



UNIVERSITY of
LOUISIANA
L A F A Y E T T E

Lecture 8

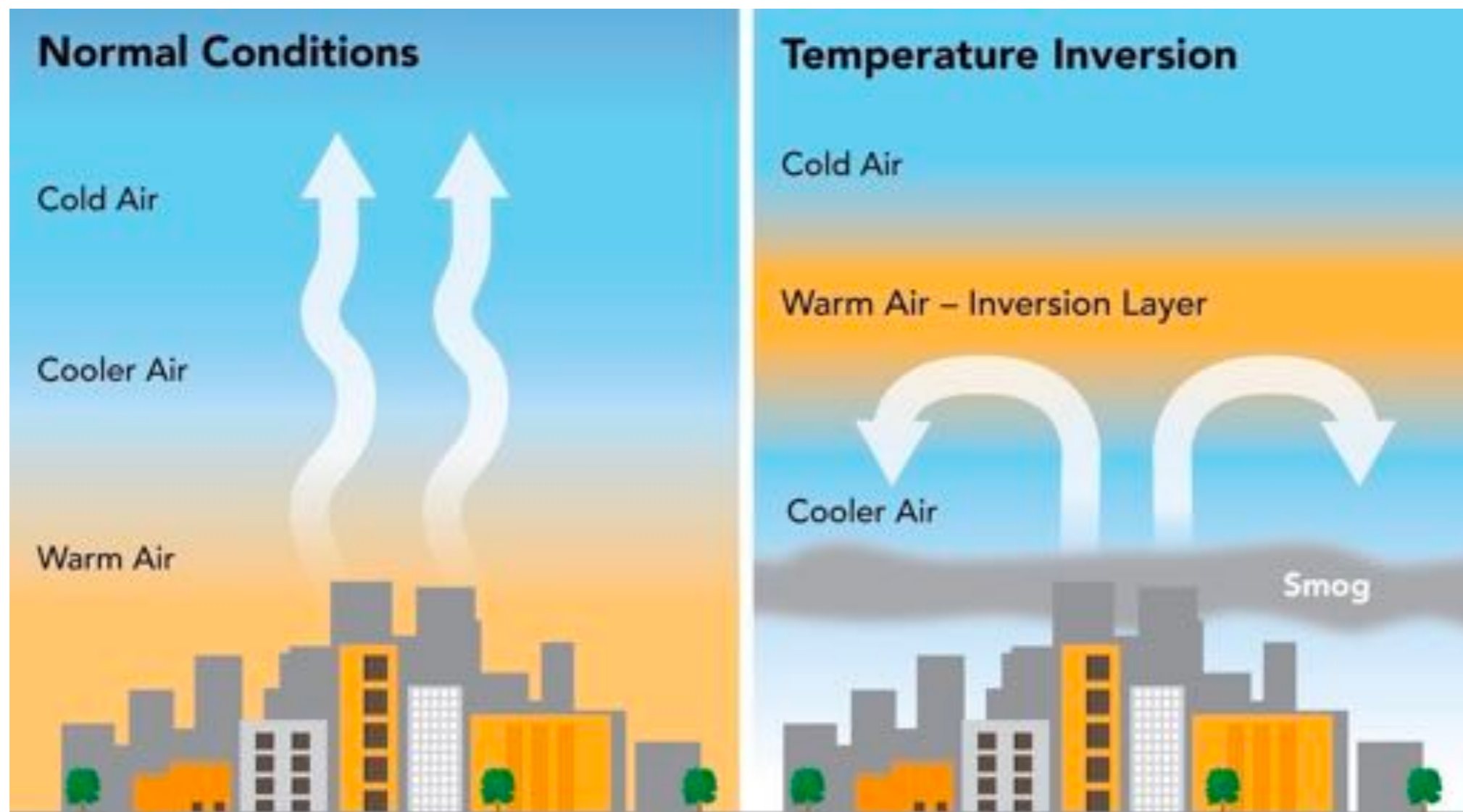
Thermal Inversion Prediction via WeatherLore Model

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Thermal Inversion

- Thermal inversion is common natural phenomenon
- Atmospherically, near-surface air temperature $>$ that above the surface



Source: <https://lotusarise.com/temperature-inversion-upsc/>

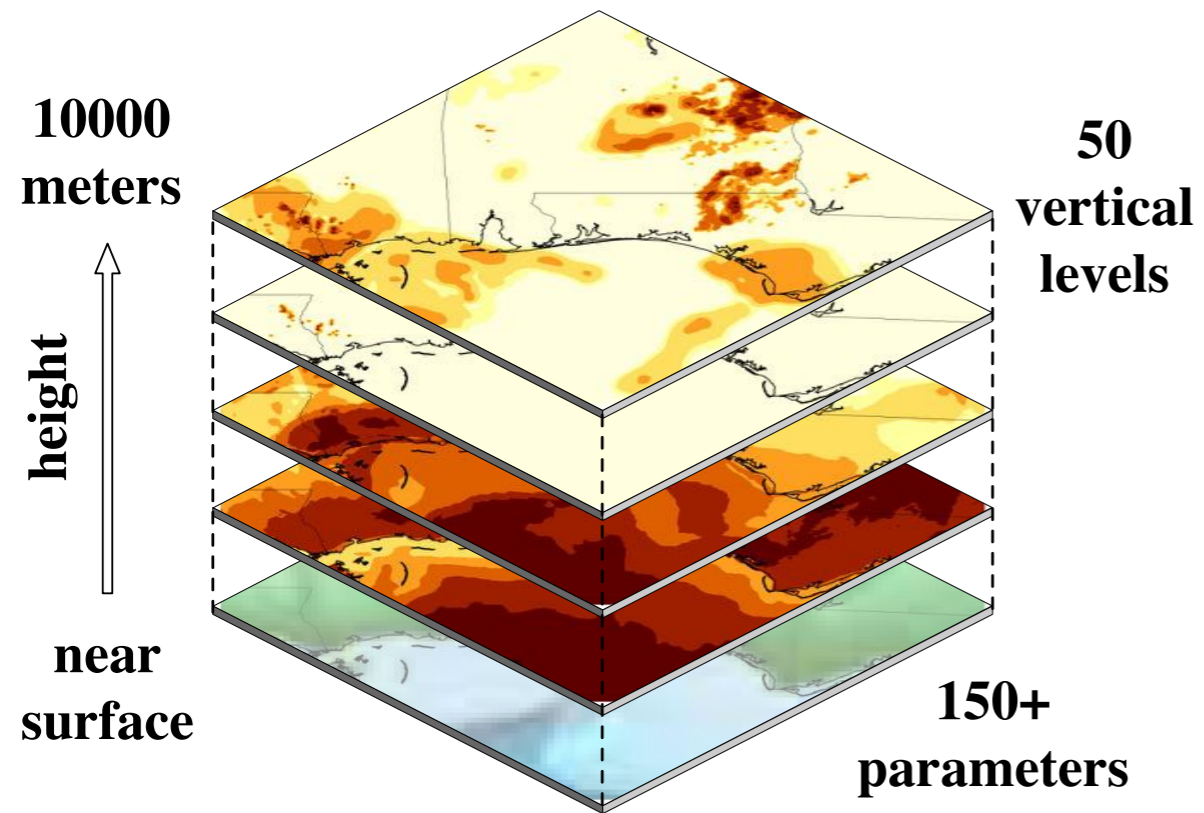
Adverse Effect

- **Cause various hazards to different socio-economic sectors**
 - The changes of dissipation of pesticide spray solution in agriculture
 - PM 2.5 and black carbon percentages are higher during inversion days
 - Highly correlated to hospital visits for acute respiratory and cardiovascular diseases
 - A hidden cause of Titanic Disaster 1912 (from FOX Weather News)
<https://www.foxweather.com/lifestyle/titanic-weather-thermal-inversion-mirage-optical-illusion>

Our Goal

- **Challenges**
 - ▶ Lacking of appropriate datasets
 - ▶ Lacking of an accurate prediction model
- **Developing the first AI-based holistic framework for accurate temperature inversion prediction**
 - ▶ Creating a professional dataset for thermal inversion purpose
 - ▶ Propose a method for thermal inversion forecasting

Two Data Sources



WRF-HRRR (2.4G per day)

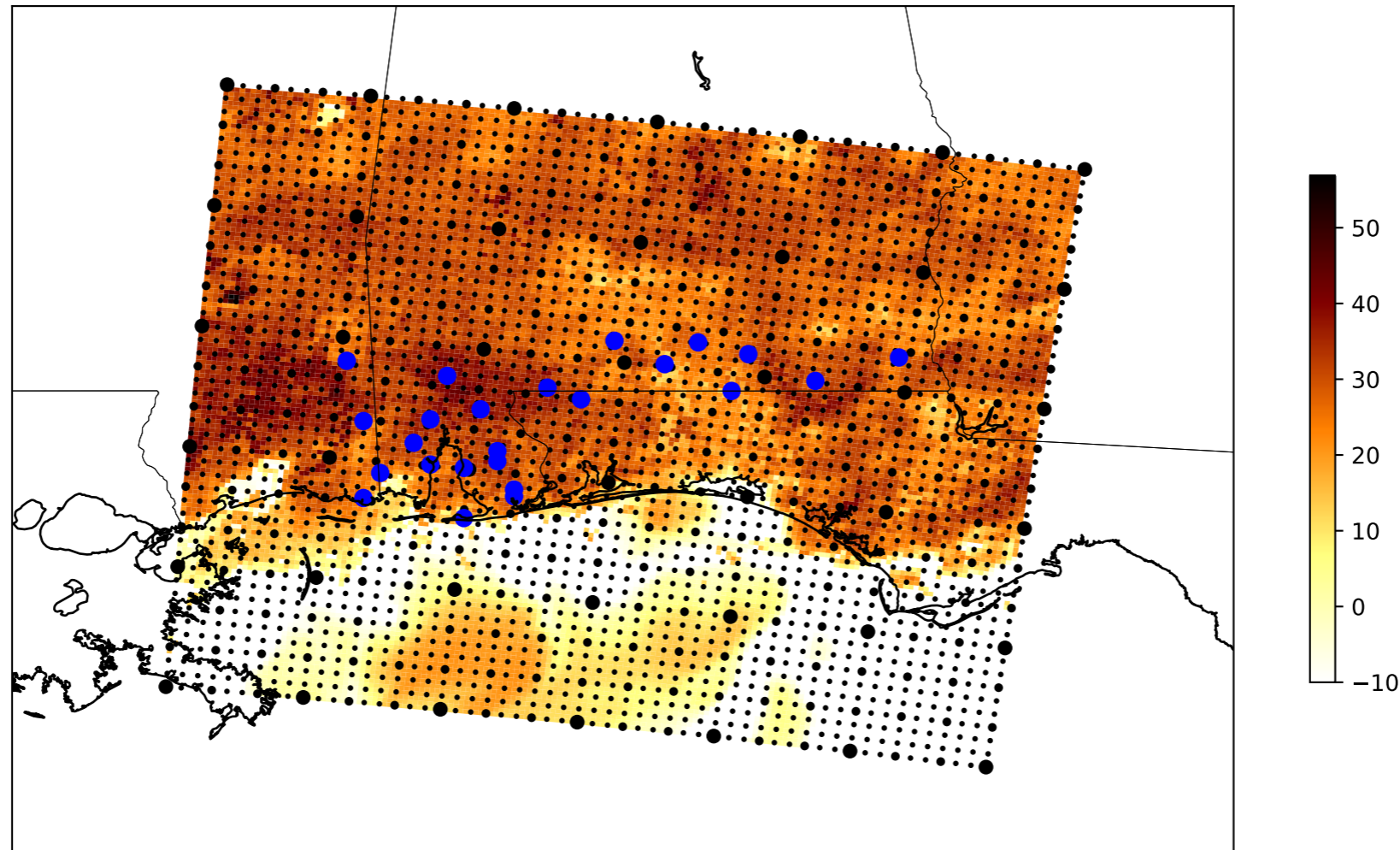


Mesonet (small)

	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

Dataset Design

- **South Alabama**

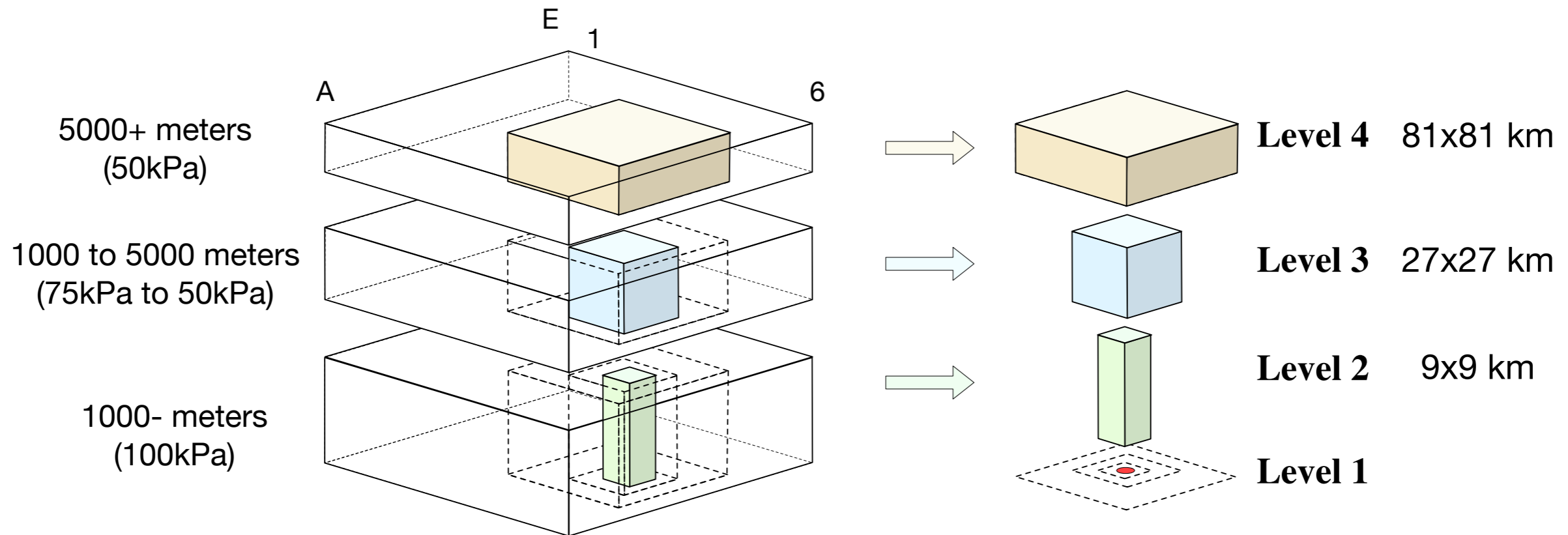


Range

latitude: 29.23 to 32.83

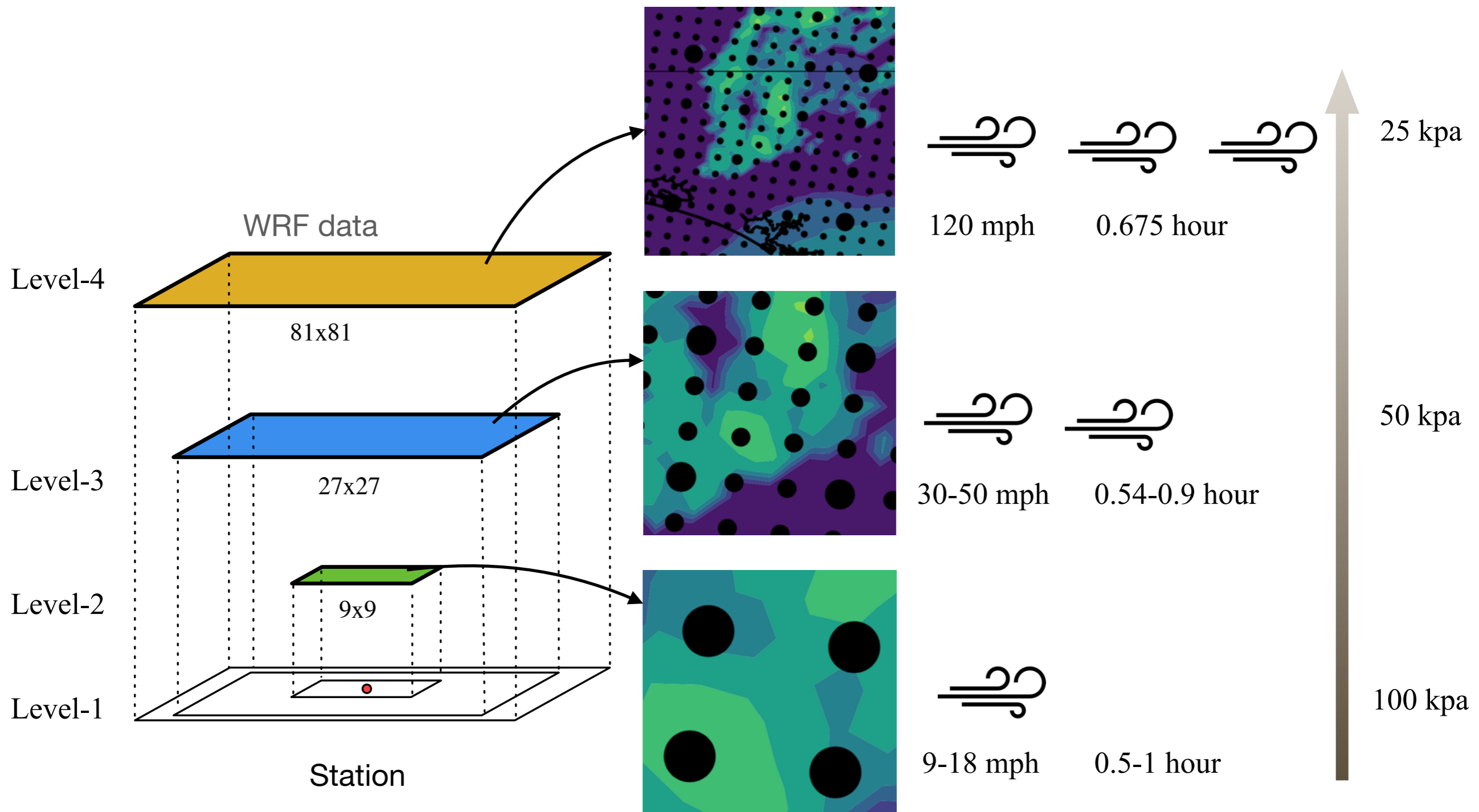
longitude: -89.68 to -84.18

Dataset Design



Coordinate: {A-E}{1-6}:{1-9}:{1-9}

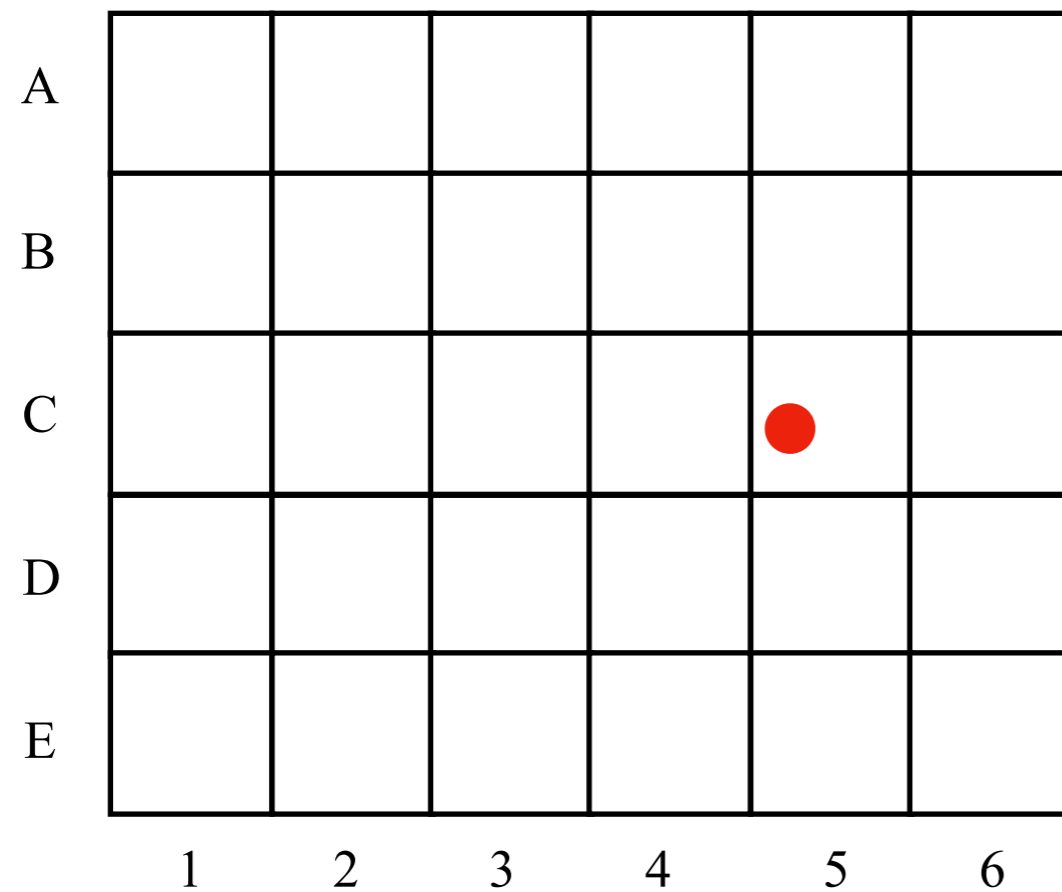
Dataset Processing



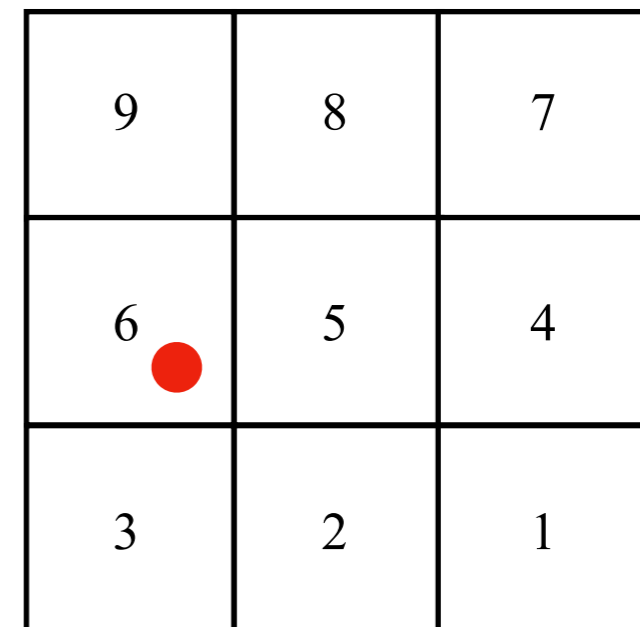
Dataset Design

- **Coordinating**

Level-2 coordinating



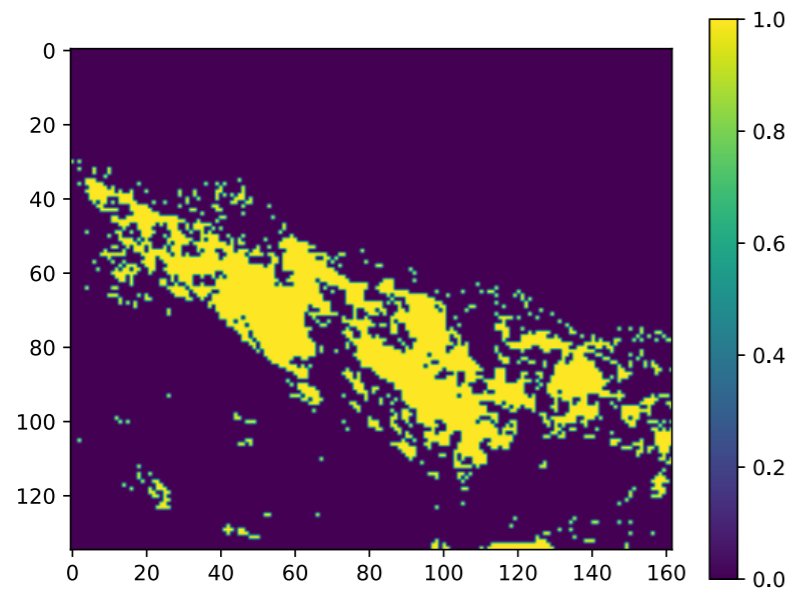
Level-3 and Level-4 coordinating



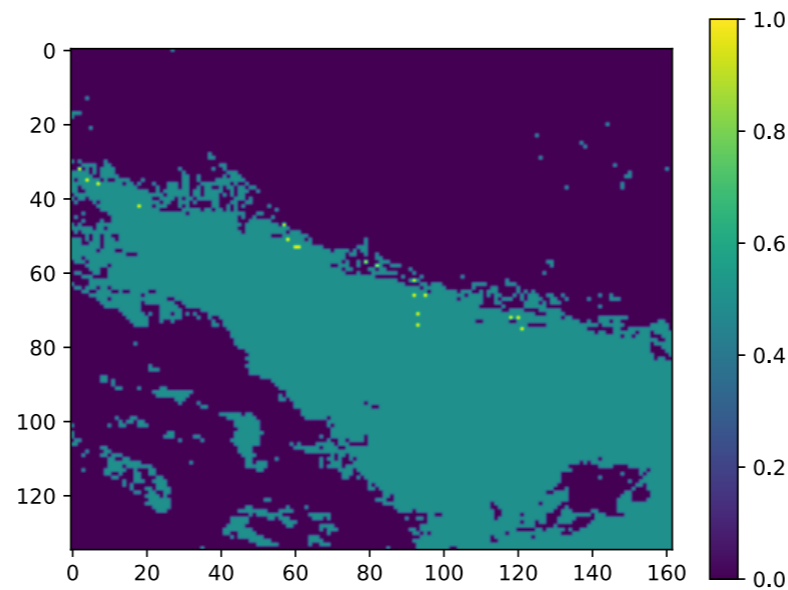
Station Coordinating Index format: {A-E} {1-6} : {1-9} : {1-9}

Dataset Design

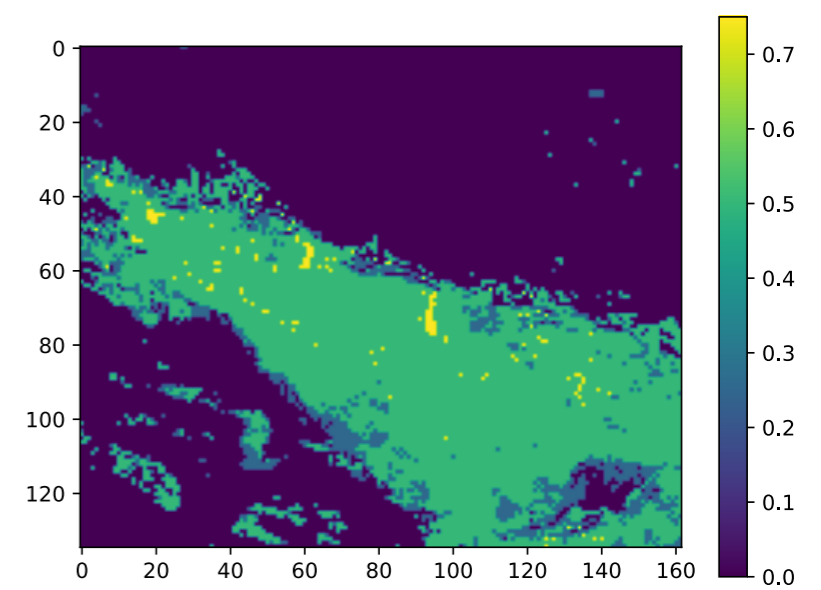
- Quantifying



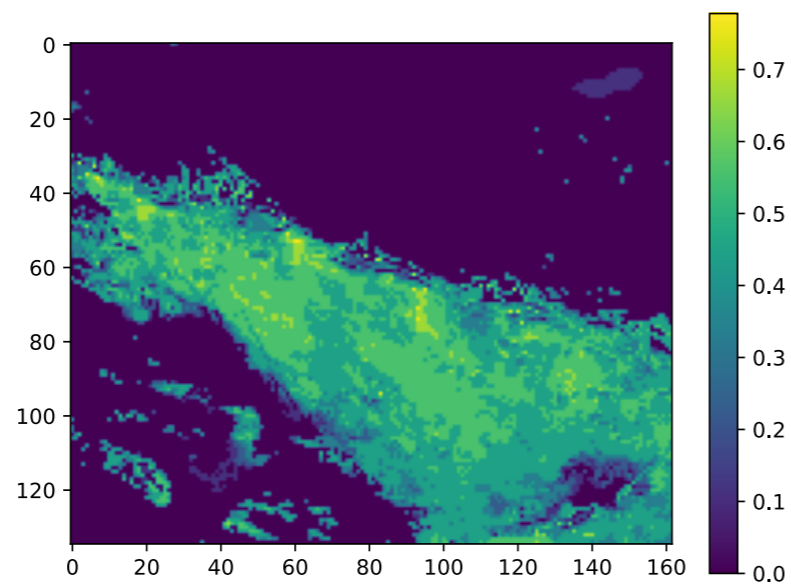
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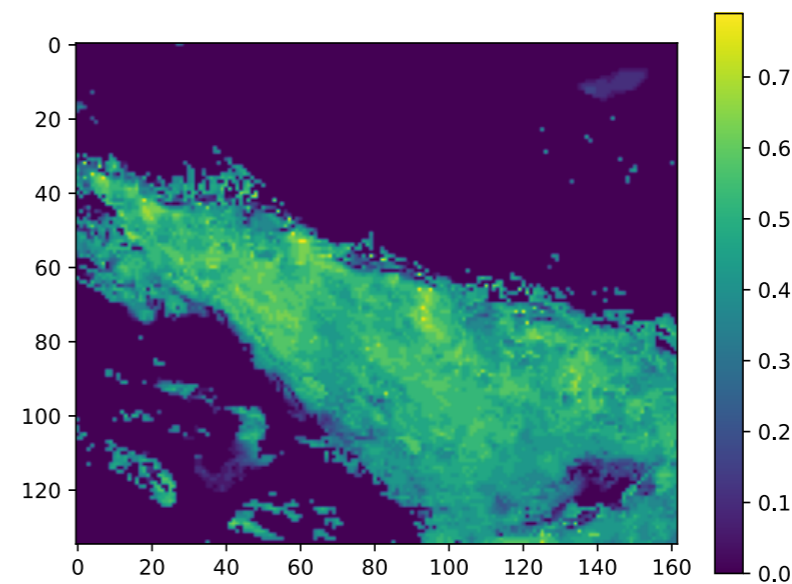
class = 3



class = 5



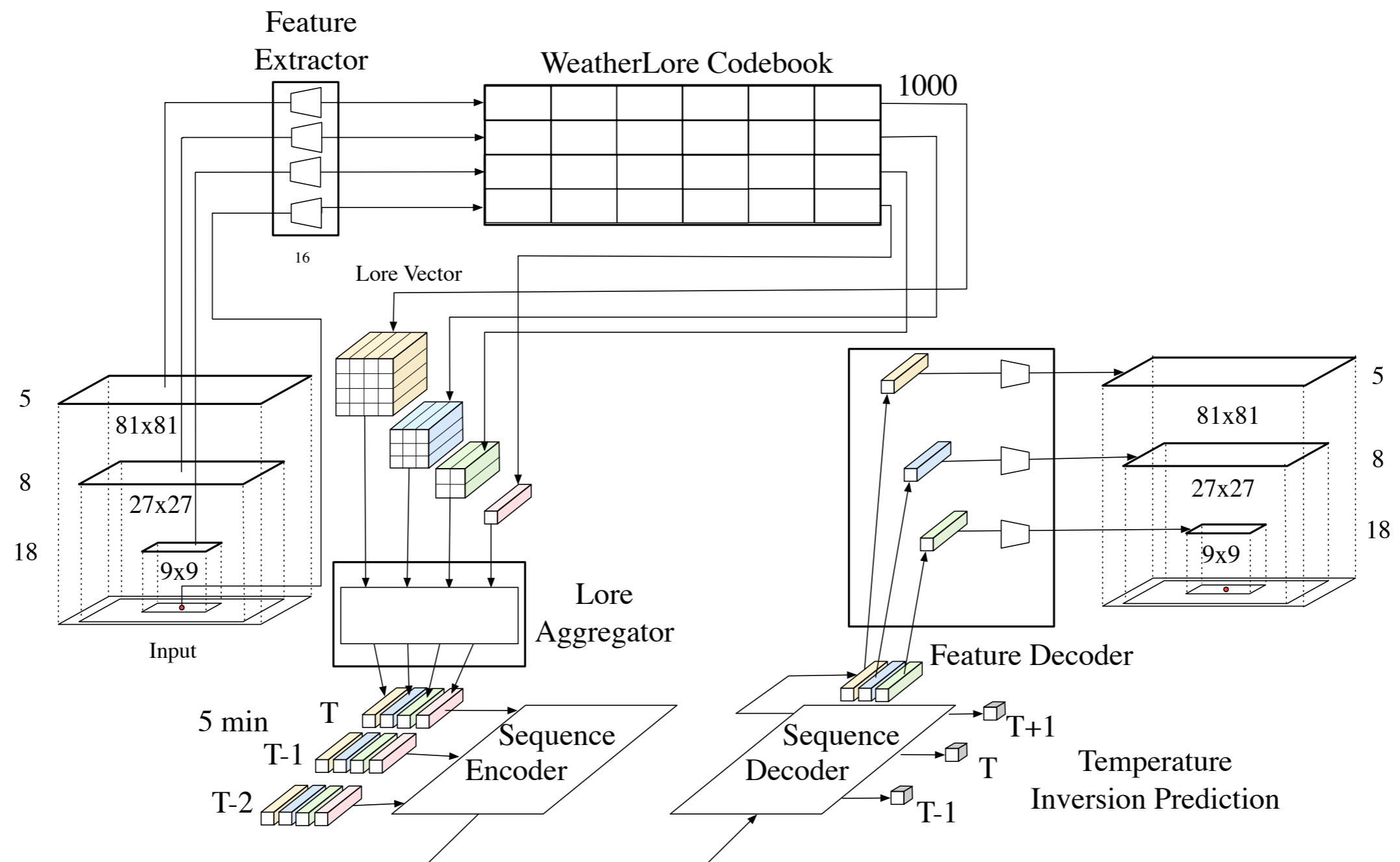
class = 10



class = 20

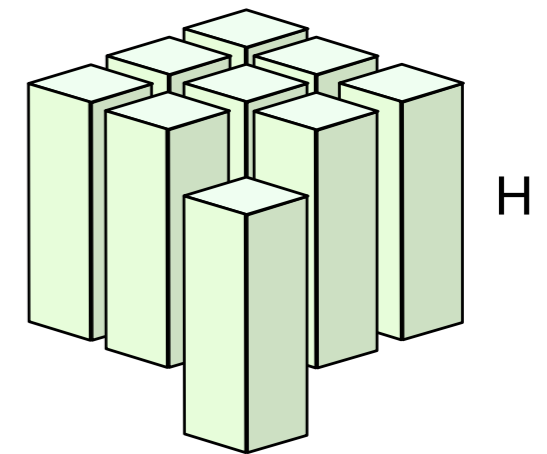
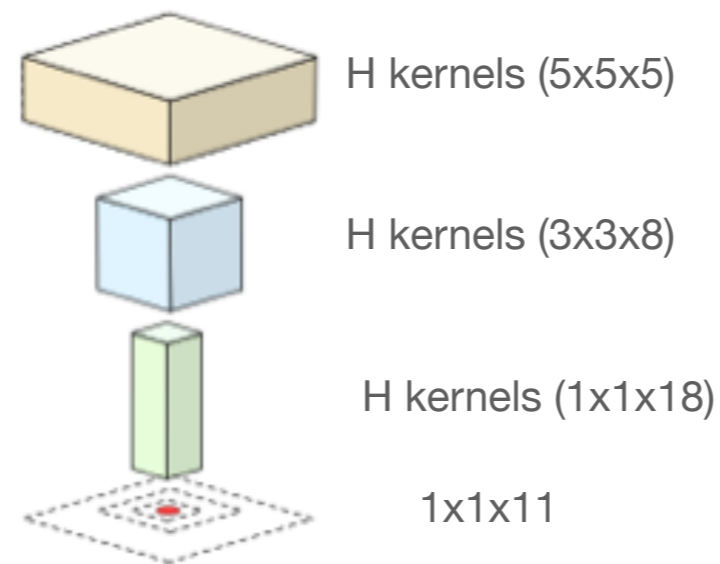
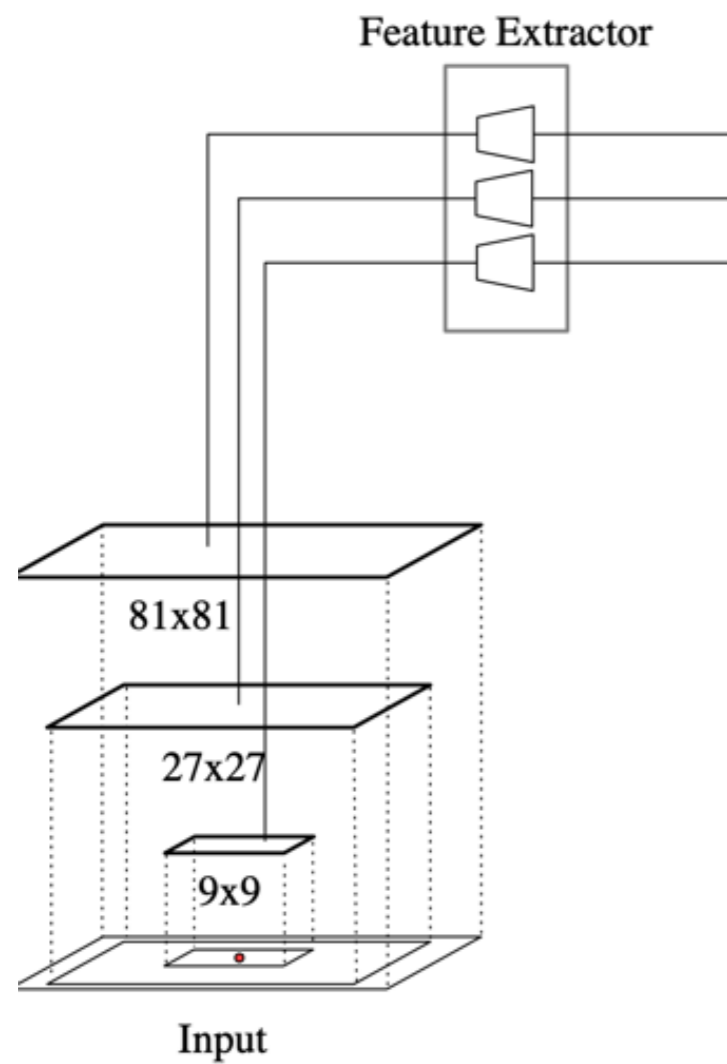
WeatherLore Model

- Take our crafted dataset as input
- Make accurate temperature inversion prediction over next few time horizons, i.e., next T mins, $2T$ mins ...



Model Design

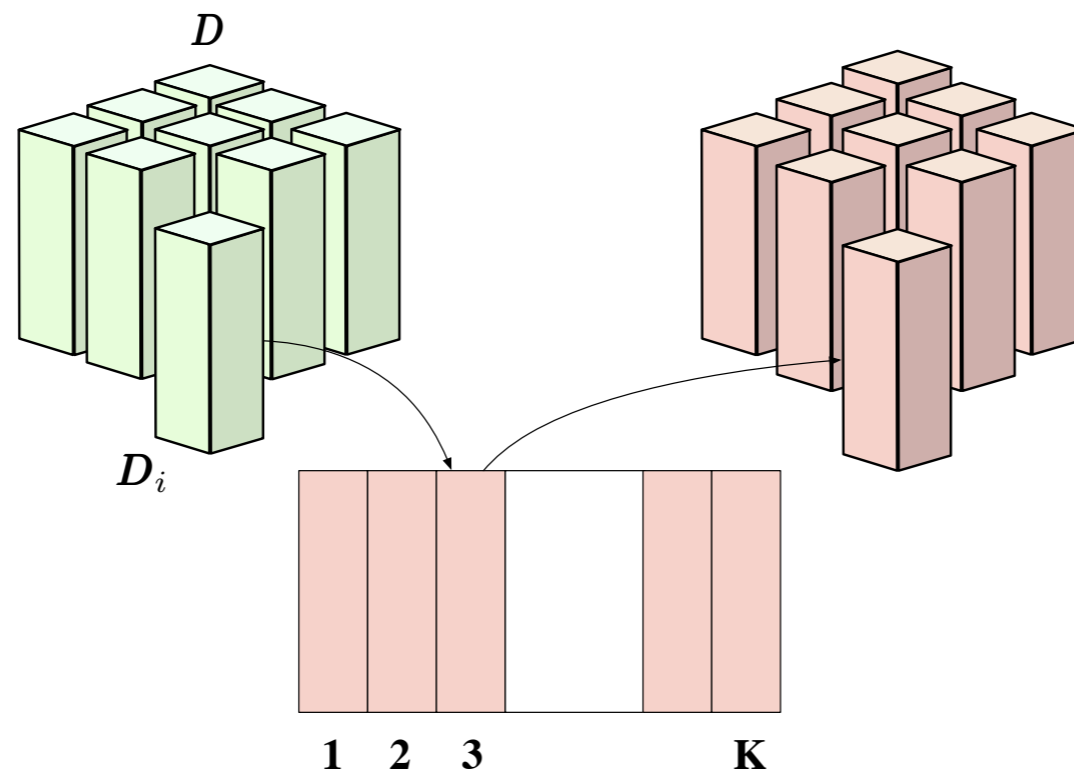
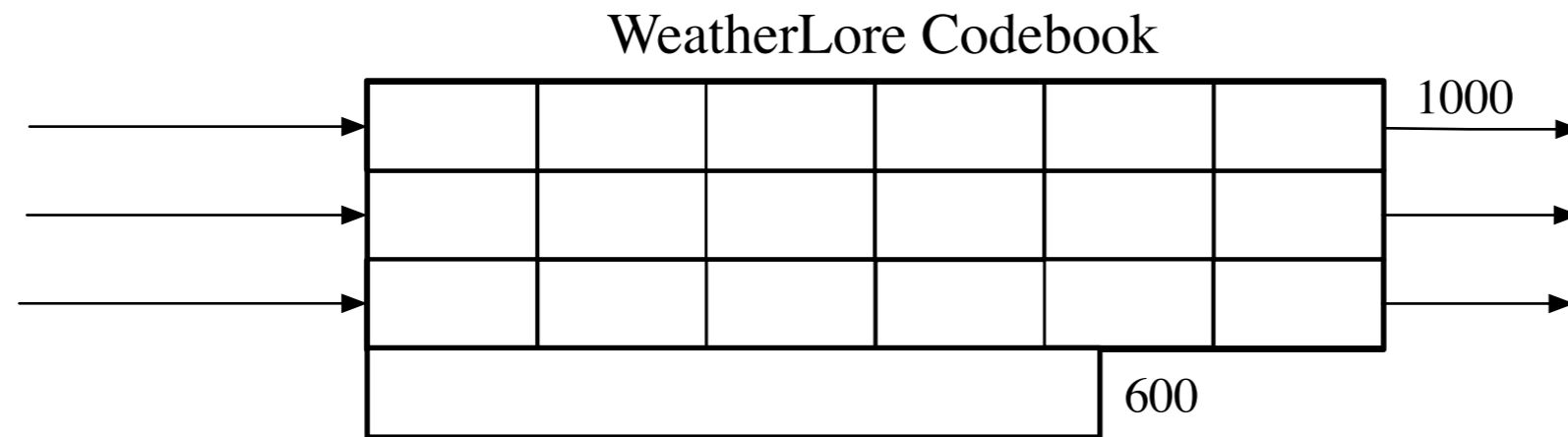
- Feature Extractor



Level 4: 23x23xH
Level 3: 7x7xH
Level 2: 3x3xH
Level 1: 1x1xH

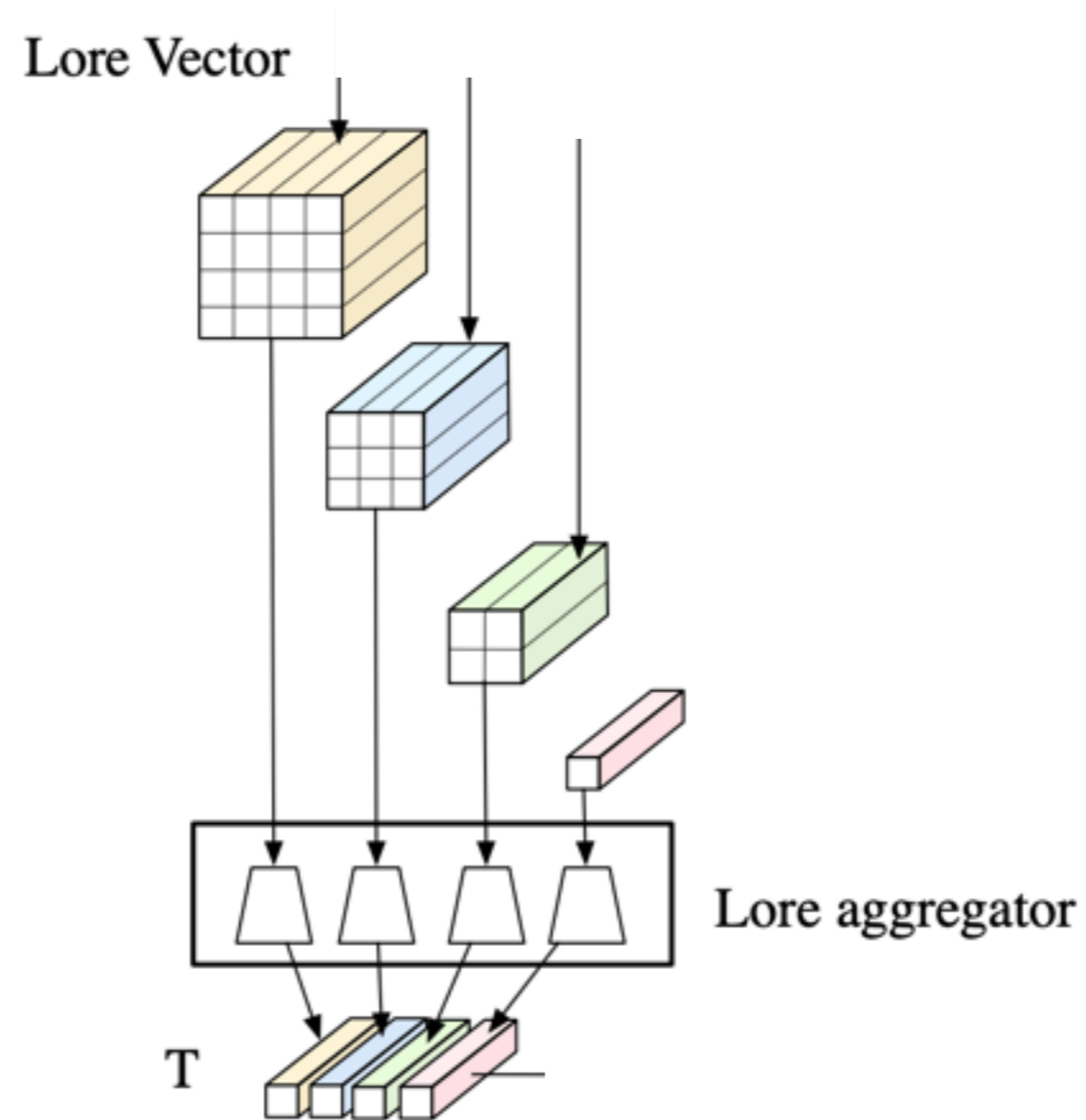
Model Design

- WeatherLore Codebook



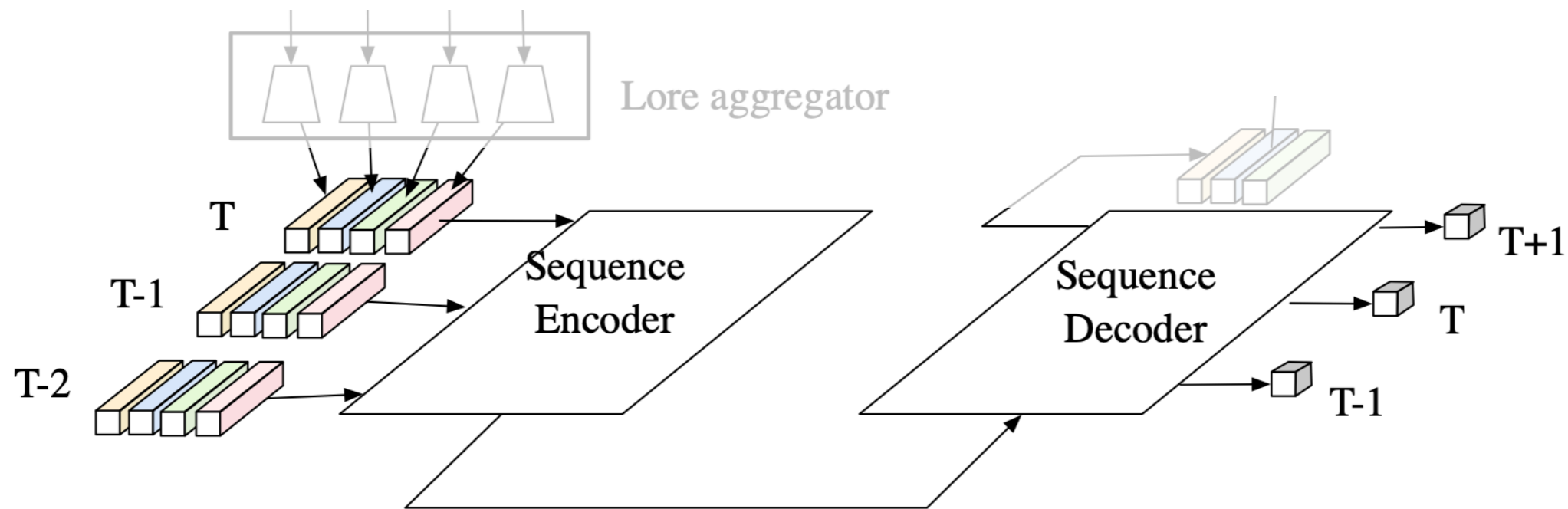
Model Design

- Lore Aggregator



Model Design

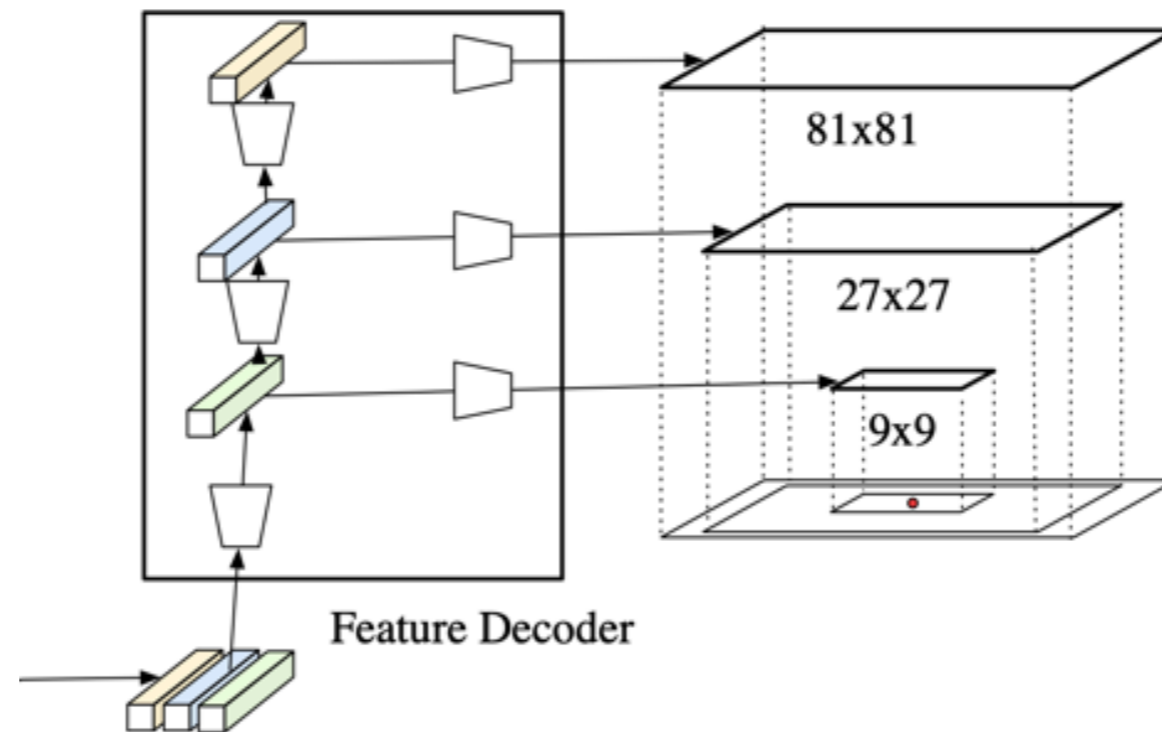
- **Sequence Encoder/Decoder**



- 0: Non-temperature inversion
- 1: Low temperature inversion
- 2: Medium temperature inversion
- 3: High temperature inversion

Model Design

- Feature Decoder



Reconstructing next M intervals' weather patterns

Experiments

- Five Mesonet Stations:
 - ▶ Agricola, Elberta, Mobiledr, Dixie, and Foley
- Data period
 - ▶ 2017 and 2018 for training
 - ▶ 2019 or testing

Mesonet:

2m temperature, 10 temperature, total radiation, quantum radiation, 2m wind speed, 10 wind speed, vertical wind speed, 2m wind direction, 10m wind direction, 2m relative humidity, and 10m relative humidity

It takes 16 minutes to produce all datasets. The dataset size is around 120MB for each quarter.

Id	Feature	Height	level
1	Maximum/Composite radar reflectivity	0	2
2	Wind speed (gust)	0	2
3	Temperature:K	100000 Pa	2
4	Dew point temperature:K	100000 Pa	2
5	U component of wind	100000 Pa	2
6	V component of wind	100000 Pa	2
7	2 metre temperature:K	2 m	2
8	Potential temperature:K	2 m	2
9	2 metre specific humidity:kg kg ⁻¹	2 m	2
10	2 metre dewpoint temperature:K	2 m	2
11	2 metre relative humidity:%	2 m	2
12	2 metre specific humidity:kg kg ⁻¹	2 m	2
13	2 metre dewpoint temperature:K	2 m	2
14	10 metre U wind component:m s ⁻¹	10 m	2
15	10 metre V wind component:m s ⁻¹	10 m	2
16	10 metre wind speed:m s ⁻¹ (max)	10 m	2
17	Upward long-wave radiation flux:W m ⁻²	10 m	2
18	Downward short-wave radiation flux:W m ⁻²	10 m	2
19	Derived radar reflectivity	1000 m	2
20	Derived radar reflectivity:dB	4000 m	3
21	Temperature:K (instant)	50000 Pa	3
22	Dew point temperature:K	50000 pa	3
23	U component of wind:m s ⁻¹	50000 Pa	3
24	V component of wind:m s ⁻¹	50000 Pa	3
25	Relative humidity:%	isothermZero	3
26	U component of wind:m s ⁻¹	highestTroposphericFreezing	3
27	Derived radar reflectivity	isothermal 263 K	4
28	U component of wind:m s ⁻¹	25000 Pa	4
29	V component of wind:m s ⁻¹	25000 Pa	4
30	U component of wind:m s ⁻¹	30000 Pa	4
31	V component of wind:m s ⁻¹	30000 Pa	4

Experiments

- **Setting**

Inputs:

Level-2: $9 \times 9 \times 18$

Level-3: $27 \times 27 \times 8$

Level-4: $81 \times 81 \times 5$

Feature Extractor:

$H = 16$

Codebook:

Level-1: 600×16

Others: 1000×16

Sequence Encoder/Decoder:

Inputs: 12 continues time slot, with 5 minutes interval

Outputs: 6 continues time slot

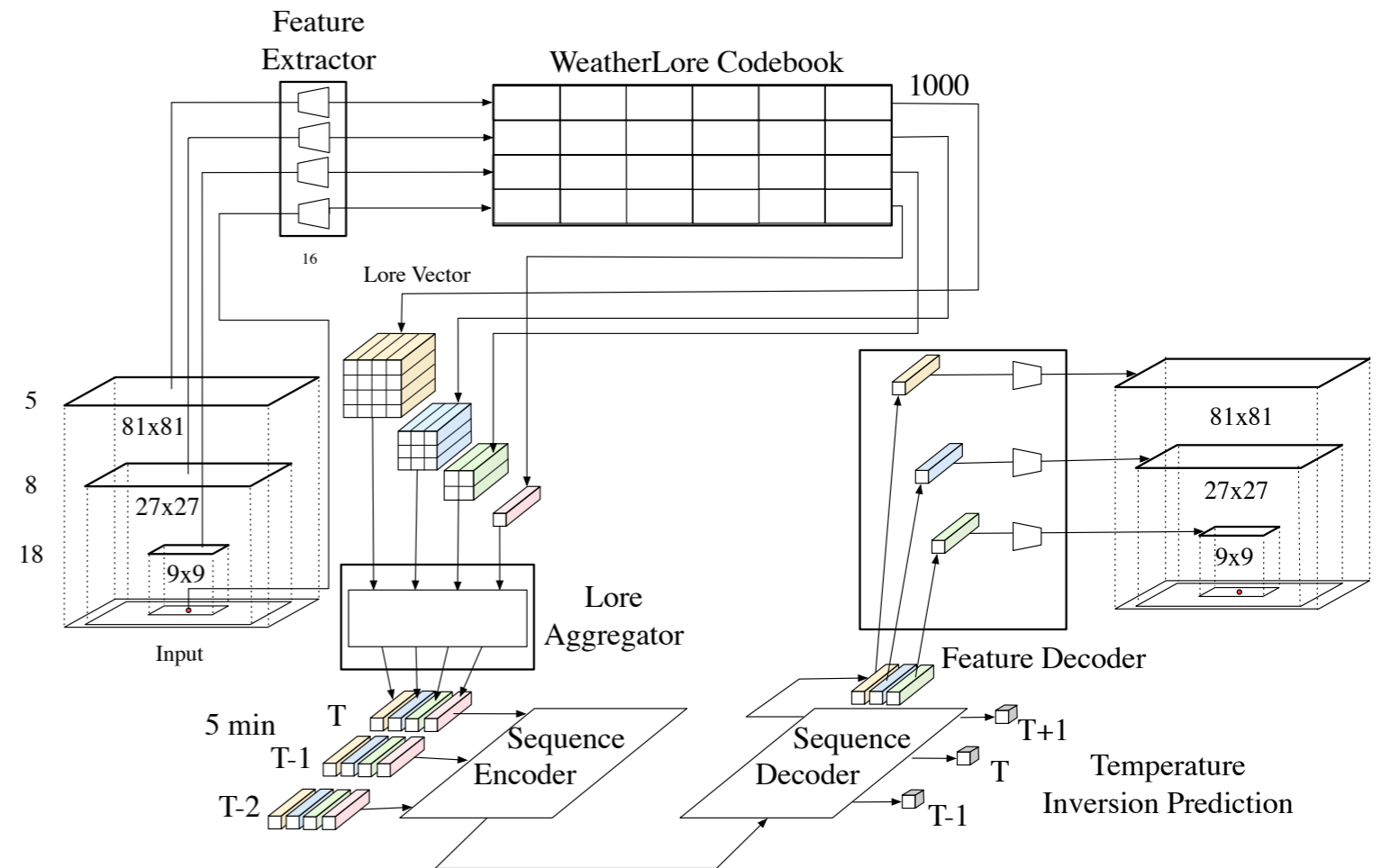
Hidden state size: 64

Feature Decoder:

Class:2

Outputs:

Size: 1×6



Experiments

- Temperature inversion forecasting results for 5 stations in four quarters

Accuracy Rates	JFM				AMJ				JAS				OND			
	5	15	30	60	5	15	30	60	5	15	30	60	5	15	30	60
Elberta	88.5	86.3	82.9	76.1	92.4	91.2	90.8	87.8	93.4	91.0	88.7	83.5	86.6	82.2	81.7	75.6
Agricola	92.7	91.1	80.5	75.6	92.1	90.0	85.5	81.4	93.2	87.6	81.1	73.4	86.5	84.8	81.5	77.3
Mobiledr	83.0	82.1	77.6	73.1	90.6	87.2	85.5	80.5	92.7	90.8	84.4	76.8	85.7	83.6	78.8	72.0
Dixie	89.6	83.3	82.9	77.4	93.1	88.1	87.8	82.1	94.2	93.3	92.5	89.7	88.0	82.6	80.4	74.3
Foley	85.4	82.1	80.8	77.3	90.2	89.5	87.3	85.0	93.5	92.4	90.3	88.2	85.4	81.3	80.5	75.1

Experiments

- **Comparative results in terms of Acc (accuracy), Pre (precision), and Rec (recall) at Elberta station in four quarters**

Period	Quarter	JFM			AMJ			JAS			OND		
	Models	Acc	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec	Acc	Pre	Rec
5 min	SVM	77.0	68.1	71.3	69.6	69.8	71.6	68.5	77.6	69.7	71.4	72.5	74.8
	LSTM	79.8	71.4	77.9	70.5	72.4	65.5	68.4	69.3	75.5	72.7	71.7	70.8
	WeatherLore	88.5	90.3	90.1	92.4	91.5	92.7	93.4	90.7	90.4	86.6	87.4	85.1
1 hour	CNN	65.1	63.5	58.9	67.2	70.4	59.8	70.5	73.3	72.1	61.6	70.0	68.5
	CNN-LSTM	67.2	69.3	60.5	67.8	71.1	63.0	75.5	74.2	75.0	65.9	72.1	71.8
	U-Net	73.0	72.3	66.5	69.1	75.5	68.2	77.3	75.0	77.3	70.2	73.3	72.0
	WeatherLore	76.1	78.4	78.3	87.8	83.2	86.6	83.5	83.0	85.1	75.6	76.1	77.4

Experiments

- **Comparison between WeatherLore model and its variants for five Mesonet stations**

Metrics	Elberta			Agricola			Mobiledr			Dixie			Foley		
	Pre	Acc	Rec	Pre	Acc	Rec	Pre	Acc	Rec	Pre	Acc	Rec	Pre	Acc	Rec
Lore-Code	79.7	78.4	77.2	76.2	79.4	78.2	83.3	86.7	84.1	79.3	78.1	78.7	80.6	81.2	81.5
Lore-Data	76.5	73.0	75.4	77.1	78.0	75.2	72.7	73.4	75.6	73.4	72.0	73.2	71.5	73.3	72.0
Lore-2	88.5	90.3	89.7	90.8	89.1	84.6	82.7	88.4	82.7	87.9	89.6	87.5	84.6	88.3	85.7
WeatherLore	88.7	90.9	91.5	92.7	89.6	84.7	83.0	88.6	85.2	89.6	90.0	88.0	85.4	88.5	86.1

Conclusion

- **Create a dataset for studying the thermal inversion**
- **Propose the first thermal inversion forecasting model**
- **Evaluate the performance on a variety of Mesonet stations**