMP	0.502	0.531	0.564	0.601	0.632	0.670
	HUMI	4.431	4.507	4.552	4.707	5.122	5.802
Atmore	PRES	1.087	1.133	1.139	1.156	1.184	1.235
	WSPD	0.396	0.552	0.572	0.658	0.709	0.833
	TEMP	0.424	0.468	0.471	0.475	0.479	0.485
	HUMI	1.852	1.873	1.893	1.905	1.933	2.015
Elberta	PRES	1.075	1.213	1.245	1.309	1.452	1.607
	WSPD	0.492	0.528	0.556	0.584	0.614	0.656

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - \hat{x}_i\right)^2}{N}}$$

Table 1: Parameter information

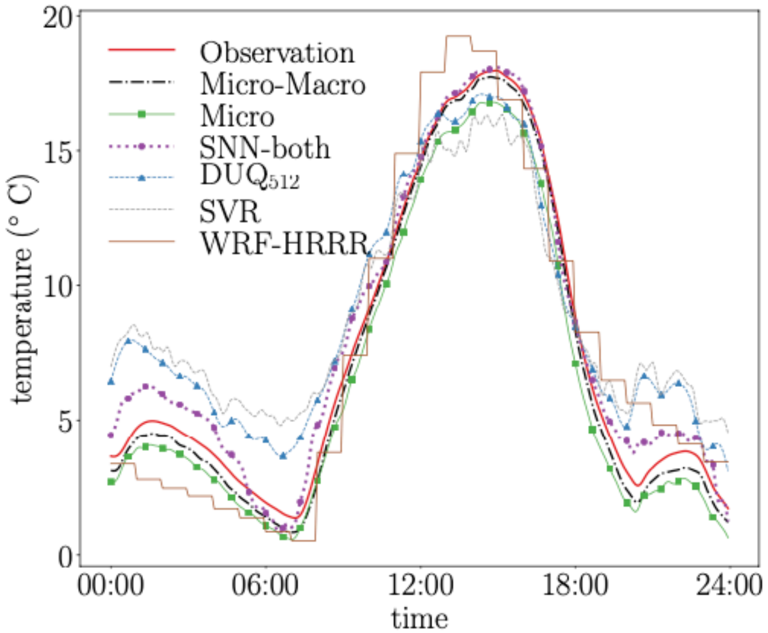
Parameter	Measurement	Mounting Height	Measuring Range
TEMP	Air Temperature	2 m	-40 to 60°C
HUMI	Relative Humidity	2 m	0 to 100%
PRES	Atmospheric Pressure	1.5m	600 to 1060mb
WSPD	Wind Speed	2 m	0 to 100 m/s

Comparisons

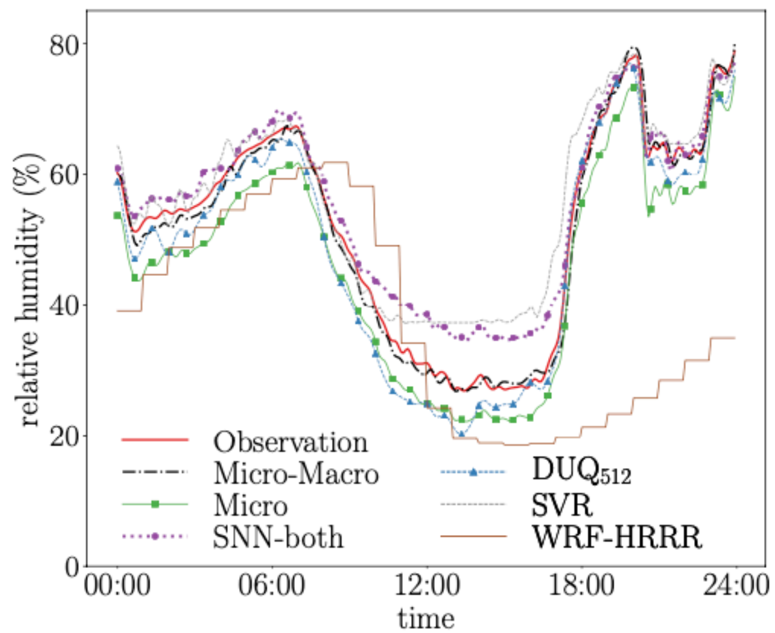
	Atmore				Elberta			
	TEMP	HUMI	PRES	WSPD	TEMP	HUMI	PRES	WSPD
WRF-HRRR	2.412	20.471	1.648	1.112	1.633	14.296	1.554	1.412
SVR	3.581	20.507	5.209	1.306	1.734	22.953	6.752	1.887
SNN-Micro	0.668	9.137	5.373	0.354	1.381	4.387	4.927	0.265
SNN-both	0.619	7.611	4.959	**0.330**	0.804	4.250	4.337	**0.264**
DUQ_{512}	0.812	5.668	2.714	0.592	0.645	3.524	3.513	0.541
$DUQ_{512-512}$	0.657	5.354	2.667	0.585	0.632	3.326	3.225	0.489
Micro-Macro	**0.502**	**4.431**	**1.087**	0.396	**0.424**	**1.852**	**1.075**	0.492

RMSE values of different methods for 5-minute prediction

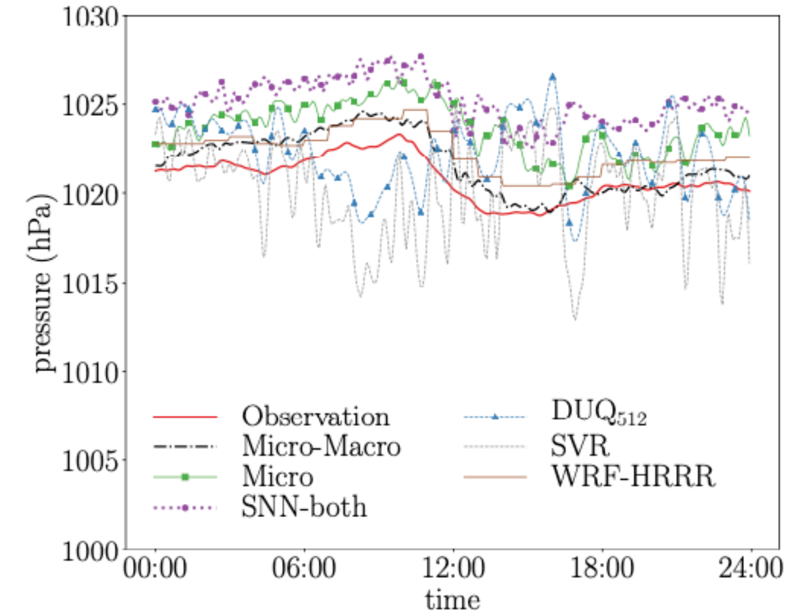
One-day Prediction



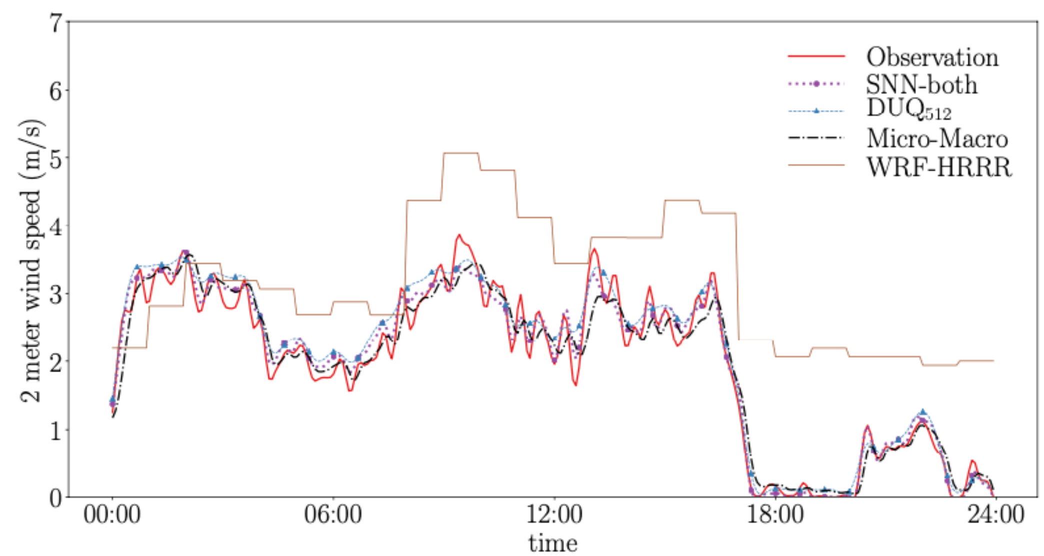
(a) temperature



(b) humidity



(c) pressure



(d) Wind speed

Please see our article for details

https://prefer-nsf.org/pdf/PREFER_Modelet_Evaluation.pdf