2019 IEEE INTERNATIONAL WORKSHOP ON METROLOGY FOR AGRICULTURE AND FORESTRY

PORTICI, ITALY
OCTOBER 24-26, **2019**

PROCEEDINGS

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Saturday, October 26

Special Session - Advanced ground-based technologies for assessing vadose zone properties and processes

Room: Chinese Hall - Sala Cinese, Royal Palace of Portici
Chairs: *Giorgio Cassiani, Università di Padova, Italy*
Paolo Castiglione, Metergroup Inc. and Washington State Uni. USA

Special Session - Remote and proximal sensing metrics for the characterization of agricultural and forestry systems - PART I

Room: White Hall - Sala Bianca, Royal Palace of Portici
Chairs: *Guido D'Urso, University of Naples, Italy*
Francesco Vuolo, BOKU, Austria

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Combining satellite data and Machine Learning techniques for irrigation Decision Support Systems

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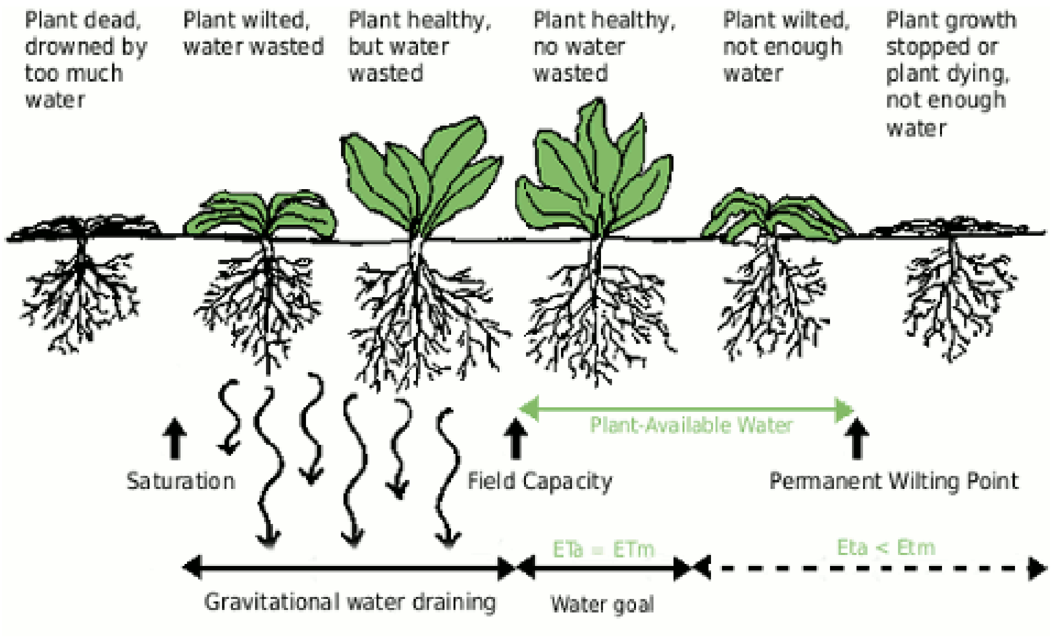
Irrigation water management

Inefficient irrigation practices are among the primary sources of freshwater waste.

Irrigation scheduling may be inconsistent with the actual crop needs.



(image source: theorangegardener.org)

Decision Support Systems

Managing irrigation systems is not straightforward.

Decision Support Systems (DSS) could be powerful tools helping authorities and stakeholders.

Benefits include water waste reduction, optimal crop growth and hazard mitigation.

Soil Moisture: a key variable

Knowing the current and expected soil moisture (SM) is fundamental in developing an efficient irrigation DSS.

Direct SM measurement

- high accuracy
- low representiveness over extended areas

Remote SM measurement

- worldwide coverage
- easily accessible
- less accurate than probes

(image source: sentinel.esa.int)

Soil Water Index

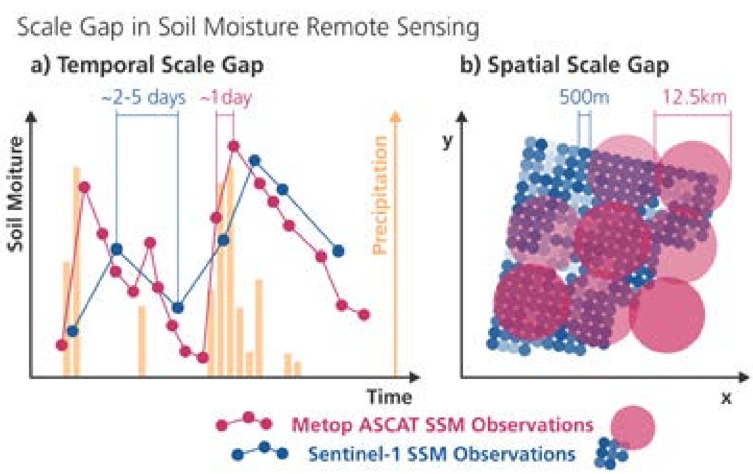
In this research SM is described through the **Soil Water Index** (SWI), available on *Copernicus Global Land Service,* providing an estimate the degree of saturation at various depths in the soil starting from satellite surface SM measurements.

Sentinel-1/C-band surface SM
(high spatial resolution, low frequency)

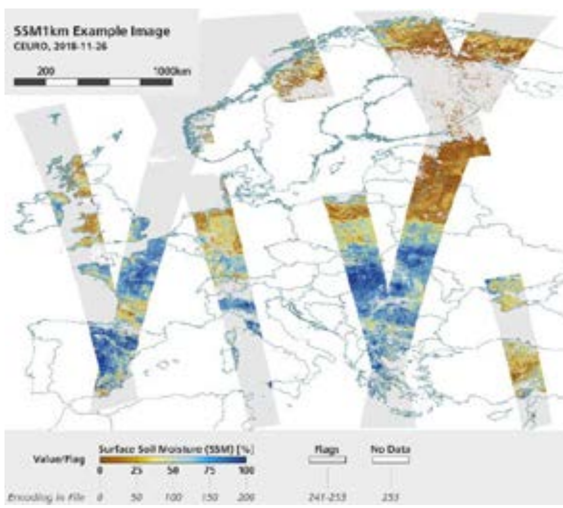
+

MetOP/ASCAT surface SM
(low spatial resolution, high frequency)

New product released in April 2019 with 1-km resolution and daily frequency



(image source: Bauer-Marschallinger et al., 2018)



(image source: land.copernicus.eu)

Reference: Bauer-Marschallinger, et al. (2018). Soil moisture from fusion of scatterometer and SAR: closing the scale gap with temporal filtering. Remote Sensing, 10(7), 1030.

Soil Moisture forecast

The SWI evolution is forecasted through a data-driven approach and two techniques are tested: an **Artificial Neural Network** (ANN) and the **ANFIS** model.

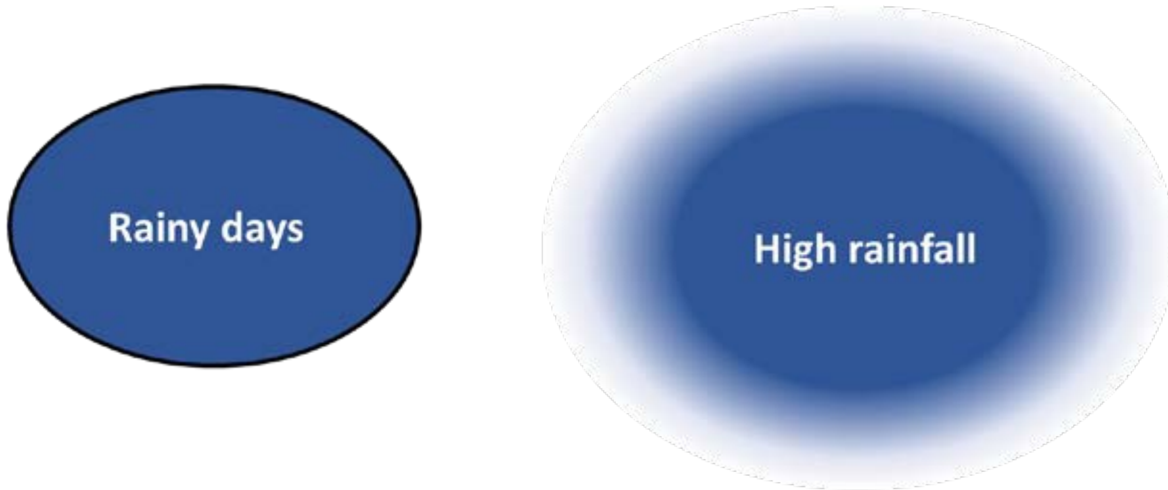
Meteorological data and past SWI observations are used as inputs.

Study area

Agricultural fields in the Veneto region (Italy), between Venice and Padua.
Irrigation here is managed through the help of a wide network of channels.

ANFIS: what is it?

ANFIS (Adaptive Network-based Fuzzy Inference System) is a particular type of artificial neural network that performs a **fuzzy logic** *if-then* inference.



Crisp set
element ∈ *set* → 1
element ∉ *set* → 0

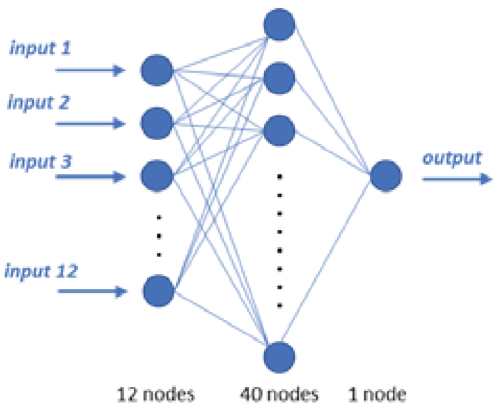
Fuzzy set
element ∈ *set* → (0,1]
element ∉ *set* → 0

In this research, 3 membership functions have been defined for each input:

$$f_{\mathrm{memb}}(x;\mu,\sigma,\nu,\alpha) = \exp\left[-\frac{|x-\mu|^{\nu}}{\sigma^2}\,\frac{1}{1+e^{-\alpha x}}\right]$$

Models structure and inputs

ANN

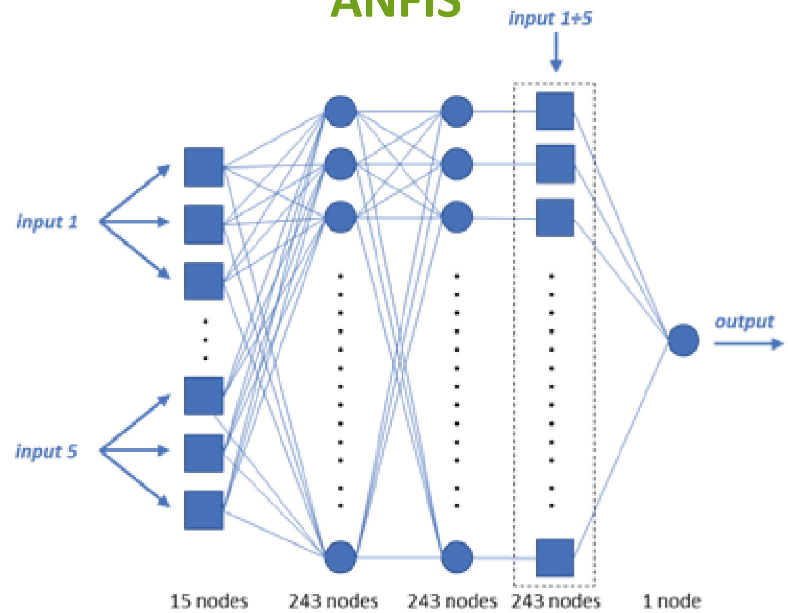


$$R_t,\ R_{t-1},\ R_{t-2},\ R_{t-3},\ R_{t-4},$$
$$T_t,\ \overline{T}_{t-3,t-1},$$
$$RH_t,\ \overline{RH}_{t-3,t-1},$$
$$ws_t,\ \overline{ws}_{t-3,t-1},$$
$$SWI_{t-4}$$

Symbol	Description
R_t	Rainfall on day t
T_t	Mean temperature on day t[a]
RH_t	Mean relative humidity on day t
ws_t	Mean wind speed on day t
SWI_t	Soil Water Index on day t
$\overline{X}_{t_1,t_2}$	Mean of variable X over days $t_1 \div t_2$
$X^{cum}_{t_1,t_2}$	Cumulative value of variable X over days $t_1 \div t_2$

[a] The mean temperature T_t has been computed as the arithmetic mean of the minimum and maximum daily temperature.

ANFIS



$$R^{cum}_{t-4,t},\quad \overline{T}_{t-4,t-1},\quad \overline{RH}_{t-4,t-1},\quad \overline{ws}_{t-4,t-1},\quad SWI_{t-4}$$

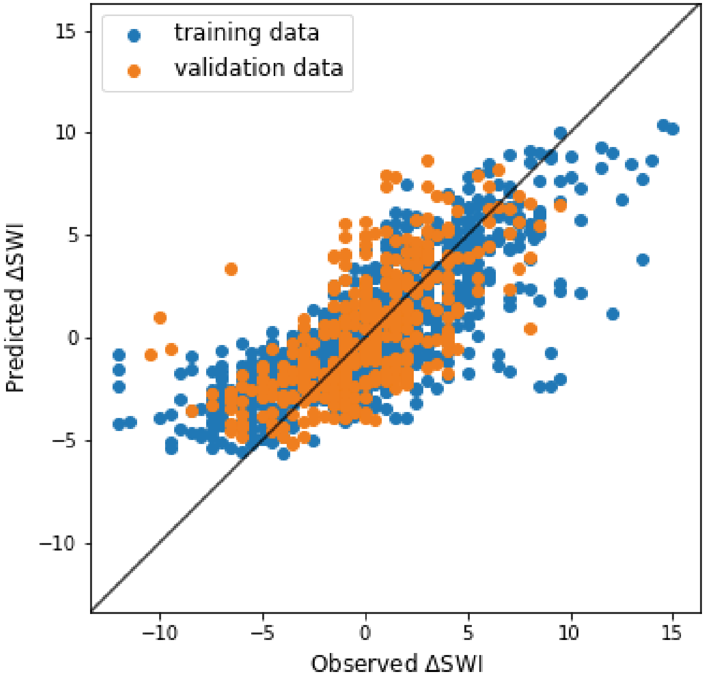
Target/Output: $\Delta SWI_{t\text{-}4,t}$

2015÷2017 → calibration

2018 → validation

Results

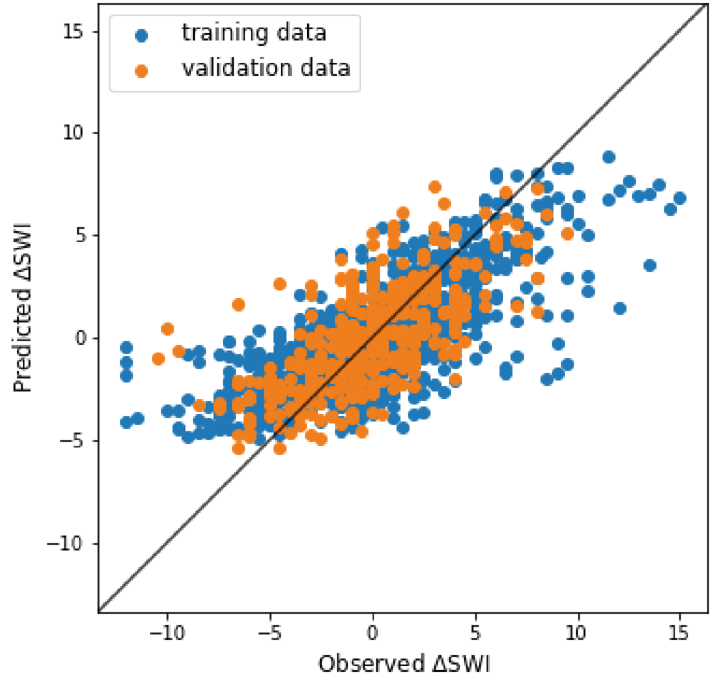
ANN



Training *NSE* = 0.599
Training *RMSE* = 2.55 %

Validation *NSE* = 0.371
Validation *RMSE* = 2.65 %

ANFIS



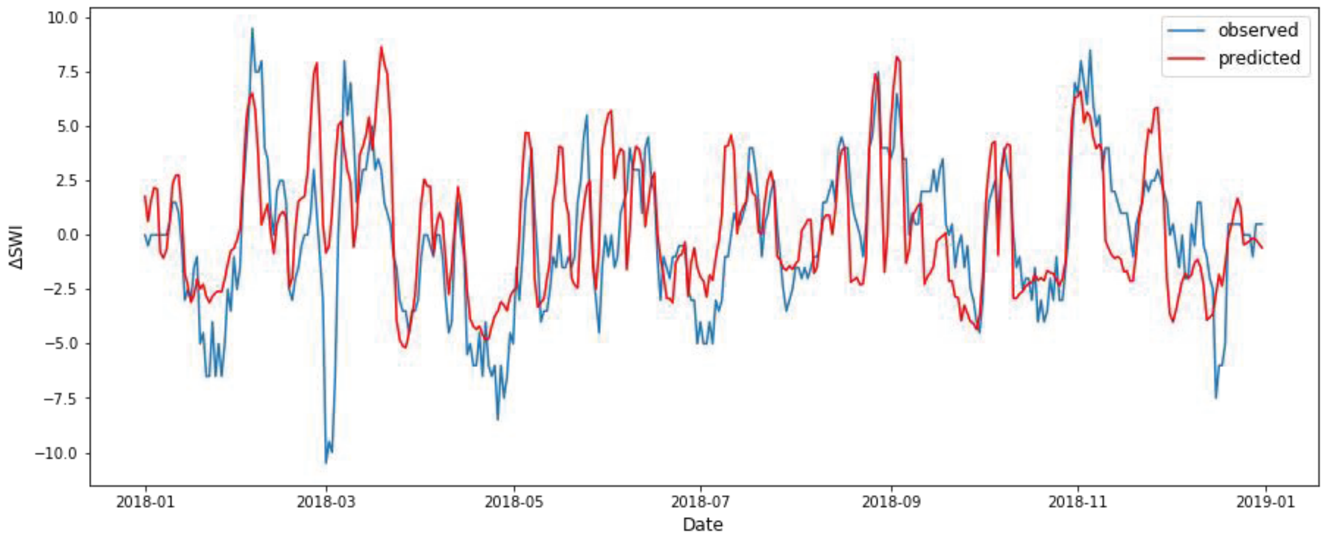
Training *NSE* = 0.553
Training *RMSE* = 2.70 %

Validation *NSE* = 0.460
Validation *RMSE* = 2.46 %

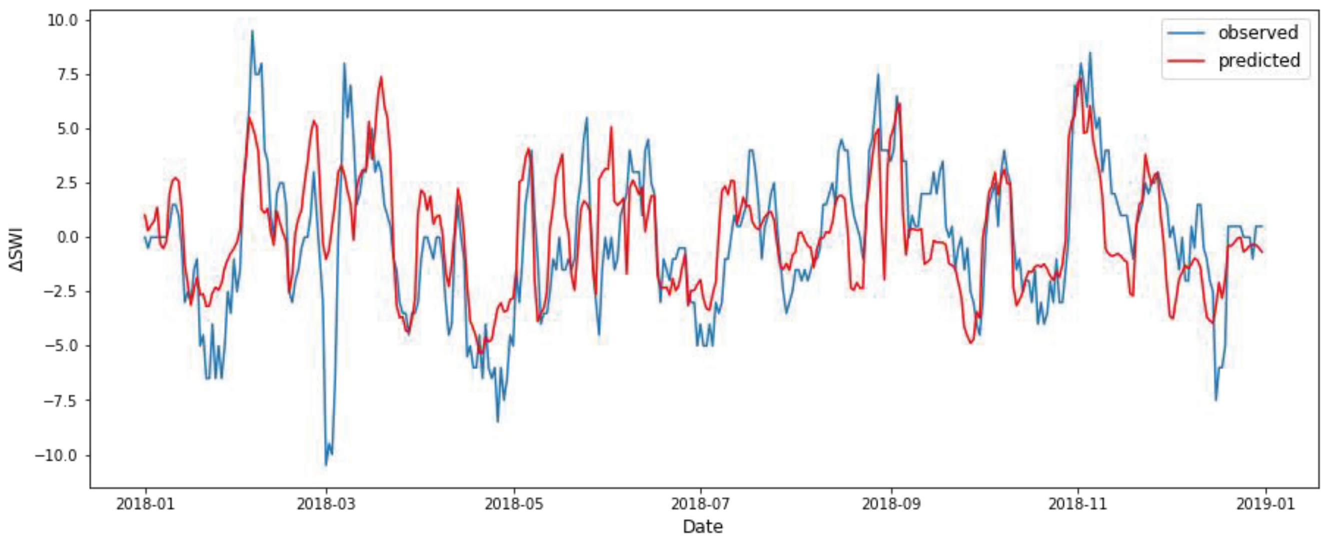
Results

Validation data

ANN

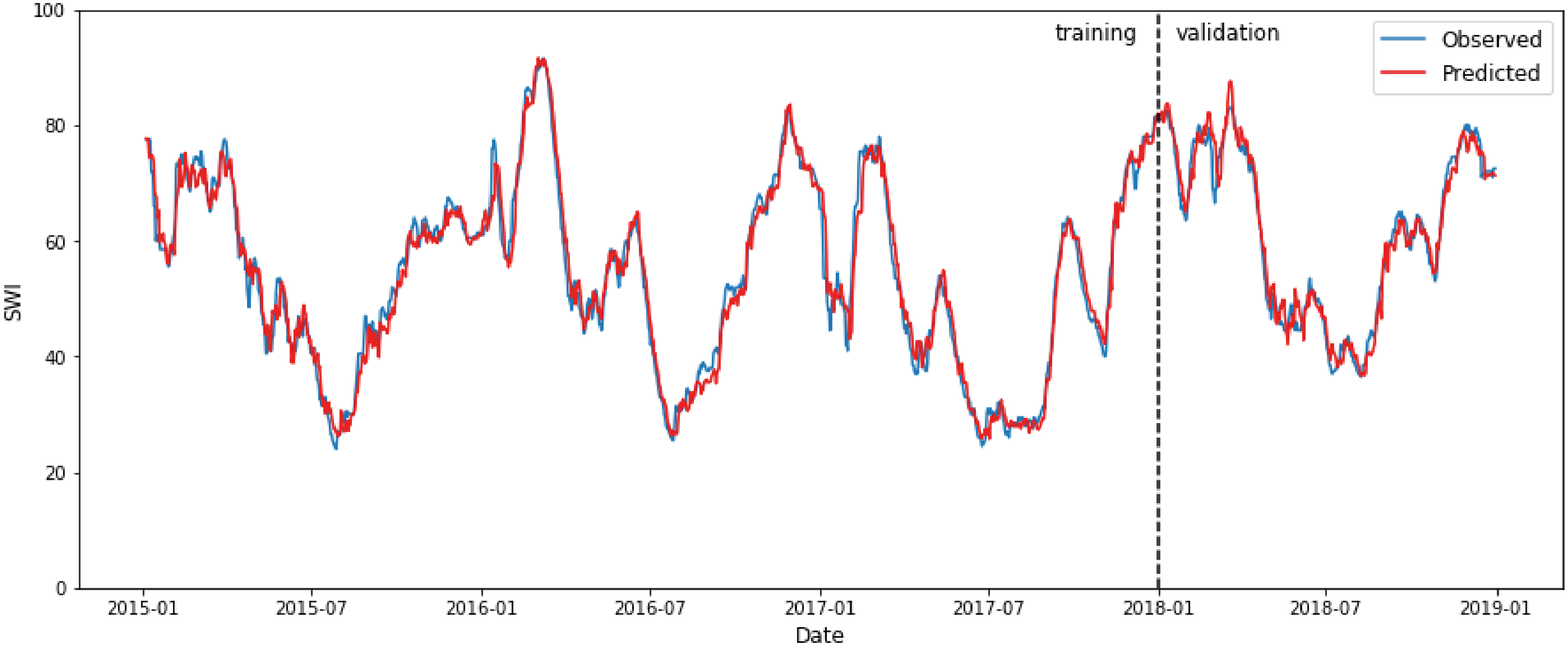


ANFIS



Results

ANFIS



Conclusions

Recap

- DSS are powerful tools for water management
- SM is a fundamental variable for an irrigation DSS
- Satellite SM measurements are easily accessible and accurate
- Machine Learning techniques are proper to predict SM evolution
- ANFIS seems to perform better than ANN

Further developments

- More data, better results!
- Consider actual crops and phenological stages
- Consider human intervention (irrigation)
- SWI calibration through *in situ* measurements