Non-uniform spatial downscaling of climate variables

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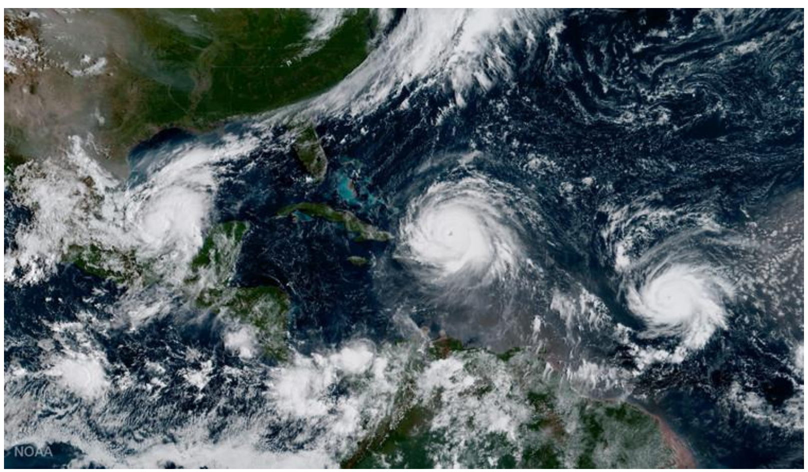
Outline

1. **Climate downscaling**
2. Recent work on statistical downscaling
3. Motivation and proposed downscaling framework
4. Model development
5. Experiment and results
6. Conclusion

From global climate models to local impact

> Evacuating millions is not an 'effective or sustainable' response to hurricane threats.

CNBC, September 2017



From left to right: Katia, Irma and Jose hurricanes

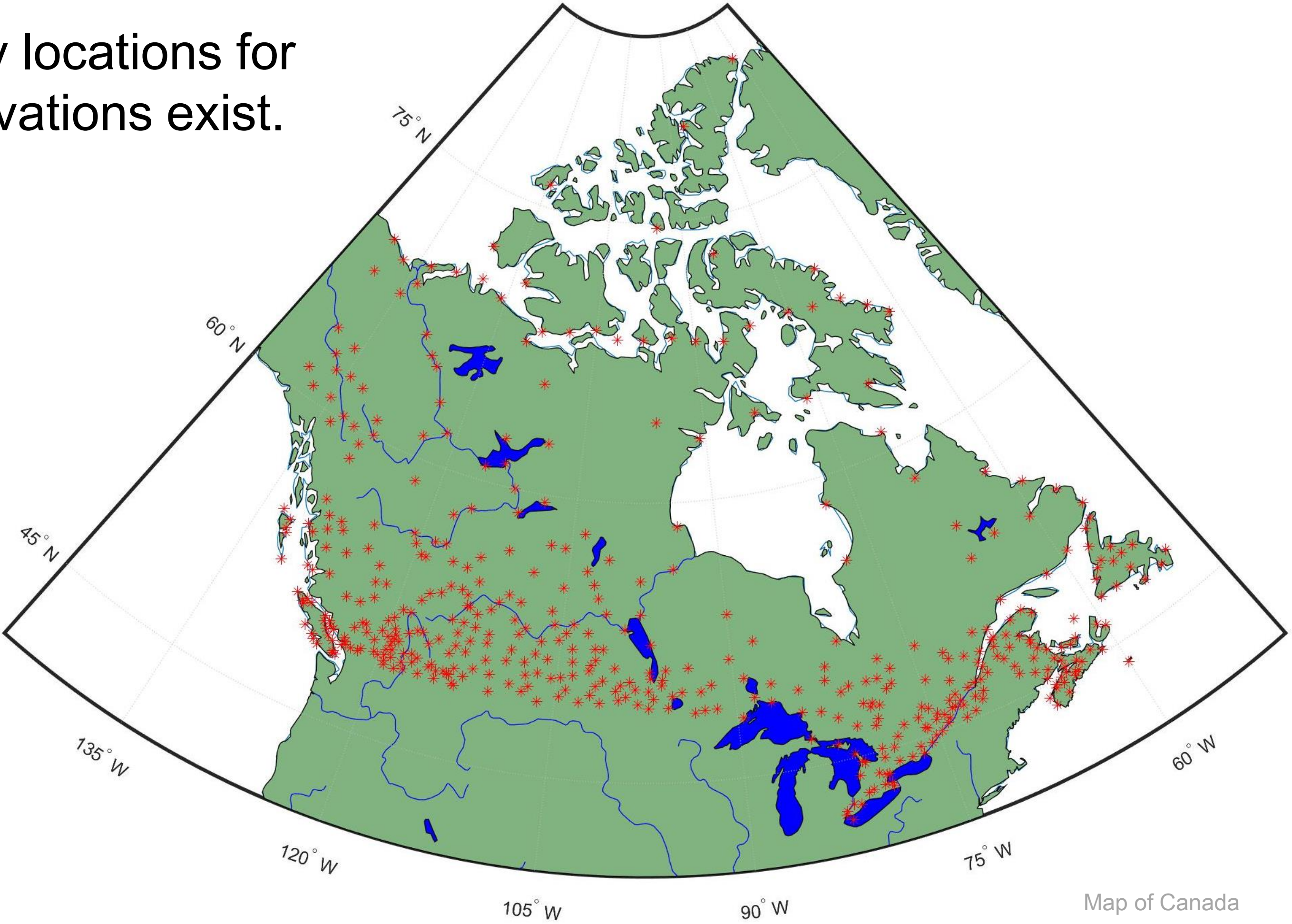
NOAA, 2017

September 2017: Hurricane IRMA, Dominican Republic

Reuters, 2017

A challenge for regional climate studies

There are many locations for which no observations exist.

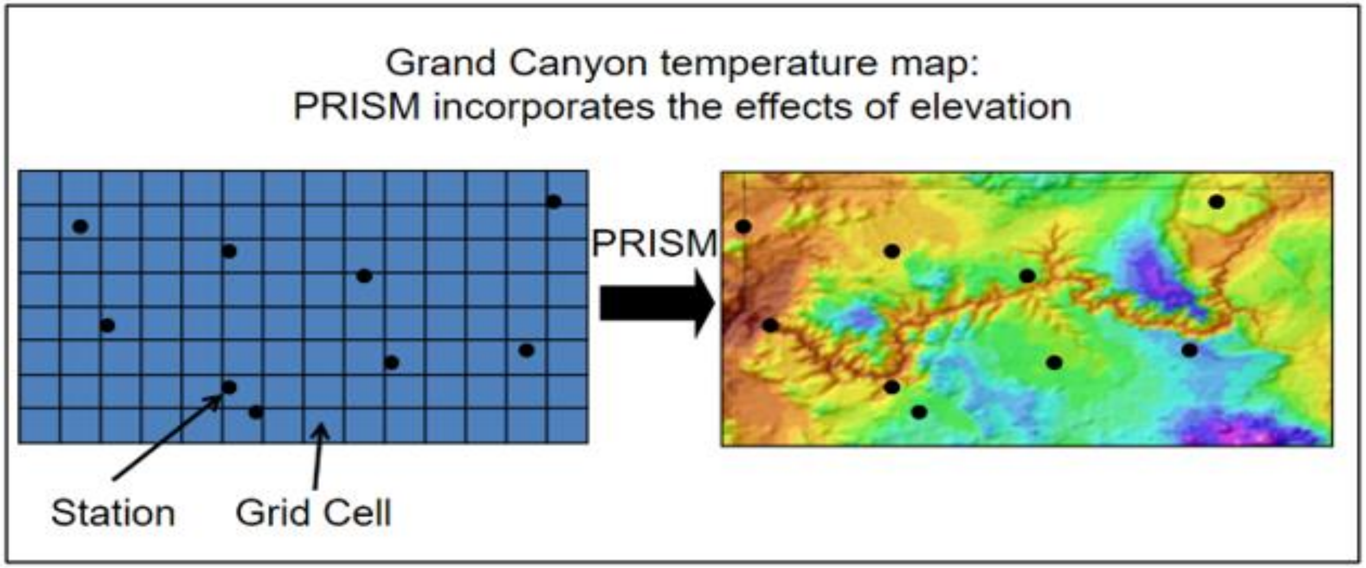


Map of Canada

Gridded products
A replacement for pure observational data

Some existing gridded products:

- CaPA
- NRCan
- PRISM…



Credit: Daly, 2016

Gridded products
From GCMs…

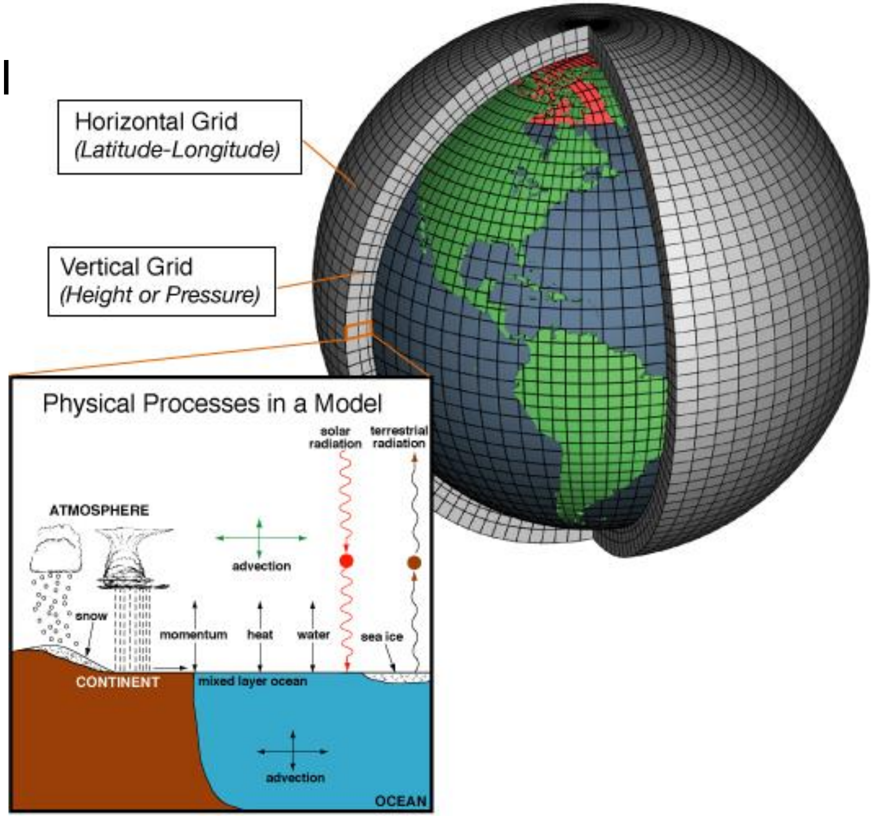
- General circulation model (GCM):

A system of interacting mathematical model

- Not data-driven.
- Based on scientific first principles
  - Meteorology
  - Geophysics
  - Oceanography…

- Discretization into grid boxes.

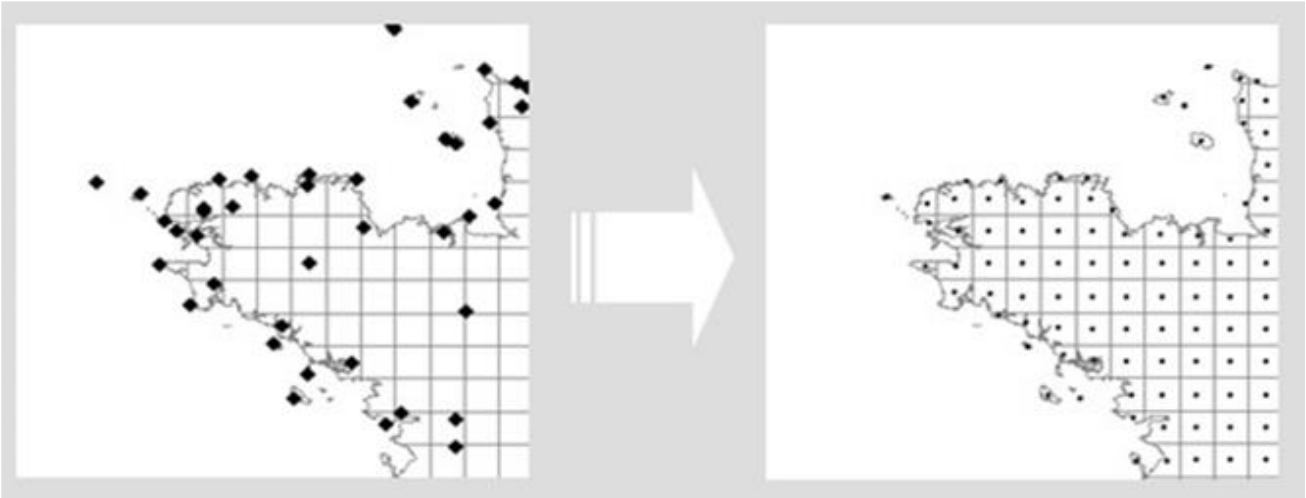
Output: Projections + Reanalysis



Credit: A. Banerjee, C. Monteleoni, 2014

Gridded products
… To reanalysis datasets

GCMs are also used to obtain the gridded reanalysis products as a replacement for pure observational data.



Credit: EUJRC, 2017

Climate downscaling

Two major approaches:

- Dynamical downscaling
  - ➔ physically consistent
  - ➔ computationally expensive
  - ➔ not fine-grained enough
- **Statistical downscaling**
  - ➔ relatively inexpensive
  - ➔ challenging if insufficient historical data

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Recent work on CNNs for downscaling

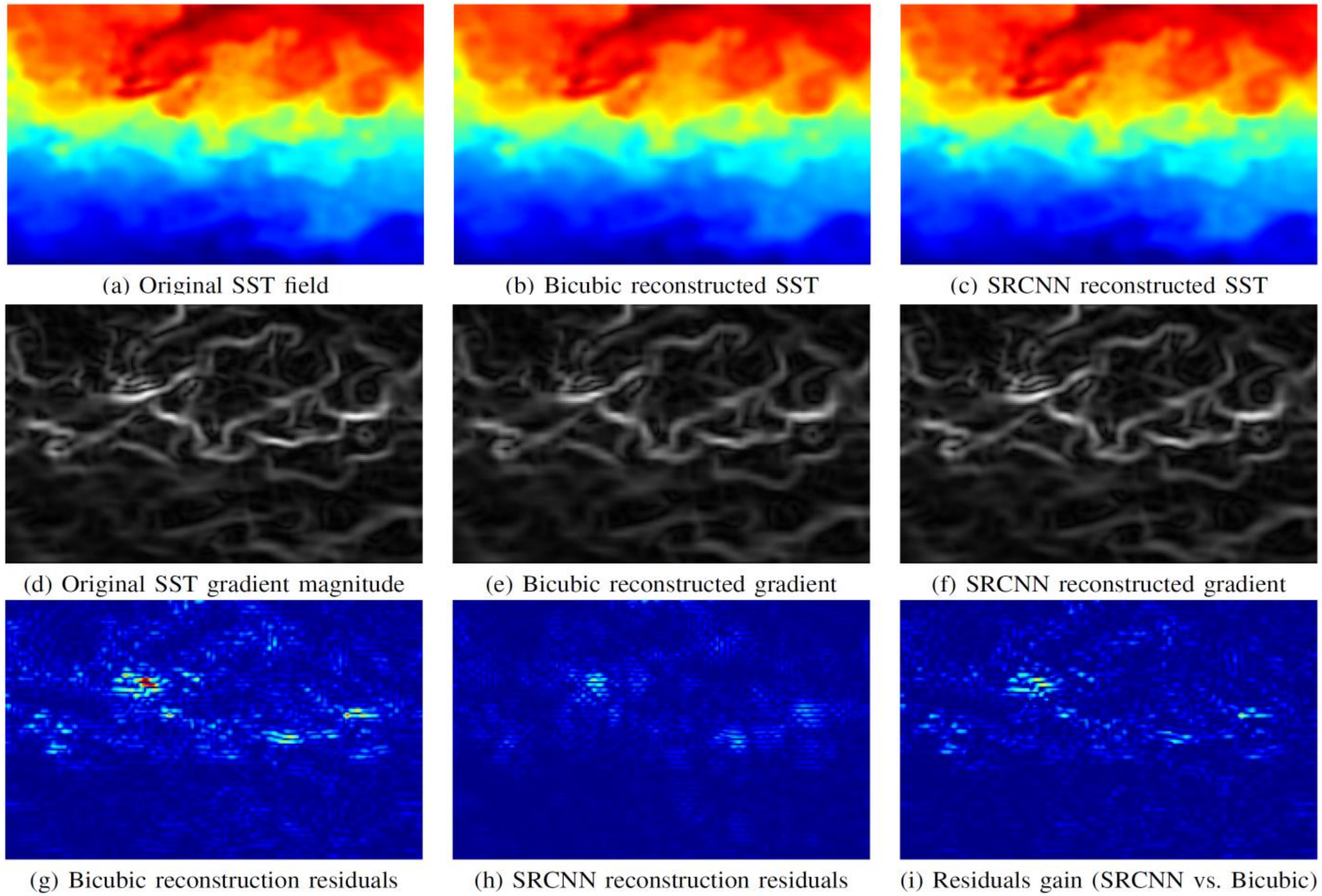

Fig. 4. Top row: Original and reconstructed SST fields. Middle row: Original and reconstructed gradient magnitudes. Bottom row: residuals between original and reconstructed SST fields (g and h), and residuals difference between bicubic and SRCNN reconstructed SST fields (i).

(Ducournau and Fablet, 2016)

Recent work on CNNs for downscaling

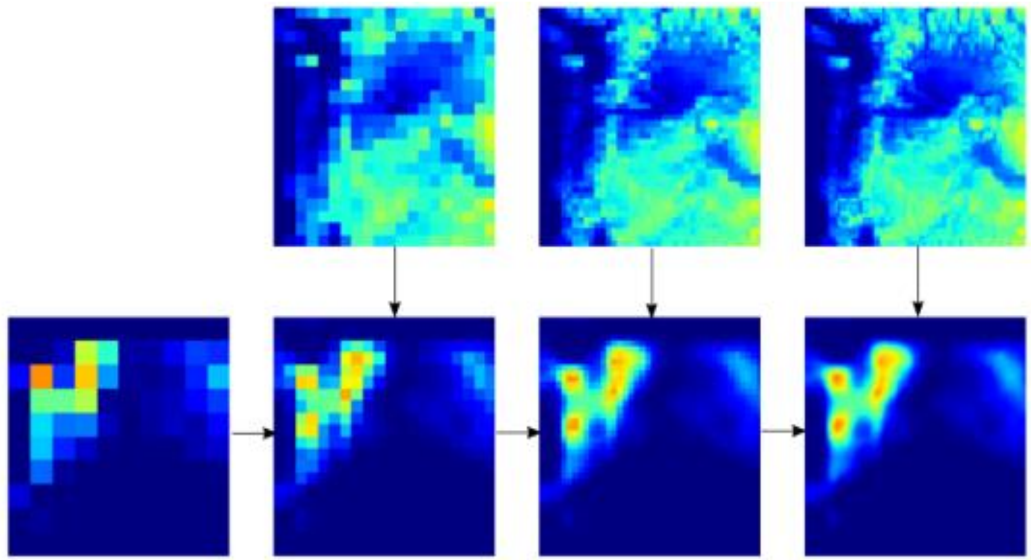

Figure 3: Layer by layer resolution enhancement from DeepSD using stacked SRCNNs. Top Row: Elevation, Bottow Row: Precipitation. Columns: 1.0°, 1/2°, 1/4° and 1/8° spatial resolutions.

(Vandal et al, 2017)

Recent work on CNNs for downscaling

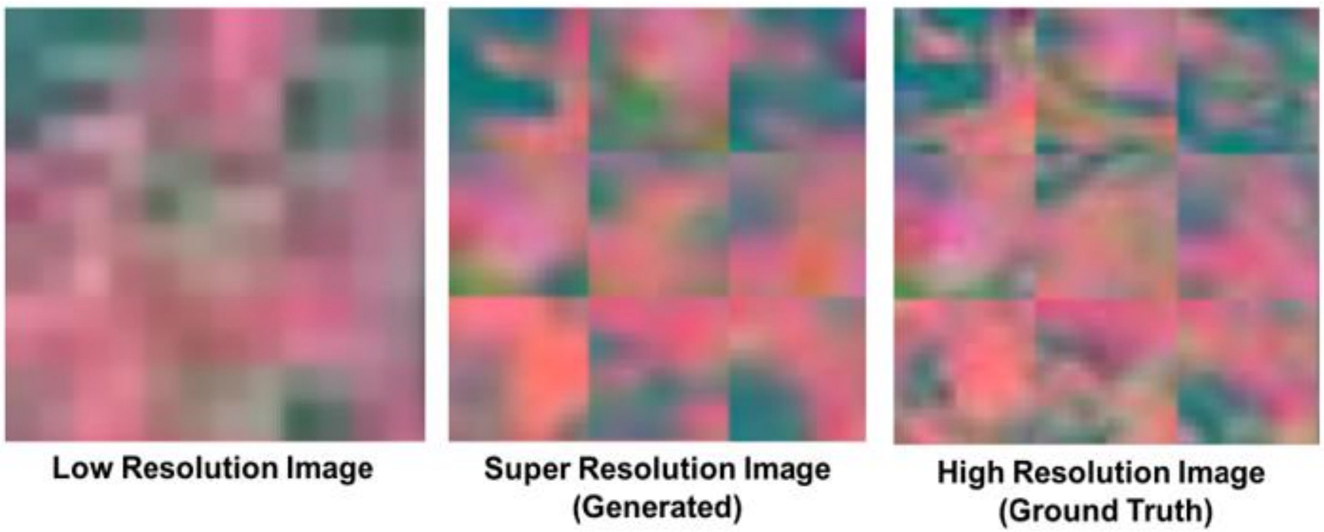

Figure 7. Generated climate image samples from pixel recursive super resolution model. Red represents cloud fraction(clt), Green represents eastward near-surface wind(uas), Blue represents northward near-surface wind(vas). Cyclone center is distinguished as dark cyan cluster on right-side ground truth image. (Left : Low resolution input. Center : Generated climate image output. Right : Ground Truth input.)

(Kim et al, 2017)

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Proposed downscaling framework

Objective:

Statistical downscaling method that learns from gridded reanalysis data and local station data.

Used for: **Task 1** : downscaling to locations *with* observational record,

Task 2: downscaling to locations *without* observational record;

Inputs Reanalysis datasets

Target Weather stations observational records

Models MLR, ANN, ELM, LSTM

Proposed downscaling framework

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Target Weather stations observational records

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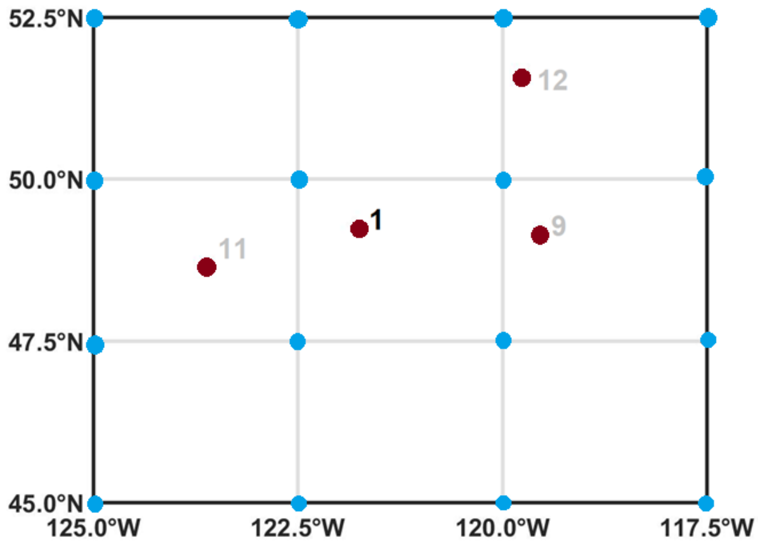

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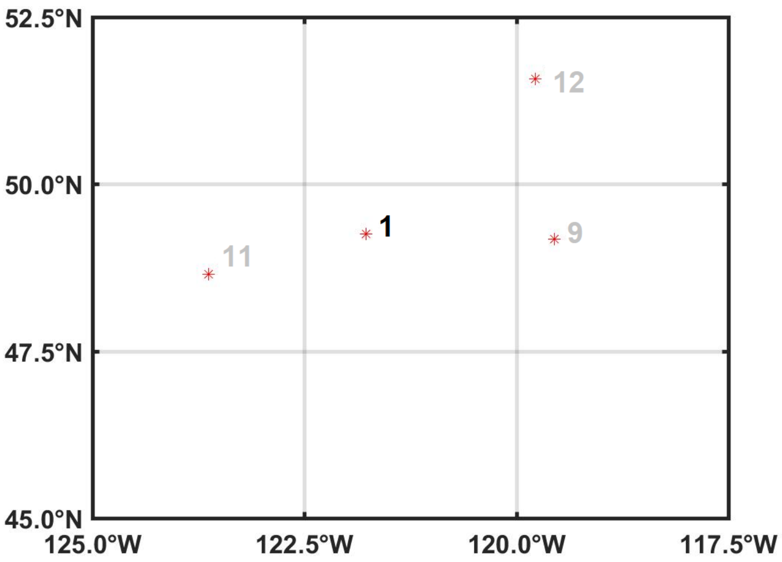
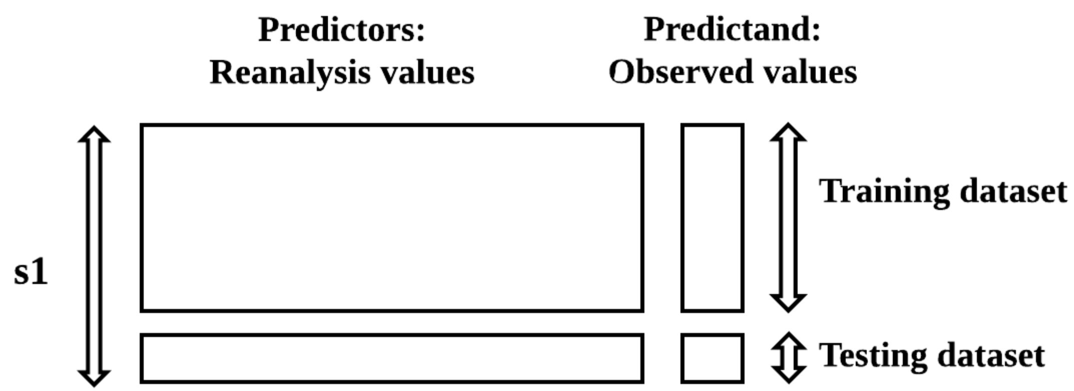
Model development

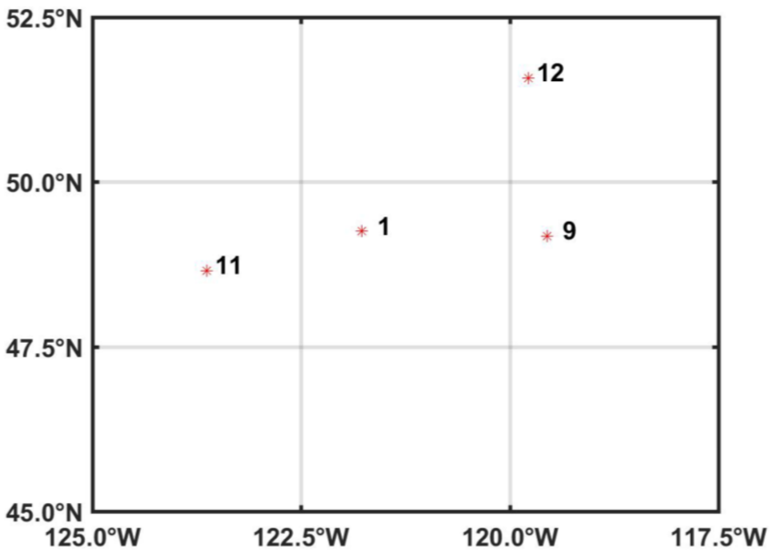
Task 1: Downscaling to locations with observational record

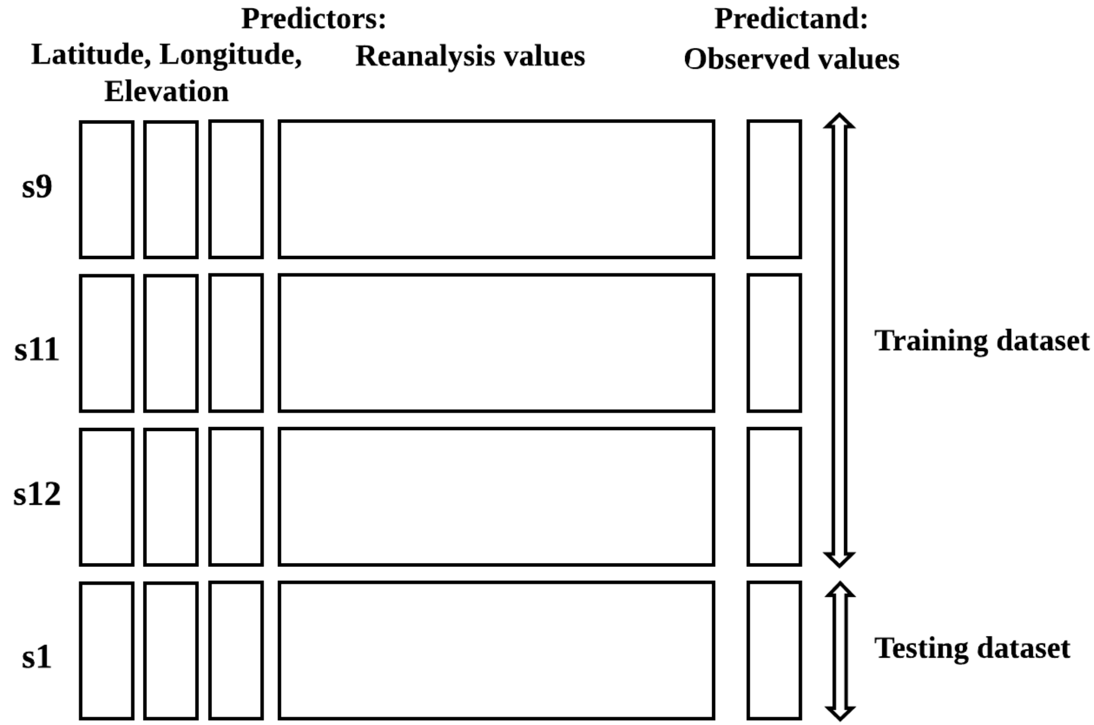




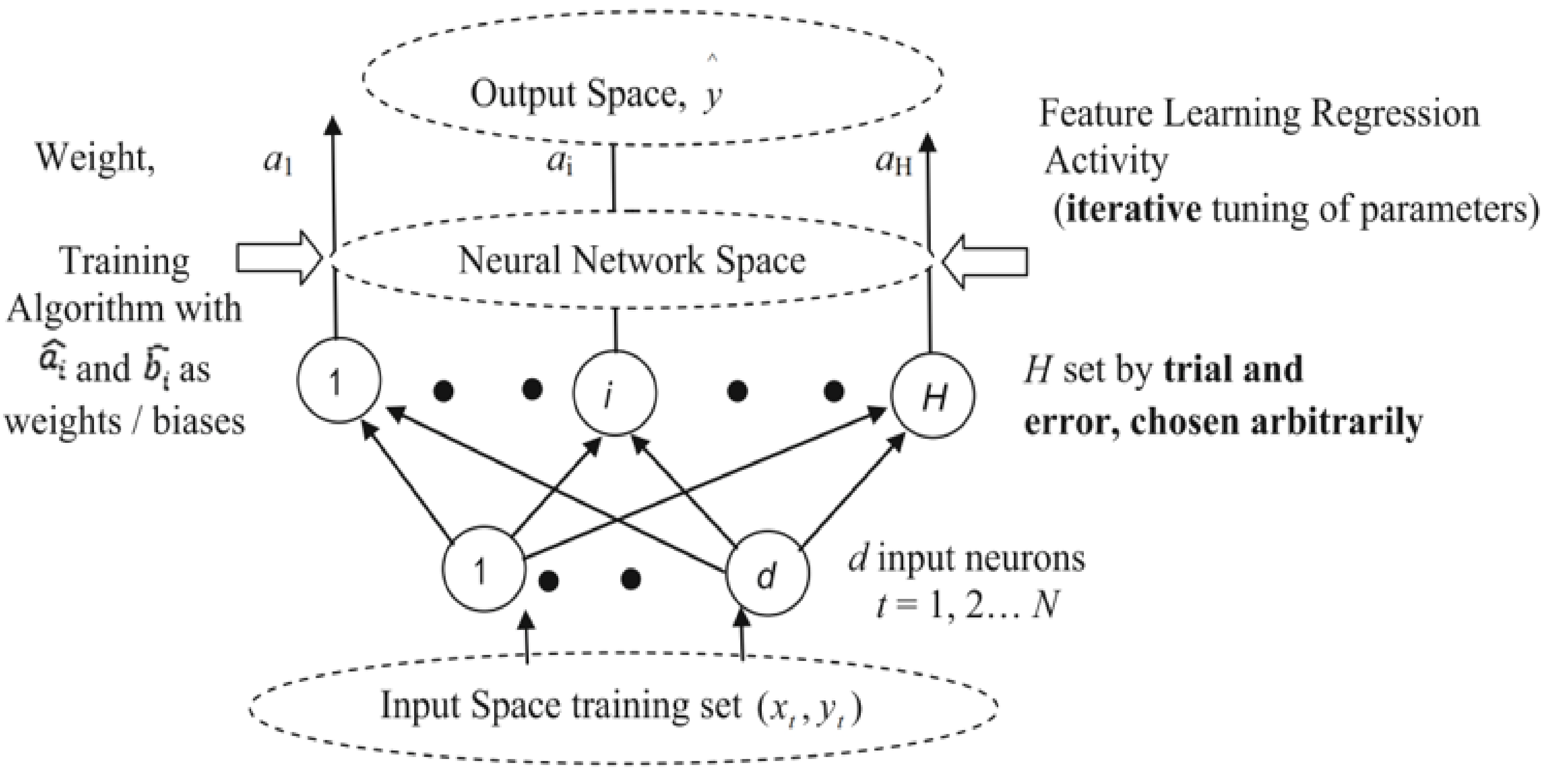
Model development

Task 2: Downscaling to locations without observational record



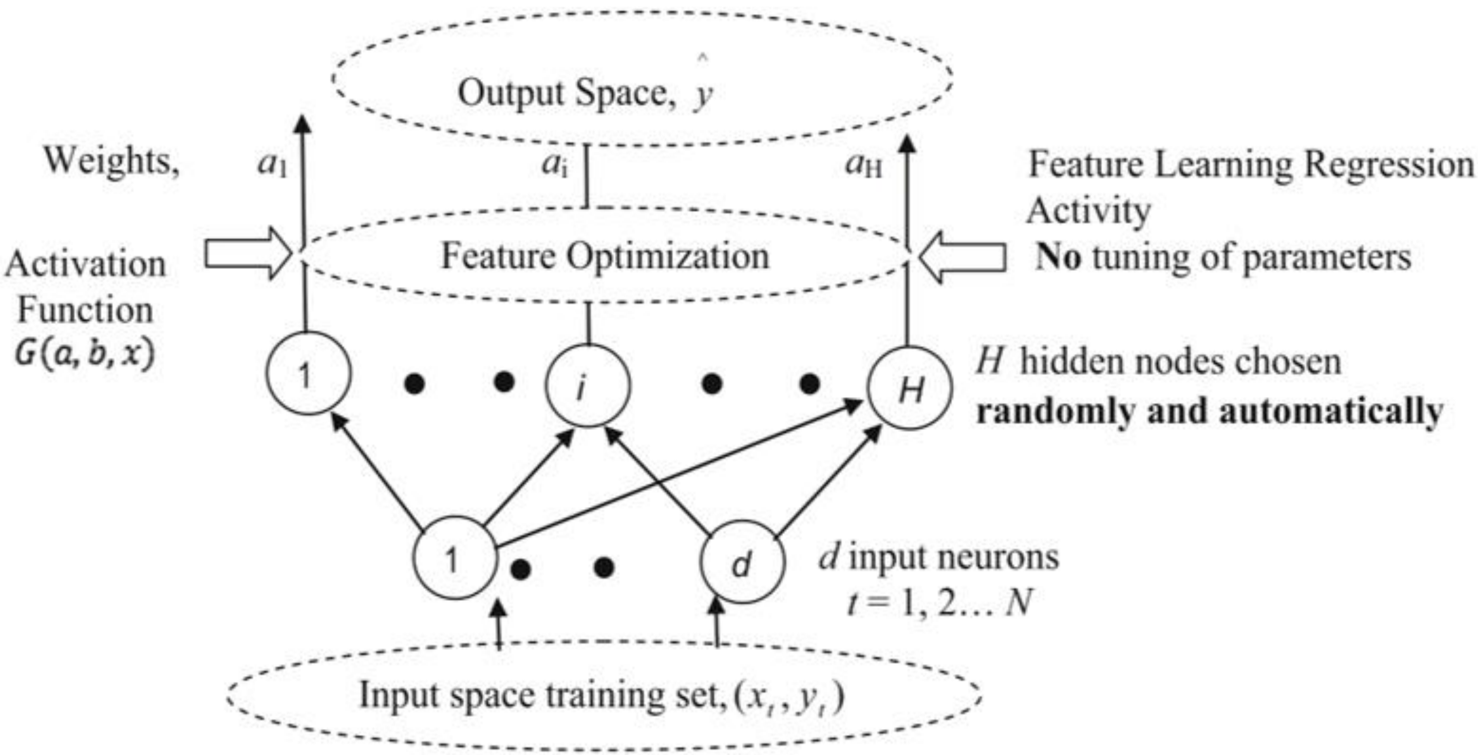


Learning model 1/3
Artificial Neural Network



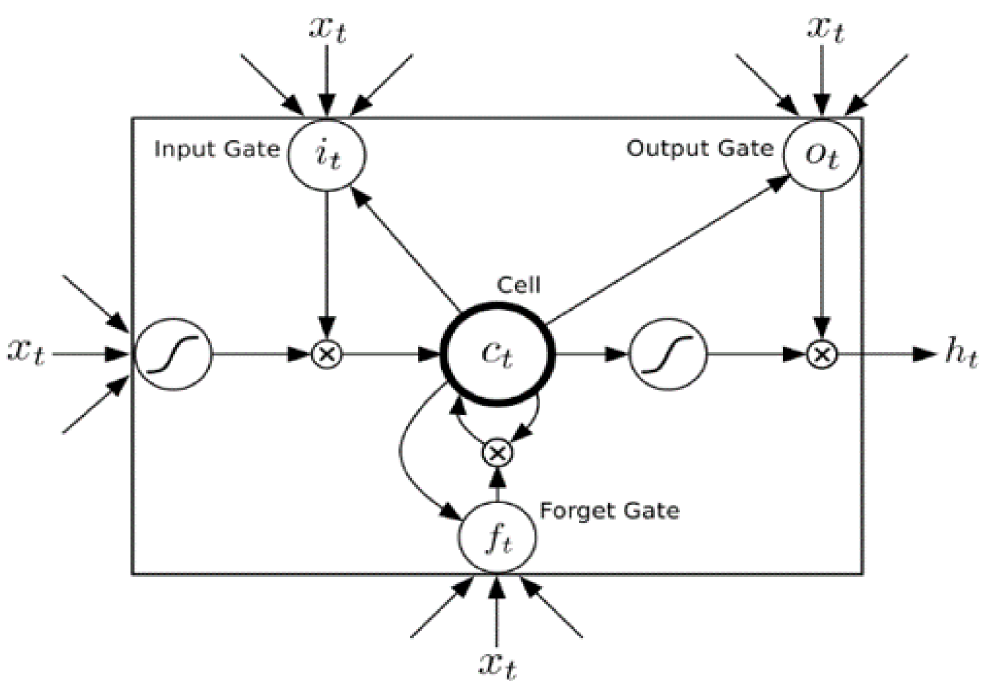
(Deo et al., 2017)

Learning model 2/3
Extreme Learning Machine



(Deo et al, 2017)

Learning model 3/3
Long Short-Term Memory



(Graves, 2015)

Input gate: scales input to cell (write)
Output gate: scales output from cell (read)
Forget gate: scales old cell value (reset)

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Experiment

Climate variables: daily air temperature

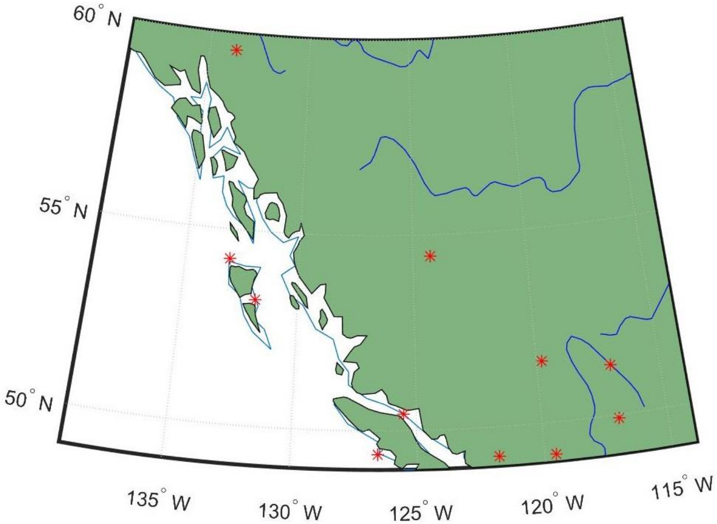
Study area: British Columbia, Canada

Data:

- Local observations (OBS): Environment and Climate Change Canada Network
- Global models (GCM): NCEP/NCAR reanalysis dataset

Learning algorithms:

MLR, ANN, ELM, LSTM.



British Columbia, Canada

Results

Task 1: Downscaling to locations with observational record

Station	Task 1				
	Method	Model structure	$RMSE$	R^2	$R^2\%$ inc.
1	ANN	(16-32-1)	1.92	0.91	2%
2	ANN	(16-25-1)	2.59	0.94	1%
3	LSTM	(16-20-1),lb=6	1.30	0.94	11%
4	ANN	(16-27-1)	1.03	0.94	3%
5	ANN	(16-33-1)	**4.00**	**0.84**	**3**%
6	LSTM	(16-20-1),lb=6	2.13	0.96	4%
7	ANN	(16-29-1)	1.30	0.92	2%
8	ANN	(16-19-1)	**0.85**	**0.96**	**1**%
9	LSTM	(16-20-1),lb=6	2.18	0.95	3%
10	LSTM	(16-20-1),lb=6	1.98	0.95	4%
11	ANN	(16-25-1)	1.34	0.95	1%
12	LSTM	(16-20-1),lb=6	2.28	0.94	5%

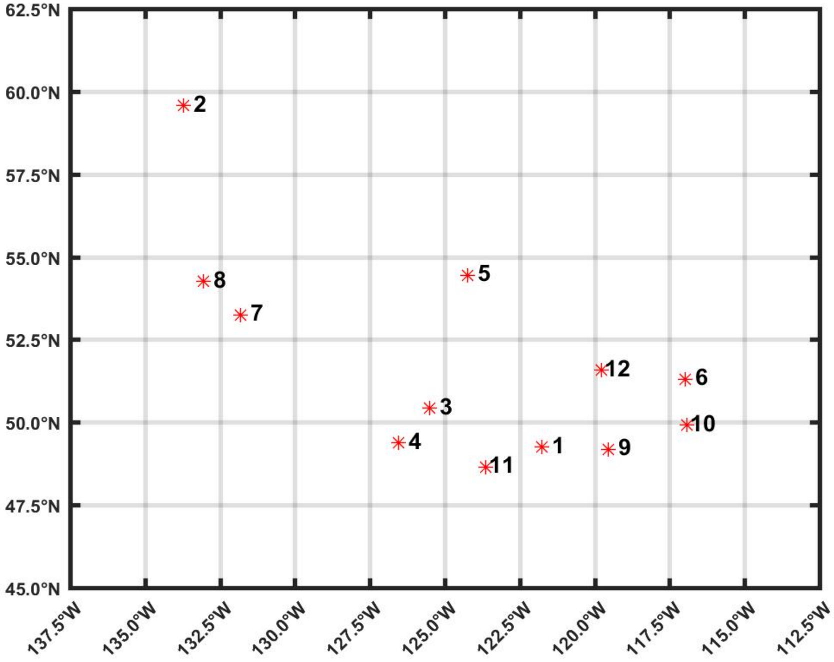
Results

Task 2: Downscaling to locations without observational record

Station	Task 2				
	Method	Model structure	$RMSE$	R^2	R^2% inc.
1	ANN	(19-35-1)	1.83	0.92	18%
2	ANN	(19-35-1)	2.68	0.93	15%
3	LSTM	(19-20-1),lb=6	1.48	0.92	39%
4	ANN	(19-39-1)	1.10	0.92	3%
5	LSTM	(19-20-1),lb=6	**3.26**	**0.90**	**5**%
6	LSTM	(19-20-1),lb=6	2.33	0.95	45%
7	ANN	(19-27-1)	1.40	0.91	6%
8	ANN	(19-19-1)	**0.90**	**0.95**	**13**%
9	LSTM	(19-20-1),lb=6	2.30	0.94	59%
10	LSTM	(19-20-1),lb=6	1.93	0.95	5%
11	ANN	(19-28-1)	1.38	0.95	8%
12	LSTM	(19-20-1),lb=6	2.40	0.94	8%

Results: Highest and lowest accuracy

Daily temperature		
	Task 1	Task 2
	Highest accuracy	
Station	**s8**	**s8**
Model	ANN	ANN
Model Structure	(16-19-1)	(19-19-1)
$RMSE$	0.85	0.90
R^2	**0.96**	**0.95**
R^2% inc.	1%	13%
	Lowest accuracy	
Station	**s5**	**s5**
Model	ANN	LSTM
Model Structure	(16-33-1)	(19-20-1, lb=6)
$RMSE$	4.00	3.26
R^2	**0.84**	**0.90**
R^2% inc.	3%	5%



British Columbia, Canada

Results: Highest and lowest accuracy

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	Highest accuracy	
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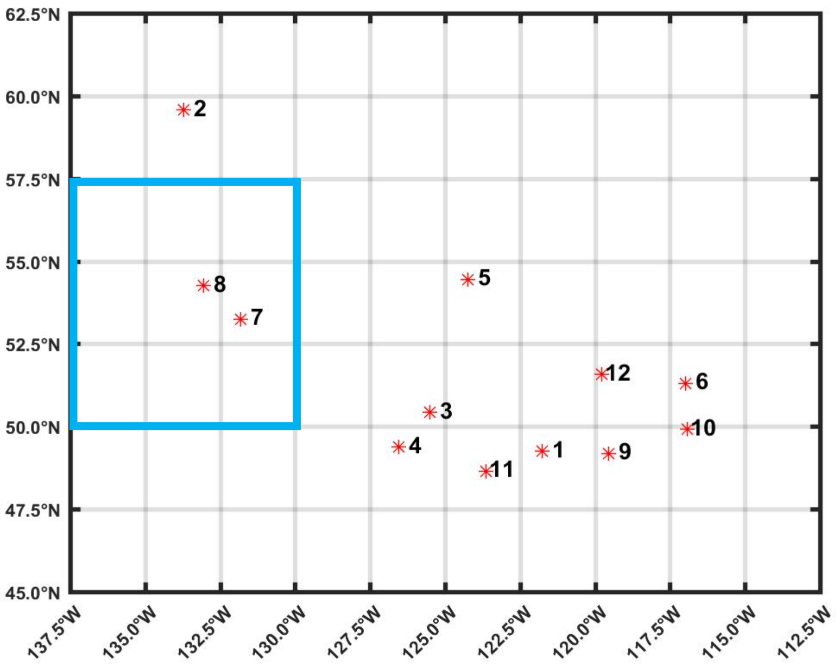
Model Structure	(16-19-1)	(19-19-1)
$RMSE$	0.85	0.90
R^2	**0.96**	**0.95**
R^2% inc.	1%	13%
	Lowest accuracy	
Station	**s5**	**s5**
Model	ANN	LSTM
Model Structure	(16-33-1)	(19-20-1, lb=6)
$RMSE$	4.00	3.26
R^2	**0.84**	**0.90**
R^2% inc.	3%	5%



British Columbia, Canada

Results: Highest and lowest accuracy

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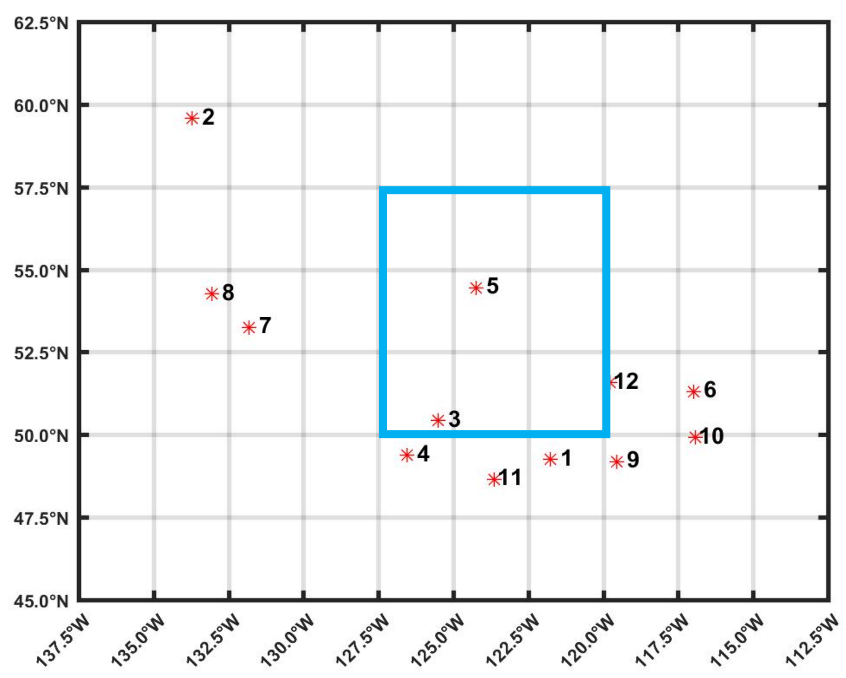


British Columbia, Canada

Additional results
Downscaling precipitations

Target	Observational records from ECCC dataset: • Monthly precipitations
Input features	Reanalysis dataset from NCEP/NCAR reanalysis: • temperature + precip • cloud forcing net longwave flux • upward solar radiation fluxes • downward solar radiation fluxes • u-wind • v-wind • relative humidity • Sea level pressure
Study area	12 stations across British Columbia, Canada
Learning algorithms	ANN

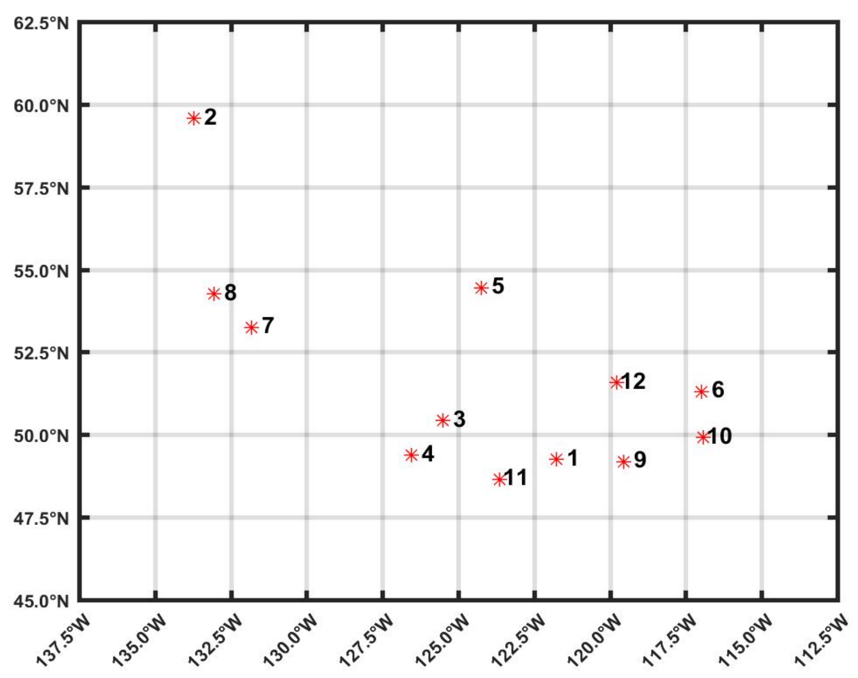
Additional results

Downscaling precipitations

Station	Monthly precipitations					
	ANN	**Task 1**		**ANN**	**Task 2**	
	Model structure	$RMSE$	R^2	Model structure	$RMSE$	R^2
s1	(144-17-1)	0.576	0.860	(147-17-1)	1.051	0.888
s2	(144-07-1)	1.299	0.827	(147-07-1)	0.456	0.581
s3	(144-17-1)	0.538	0.749	(147-17-1)	1.427	0.877
s4	(144-17-1)	0.199	0.856	(147-17-1)	**1.664**	**0.916**
s5	(144-17-1)	**0.673**	**0.616**	(147-17-1)	0.594	0.490
s6	(144-07-1)	0.625	0.619	(147-07-1)	0.397	0.752
s7	(144-17-1)	**0.335**	**0.893**	(147-17-1)	0.972	0.831
s8	(144-17-1)	0.160	0.807	(147-17-1)	1.163	0.775
s9	(144-07-1)	0.647	0.624	(147-07-1)	**0.497**	**0.390**
s10	(144-07-1)	0.896	0.649	(147-07-1)	0.651	0.701
s11	(144-07-1)	0.299	0.888	(147-07-1)	1.046	0.869
s12	(144-07-1)	0.750	0.829	(144-07-1)	0.489	0.637

Additional results
Downscaling precipitations

Monthly precipitations		
	Task 1	Task 2
	Highest accuracy	
Station	**s7**	**s4**
Model Structure	(144-17-1)	(147-17-1)
$RMSE$	0.335	1.664
R^2	**0.893**	**0.916**
	Lowest accuracy	
Station	**s5**	**s9**
Model Structure	(144-17-1)	(147-07-1)
$RMSE$	0.673	0.497
R^2	**0.616**	**0.390**



British Columbia, Canada

Additional results
Downscaling precipitations

Monthly precipitations		
	Task 1	Task 2
	Highest accuracy	
Station	**s7**	**s4**
Model Structure	(144-17-1)	(147-17-1)
$RMSE$	0.335	1.664
R^2	**0.893**	**0.916**
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Model Structure	(144-17-1)	(147-07-1)
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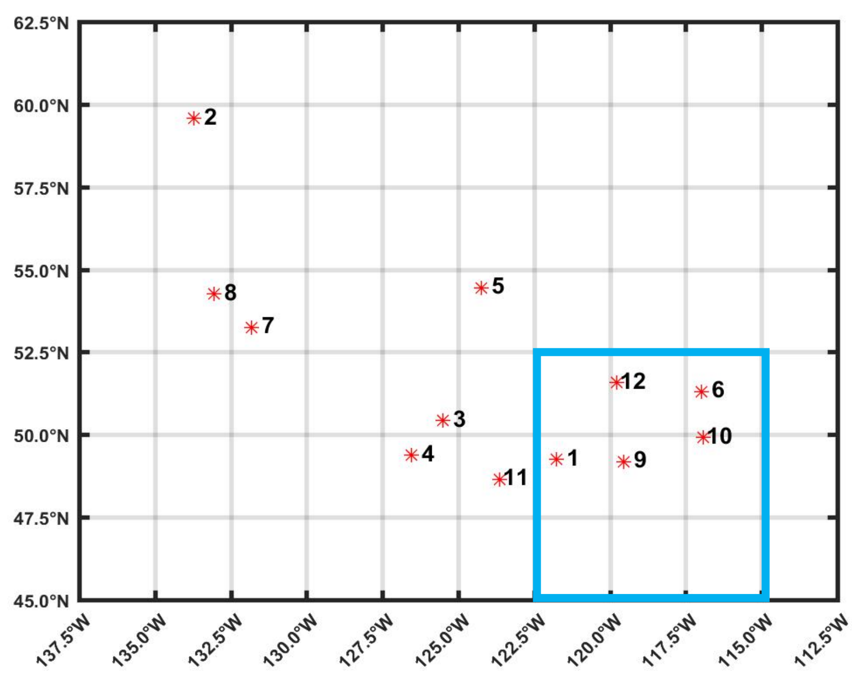

British Columbia, Canada

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Summary

New simple method for downscaling climate variables that learns from gridded reanalysis data and local station data.

- Learns non-linear relationships and seasonal dependencies on given grid nodes across time series
- Learns from non-uniform data fields
- Can be used for new locations where no historical observational data is available
- Can be applied to any region
- Can be used with different types of neural networks

Future work:

- Analysis of climate extremes and seasons analysis
- Conv-LSTM for radar data

Thanks!

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