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Classification of Irrigation Systems at Field Level from Soil Moisture and Actual Evapotranspiration Time Series

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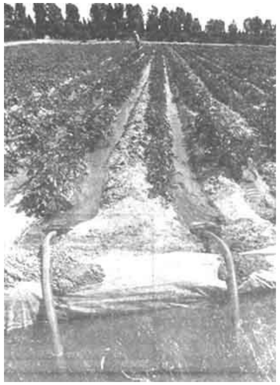
Introduction

Why obtaining classification maps of irrigation systems?
Mitigating water demands

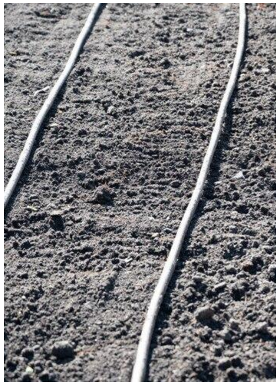
1. Replace the simplistic assumption of irrigation scenarios used in many Land Surface Models (LSM). -> reduce uncertainty.
2. Promote and supervise the shift towards more sustainable and efficient irrigation methods. -> optimize water use.

FLOOD

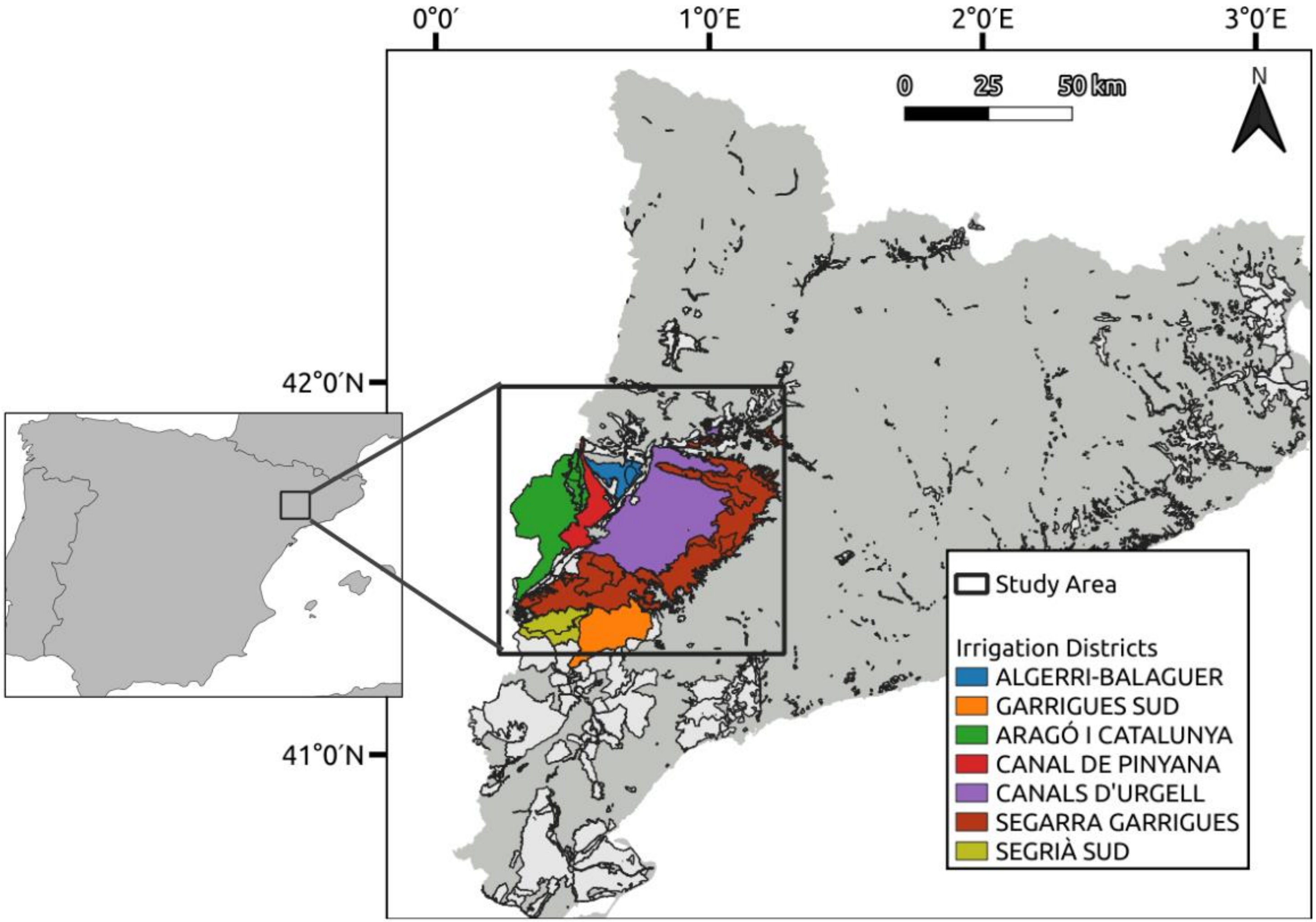


SPRINKLER

DRIP

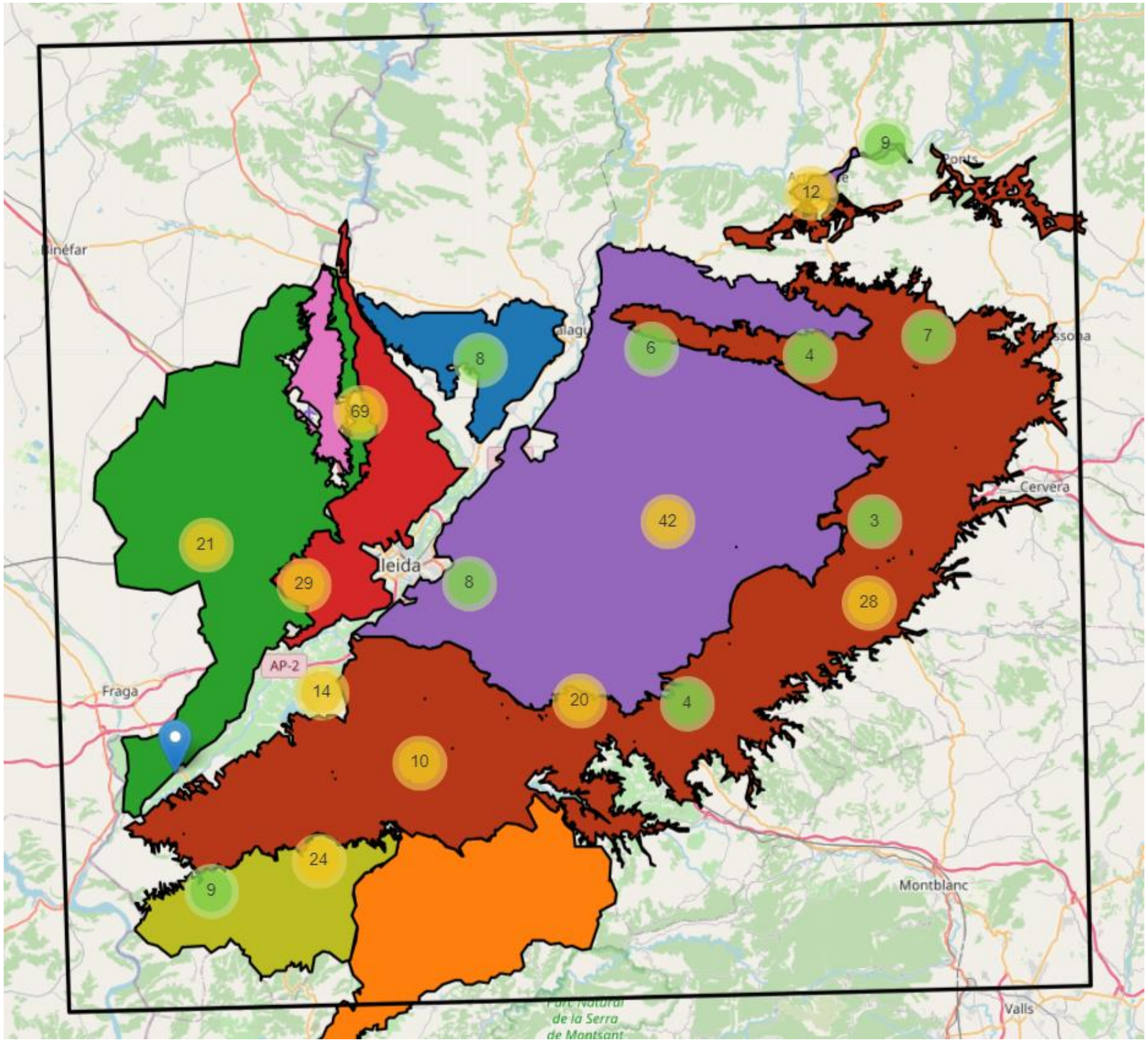


Study Area



0°0′
1°0′E
2°0′E
3°0′E
42°0′N
41°0′N
0
25
50 km
N
Study Area
Irrigation Districts
ALGERRI-BALAGUER
GARRIGUES SUD
ARAGÓ I CATALUNYA
CANAL DE PINYANA
CANALS D'URGELL
SEGARRA GARRIGUES
SEGRIÀ SUD

Field Campaign - Distribution of Fields



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Field Campaign - Number of Fields

IRRIGATION SYSTEM	CROP TYPE	Number of Fields			FIELD LEVEL	PIXEL LEVEL
		2018	2019	2020		
DRIP	FRUIT and NUT TREES	78	78	78	234	24201
	VINEYARD	12	12	12	36	4599
	OLIVE	11	11	11	33	3201
SPRINKLER	MAIZE	8	8	8	24	10950
	DOUBLE CROPS	55	56	56	167	43849
	ALFALFA	7	7	7	21	3777
FLOOD	WINTER CEREALS	9	9	9	27	444
	MAIZE	14	14	13	41	1322
	DOUBLE CROPS	32	33	33	98	5859
	ALFALFA	9	9	9	27	2733
	FRUIT and NUT TREES	18	18	18	54	1734
NOT IRRIGATED	WINTER CEREALS	40	36	40	116	27584
	FRUIT and NUT TREES	13	13	13	39	1578
	VINEYARD	7	7	7	21	867
	OLIVE	17	17	17	51	6231
TOTAL		330	328	331	989	138929

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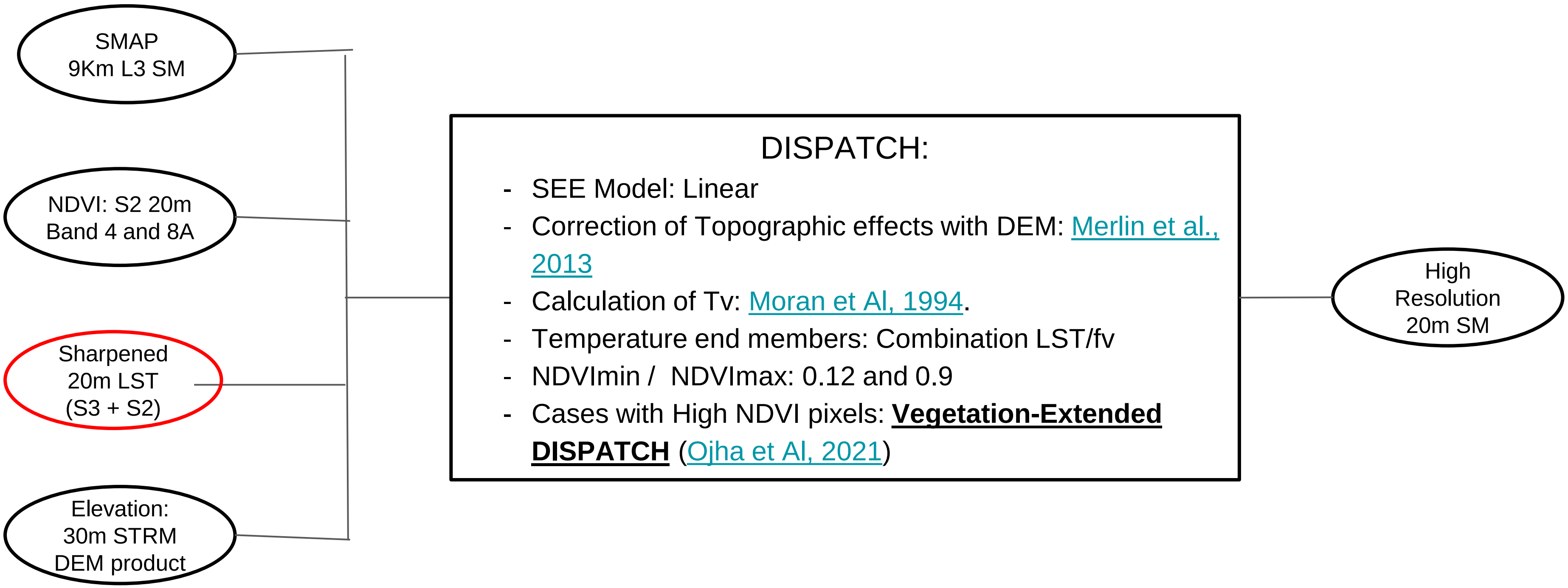
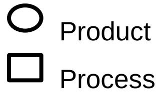
Input Dispatch SM



On going validation of the product with in-situ SM values in different sites in the area...

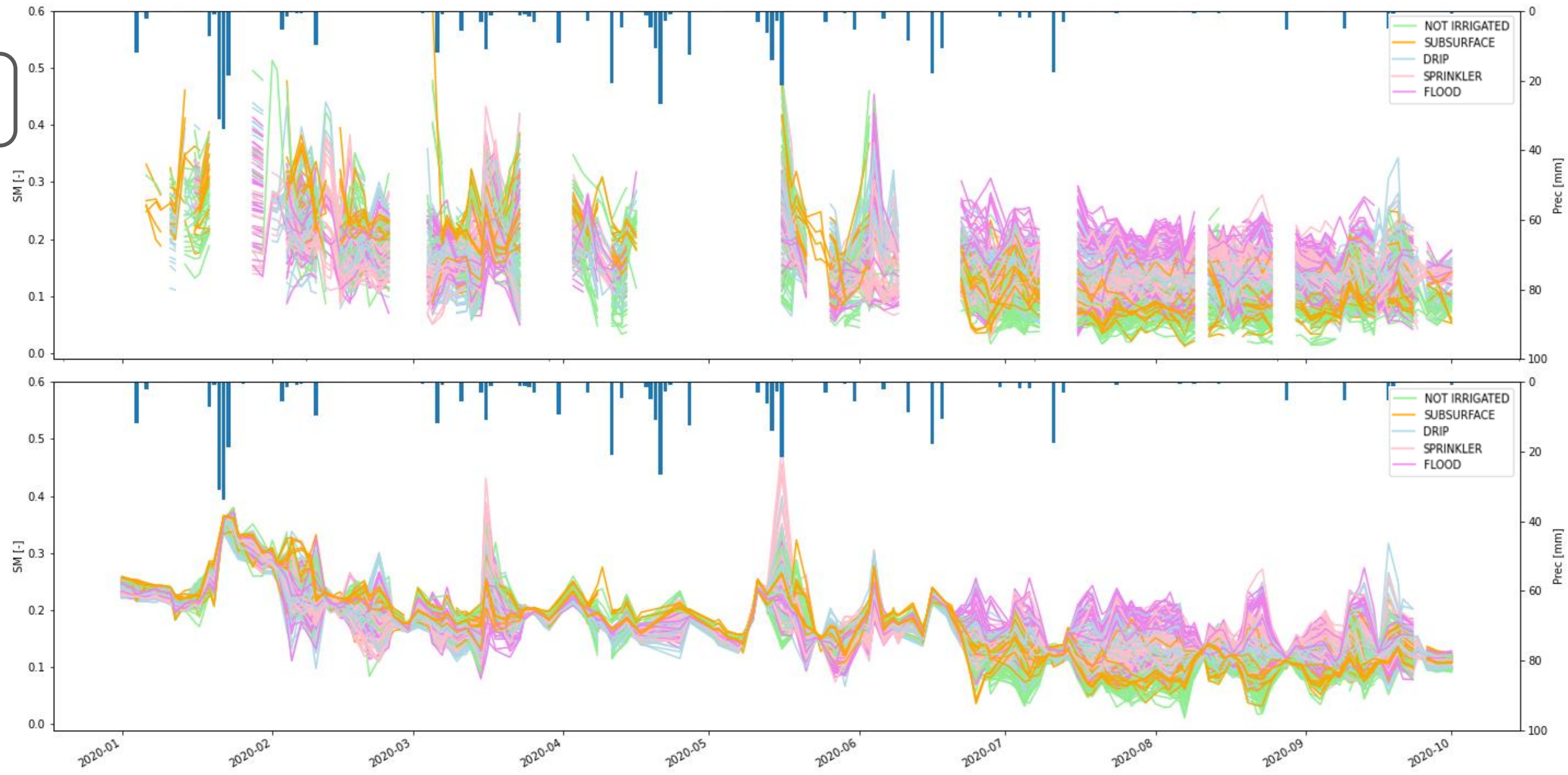


Input Dispatch SM

Dispatch 20m SM
With GAPS

SMAP 9 Km
SM

Dispatch
20m SM
Filled



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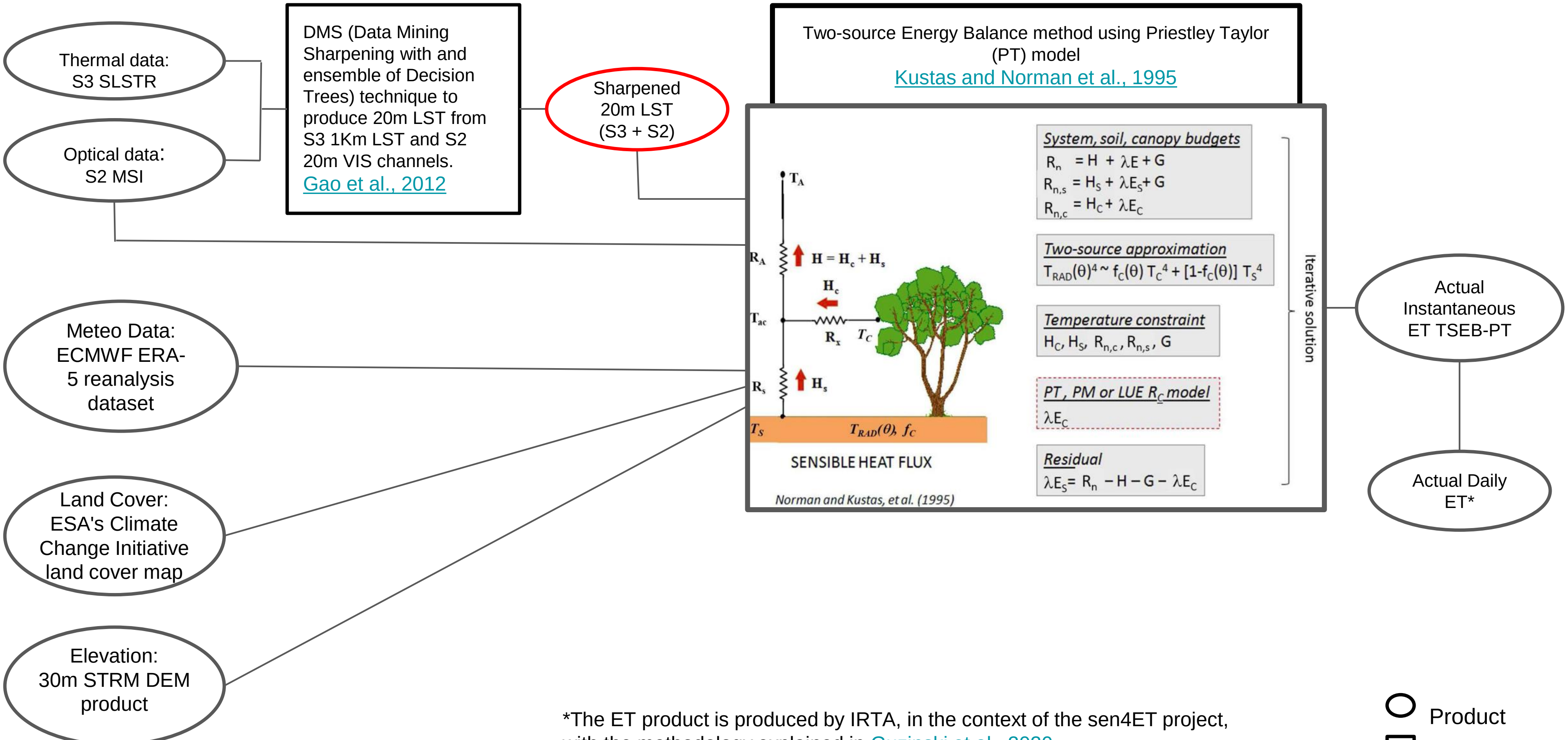
Input ETact



*The ET product is produced by IRTA, in the context of the sen4ET project, with the methodology explained in Guzinski et al., 2020.

Product
Process

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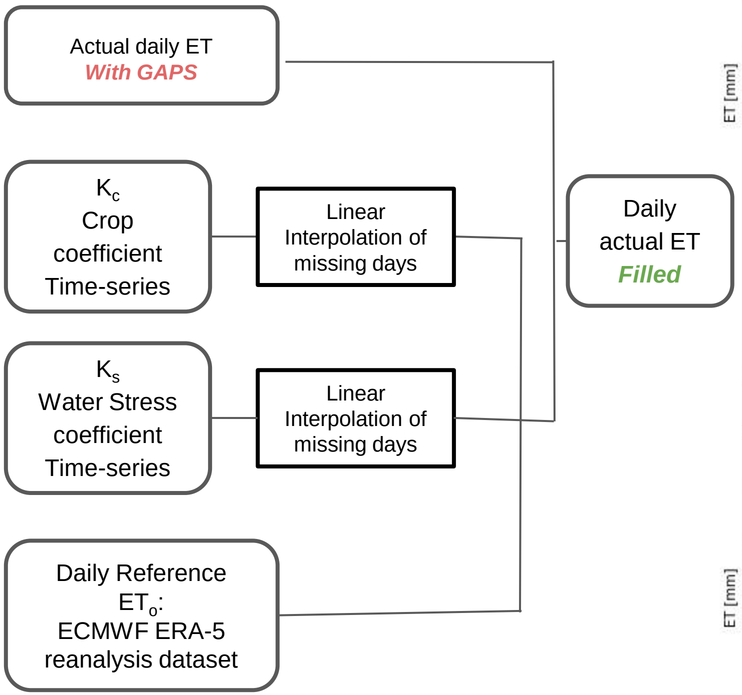
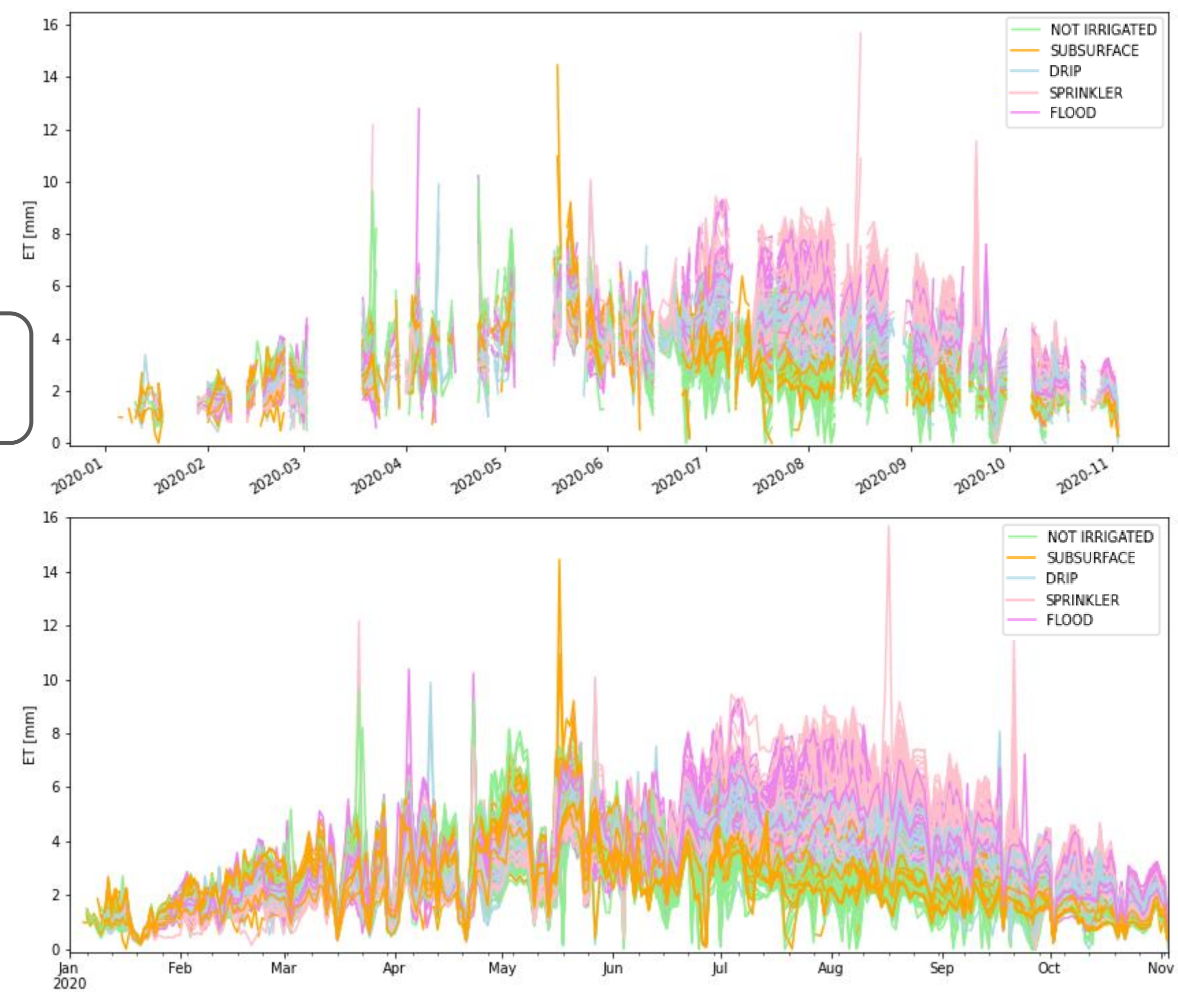
Input ETact



Actual daily ET
With GAPS
K_c
Crop coefficient Time-series
Linear Interpolation of missing days
K_s
Water Stress coefficient Time-series
Linear Interpolation of missing days
Daily Reference ET_o:
ECMWF ERA-5 reanalysis dataset
Daily actual ET
Filled



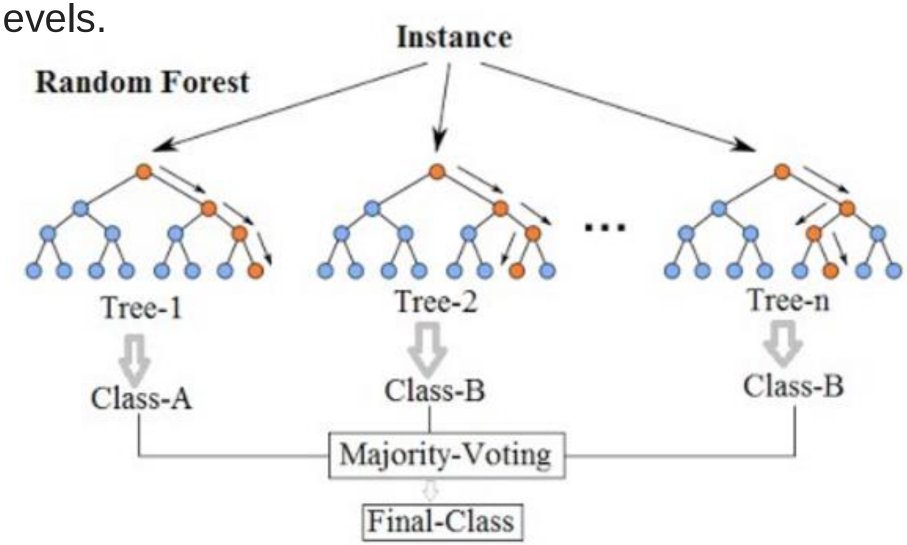
ET [mm]
NOT IRRIGATED
SUBSURFACE
DRIP
SPRINKLER
FLOOD
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
Jan 2020
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov

Time Series Forest

Time series forest is a random forest adapted to detect temporal features.

Selected because:

1. Widely used: used as a **benchmark** to test more advanced models.
2. **Computationally efficient**.
3. **It avoids overfitting** (using strategies like bootstrap and random interval selection).
4. **Easy to inspect results**: Feature extraction = Interpretability.
5. **Easy to quantify results**: Confidence levels.



Source:
Deng, H., Runger, G., Tuv, E., & Vladimir, M. (2013). A time series forest for classification and feature extraction. Information Sciences, 239, 142-153.

Rocket (RandOm Convolutional KErnel Transform)

It is a kernel-approach classification inspired by convolutional neural network. It has only a single layer of convolution (NO learning of the weights) but with a large number of kernels, with their parameters randomly initialized (length, dilation, padding, weights and biases).

Selected because:

1. **State-of-the-art accuracy**
2. **Low computational requirements**.
3. Only one Hyperparameters (number of kernels).

	Rocket
length	$\{7, 9, 11\}$
weights	$\mathcal{N}(0, 1)$
bias	$\mathcal{U}(-1, 1)$
dilation	random
padding	random

Source:
Dempster, A., Petitjean, F., & Webb, G. I. (2020). ROCKET: exceptionally fast and accurate time series classification using random convolutional kernels. Data Mining and Knowledge Discovery, 34(5), 1454-1495.

ResNET

It is a Deep Neural Network.

Selected because:

- **State-of-the-art accuracy**
- **Best performing** in tests with different number of databases from different disciplines.
- Can retrieve very complex features, it works very well with **large Datasets**.

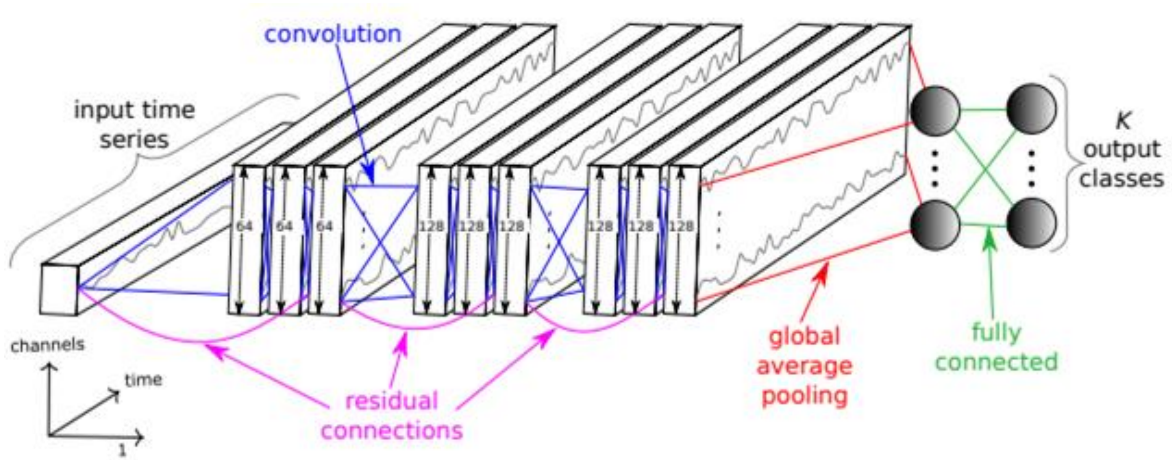


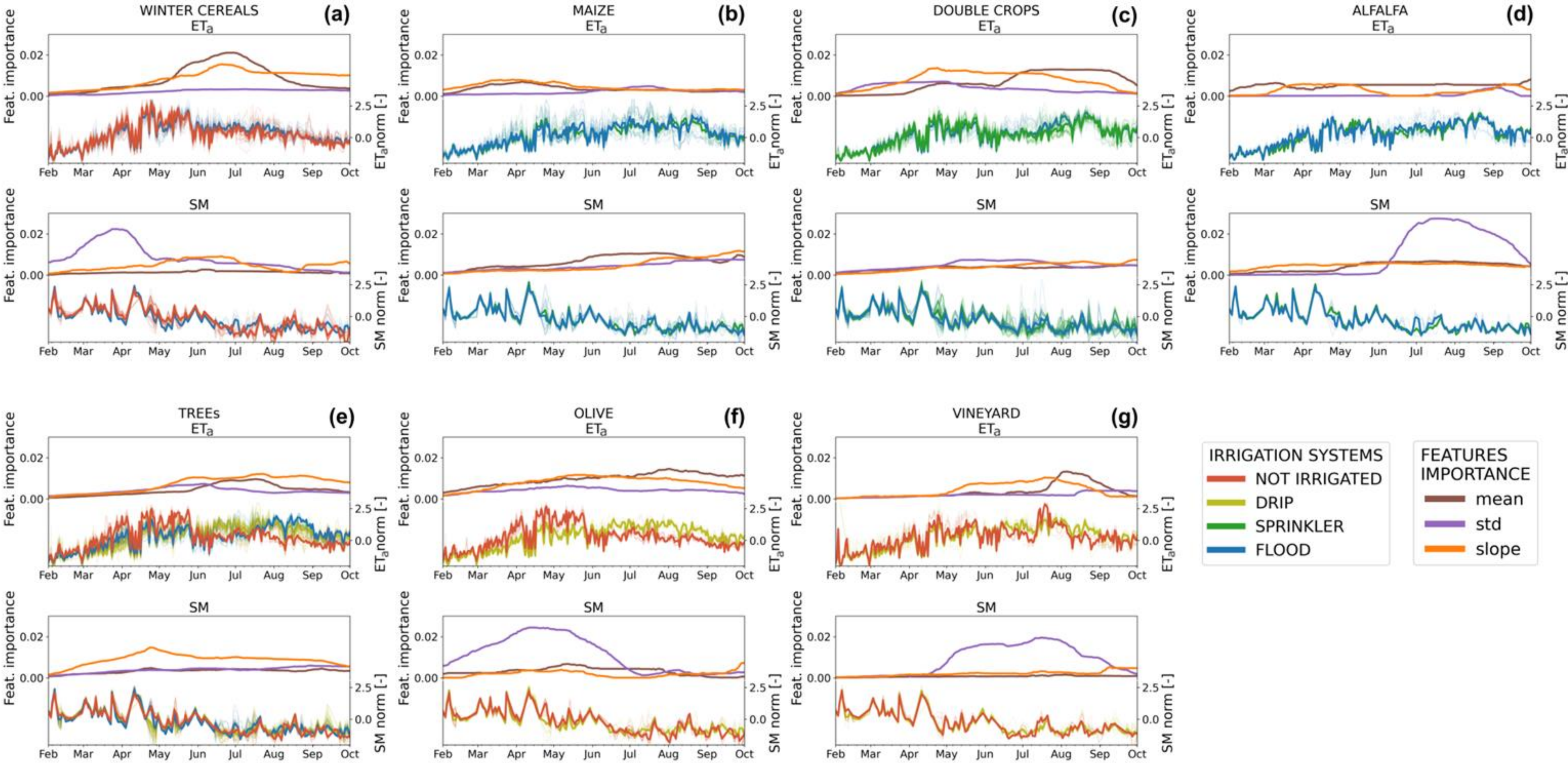
Fig. 6: The Residual Network's architecture for time series classification.

Source:
Wang Z, Yan W, Oates T (2017b) Time series classification from scratch with deep neural networks: A strong baseline. In: International Joint Conference on Neural Networks, pp 1578–1585.

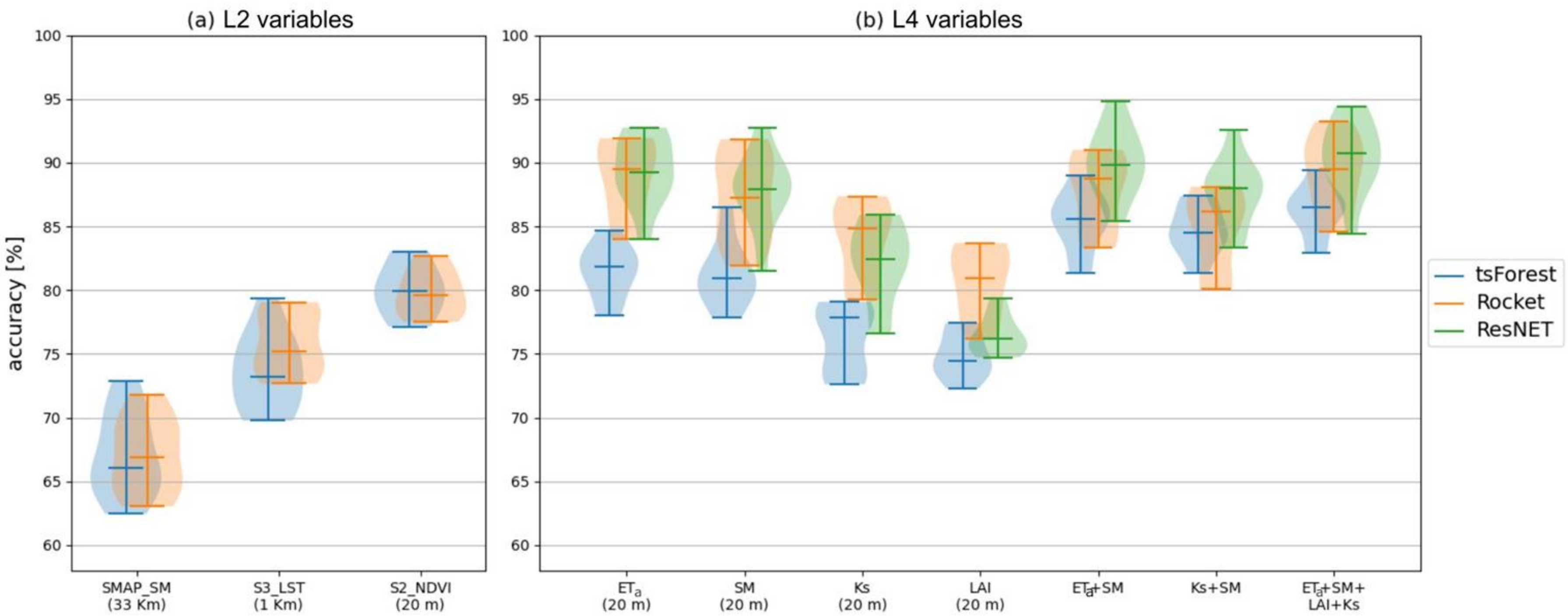
Results I

Variables	Crop types							RESULTS	
	Winter Cereals	Maize	Double Crops	Alfalfa	Fruit & Nut Trees	Olives	Vineyards	Aggregated Models	General Model
ET_a-TSEB	81.25%	48.82%	91.67%	72.00%	74.88%	**74.33%**	96.19%	78.15%	79.33%
ET_a-TSEB cropped	73.37%	58.82%	89.58%	70.00%	72.33%	70.00%	94.76%	75.41%	-
SM Dispatch	88.75%	**76.47%**	91.67%	66.67%	73.18%	73.33%	80.95%	78.36%	74.25%
SM Dispatch cropped	82.88%	70.00%	91.67%	66.67%	75.58%	64.67%	80.95%	78.26%	-
ET_a+SM	**90.62%**	70.00%	**93.75%**	**73.33%**	**81.71%**	69.67%	96.67%	**83.39%**	**81.89%**
ET_a+SM cropped	86.88%	68.82%	91.67%	66.67%	78.45%	65.33%	**100.00%**	81.47%	-

Results II

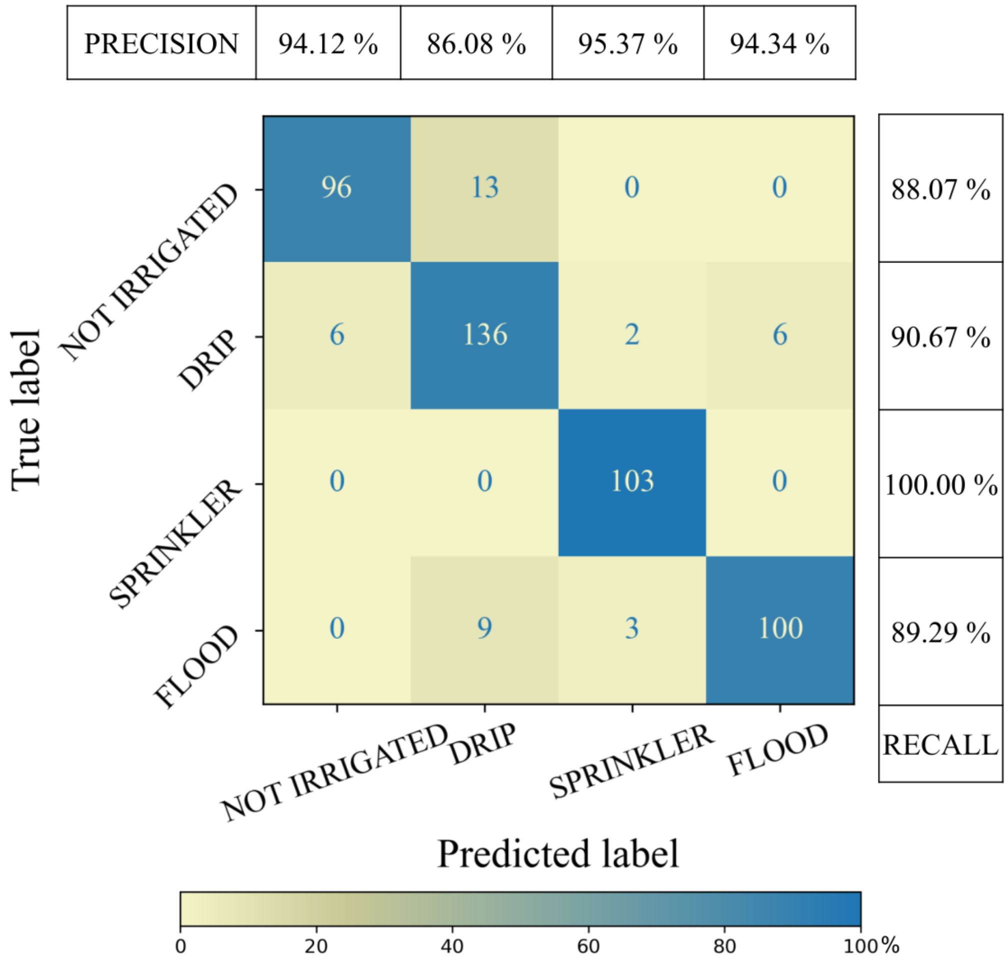

WINTER CEREALS
(a)
MAIZE
(b)
DOUBLE CROPS
(c)
ALFALFA
(d)
TREEs
(e)
OLIVE
(f)
VINEYARD
(g)
ETa
SM
Feat. importance
ETa norm [-]
SM norm [-]
0.02
0.00
2.5
0.0
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
IRRIGATION SYSTEMS
NOT IRRIGATED
DRIP
SPRINKLER
FLOOD
FEATURES IMPORTANCE
mean
std
slope

Results III



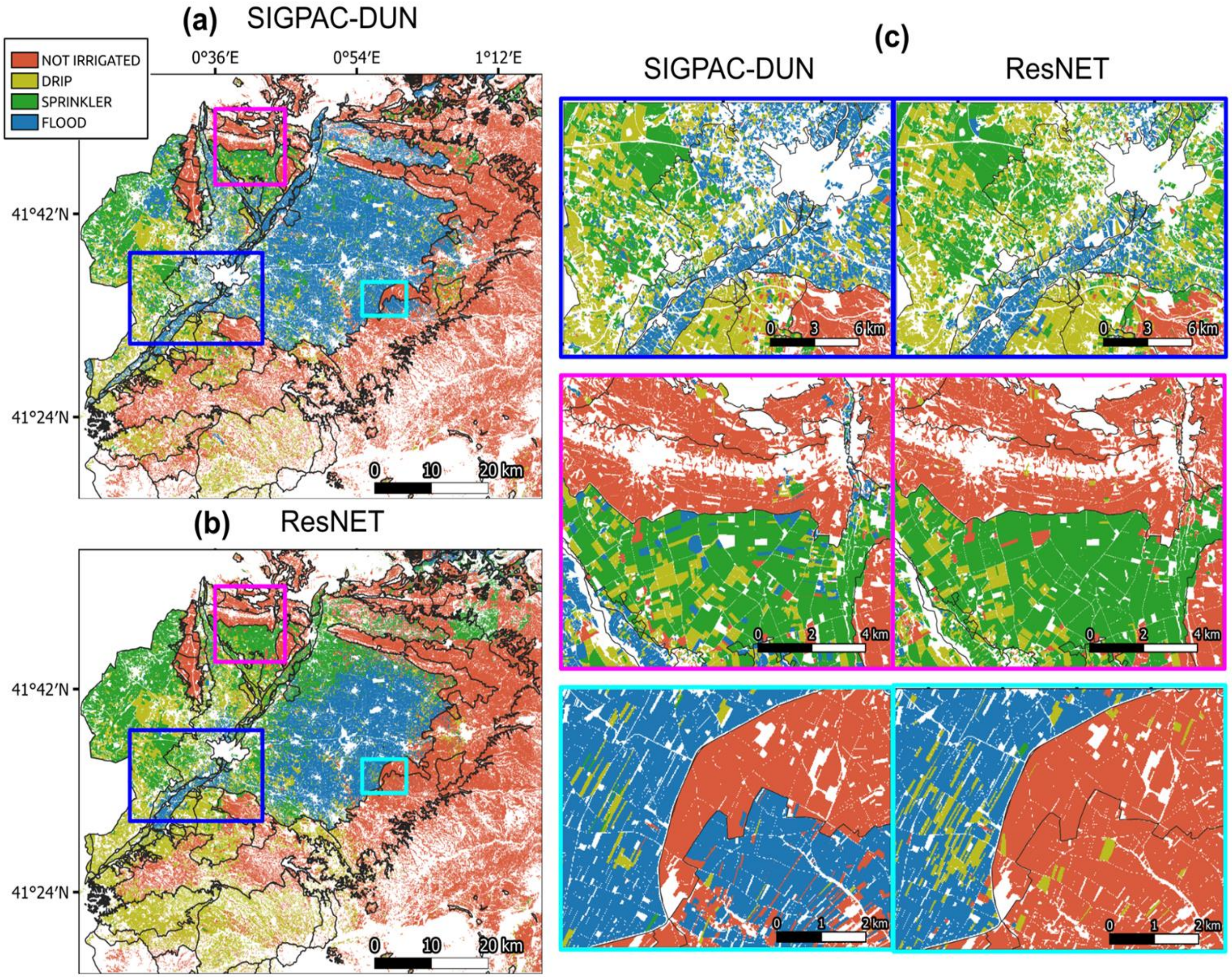
METRICS (%)	MODELS		
	tsForest	ROCKET	ResNET
Accuracy	81.59 +/- 2.14	82.45 +/- 1.62	**86.59** +/- 2.79
Precision	81.73 +/- 1.90	83.28 +/- 1.62	**87.39** +/- 2.26
Recall	81.59 +/- 2.14	82.45 +/- 1.62	**86.59** +/- 2.79
Kappa	73.77 +/- 2.84	74.64 +/- 2.33	**81.30** +/- 3.61

Results IV



	MODELS		
METRICS (%)	tsForest	ROCKET	ResNET
Accuracy	85.29 ± 2.41	87.56 ± 2.95	**90.10** ± 2.70
Average Precision	85.43 ± 2.53	88.80 ± 3.12	**90.33** ± 2.78
Average Recall	84.76 ± 2.51	86.81 ± 3.17	**90.02** ± 2.76

Comparison: SIGPAC 2021



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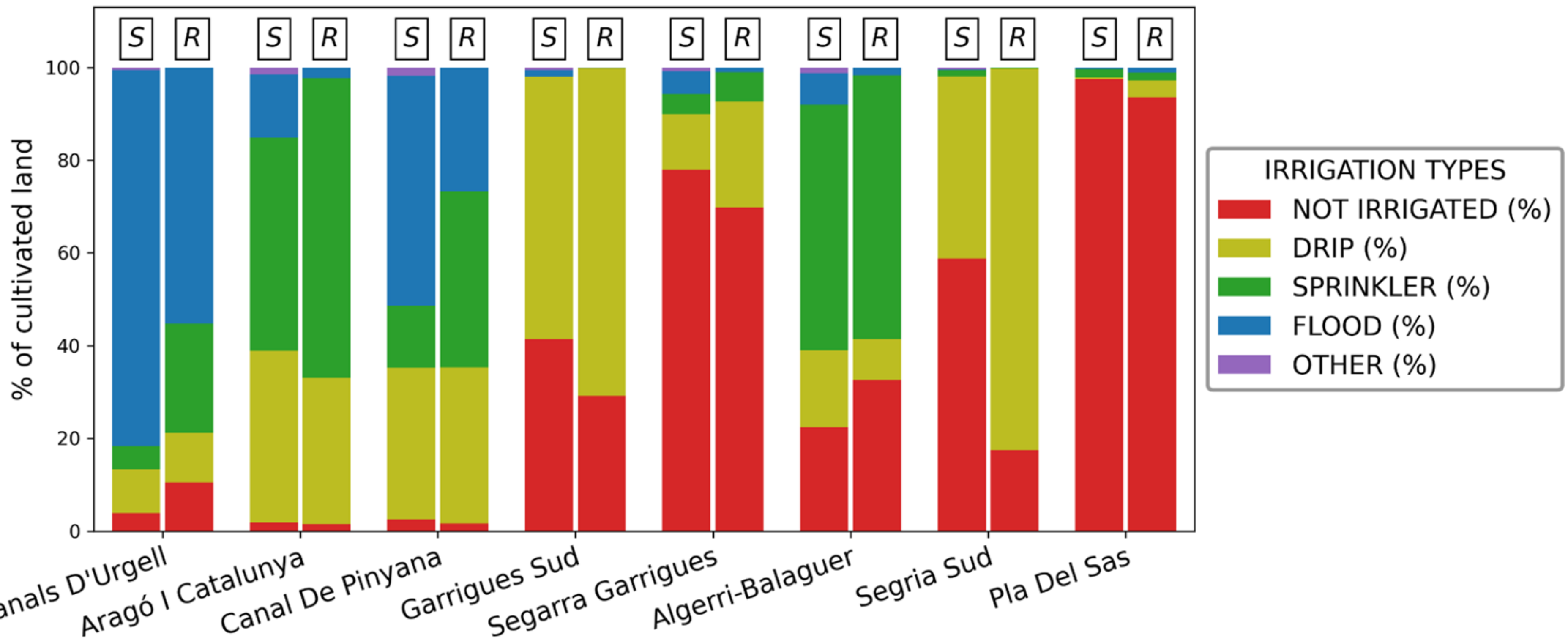
Comparison: SIGPAC 2021



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Comparison: Literature data (partial)

Irrigation District	IRR systems	Literature[1]	SIGPAC-DUN	ResNET
Canals d'Urgell	FLOOD	90 %	81 %	55 %
	DRIP	4 %	10 %	11 %
	SPRINKLER	2 %	5 %	24 %
	NOT IRRIGATED	0 %	4 %	11 %
Canal de Pinyana	FLOOD	79 %	50 %	27 %
	DRIP	10 %	33 %	34 %
	SPRINKLER	10 %	13 %	38 %
	NOT IRRIGATED	0 %	3 %	2 %
Canal d'Aragó i Catalunya	FLOOD	18 %	14 %	2 %
	DRIP	28 %	37 %	32 %
	SPRINKLER	54 %	46 %	65 %
	NOT IRRIGATED	0 %	2 %	1 %

[1] Literature are administrative data taken from [1] for "Canal d'Aragó i Catalunya" and from [2] for "Canals d'Urgell" and "Canal de Pinyana".

[1] J. Dari, L. Brocca, P. Quintana-Seguí, M. J. Escorihuela, V. Stefan, and R. Morbidelli, "Exploiting high-resolution remote sensing soil moisture to estimate irrigation water amounts over a mediterranean region," *Remote Sensing*, vol. 12, p. 2593, 8 2020.

[2] L. Cots Rubió, J. Monserrat Viscarri, and J. Barragán Fernández, "El regadiu a lleida. resultats de diverses avaluacions a la zona regable dels canals d'urgell (lleida)," *Quaderns agraris, 2014, núm. 36, p. 23-50*, 2014.

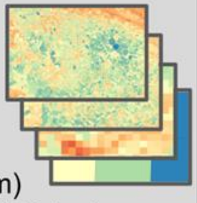
Summary: Framework

a) Input Data → **b) Processing** → **c) Classification** → **d) Post-processing**

a) Input Data

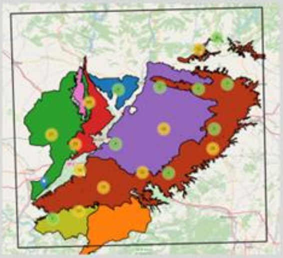
1. **HYDROLOGICAL VARIABLES**

Level 4 Data:
- ET (20m)
- SM (20m)
- LAI (20m)
- K_s (20m)



Level 2 Data:
- NDVI (20 m)
- SMAP SM (33 km)
- LST (1 km)

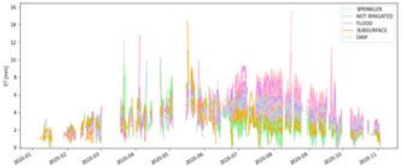
2. **GROUND TRUTH IRRIGATION SYSTEMS DATASET**



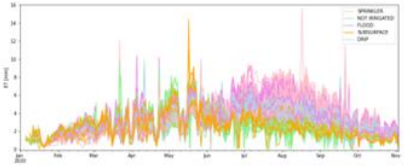
b) Processing

3. **GROUND TRUTH FIELD SHAPE EXTRACTION**

4. **ANNUAL TIME-SERIES EXTRACTION**



5. **GAP FILLING**



c) Classification

6. **AI MODELS SELECTION:**
- Time series Forest
- ROCKET
- ResNET (Deep Learning)

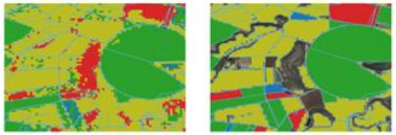
7. **TRAIN + TEST DATASET**
> 300 fields collected for 3 different years (total of around 900 time-series samples).

8. **PREDICTION**
Classification of time-series to create annual Irrigation types maps for the entire study area.

9. **OUTPUTS**
- Not Irrigated
- Drip
- Sprinkler
- Flood

d) Post-processing

10. **LABEL AGGREGATION**
All pixels contained in the same field get same irrigation type (from majority of prediction). One field = One irrigation type.



11. **TEMPORAL POST-PROCESSING**
Comparison of all years: correct unrealistic irrigation types when a single year is different.

Thank you!

Any questions?