ENVIRONMENTAL INTELLIGENCE | LAB

# FRIDA

## AN NEW AI-ENHANCED, IMPACT-BASED APPROACH TO DROUGHT CHARACTERIZATION

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CLINT CLIMATE INTELLIGENCE

# ACKNOWLEDGMENTS

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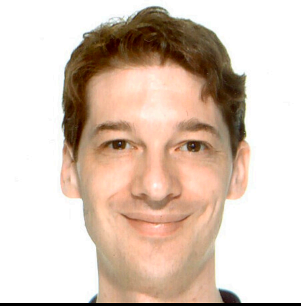

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Research funded by

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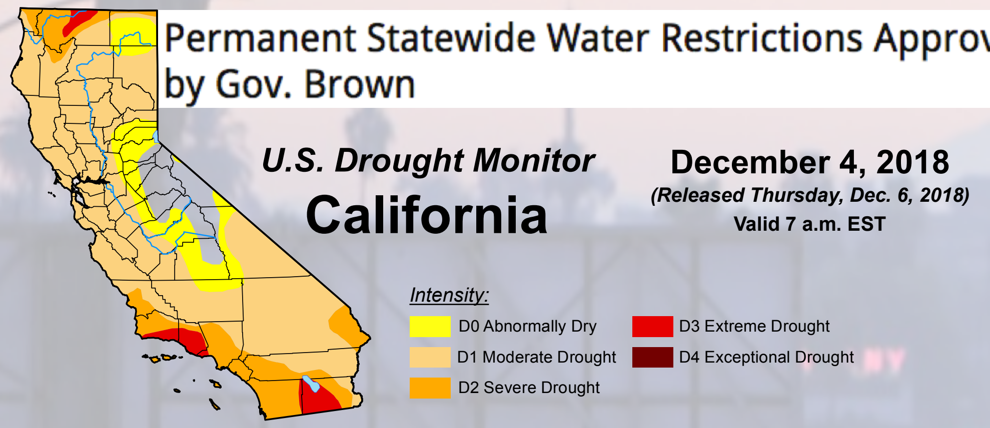
# EMERGING NEED FOR DROUGHT MANAGEMENT


Permanent Statewide Water Restrictions Approved by Gov. Brown



# EMERGING NEED FOR DROUGHT MANAGEMENT



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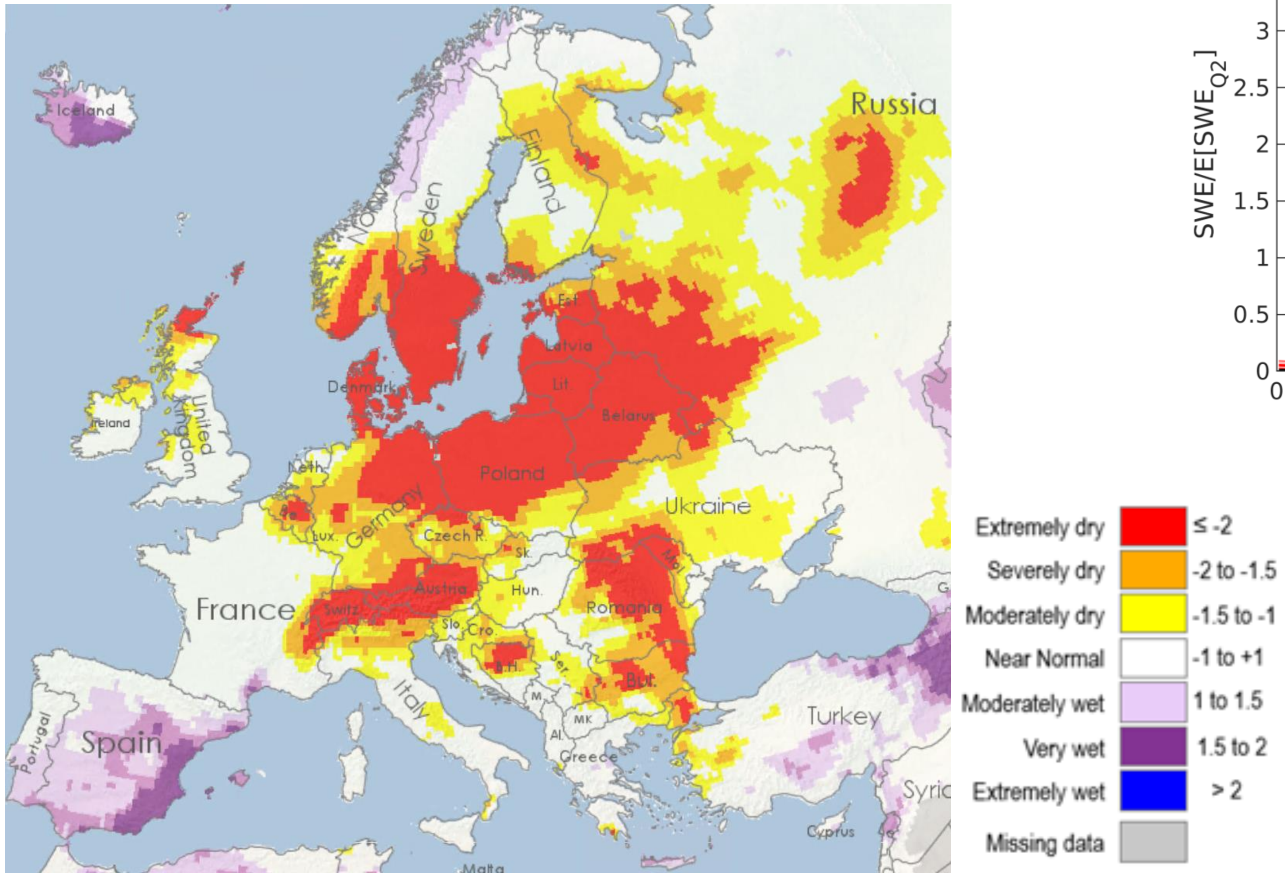
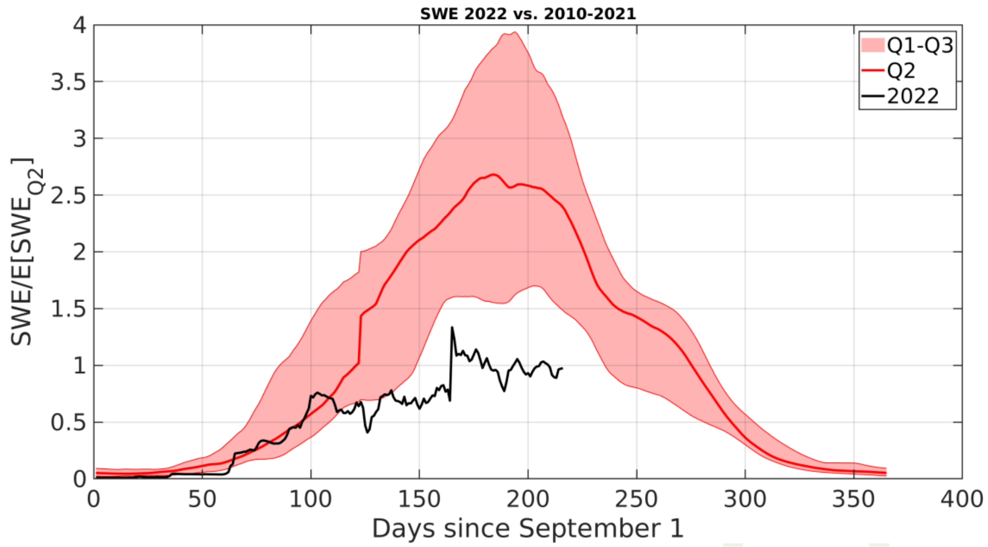
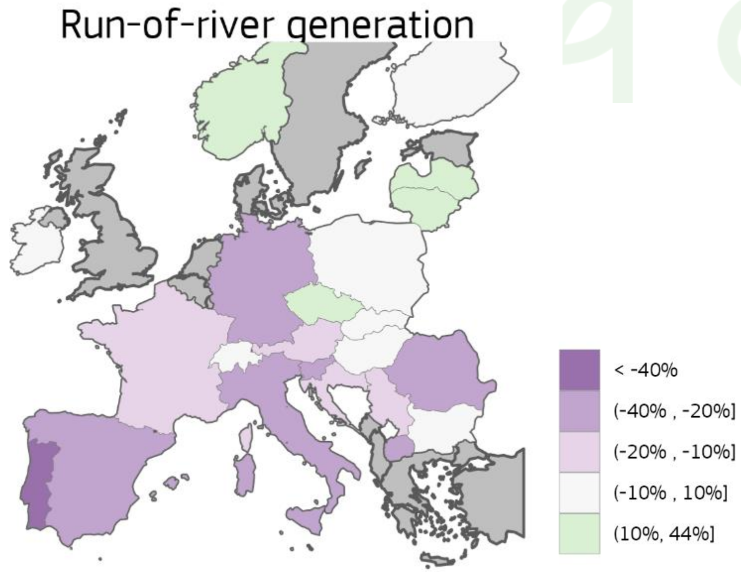



***Figure 2:*** *Standardized Precipitation Index SPI-1 in March 2022.*

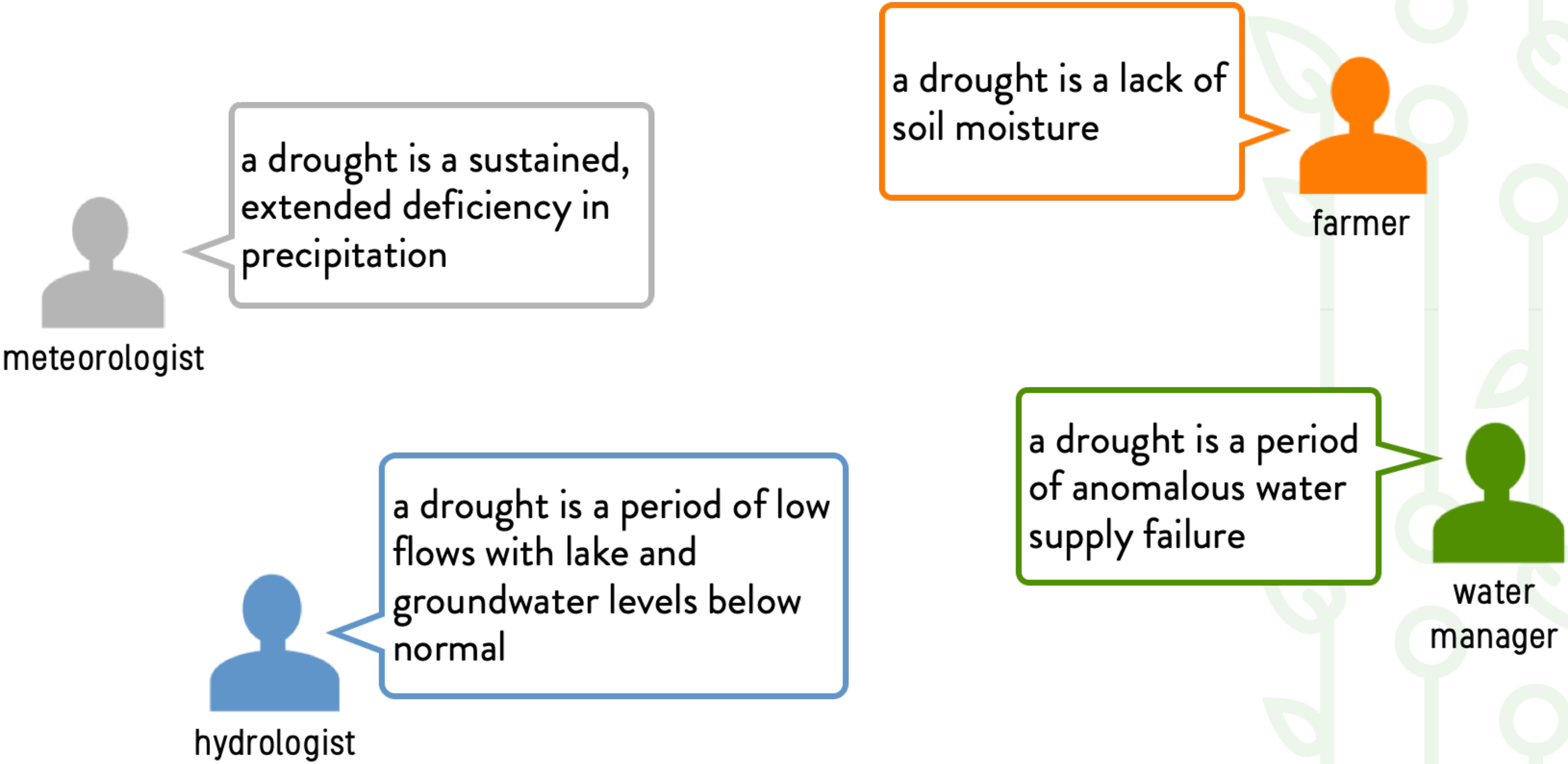


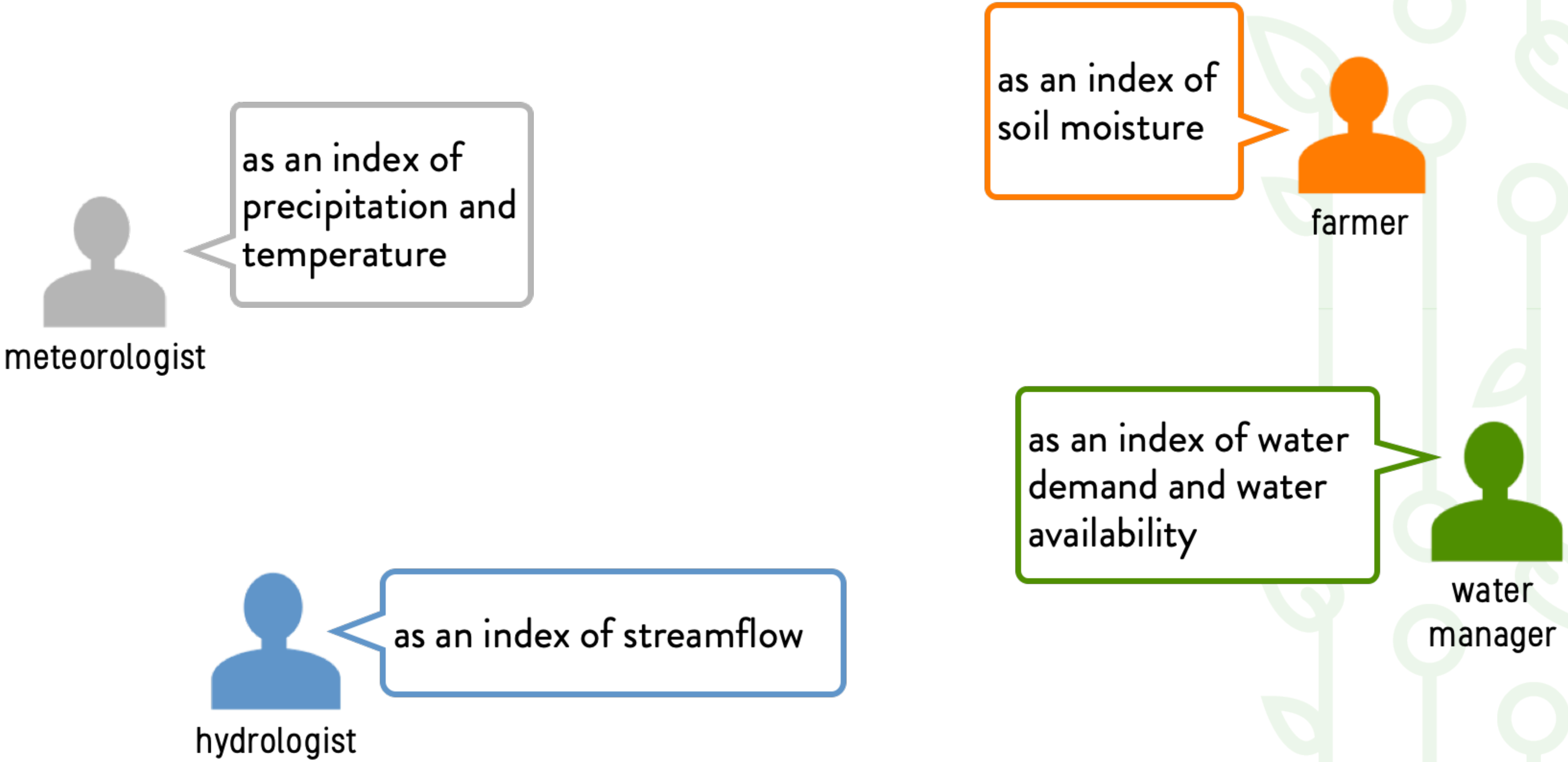

source: Toreti et al., Drought in Europe April 2022, GDO Analytical Report

# THE CHALLENGE OF DROUGHT DEFINITION





# THE CHALLENGE OF DROUGHT DEFINITION



# EXAMPLE: AGRICULTURAL DROUGHTS IN NORTHERN ITALY


- Indexes generally agree in detecting dry periods
- Results show differences in the onset, termination, and persistence
- Results strongly depend on time aggregation

# A VIRTUOUS EXAMPLE

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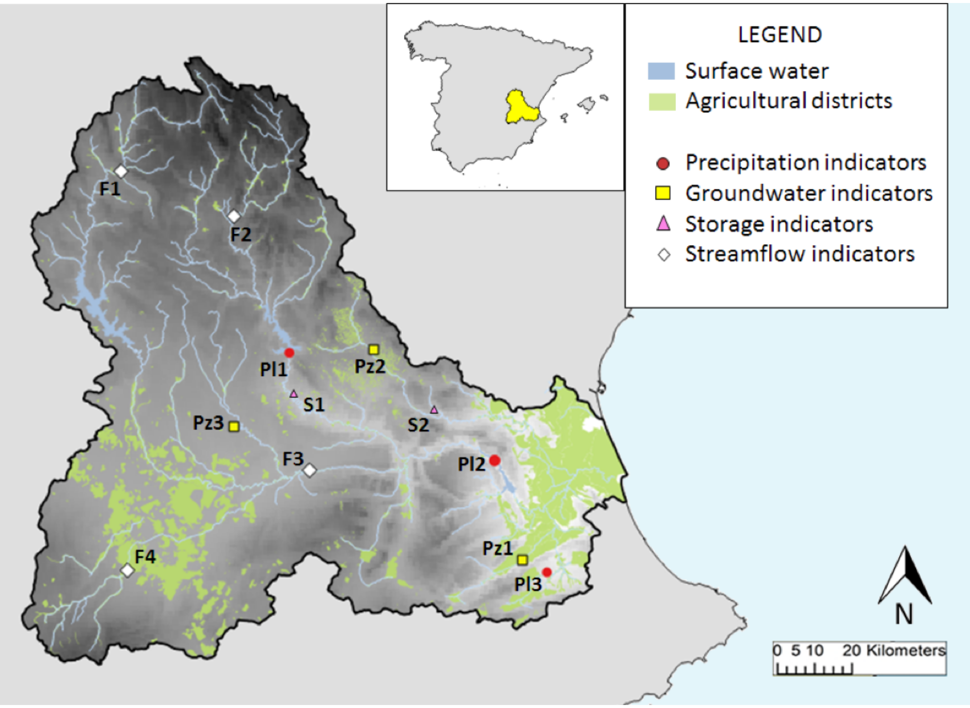
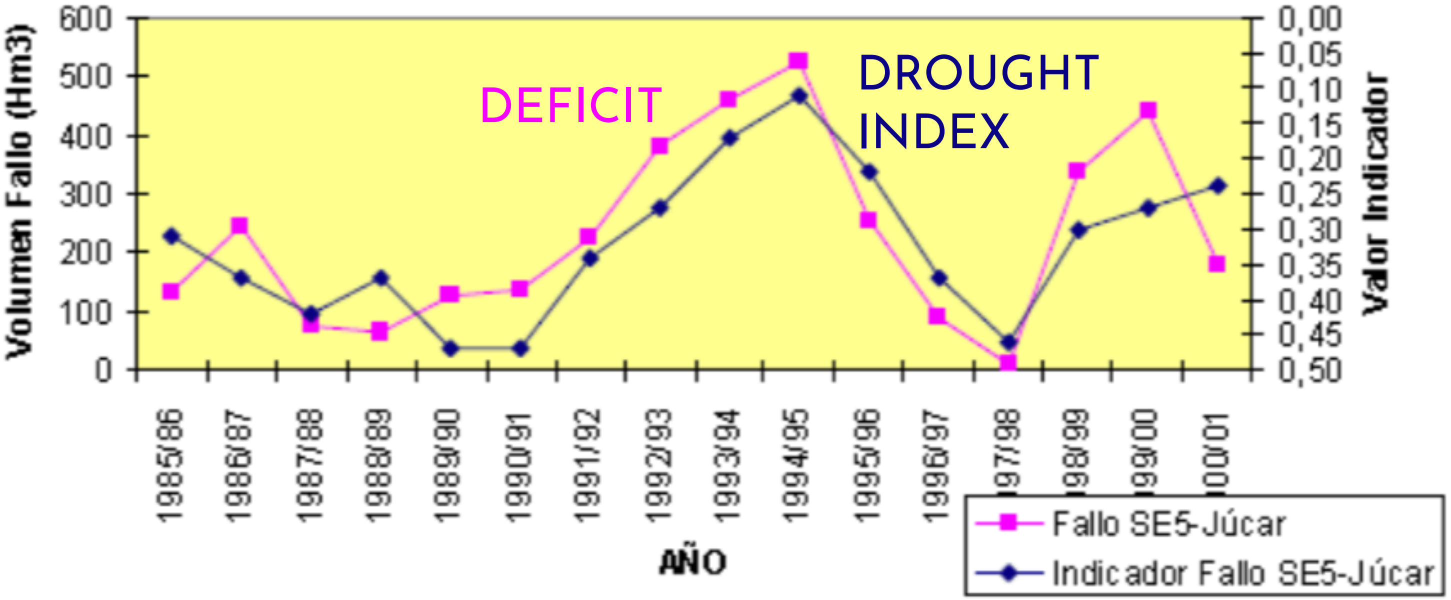
Spanish Drought Management Plans rely on basin-specific drought indexes.

In the Jucar river basin, the index is defined as a linear combination of 12 predictors.

| | |
|---|---|
| S1 | Cumulated storage of Alarcón, Contreras, and Tous reservoirs |
| S2 | Storage at Forata |
| F1 | Flow measurement in the upper basin |
| F2 | Flow measurement in the upper basin |
| F3 | Flow measurement in the middle basin |
| F4 | Flow at the Jardín tributary |
| Pl1 | Pluviometer measurement in the Contreras reservoir |
| Pl2 | Pluviometer measurement in the Tous reservoir |
| Pl3 | Pluviometer measurement in the Bellús reservoir |
| Pz1 | Piezometric level in the southeast |
| Pz2 | Piezometric level in the center |
| Pz3 | Piezometric level in the west |



# CAN WE AUTOMATIZE THIS PROCESS?

# THE FRIDA METHOD

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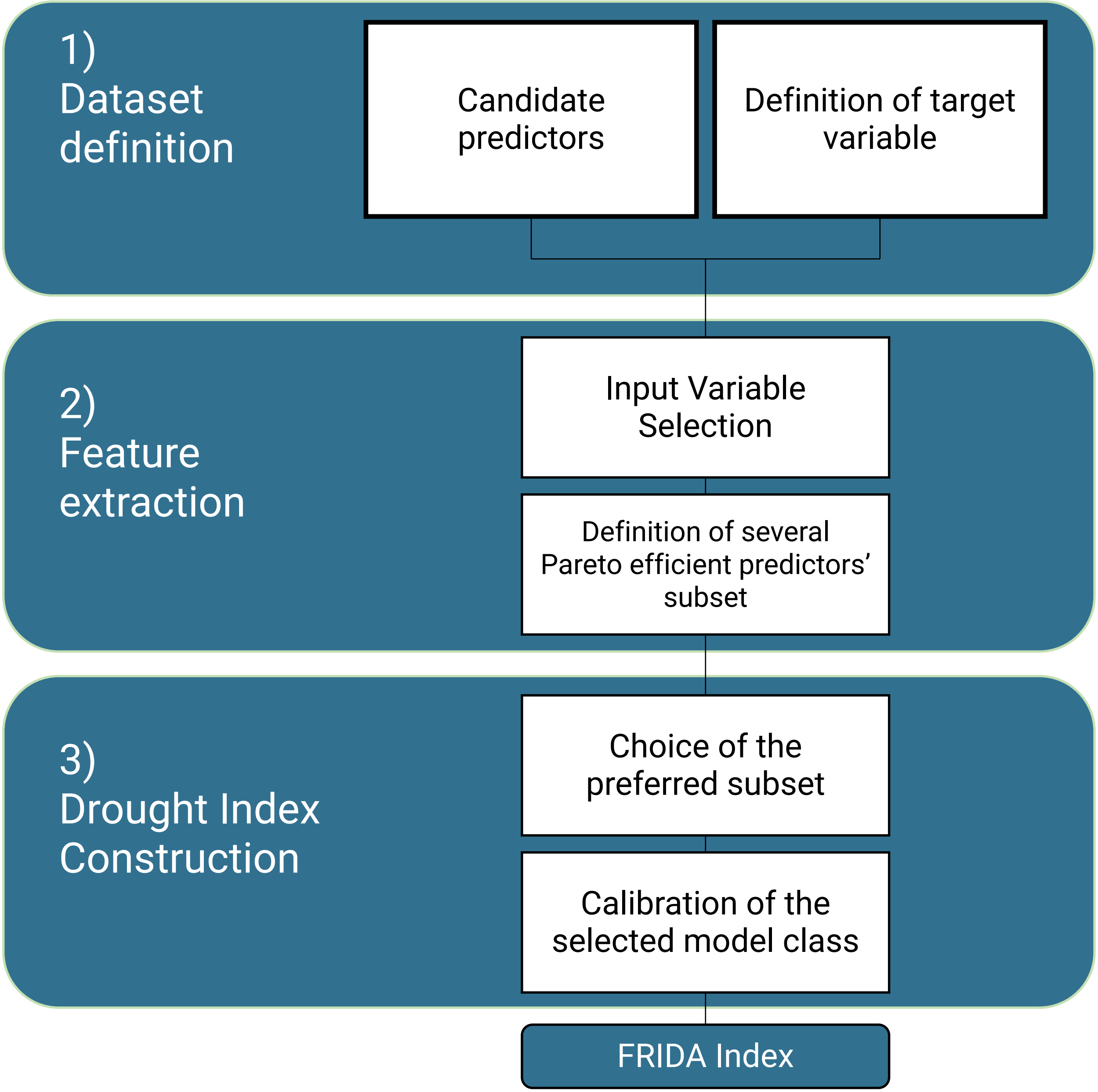


# THE FRIDA METHOD



**1) Dataset definition**

- Candidate predictors
- Definition of target variable

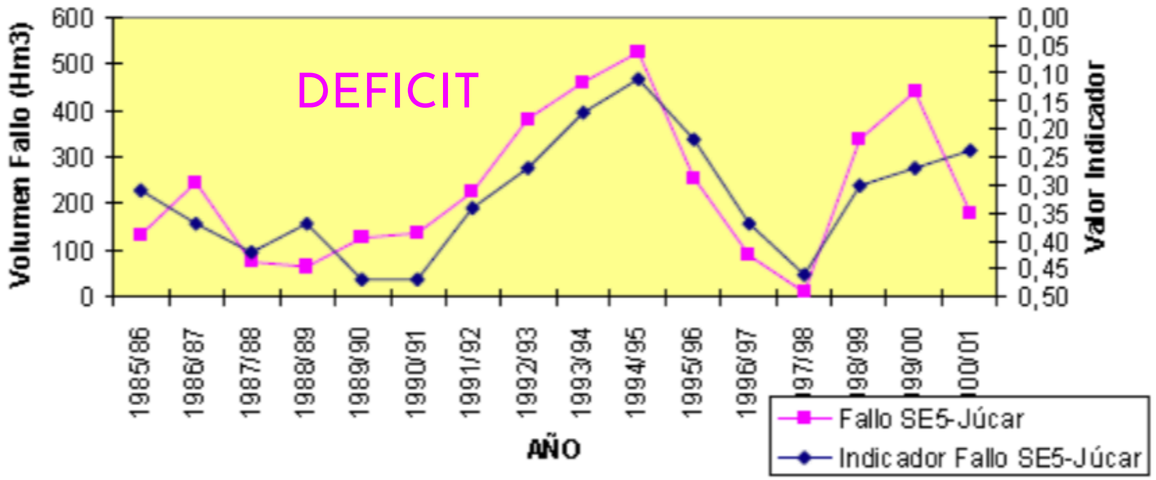
**2) Feature extraction**

- Input Variable Selection
- Definition of several Pareto efficient predictors' subset

**3) Drought Index Construction**

- Choice of the preferred subset
- Calibration of the selected model class

**FRIDA Index**



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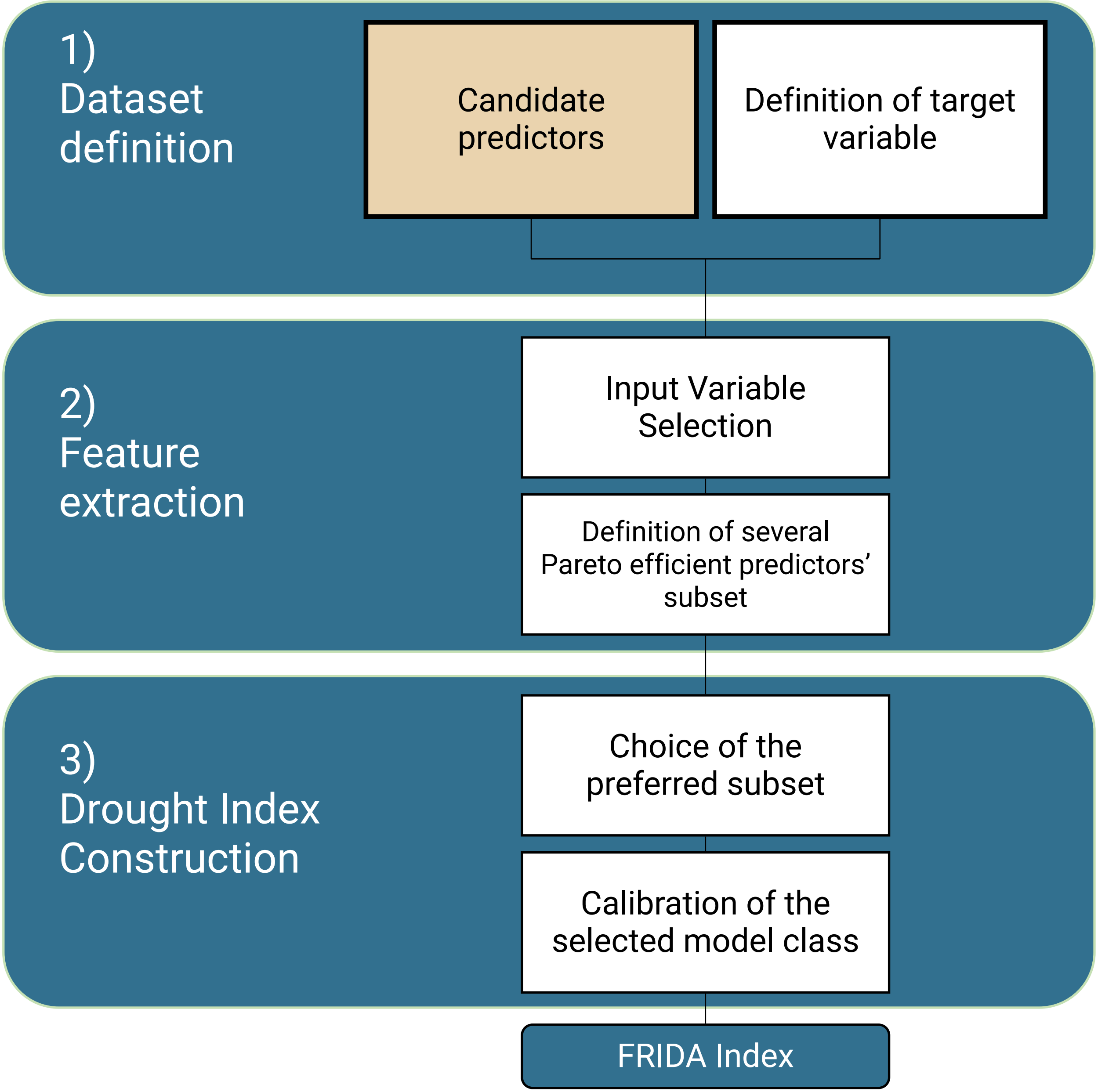


## Candidate predictors

| | | |
|---|---|---|
| Time information | date | Date of the measurement |
| | Moy | Month of the year |
| Observed variables | In A | Inflow to Alarcón reservoir |
| | In C | Inflow to Contreras reservoir |
| | In T | Inflow to Tous reservoir |
| | Out A | Outflow from Alarcón reservoir |
| | Out C | Outflow from Contreras reservoir |
| | T1 | Temperature in the west |
| | T2 | Temperature in the center |
| | T3 | Temperature in the east |
| Indicators | $SPI_3$ | SPI at 3 months time aggregation |
| | $SPEI_3$ | SPEI at 3 months time aggregation |
| | $SPI_6$ | SPI at 6 months time aggregation |
| | $SPEI_6$ | SPEI at 6 months time aggregation |
| | $SPI_{12}$ | SPI at 12 months time aggregation |
| | $SPEI_{12}$ | SPEI at 12 months time aggregation |

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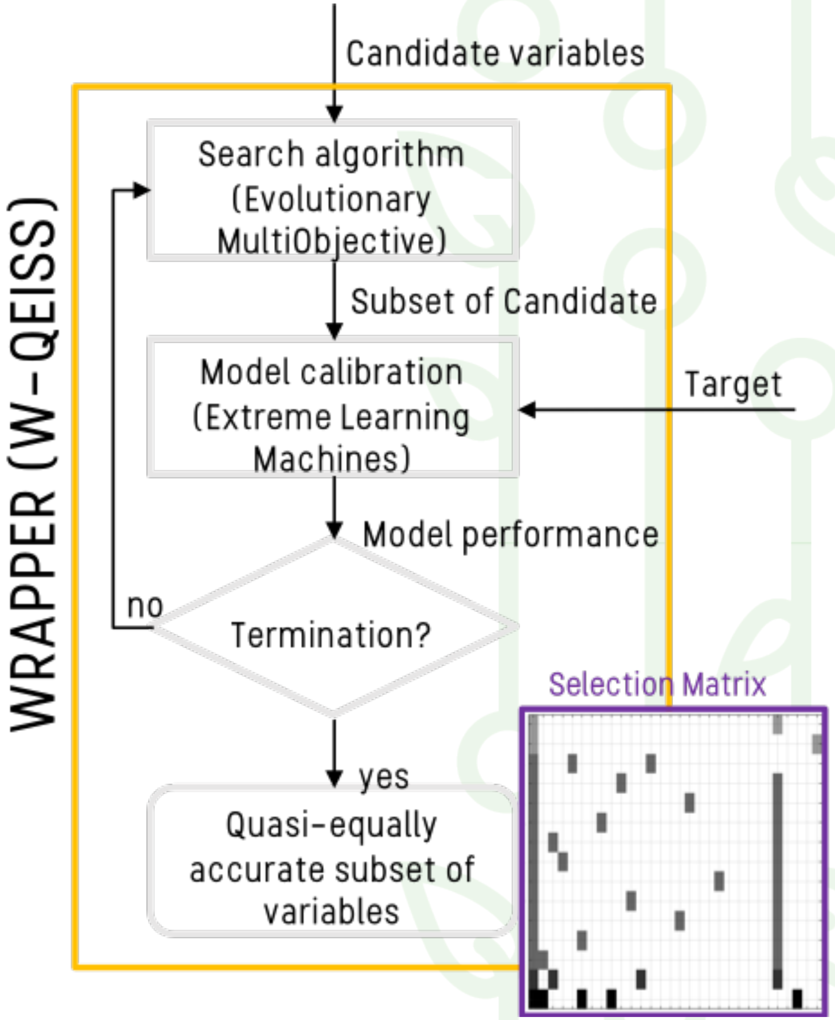


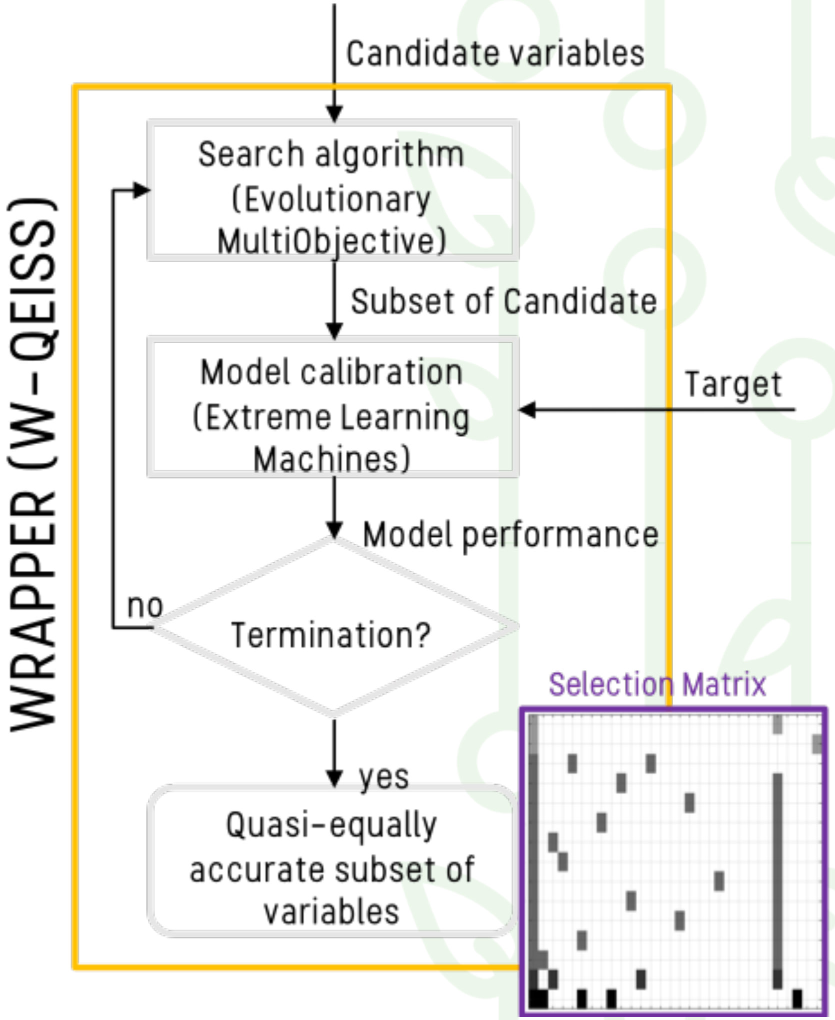

Karakaya et al., 2016, IEEE Transactions on Cybernetics

# MODEL PERFORMANCE

- Predictive accuracy: $f_1(S) = SU\left(y, \hat{y}(S)\right)$
- Model complexity: $f_2(S) = |S|$
- Relevance: $f_3(S) = \sum_{x_i \in S} SU(x_i, y)$
- Redundancy: $f_4(S) = \sum_{x_i, x_j \in S, i<j} SU(x_i, y)$

Simmetric Uncertainty:

$$SU(A, B) = \left[\frac{2 \bullet (H(A) + H(B) - H(A, B))}{H(A) + H(B)}\right]$$

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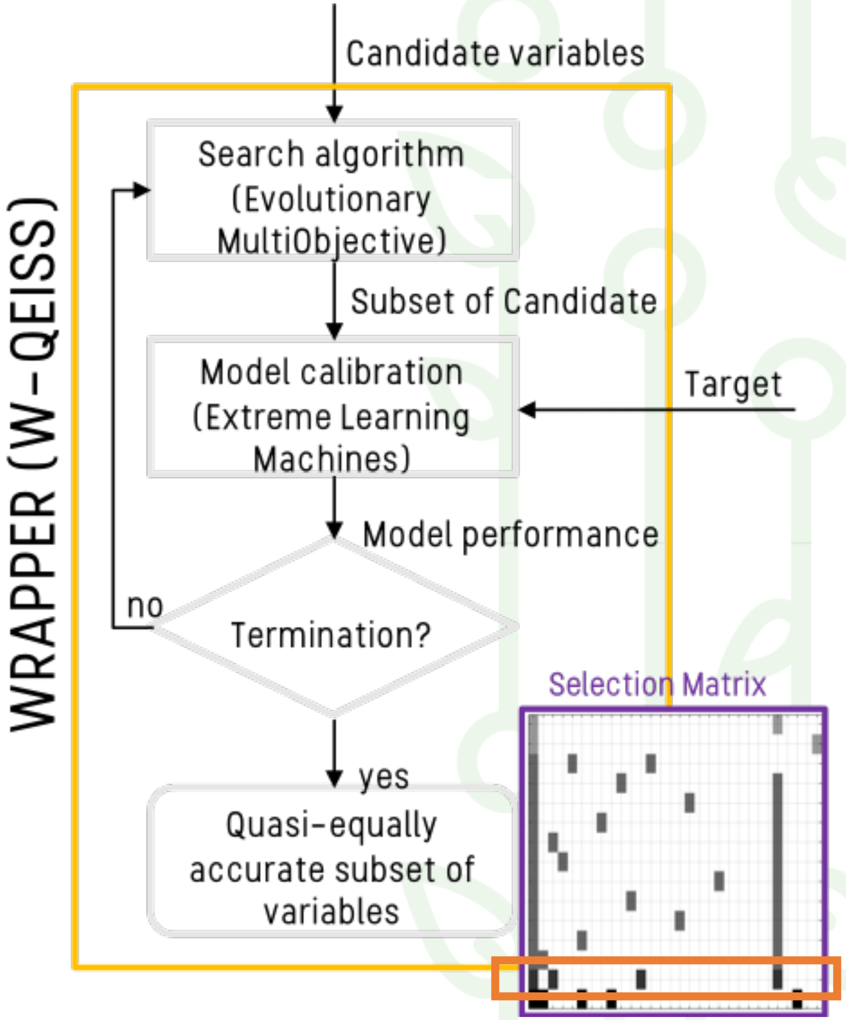

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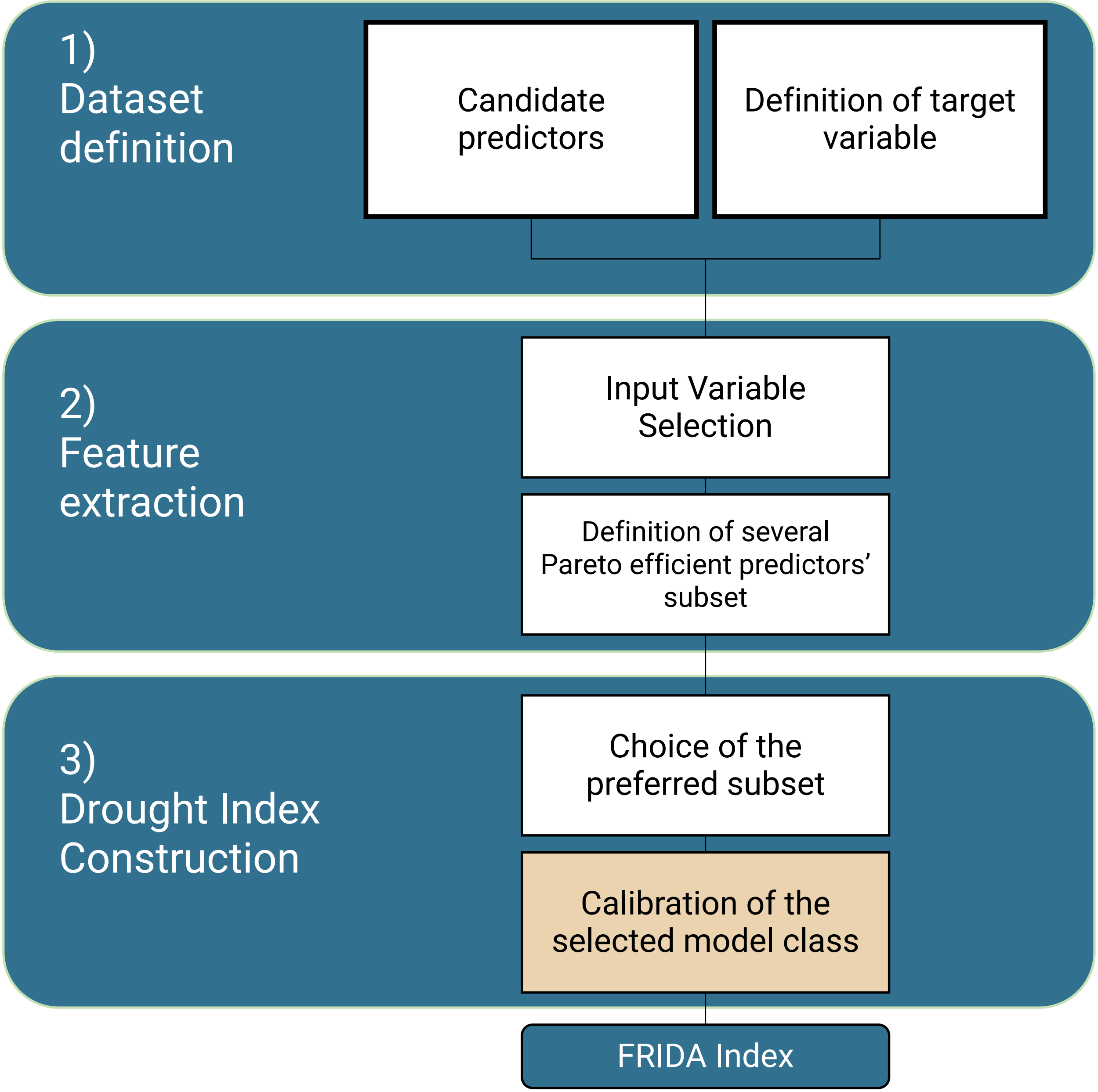
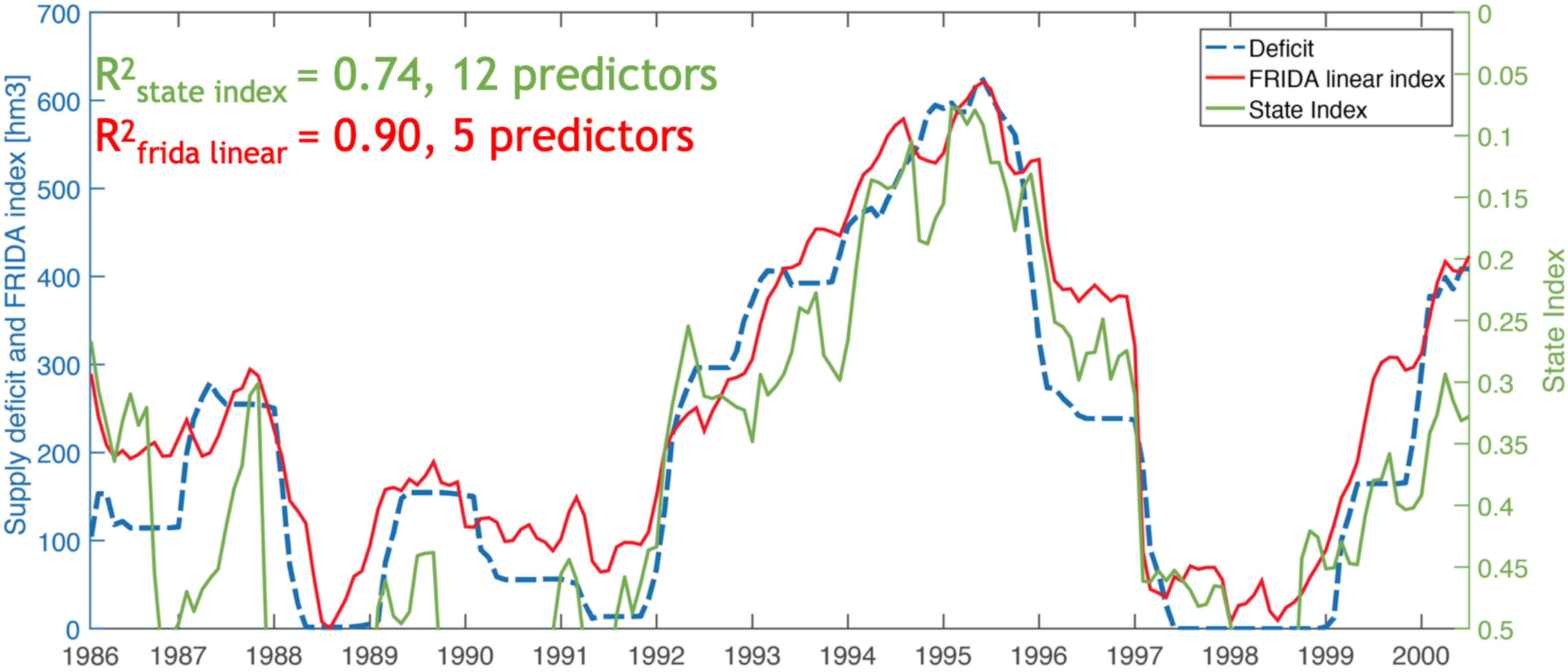



- Extreme Learning Machine
- Artificial Neural Network
- Linear Model

# FRIDA APPLICATION IN THE JUCAR RIVER BASIN




SELECTED PREDICTORS:

1. Month of the year
2. Storage of Alarcon, Contreras, and Tous
3. Streamflow in middle basin
4. Piezometer in the center
5. SPEI over 6 months

Zaniolo et al., 2018, HESS

# FRIDA APPLICATION IN THE LAKE COMO BASIN

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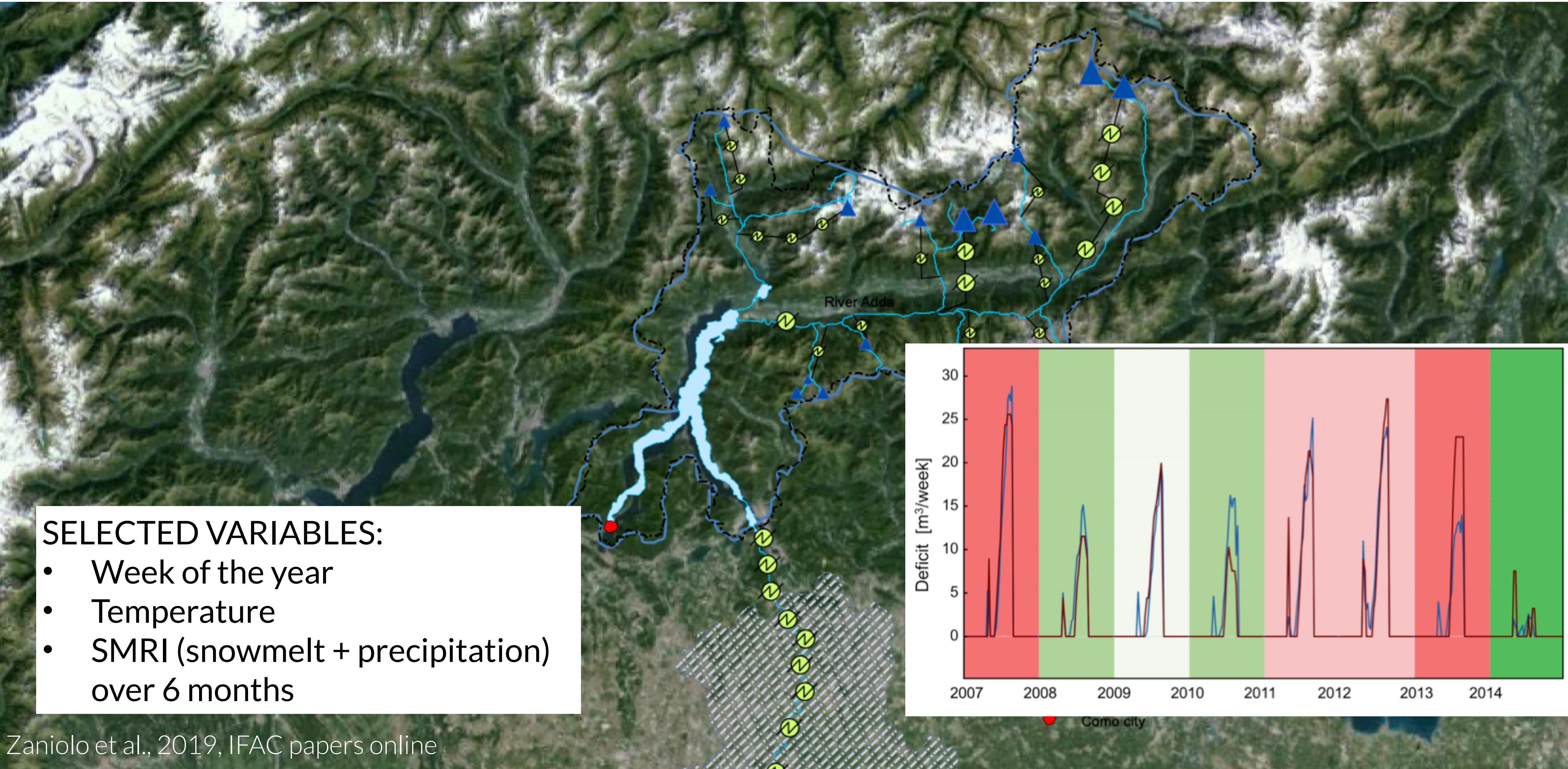


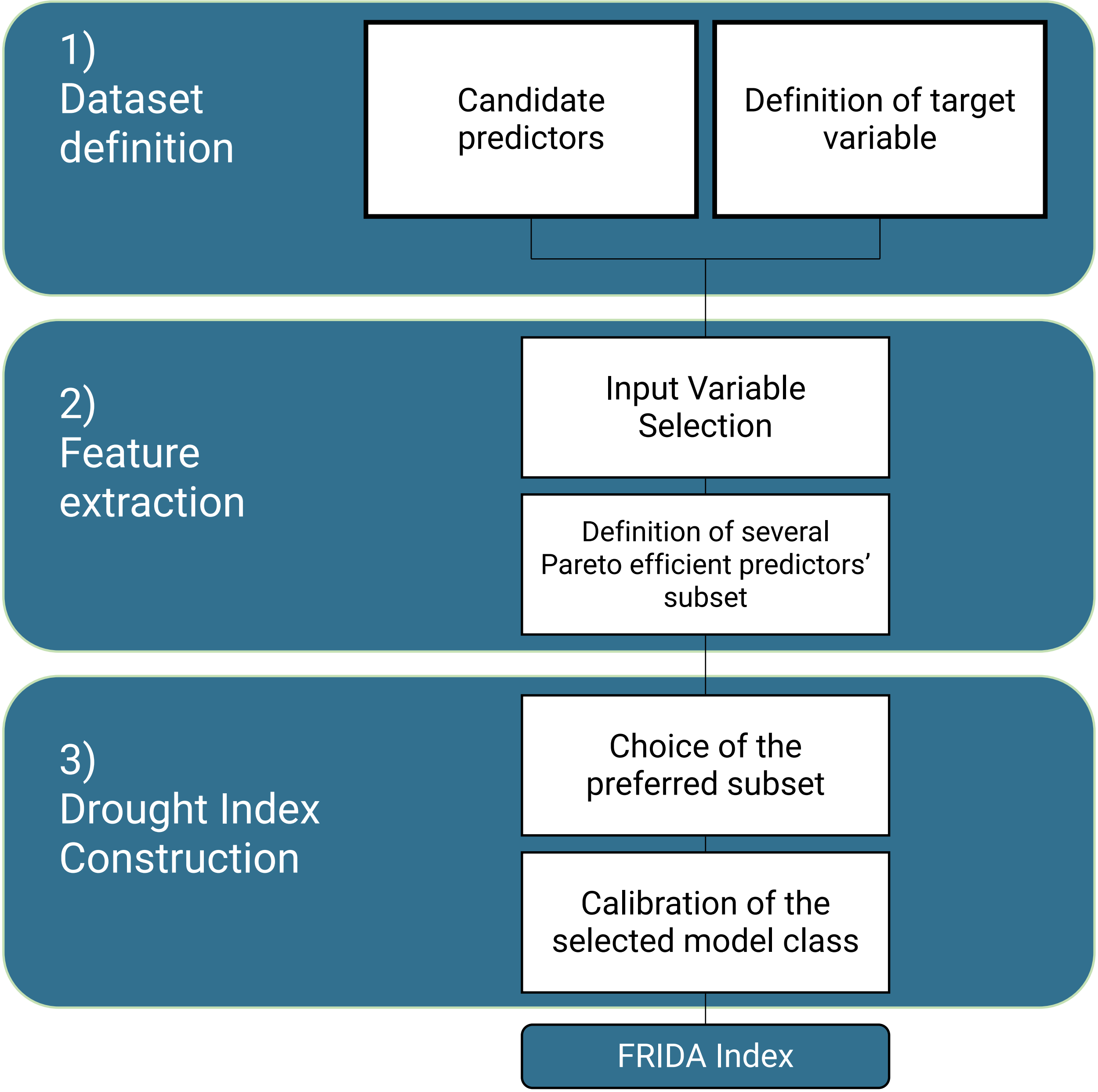

SELECTED VARIABLES:

- Week of the year
- Temperature
- SMRI (snowmelt + precipitation) over 6 months

Zaniolo et al., 2019, IFAC papers online

# CAN WE UPSCALE FRIDA FOR REGIONAL/CONTINENTAL STUDIES?

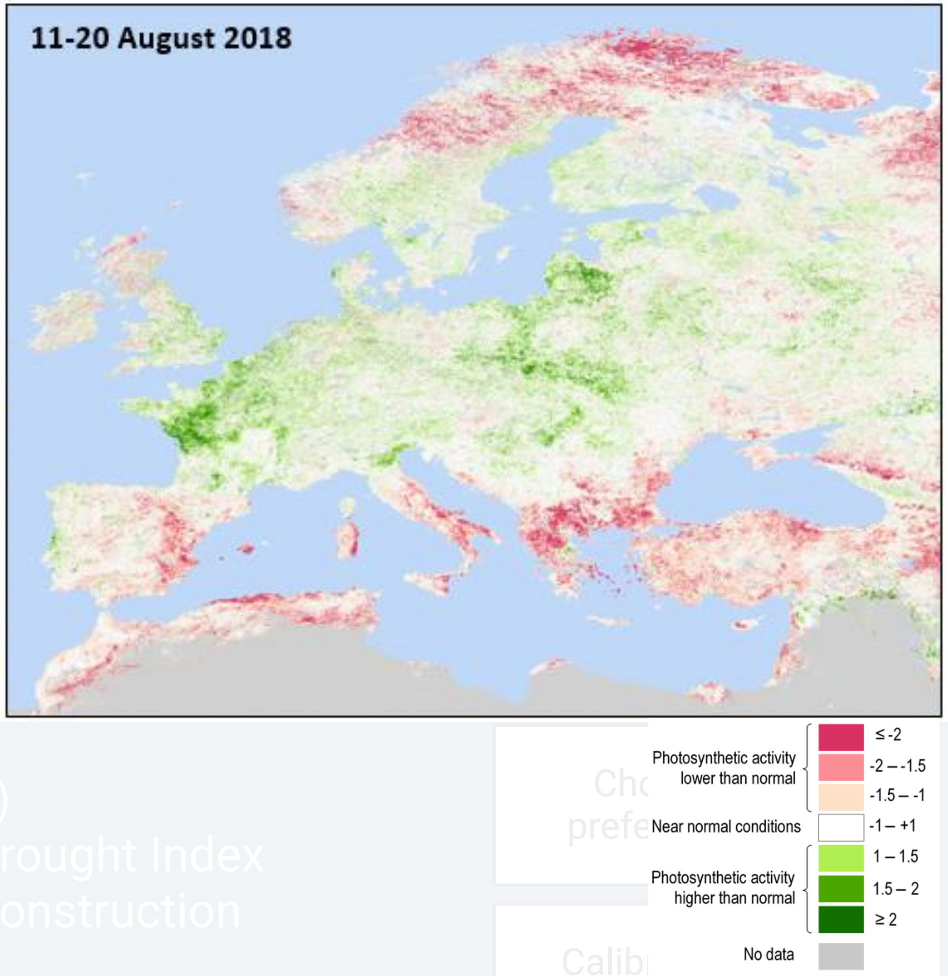
# UPSCALING CHALLENGES




- Lack of local data on water deficits
- Spatially correlated drivers
- Drought heterogeneity over space
- Computational complexity

# UPSCALING CHALLENGES





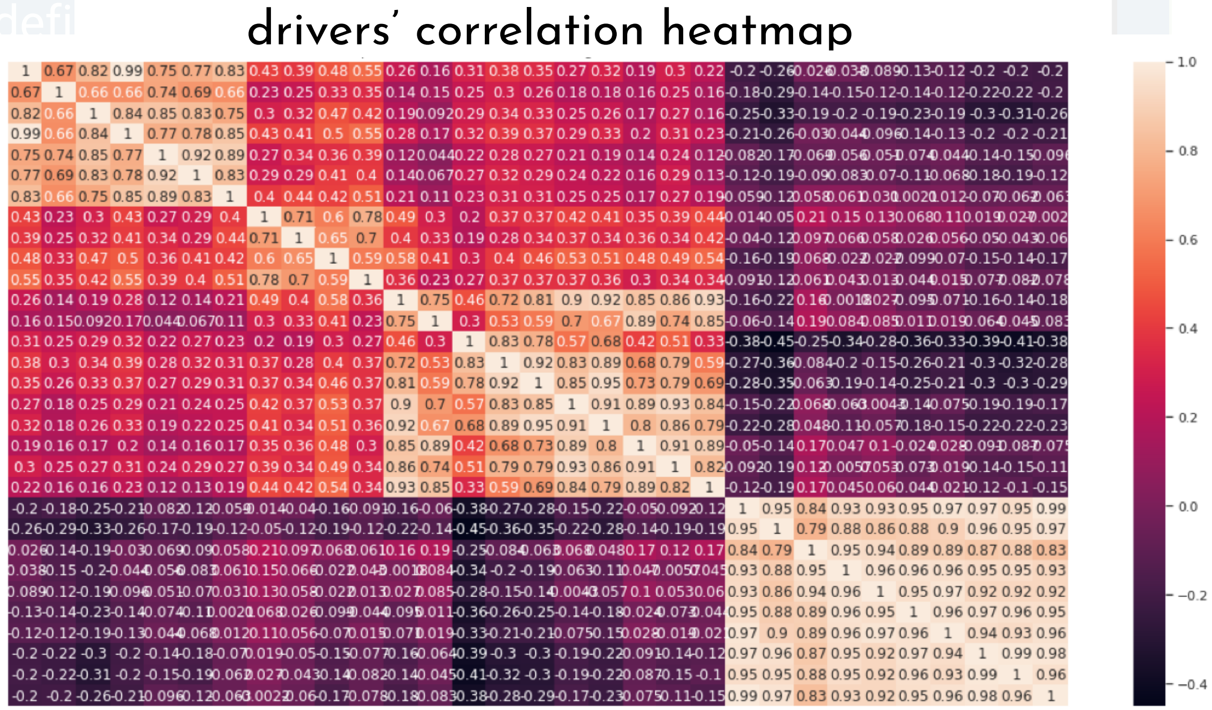

source: Copernicus European Drought Observatory

- Lack of local data on water deficits

  Satellite-derived information on crop status (e.g., FAPAR, NDVI)

- Spatially correlated drivers
- Drought heterogeneity over space
- Computational complexity

# UPSCALING CHALLENGES




- Lack of local data on water deficits
  Satellite-derived information on crop status (e.g., FAPAR, NDVI)
- Spatially correlated drivers
  Dimensionality reduction via PCA
- Drought heterogeneity over space
- Computational complexity

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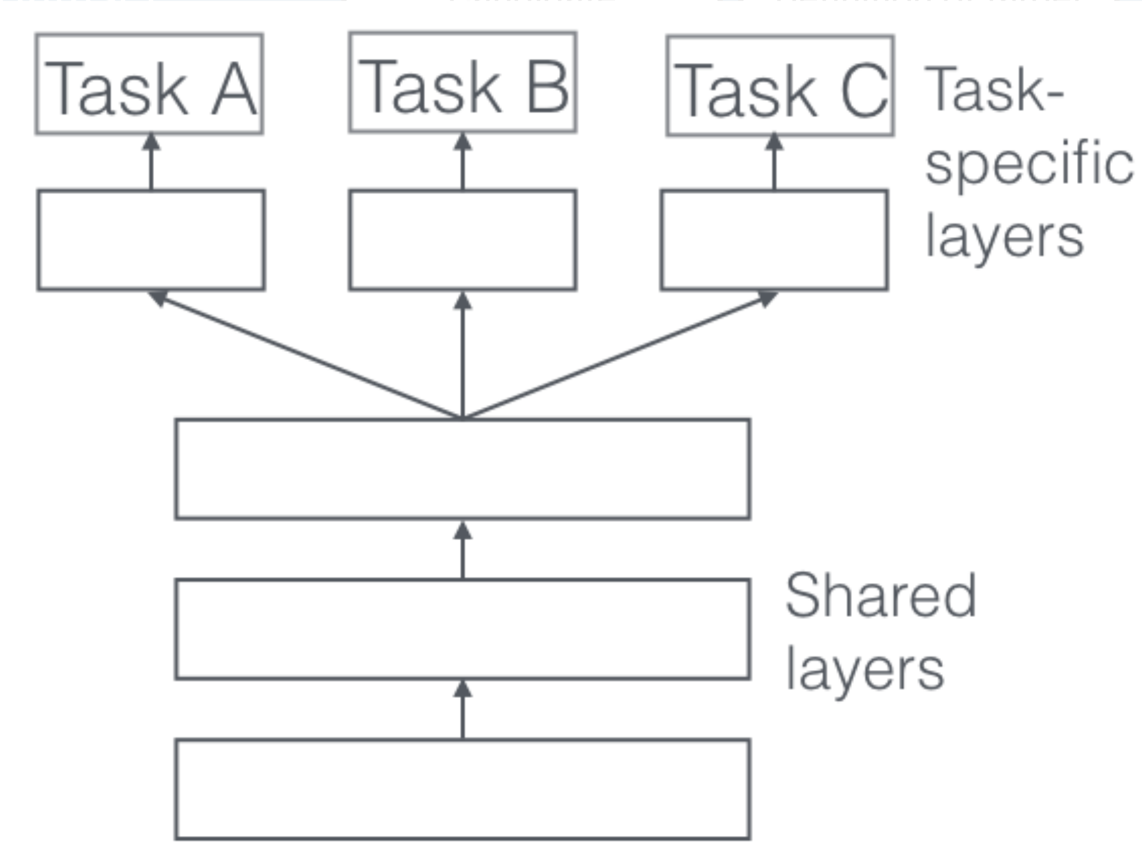
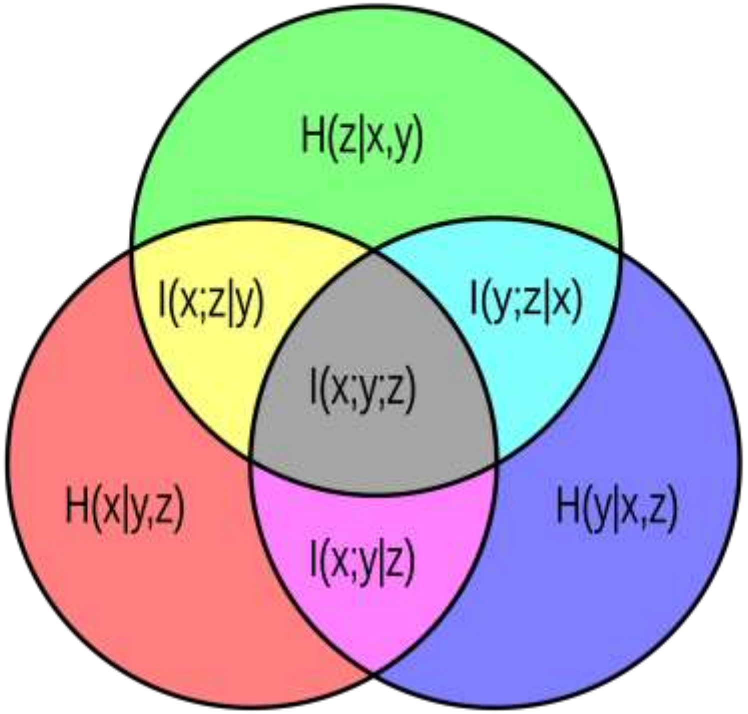



source: Ruder, 2017, arXiv:1706.05098

- Lack of local data on water deficits
  Satellite-derived information on crop status (e.g., FAPAR, NDVI)
- Spatially correlated drivers
  Dimensionality reduction via PCA
- Drought heterogeneity over space
  Multi-task Learning algorithms
- Computational complexity

# UPSCALING CHALLENGES

$$I(X,Y|Z) = I(X,Y) - I(X;Y,Z)$$




source: Beraha et al., 2019, IJCNN

- Lack of local data on water deficits
  Satellite-derived information on crop status (e.g., FAPAR, NDVI)
- Spatially correlated drivers
  Dimensionality reduction via PCA
- Drought heterogeneity over space
  Multi-task Learning algorithms
- Computational complexity
  Feature extraction via Conditional Mutual Information

# AN APPLICATION TO THE PO RIVER BASIN

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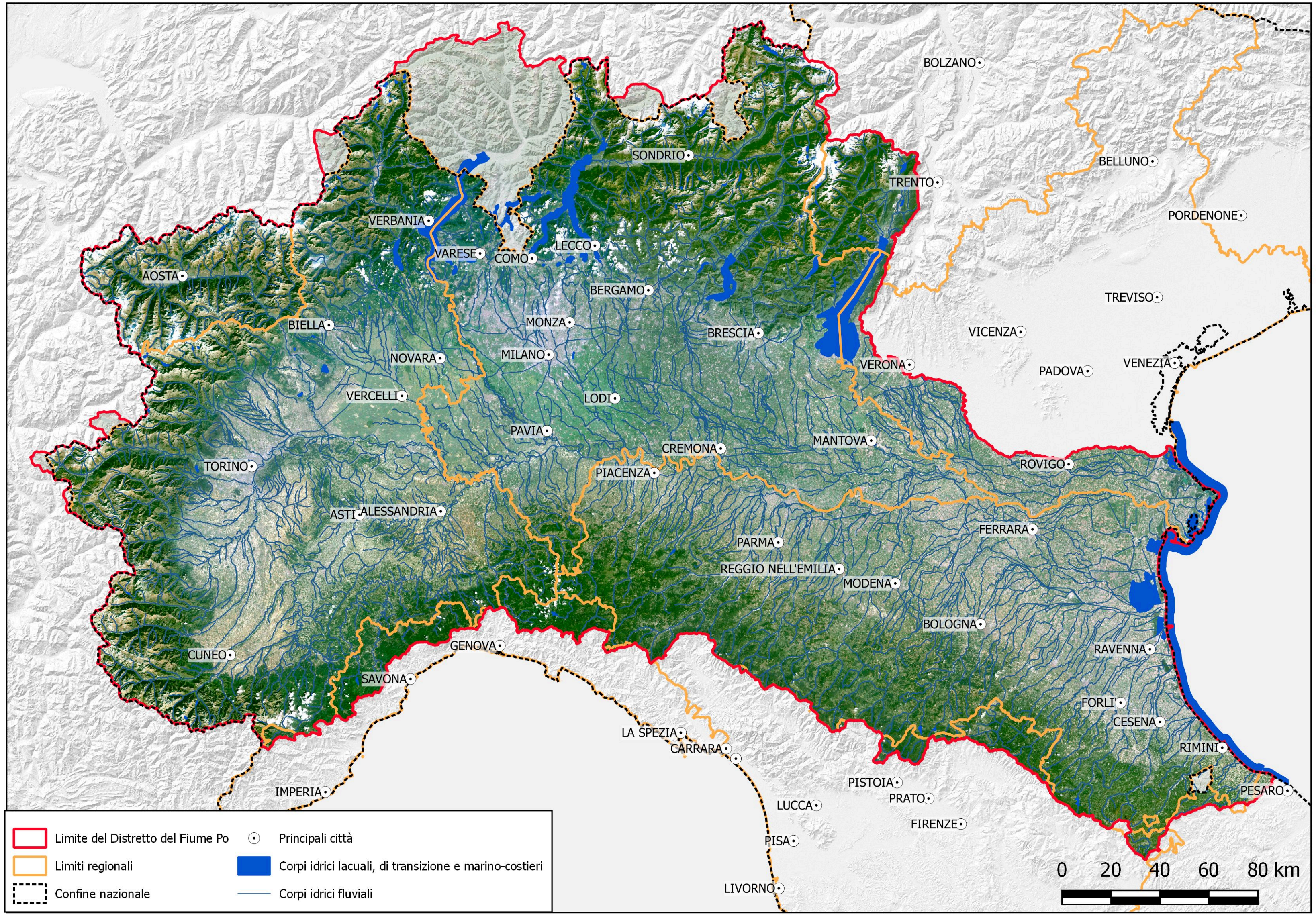



200 candidate predictors:

- Precipitation(b,t)
- Temperature(b,t)
- Snow Depth(b,t)
- Lake levels(b,t)

$b \in [B1,\ldots,B10]$

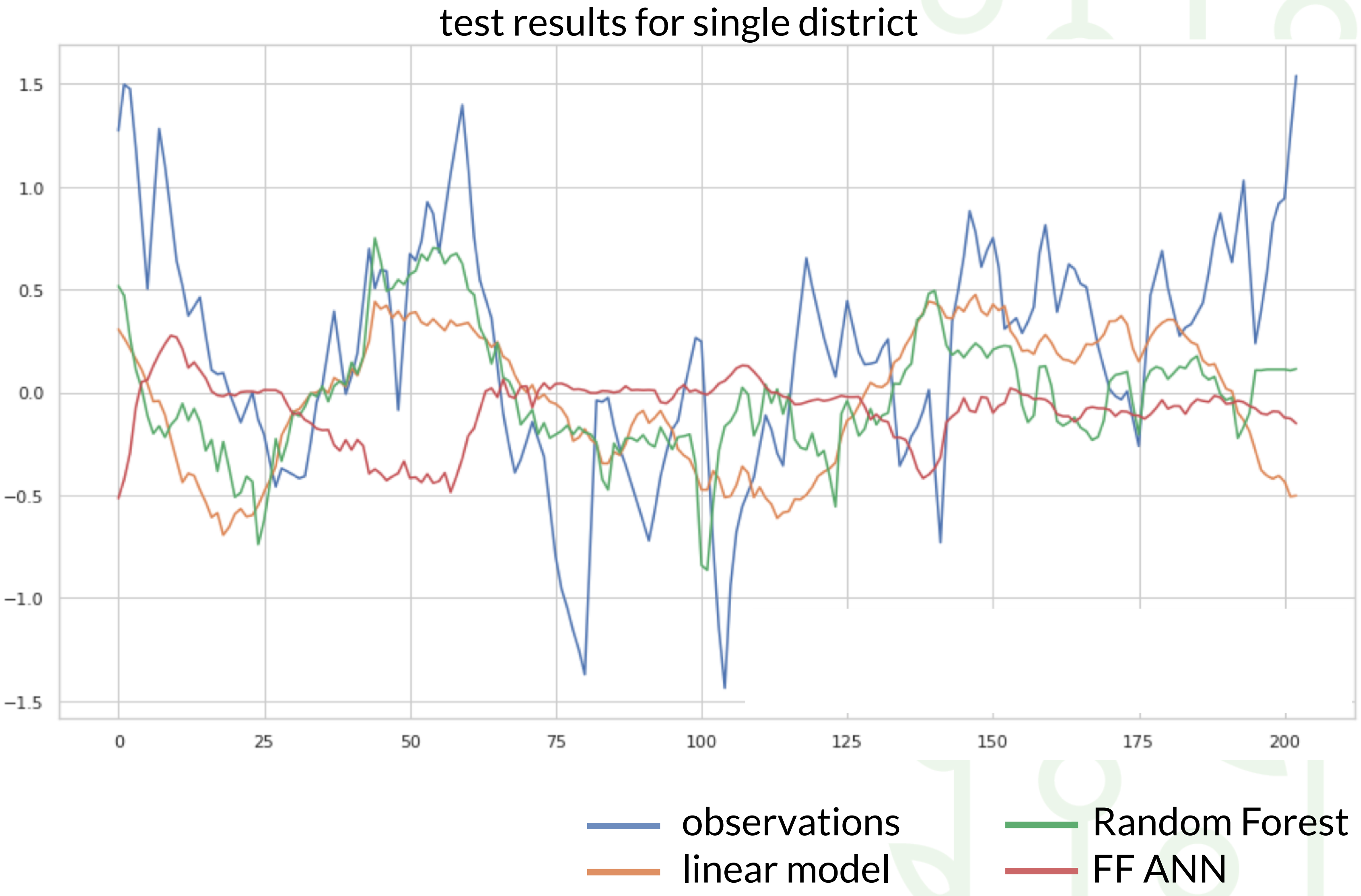
$t \in [4,8,12,16,24]$ weeks

source: Autorità di Bacino Distrettuale del Fiume Po

# PRELIMINARY RESULTS

SELECTED PREDICTORS:

- Snow 4w
- Lake levels 8w, 12w
- Precipitation 4w, 8w, 12w, 16w
- Temperature 4w, 8w



# TAKEAWAYS

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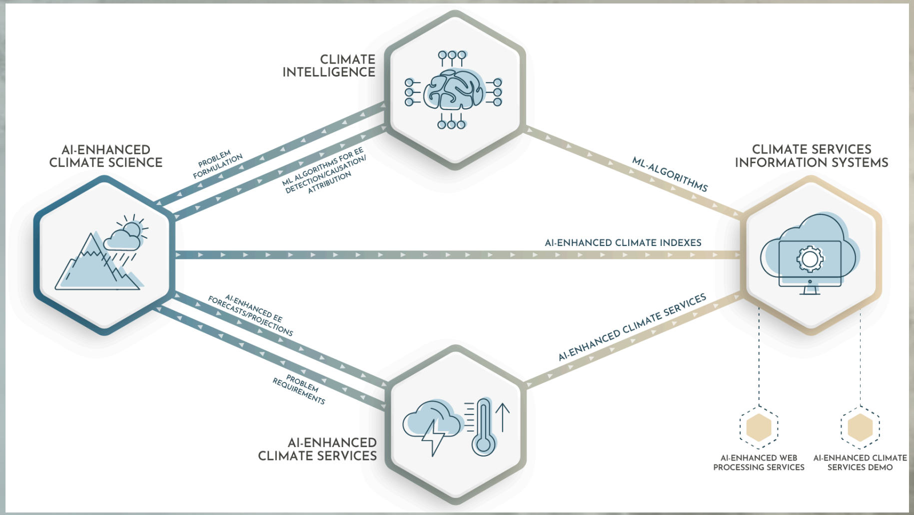


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