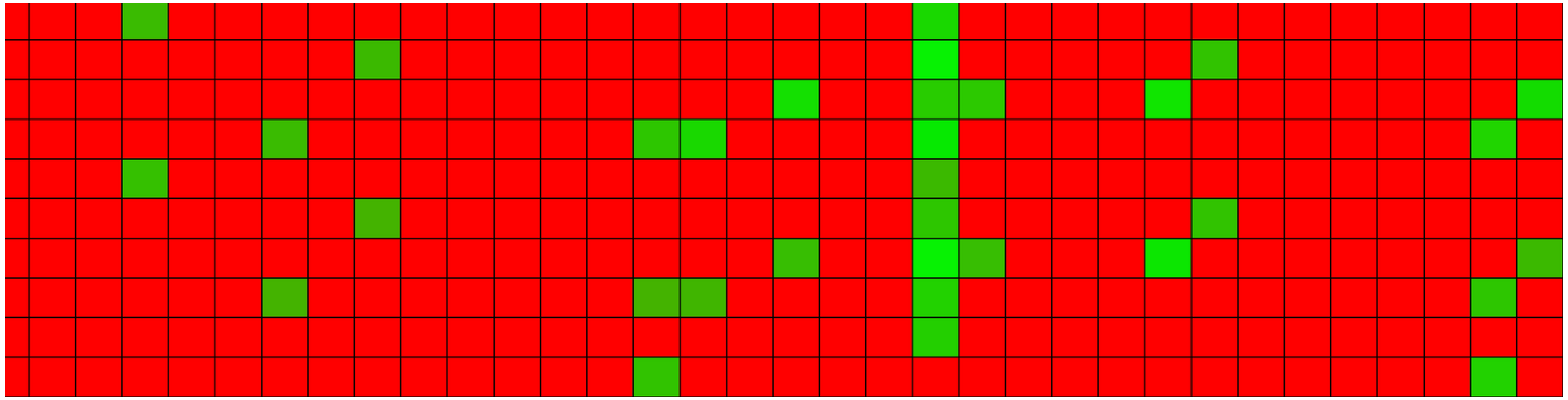
Improving sub-seasonal drought forecasting with machine learning and climate indices

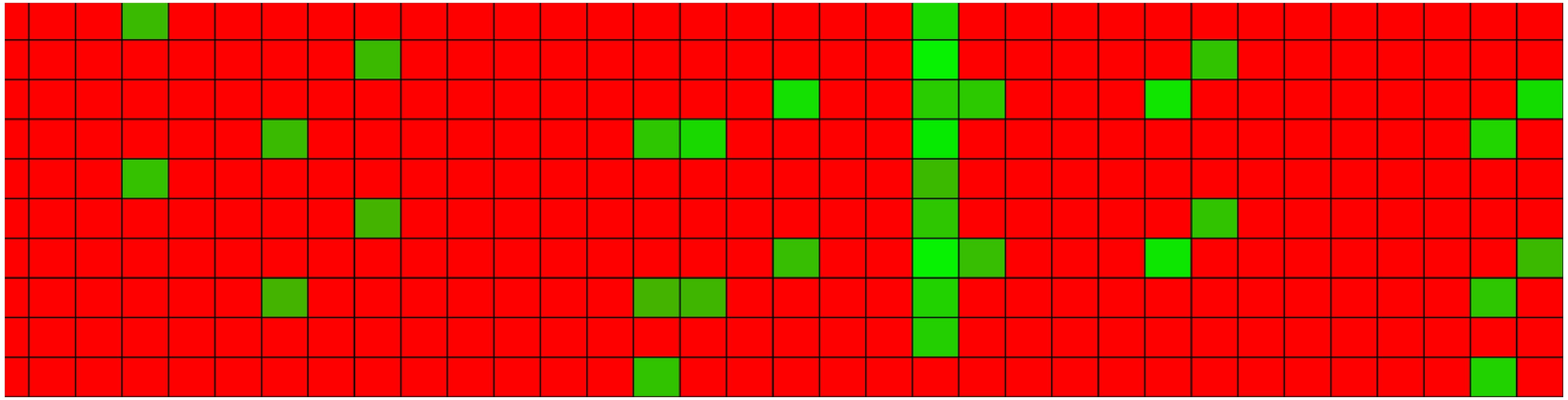
BOSSO FRANCESCO



IHE Delft, 08/12/2022

you can find the slides here!

BOSSO FRANCESCO



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Today's Agenda

this presentation will go through the following stages:

01

Intro

02

Context

03

Framework

04

Next steps

Intro

- 01 What is drought
- 02 ML for Drought
- 03 The gap

Intro

Meteorological Drought

a period of time in which a region experiences below-normal precipitation

Reduced soil moinsture,Reduced stream flow,Crop damage

Water shortage

The onset, extent and duration of drought are difficult to define

different stakeholders have varying degrees of tolerance and resilience to these events (Slette et al., 2019)

Being able to forecast them is crucial

Intro

exploitation of *statistic* and *dynamic techniques* for droughts forecasting has been and is widely studied

sub-seasonal forecasting

Earth observation data
Artificial Intelligence
Hardware (GPU,TPU)

→ AI-based prediction models

McGovern et al. (2017)

Learn from past data
Integrate physical understanding into the models
Discover additional knowledge from the data
Handle large amounts of input variables

Intro

Why to focus on sub-seasonal lead times?

Informative predictors

seasonal:
climate indices and large scale teleconnection patterns

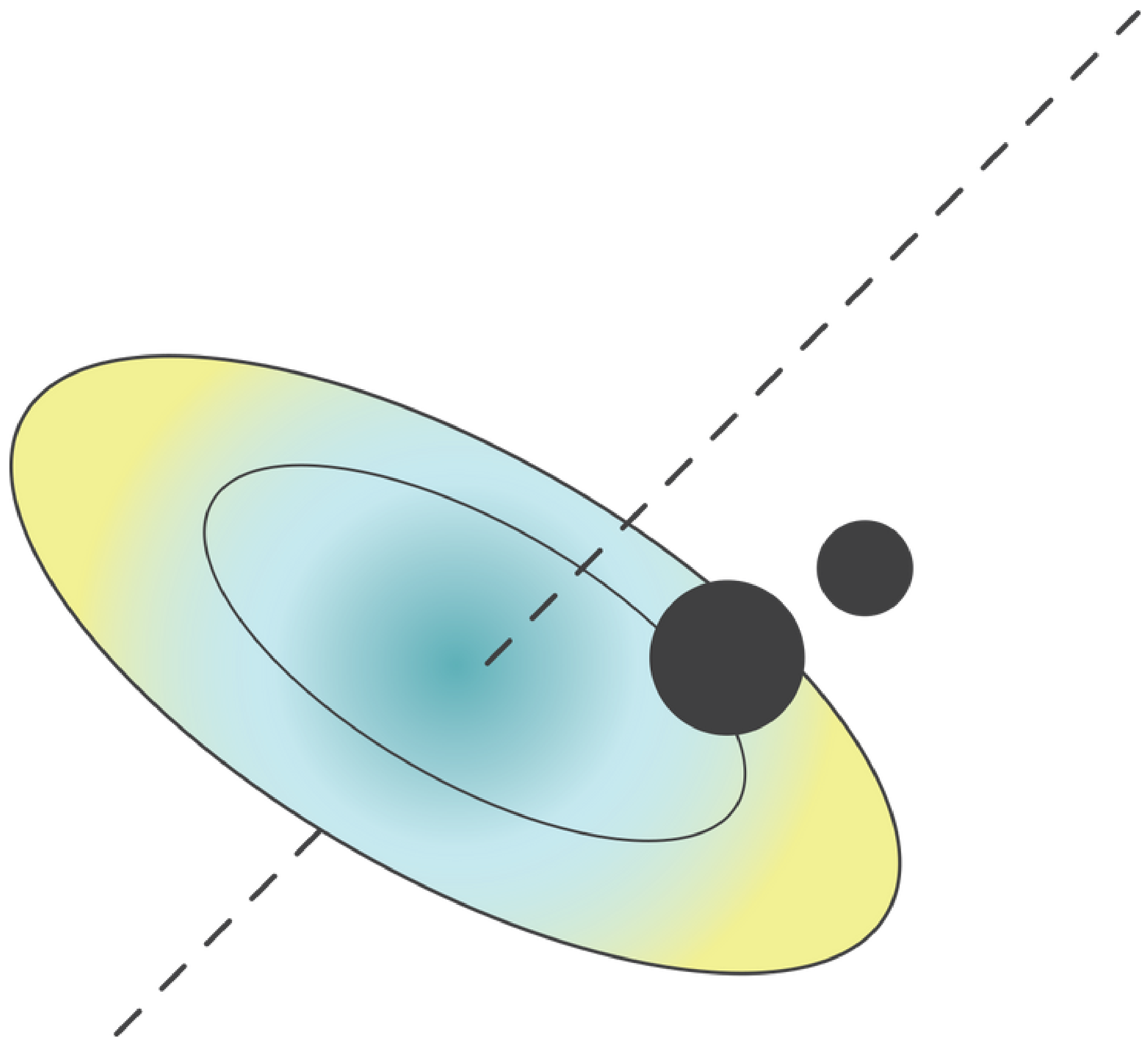
short-medium term:
local variable (precipitation, temperature)

sub-seasonal?

- short enough that the atmosphere still has memory of its initial conditions
- long enough to allow atmospheric circulation to affect the evolution of weather conditions

Context

- 01 What (our goal)
- 02 Where (study area)
- 03 How (the framework)



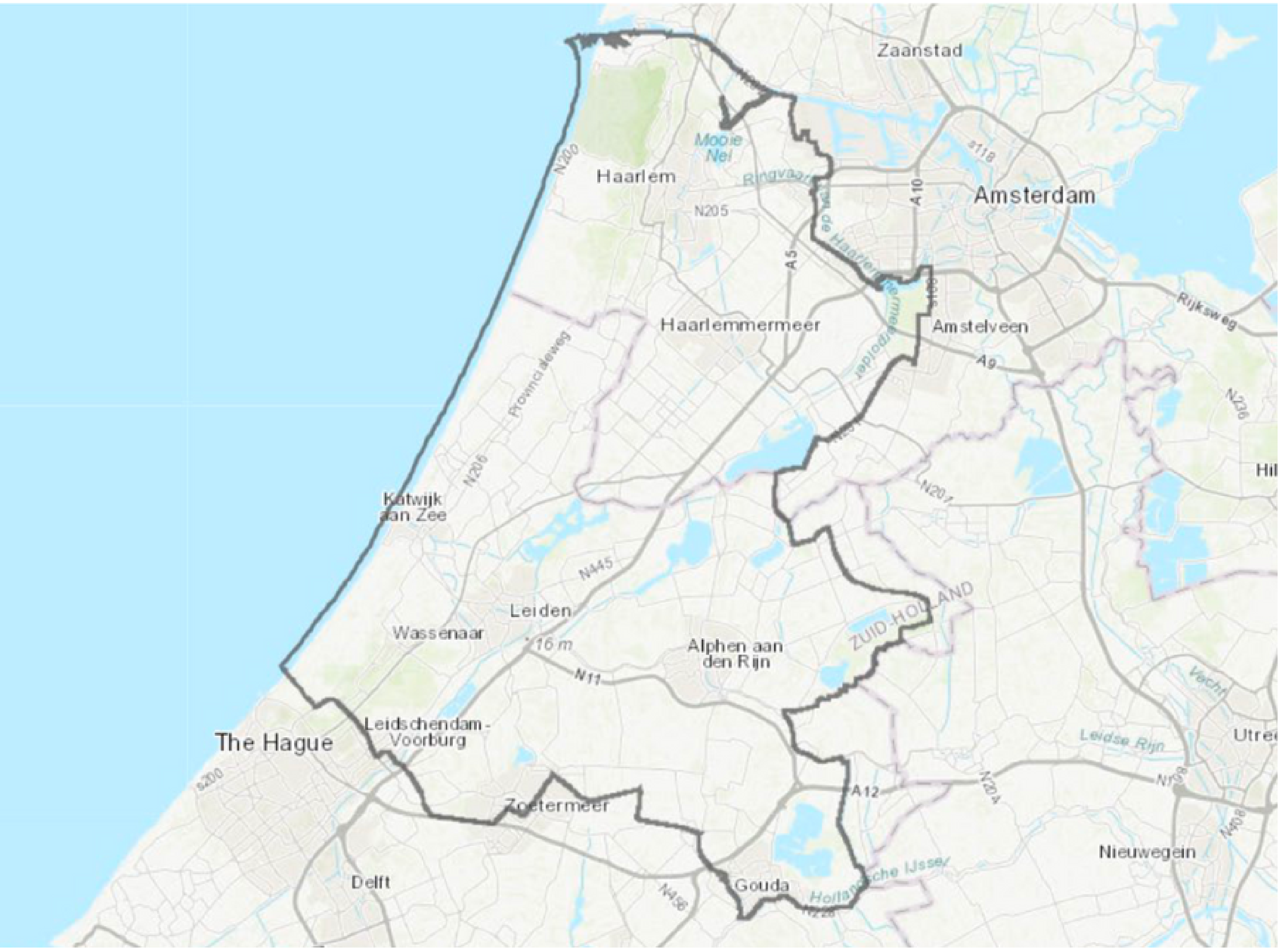
Context

- 01 What (our goal)
- 02 Where (study area)
- 03 How (the framework)

Machine Learning model for sub-seasonal precipitation forecasting

precipitation forecasting → SPI → drought forecating

Context



Rijnland

small sub-catchment of 1000 km2 at the very end of the Rhine delta in the Netherlands

water board of Rijnland is able to forecast drought at bi-weekly lead times. The goal is to extend it to a month

Context

Nino Index Phase Analysis (NIPA)

Zimmerman et al. (2016)

Giuliani et al. (2019)

Our readaptation

+

Neural Networks

Neural Network

Convolutional Neural Network

Extreme Learning Machine

Framework

- 01 NIPA
- 02 ELM

Framework

NIPA is a framework that searches for links between Global and Local variables exploiting the phases of teleconnection patterns materialized by climate indices

climate indices

El Niño Southern Oscillation (ENSO)

North Atlantic Oscillation (NAO)

SCAndinavian oscillation (SCA)

East Atlantic oscillation (EA)

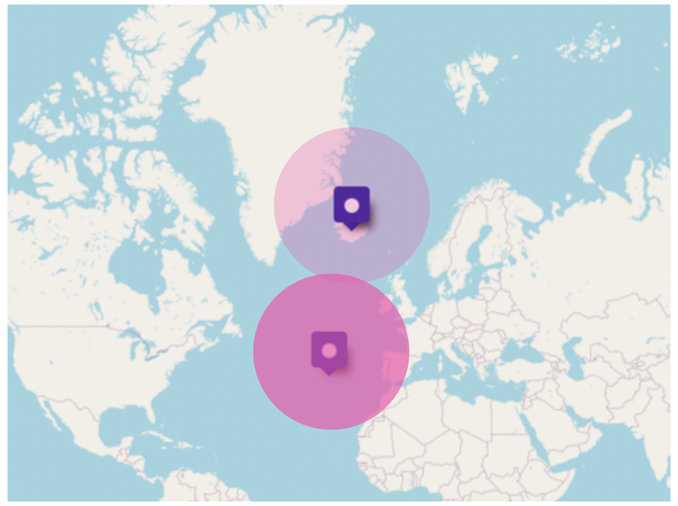
Framework

- 01 NIPA
- 02 ELM

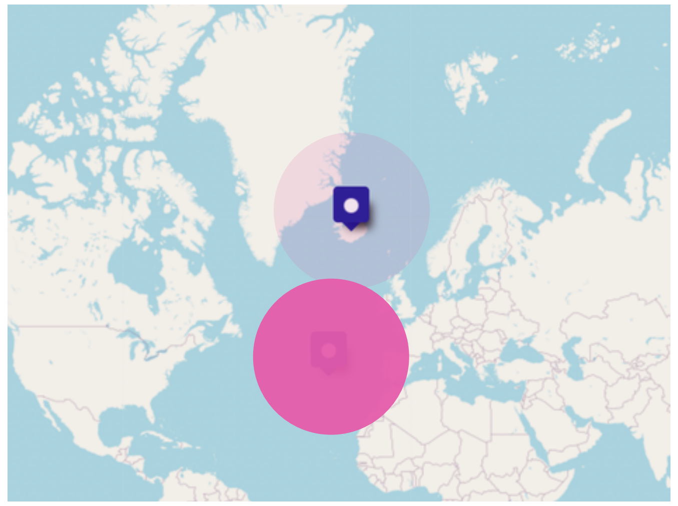
- above/below-normal temperatures in eastern United States and northern Europe
- above/below-normal temperatures in Greenland and southern Europe
- above/below-normal precipitation over northern Europe and Scandinavia
- above/below-normal precipitation over southern and central Europe

climate indices

North Atlantic Oscillation (NAO)



Phase Neg



Phase Pos

Framework

- 01 NIPA
- 02 ELM

Input
Data extraction
Phase segmentation
Correlation
PCA
output

DATA
- Local precipitation (monthly timeseries) - cumulative
- Global variable (monthly timeseries) - SLP,SST,Z500 - mean
- Climate Index (monthly timeseries) - ENSO, NAO,SCA,EA

SETTING PARAMETERS
- Month (of local precipitation)
- Aggregation level (of pre-month global data)

ERA5

Framework

SETTING PARAMETERS

- Month (of local precipitation)
- Aggregation level (of pre-month global data)

Example:

- Month 1
- Aggregation level 1

local precipitation of January and the global variable of December

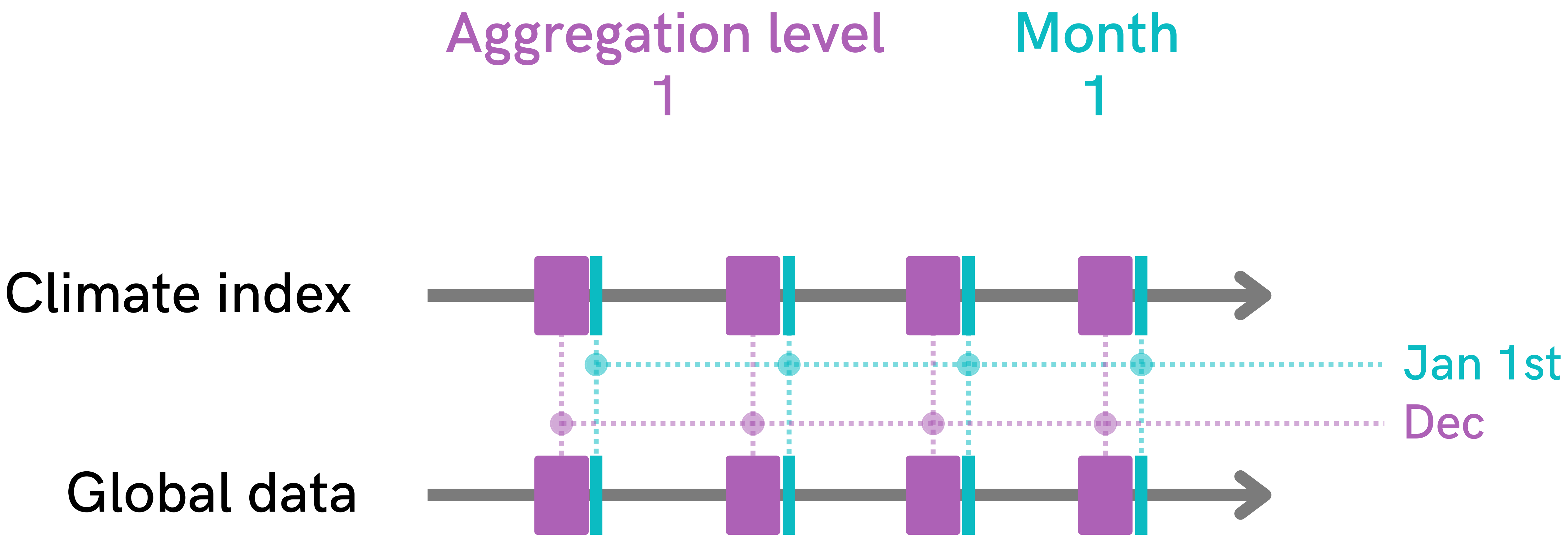
- Month 1
- Aggregation level 2

local precipitation of January and the global variable of November + December

Framework

- 01 NIPA
- 02 ELM

Input
Data extraction
Phase segmentation
Correlation
PCA
output



NOTE: this is an year-based operation. NIPA will extract the data for the December of each year

Framework

● 01 NIPA

● 02 ELM

Input

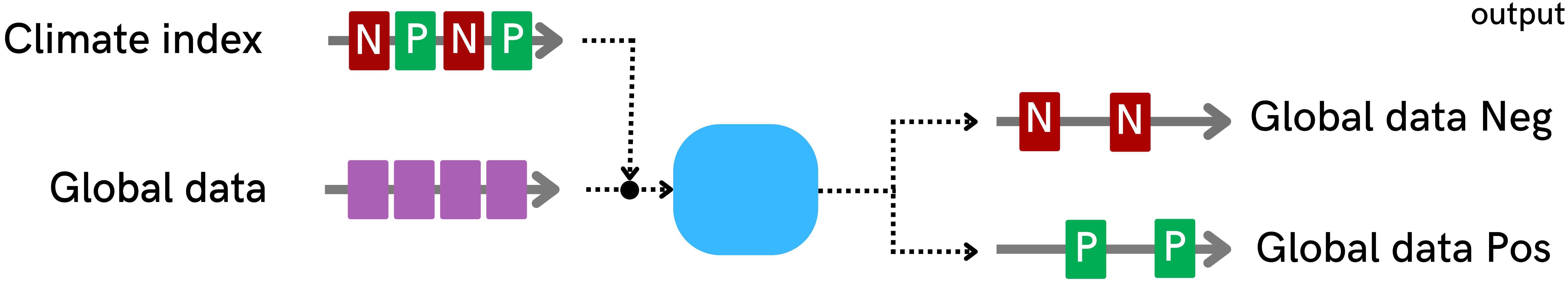
Data extraction

Phase segmentation

Correlation

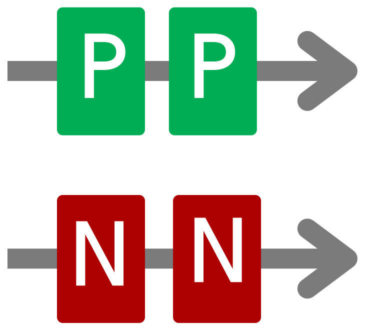
PCA

output

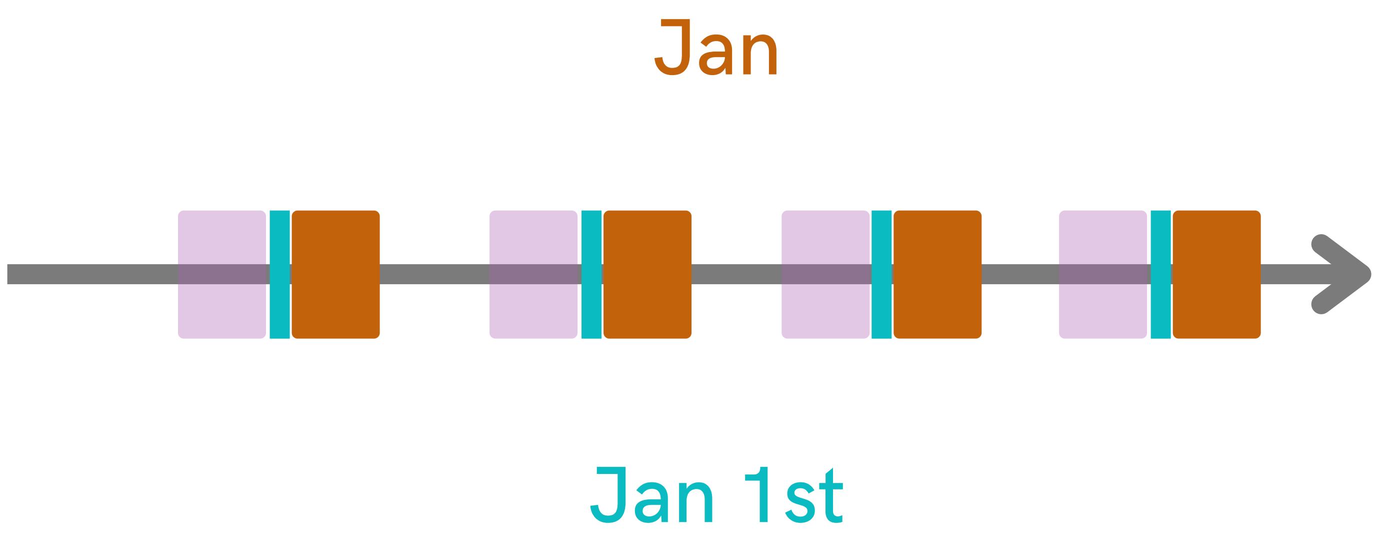


Framework

Global data Pos
Global data Neg



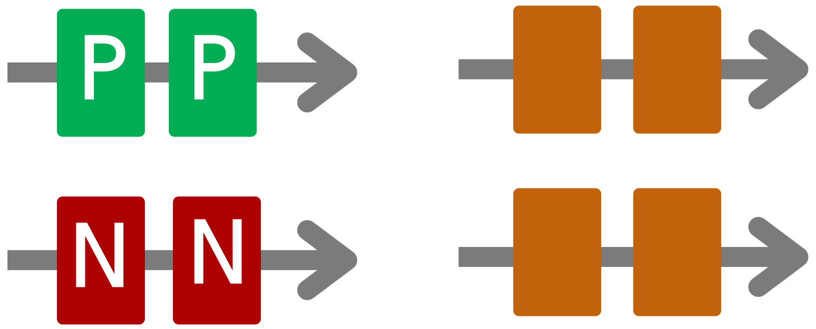
Local data



Framework

Global data Pos

Global data Neg



Local data Pos

Local data Neg

Framework

01 NIPA

02 ELM

Input

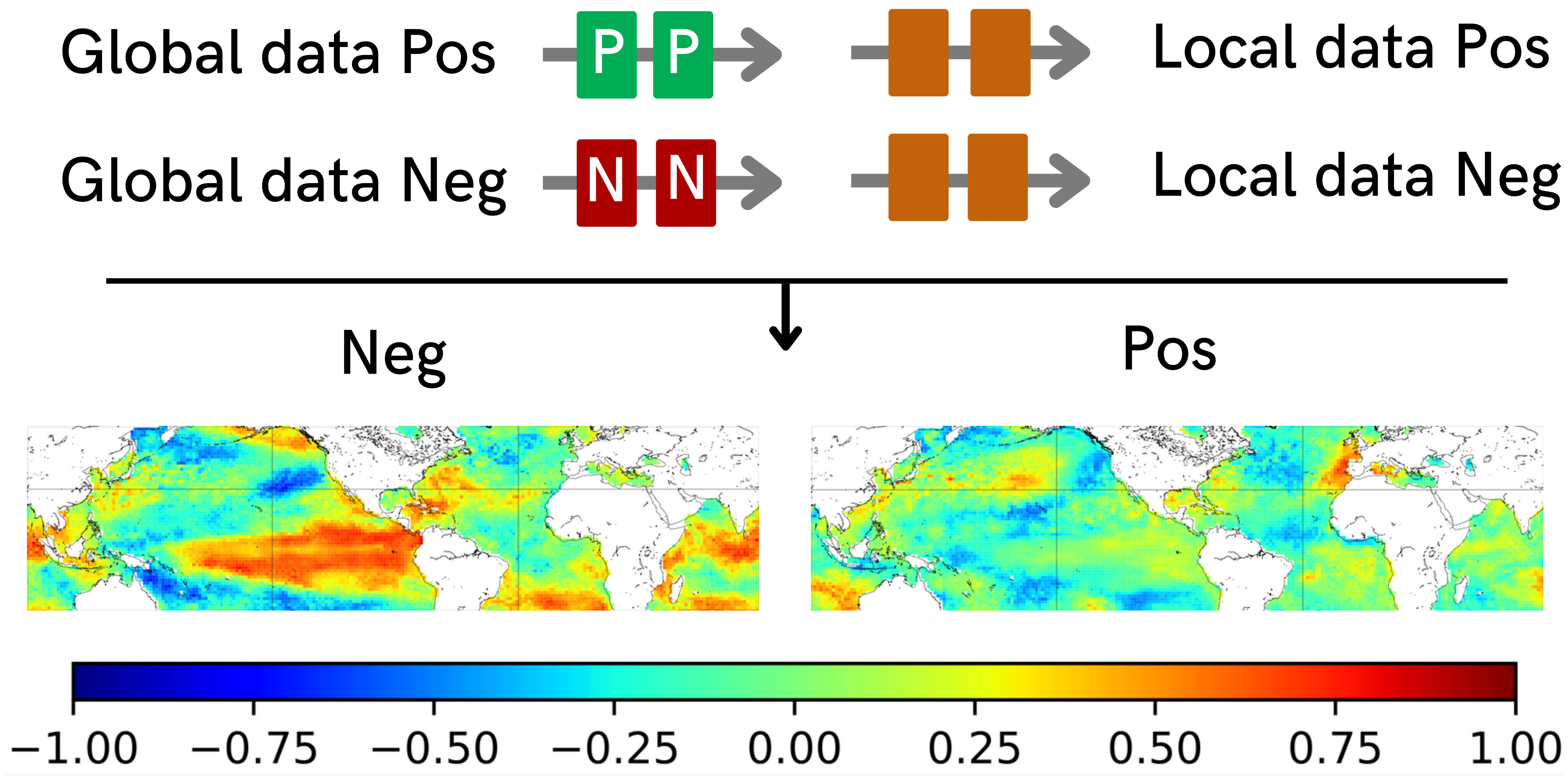
Data extraction

Phase segmentation

Correlation

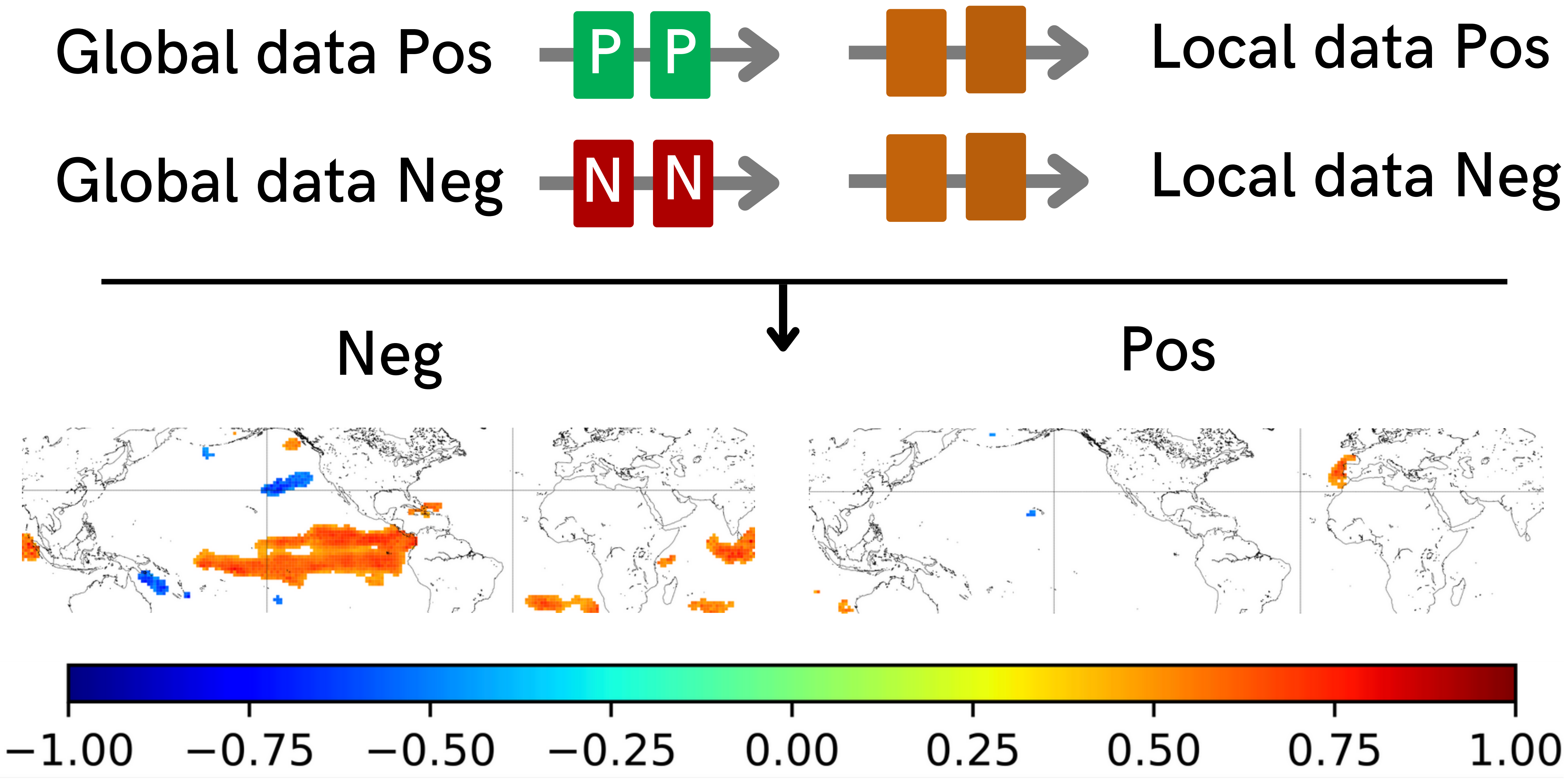
PCA

output



Correlation maps

Framework



Input

Data extraction

Phase segmentation

Correlation

PCA

output

95% of significance

+

minimum correlation threshold 0.6

+

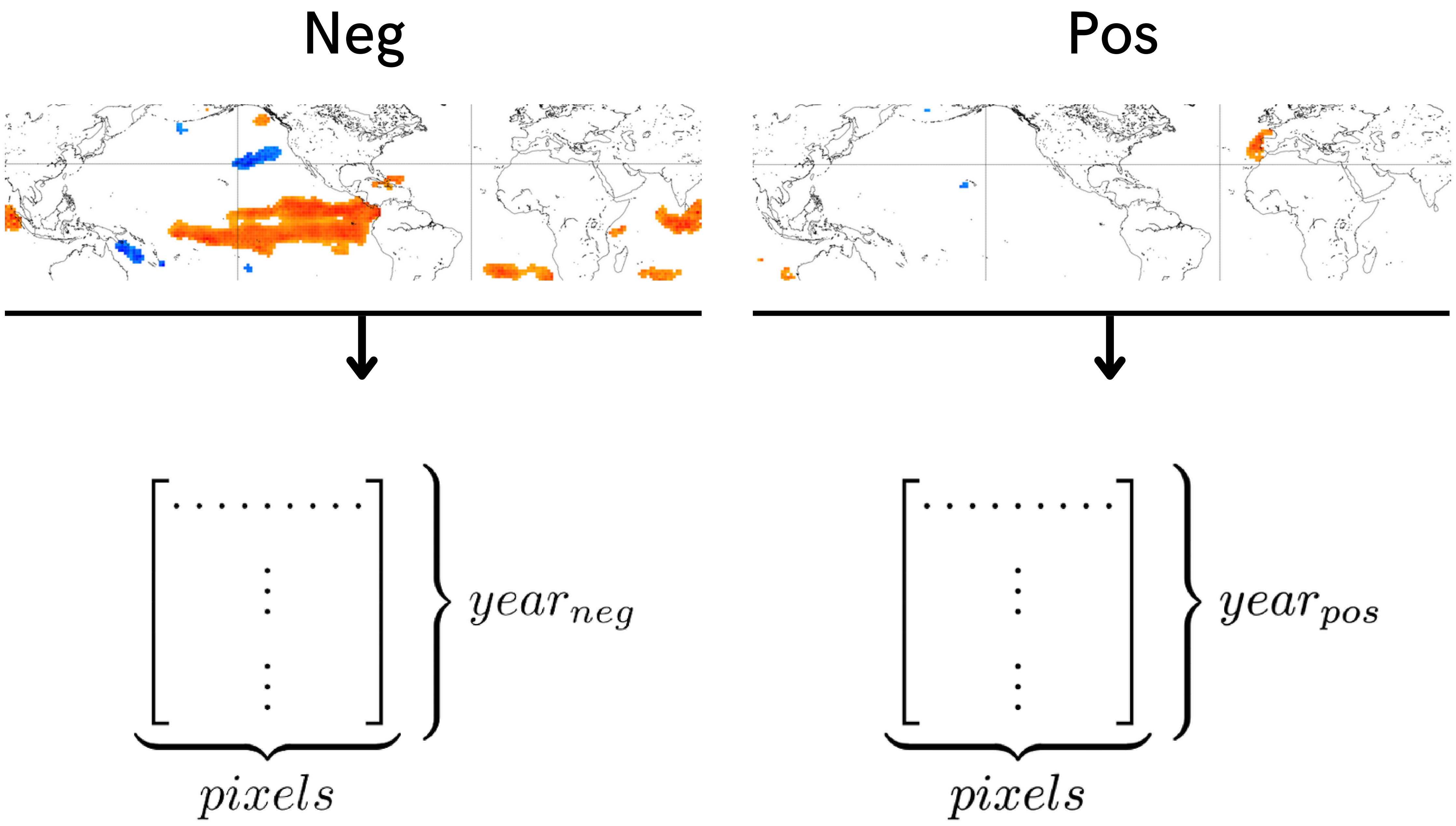
3x3 contiguous area check

Framework

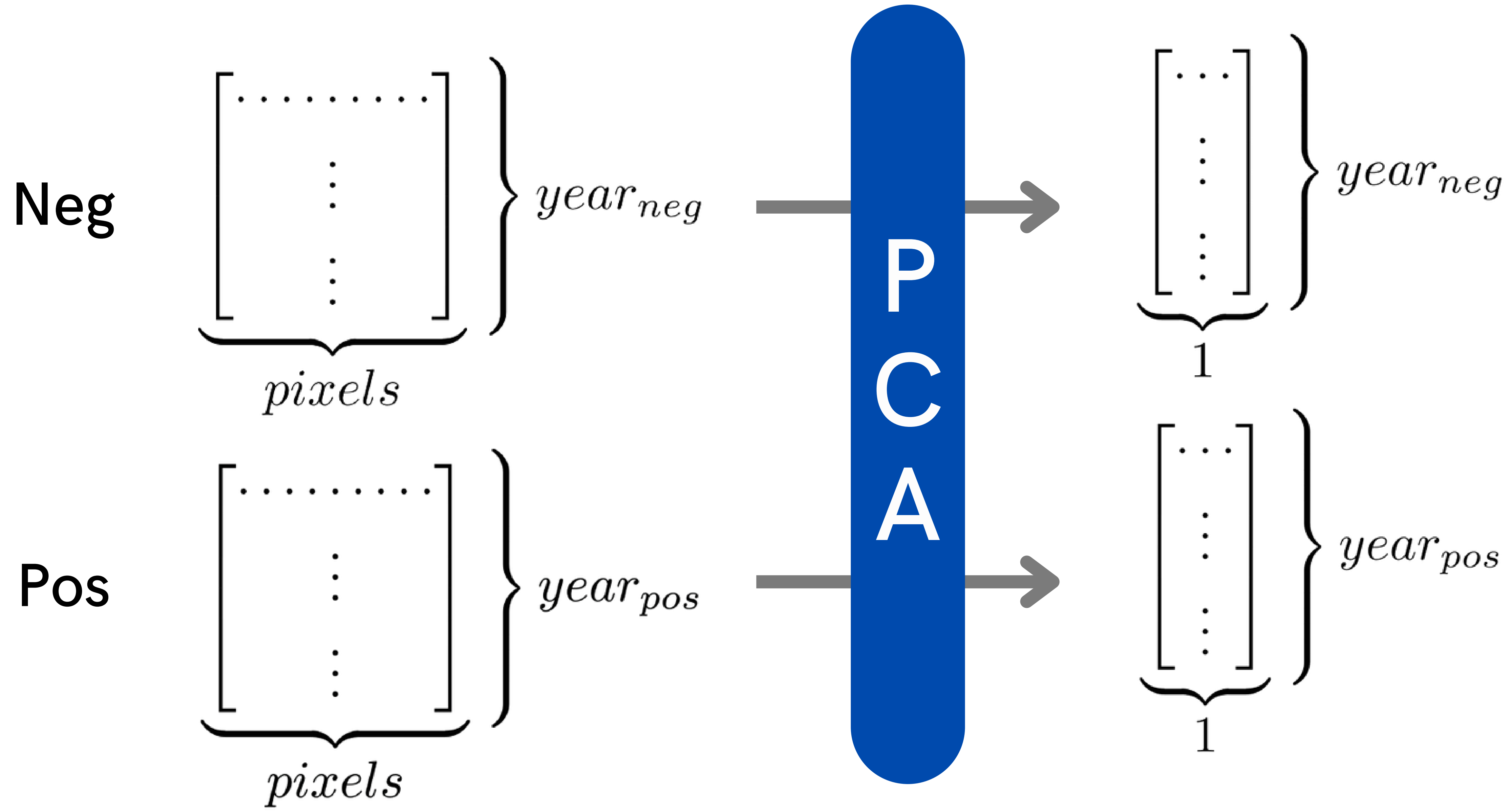
01 NIPA

02 ELM

Input
Data extraction
Phase segmentation
Correlation
PCA
output



Framework



Neg
Pos
$pixels$
$pixels$
$year_{neg}$
$year_{pos}$
PCA
$year_{neg}$
$year_{pos}$
1
1

Framework

PC1	phase_label
PC1 1979	1
PC1 1980	2
...	...
...	...
PC1 2021	2

Input
Data extraction
Phase segmentation
Correlation
PCA
output

Dataset for
1 month

Framework

This procedure can be applied

- for each Month
- for each combination of:
    - Local Precipitation
    - Global Variable (SST/SLP/Z500)
- for each aggregation level of SST/SLP/Z500 (1/2/3 month)
- for each climate signal (ENSO/NAO/SCA/EA)

After all the running of NIPA: 432 datasets.

By applying the three filtering conditions : 34 datasets

Framework

01 NIPA

02 ELM

	Jan			Feb			Mar			Apr			May			Jun		
	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500
SCA_N	0	0	0	0	0	-0,67	0	0	0	0	0	0	0	0	0	0	0	0
EA_N	0	0	0	0	0	0	0	0	0	0	-0,66	0	0	0	0	0	0	0
ENSO-mei_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NAO_N	0	0	0	0	0	0	0	0	-0,67	0	0	0	0	0	0	0	-0,71	0,75
SCA_P	0	0	0	0	0	-0,69	0	0	0	0	0	0	0	0	0	0	0	0
EA_P	0	0	0	0	0	0	0	0	0	0	-0,64	0	0	0	0	0	0	0
ENSO-mei_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NAO_P	0	0	0	0	0	0	0	0	-0,64	0	0	0	0	0	0	0	-0,64	-0,65

	Jul			Aug			Sept			Oct			Nov			Dec		
	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500
SCA_N	0	0	0	0	0,75	0	0	0	0	0	0	0	0	0	0	0	0	0
EA_N	0	0	0	0	0,84	0	0	0	0	0	-0,7	0	0	0	0	0	0	0
ENSO-mei_N	0	0,78	0	0	0,71	0,7	0	0	0	-0,82	0	0	0	0	0	0	0	-0,79
NAO_N	0	0	0	0	0,81	0	0	0	0	0	0	0	0	0	0	0	0,74	0
SCA_P	0	0	0	0	-0,66	0	0	0	0	0	0	0	0	0	0	0	0	0
EA_P	0	0	0	0	0,69	0	0	0	0	0	0,68	0	0	0	0	0	0	0
ENSO-mei_P	0	0,66	0	0	-0,87	0,66	0	0	0	0,8	0	0	0	0	0	0	0	-0,66
NAO_P	0	0	0	0	0,73	0	0	0	0	0	0	0	0	0	0	0	0,69	0

	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500
SCA_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EA_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,7	0
ENSO-mei_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NAO_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SCA_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EA_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,62	0
ENSO-mei_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NAO_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500
SCA_N	0	0	0	0	0,72	0	0	0	0	0	0	0	0	0	0	0	0	0
EA_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,73	0
ENSO-mei_N	0	0	0	0	0	0,78	0	0	0	0	0	0,65	0	0	0	0	0	0
NAO_N	0	0	0	0	0,84	0	0	0	0	0	0	0	0	-0,65	0	0	0,73	-0,67
SCA_P	0	0	0	0	0,65	0	0	0	0	0	0	0	0	0	0	0	0	0
EA_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,66	0
ENSO-mei_P	0	0	0	0	0	0,76	0	0	0	0	0	0,7	0	0	0	0	0	0
NAO_P	0	0	0	0	-0,71	0	0	0	0	0	0	0	0	-0,66	0	0	0,74	0,72

	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500
SCA_N	0	0	0	0	0	0	0	0	0	0	-0,79	0	0	0	0	0	0	0
EA_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,7	0
ENSO-mei_N	0	0	0	0	0	0	0	0	0	0	-0,7	0	0	0	0	0	-0,68	0,72
NAO_N	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SCA_P	0	0	0	0	0	0	0	0	0	0	0,68	0	0	0	0	0	0	0
EA_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,65	0
ENSO-mei_P	0	0	0	0	0	0	0	0	0	0	-0,76	0	0	0	0	0	-0,69	-0,63
NAO_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500	SST	MSLP	Z500
SCA_N	0	0	0	0	0	0	0	0,66	0	0	0	0	0	0	0	0	0	0
EA_N	0	0	0	0	0	0	0	0	0	0	0	0	0	-0,77	0	0	-0,78	0
ENSO-mei_N	0	0	0	0	0	0	0	0	0	0	0	-0,7	0	0	0	0	0	0
NAO_N	0	0	0	0	-0,67	0	0	0	0	0	0	0	0	0	0	0	0	0
SCA_P	0	0	0	0	0	0	0	-0,76	0	0	0	0	0	0	0	0	0	0
EA_P	0	0	0	0	0	0	0	0	0	0	0	0	0	0,63	0	0	0,74	0
ENSO-mei_P	0	0	0	0	0	0	0	0	0	0	0	-0,71	0	0	0	0	0	0
NAO_P	0	0	0	0	-0,73	0	0	0	0	0	0	0	0	0	0	0	0	0

Framework

The Local Data have been obtained starting from the ERA5 dataset (as the global data and the target).
The data consists of timeseries of 11 different variables referred only to the Rijnland grid cell (re-gridded on ECMWF):

Cumulative precipitation (tp)
2m temperature (t2m)
Total Cloud Cover (TCC)
Mean Evaporation Rate (MER)
Mean Surface Sensible Heat Flux (MSSHF)

Snow Depth (SD)
U-component of wind (UW)
V-component of wind (VW)
Relative Humidity (RH)
Specific Humidity (SH)
Total Column Water Vapour (TCWV)

Felsche et.al.

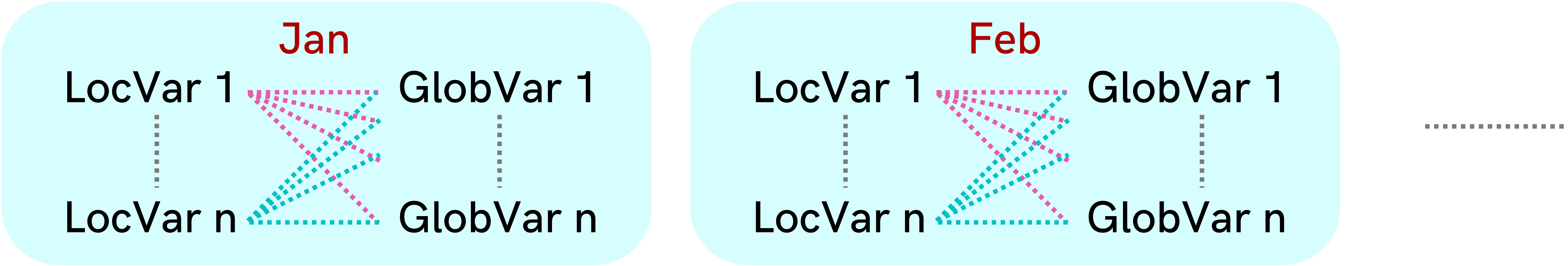
Framework

Creation of monthly-based datasets with all the possible combinations between local variables and global variables (if present).

Combinations constraints:

- Maximum 2 global variables considered for a single dataset
- Maximum 4 variables for a single dataset (global + local)

in total 13.541 combinations (datasets) have been created



Framework

Application of a *Leave One Out* (LOO) model selection procedure to:

- Select the most informative mix of global and local variables *for each month.*
- Select the best number of neurons in the hidden layer of the ELM models *for each month*
- Select the best activation function for the neurons of the hidden layers of the ELM models *for each month*

Framework

01 NIPA

02 ELM

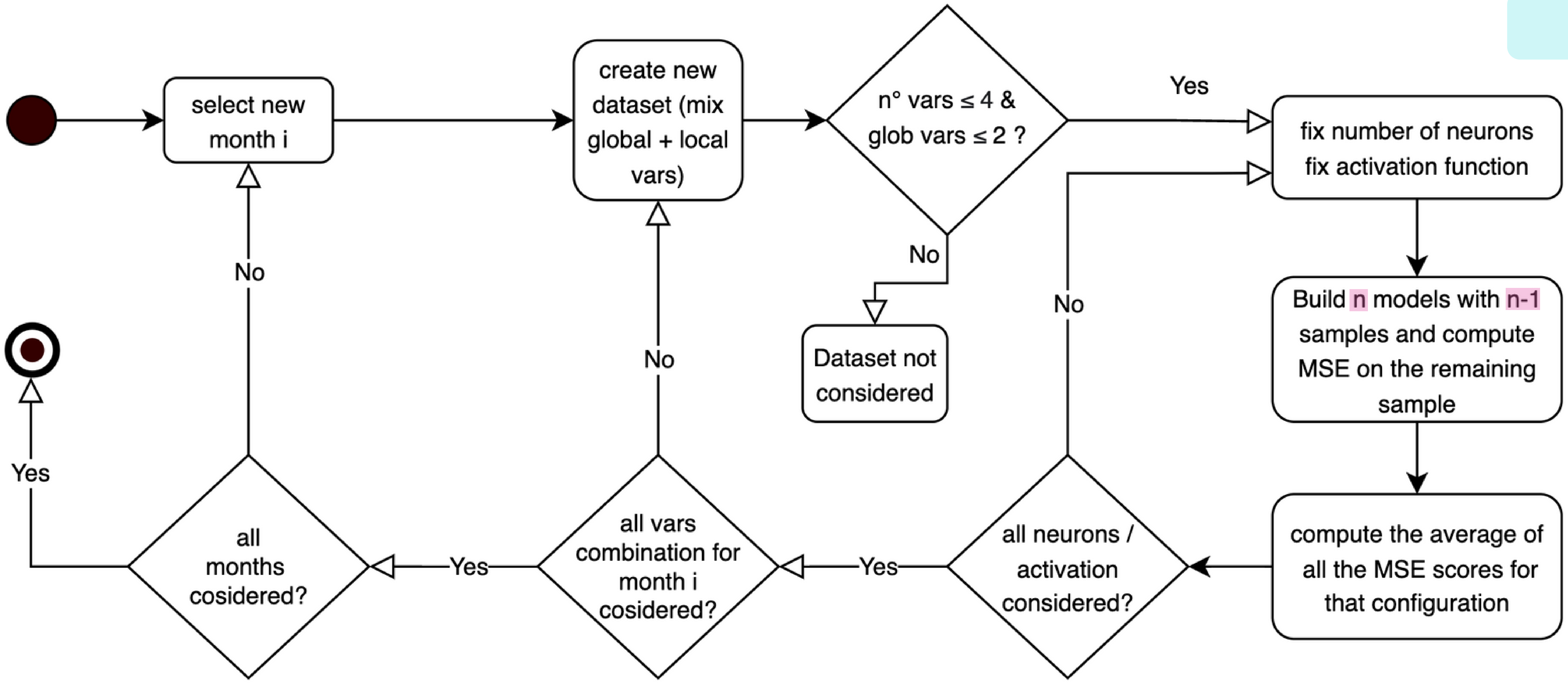
Local Data

Local/Global combinations

Model Selection

Final Results

Comparison



n = total number of samples

Framework

- 01 NIPA
- **02 ELM**

	1	2	3	4	5	6	7	8	9	10	11	12
t2m-TCC-TCWV-UW	1136.77	1096.17	993.6	1033.96	1235.78	1083.2	1769.69	2169.56	1999.84	1509.22	855.37	1030.84
t2m-TCC-TCWV-VW	792.45	1157.07	896.2	932.24	1023.3	1176.6	2114.29	1720.88	2205.18	1796.66	849.73	755.65
t2m-TCC-tp-UW	1038.49	1088.63	977.3	1015.95	1216.38	1247.02	1853.87	1955.14	1978.42	1405.76	750.29	1007.6
t2m-TCC-tp-VW	1231.12	1356.22	1003.62	921.48	1131.77	1183.61	1806.75	1754.28	2209.74	1390.09	879.6	1209.71
t2m-TCC-UW-VW	985.11	1139.13	968.54	1126.59	1099.41	1203.25	1810.71	1855.56	1682.82	1437.11	822.99	1084.57
t2m-TCWV-tp-UW	1001.08	1115.88	1203.79	908.28	1030.19	1154.62	1806.95	1918.36	1996.25	1334.13	813.21	957.55
t2m-TCWV-tp-VW	1101.01	1205.01	1091.0	1087.14	1181.95	1299.88	2272.37	2074.43	1757.31	1424.22	769.86	903.9
t2m-TCWV-UW-VW	1071.39	1158.17	994.16	941.98	1112.11	1089.73	2070.87	2150.51	1733.09	1372.57	935.32	831.81
t2m-tp-UW-VW	683.74	1051.2	793.15	899.56	1135.57	1211.52	1964.32	2087.7	1802.9	1565.64	742.54	991.9
TCC-TCWV-tp-UW	895.82	1156.45	951.0	1025.64	1066.09	1229.83	1928.64	2001.44	1568.77	1634.16	837.77	767.73
TCC-TCWV-tp-VW	1070.19	895.15	1078.36	1066.25	1198.34	1107.59	1555.76	2036.93	2074.02	1672.47	881.7	941.32
TCC-TCWV-UW-VW	1202.89	1343.99	1037.63	1105.42	945.94	1011.13	1834.21	1986.2	1866.81	1212.18	909.2	923.24
TCC-tp-UW-VW	971.23	993.72	894.99	1150.58	1200.45	1054.45	1616.44	1567.07	1570.86	1444.48	914.89	1164.83
TCWV-tp-UW-VW	1021.35	1183.97	941.41	959.78	939.39	1237.65	1522.18	2531.57	1458.46	1493.15	897.63	1143.04
SCA_Z500-1_tp-2_dataset.csv		500.97										
MER-SCA_Z500-1_tp-2_dataset.csv		592.11										
MSSHF-SCA_Z500-1_tp-2_dataset.csv		743.77										
RH-SCA_Z500-1_tp-2_dataset.csv		1051.21										
SD-SCA_Z500-1_tp-2_dataset.csv		590.71										
SH-SCA_Z500-1_tp-2_dataset.csv		593.59										
t2m-SCA_Z500-1_tp-2_dataset.csv		571.29										
TCC-SCA_Z500-1_tp-2_dataset.csv		545.17										

Local Data
Local/Global combinations
Model Selection
Final Results
Comparison

one table for each combination of neurons/activation functions (reporting the LOO validation MSE)

22 tables

Framework

Select one setting for each month having the best LOO Validation Error

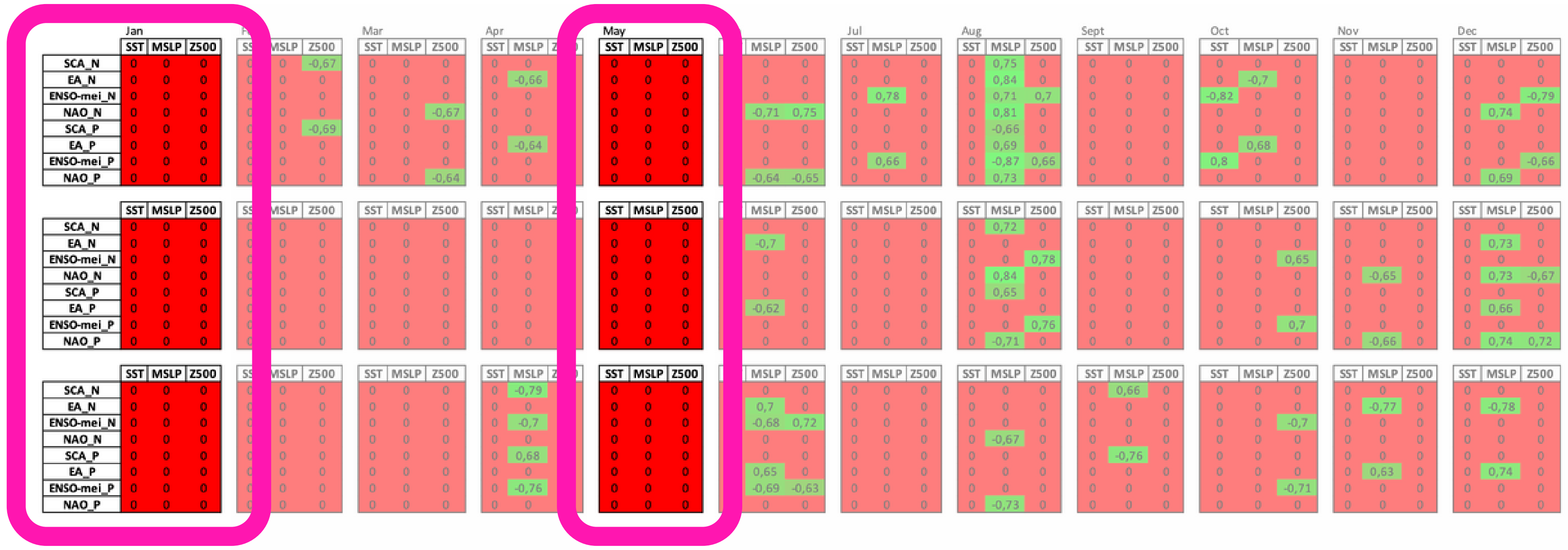
```
1:  (667.93, 9,  'relu', 'SH-t2m-UW-VW'),
2:  (425.97, 5,  'relu', 'MSSHF-TCC-VW-SCA_Z500-1_tp-2_dataset.csv'),
3:  (428.32, 8,  'relu', 'RH-UW-NAO_Z500-1_tp-3_dataset.csv'),
4:  (384.6,  12, 'sigm', 'tp-SCA_MSLP-3_tp-4_dataset.csv'),
5:  (672.03, 4,  'sigm', 'MER-RH-SH-tp'),
6:  (193.40, 5,  'sigm', 'SD-TCC-NAO_MSLP-1_tp-6_dataset.csv-EA_MSLP-2_tp-6_dataset.csv'),
7:  (676.80, 4,  'sigm', 't2m-TCC-ENSO-mei_MSLP-1_tp-7_dataset.csv'),
8:  (380.20, 9,  'relu', 'SH-tp-SCA_MSLP-2_tp-8_dataset.csv-ENSO-mei_Z500-2_tp-8_dataset.csv'),
9:  (698.42, 10, 'sigm', 'MER-SD-SCA_MSLP-3_tp-9_dataset.csv'),
10: (418.51, 12, 'sigm', 'SH-ENSO-mei_SST-1_tp-10_dataset.csv'),
11: (360.01, 12, 'sigm', 'MSSHF-EA_MSLP-3_tp-11_dataset.csv'),
12: (266.99, 10, 'sigm', 'MSSHF-VW-NAO_MSLP-1_tp-12_dataset.csv-EA_MSLP-2_tp-12_dataset.csv')
```

Framework

Select one setting for each month having the best LOO Validation Error

1: (667.93, 9, 'relu'),
2: (425.97, 5, 'relu'),
3: (428.32, 8, 'relu'),
4: (384.6, 12, 'sigm'),
5: (672.03, 4, 'sigm'),
6: (193.40, 5, 'sigm'),
7: (676.80, 4, 'sigm'),
8: (380.20, 9, 'relu'),
9: (698.42, 10, 'sigm'),
10: (418.51, 12, 'sigm'),
11: (360.01, 12, 'sigm'),
12: (266.99, 10, 'sigm')

months with no NIPA output (global climate context not considered to build the ELM). ELM must rely only on local data to make predictions

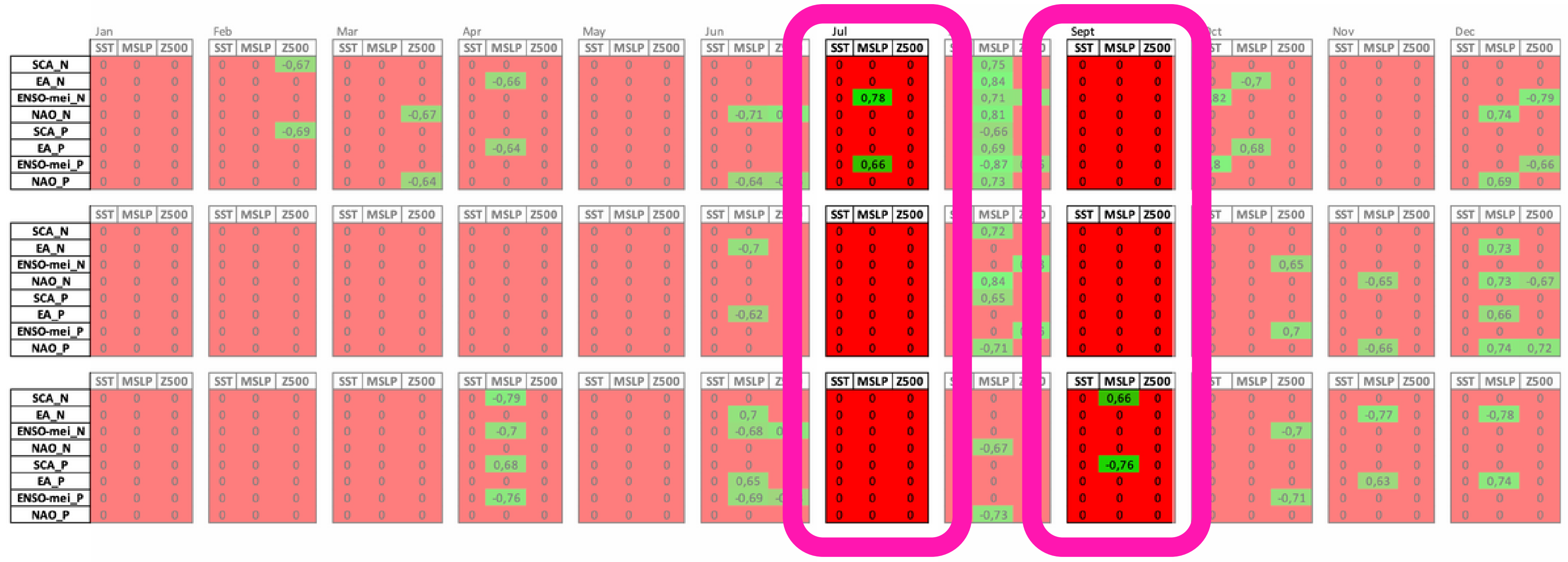


Framework

Select one setting for each month having the best LOO Validation Error

1: (667.93, 9, 'relu'),
2: (425.97, 5, 'relu'),
3: (428.32, 8, 'relu'),
4: (384.6, 12, 'sigm'),
5: (672.03, 4, 'sigm'),
6: (193.40, 5, 'sigm'),
7: (676.80, 4, 'sigm'),
8: (380.20, 9, 'relu'),
9: (698.42, 10, 'sigm'),
10: (418.51, 12, 'sigm'),
11: (360.01, 12, 'sigm'),
12: (266.99, 10, 'sigm')

months with just 1 NIPA output (out of 12 possible). ELM has only one option to consider in the global climate context. Probably the relevant climate signals for these months do not fall into the set we have considered



Framework

Build a model for each moth based on the best setting

01 NIPA

02 ELM

Local Data

Local/Global combinations

Model Selection

Final Results

Comparison

Framework

LOO plots

Framework

Giuliani et. al.

- 12 models (1 for each month)
- n° neurons: 10
- act. function: sigmoid

Pearson prediction vs target: 0.81

Our work

- 12 models (1 for each month)
- n° neurons: range (4,12)
- act. function: (sigmoid,relu)

Pearson prediction vs target: 0.63/0.66

These values are computed on the LOO validation samples

Framework

- The comparison is based on Pearson because is the same metric used in the paper (no MSE, RMSE, etc. is provided)
- Better results could be obtained by considering more climate signals to
  - produce outputs for Jan and May
  - produce more than 1 output for Jul and Sep
- Only LOO validation without testing to be consistent with Giuliani et. al. (low number of samples)

Next steps

- 01 Neural Network
- 02 Conv. Neural Net.

Next steps

Because of the lack of samples and the absence of a proper testing procedure, we plan to:

- build a single neural network for the whole period
- compare it month by month with the monthly-based ELMs

The reason why is to ***check*** if neglecting NIPA (which checks for dependencies between variables through phases of climate indices) could be compensated by the presence of more training samples able to make the neural network learn (part of) the underlying patterns by itself

Next steps

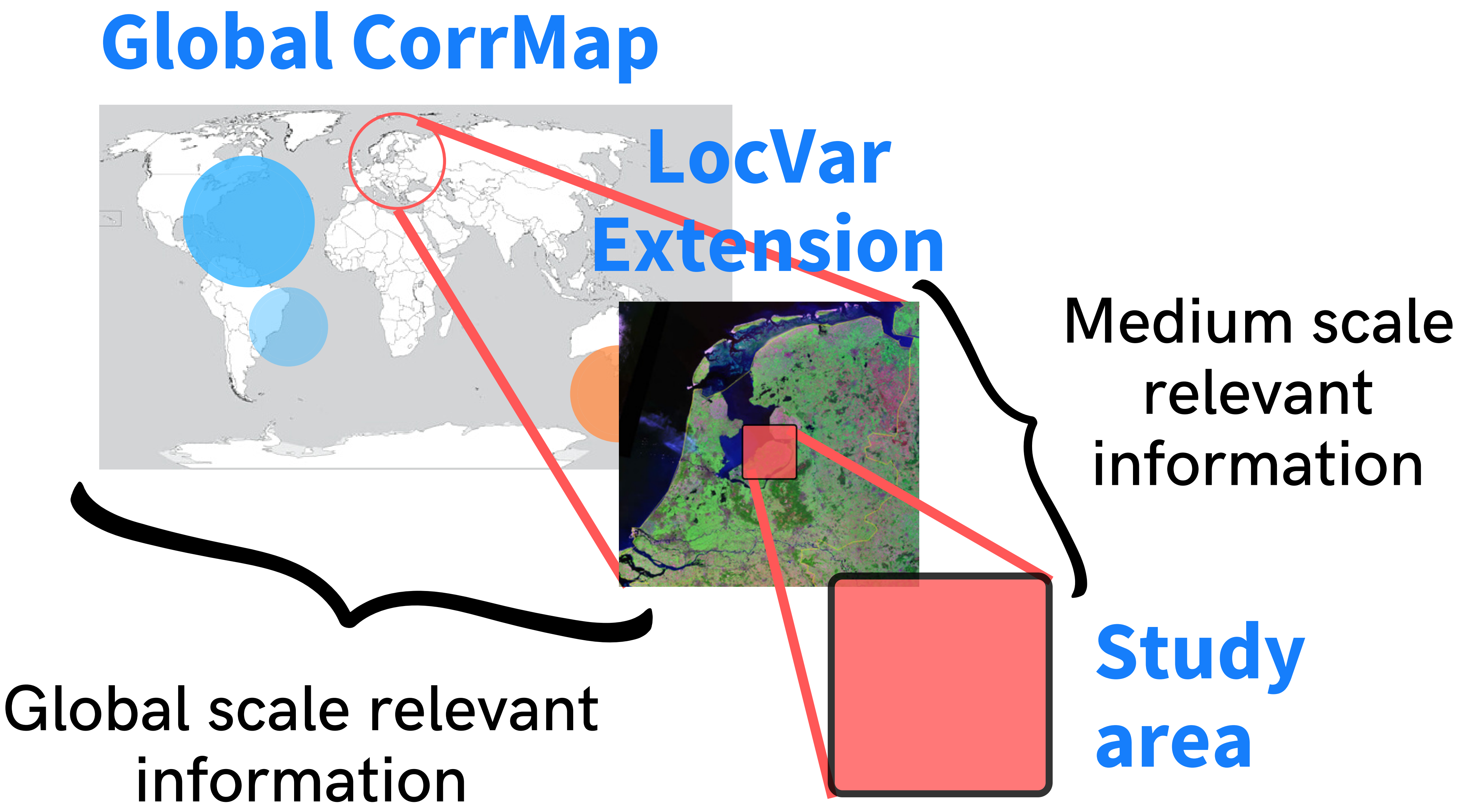
Because of the lack of samples and the absence of a proper testing procedure, we plan to:

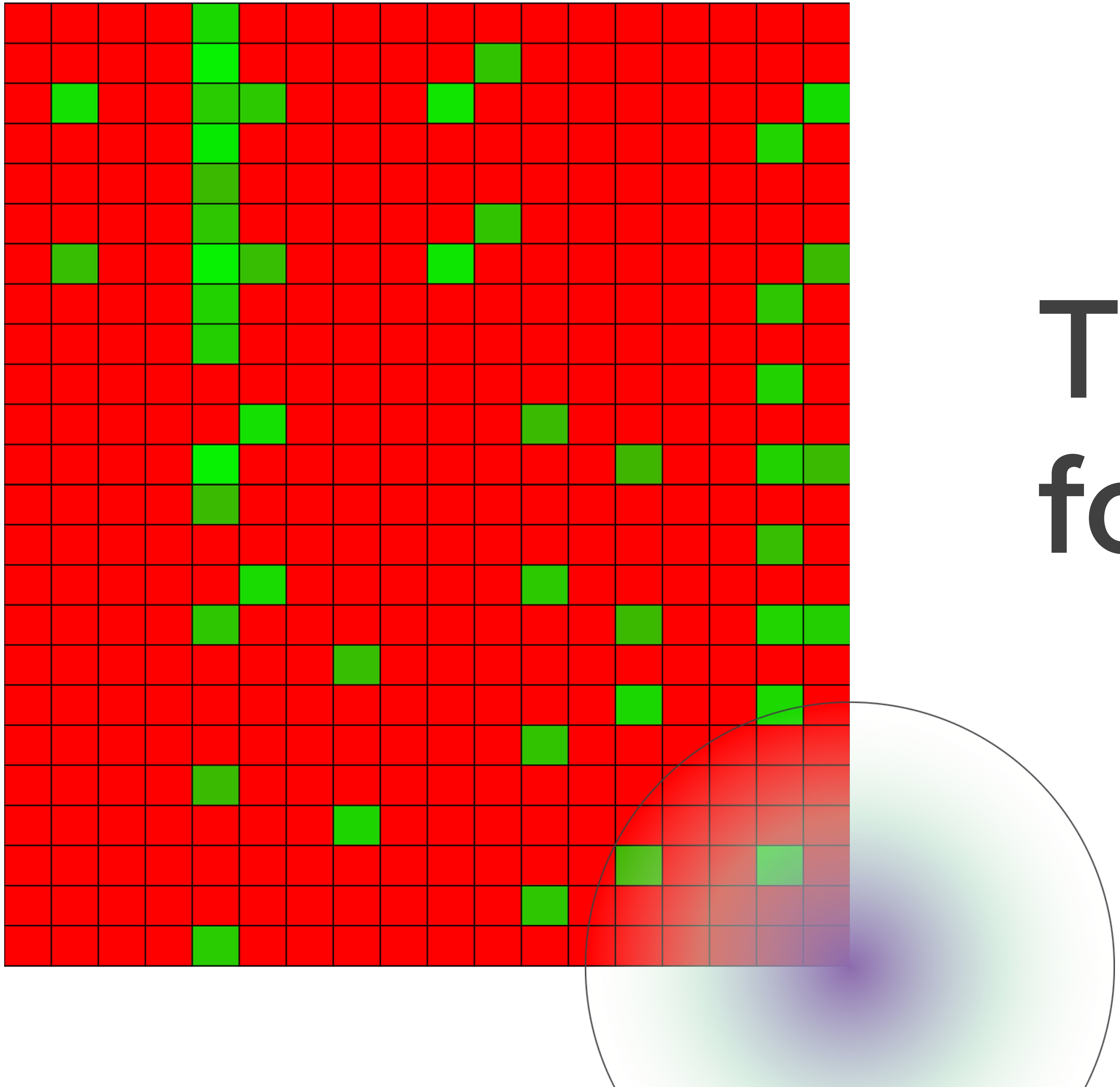
- build a single convolutional neural network for the whole period
- compare it month by month with the monthly-based ELMs

The reason why is to ***check*** if extending the area of the local variables also in the surroundings of Rijnland could bring a more exhaustive local context to the CNN which can turn into a better bridging of Global and Local climate conditions (crucial for sub-seasonal lead-times)

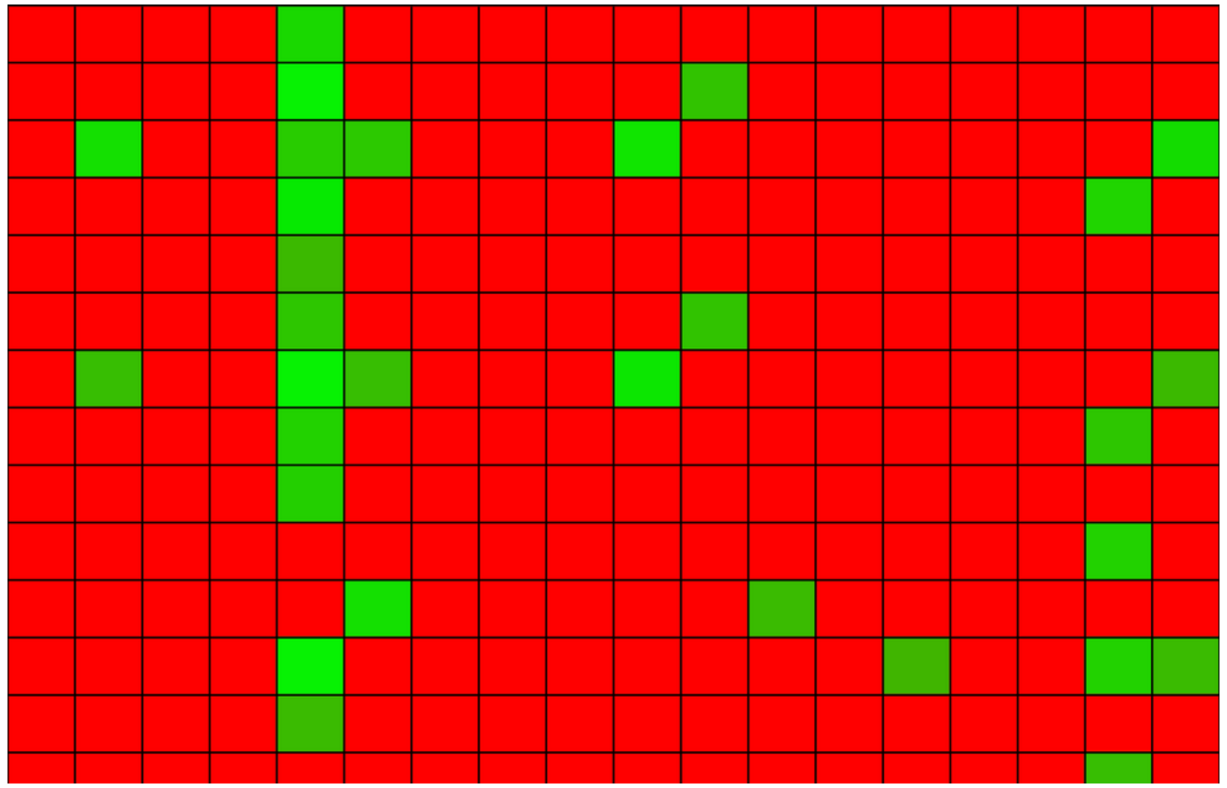
Next steps

- 01 Neural Network
- **02 Conv. Neural Net.**





Thank you for attending!



you can find the slides here!

Felsche et al. (2021)

Zimmerman et al. (2016)

Giuliani et al. (2019)

Our readaptation