# Strategies for increasing the WATer use efficiency of semi-arid Mediterranean watersheds and agrosilvopastoral systems under climate Change

Closure Meeting

**Online,** December 19th, 2023

## Satellite observations collected for Dkhila and Sodga irrigation districts and their implementation for ecohydrological modelling and estimating water use efficiency


**Team:**

Zoubeida Bargaoui (ENIT, PI); Amel Béjaoui (Engineer); Ines Boussetta (Master Student)

**In cooperation with** CRDA Siliana (dep. Agriculture Mrs Zouari) ; CTV Bargou (Agricult. Local authority. Mr Mensi) and Sodga and Dkhila farmers


http://swatchprima.com/

# Methodology

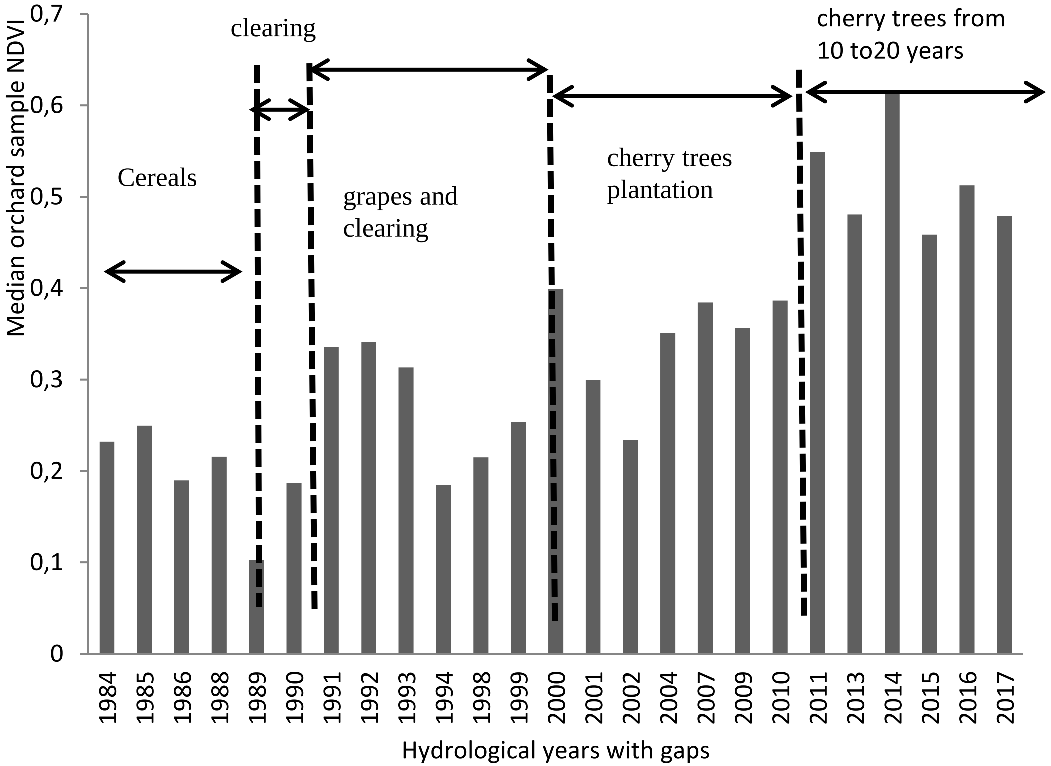
- Case of Sodga
- Using United States Geological Survey USGS website (https://earthexplorer.usgs.gov), estimation of NDVI for Sodga PID (Public Irrigation District), and June. Landsat images obtained from multispectral imaging sensors Tematic Mapper (TM) till 2013 and Operational Land Imager (OLI)
- Days with sky cover > **10%** are considered missing. Landsat images **Spatial resolution: 30 m;**
- Reflectance data are used to compute NDVI
- Spatio-temporal variability of NDVI is analyzed.

- Case of Dkhila's PID
- we use https://land.copernicus.eu/global/ data Sentinel 1 et Sentinel 2 for:
    - NDVI (Normalized Difference Vegetation Index)
    - LAI (Leaf area index)
    - SWI (soil water indice)
- Spatio-temporal variability of NDVI and LAI are analyzed.
- SWI is an index between 0 (dry soil) and 100 (saturated soil). It is daily. We used too resolutions 12.5 km and 1 km; 1 km for the assessment of the hydrological model

# PDI of Sodga- In-situ assessment of NDVI variability

The chronology of the medians of the NDVI's maps of one farmer's plot was established for the period 1984-2017. The smallest NDVIs, observed for June 1989 and June 1994, corresponds to tree cutting and replanting, as reported according to the farmer's interview.

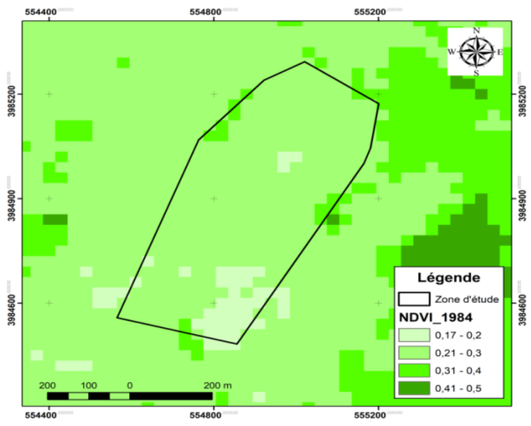
Localisation of Sodga PID



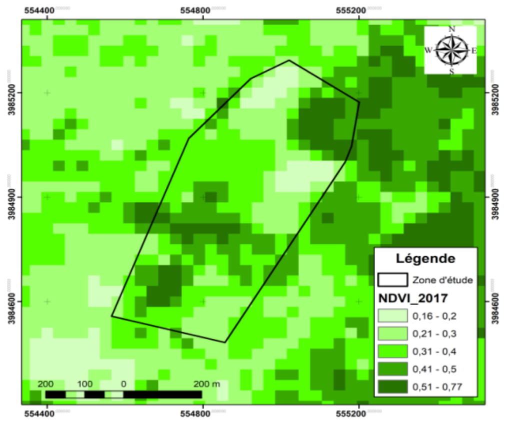

Chronology of the median NDVI of one single plot of Sodga PID with interview of its farmer

Sodga PID was implemented in1984. It was covering 120 hectares including 46 plots belonging to 54 farmers

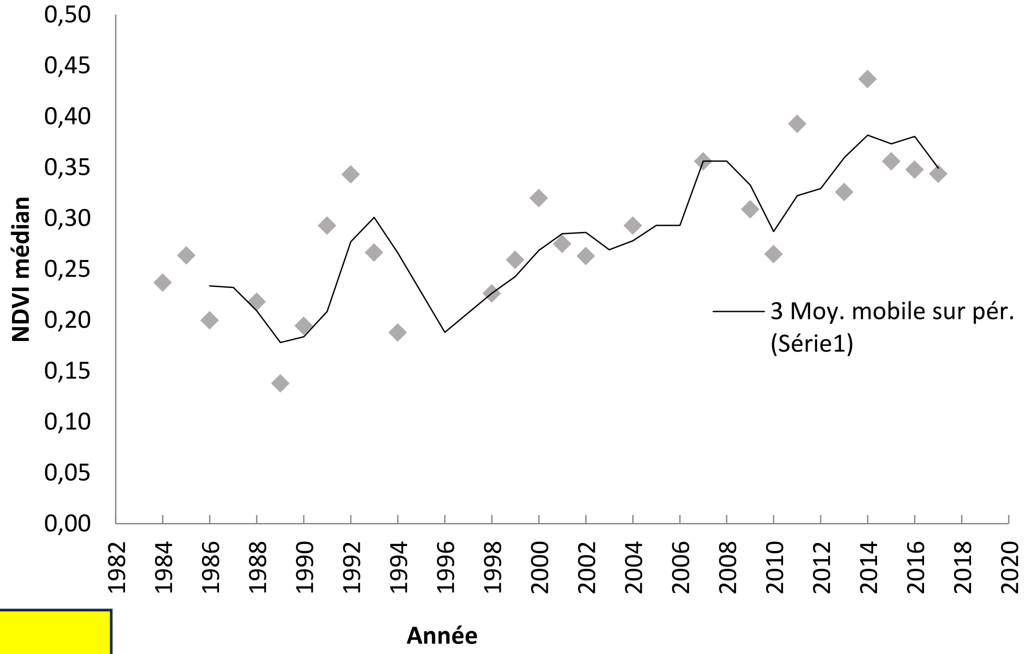
# NDVI maps and sample medians for Sodga PID for the period  June 1984-2017. 25 images with sky cover <10% were processed




June 1984




June 2017



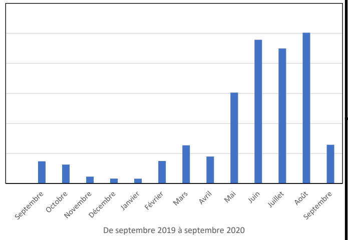

Comparison of **Sentinel 2A data for 2 days:** 28/6/ 2018 and 30/6/ 2019 with NDVI obtained using Landsat data. Aggregating NDVI data into 3 classes (sparse vegetation NDVI<0.25, moderate vegetation 0.25<NDVI<0.5 and dense vegetation NDVI >0.5) the percent of concordance is found acceptable respectively 95% and 75% for 28/6/ 2018 and 30/6/ 2019 .

- The minimums of 1989 and 1994 are available at the scale od the entire PID.
- There is an increasing trend in NDVI from 1984 to 2017 mainly due to the progress in the age of trees, also increasing of water use and fertilisation practices

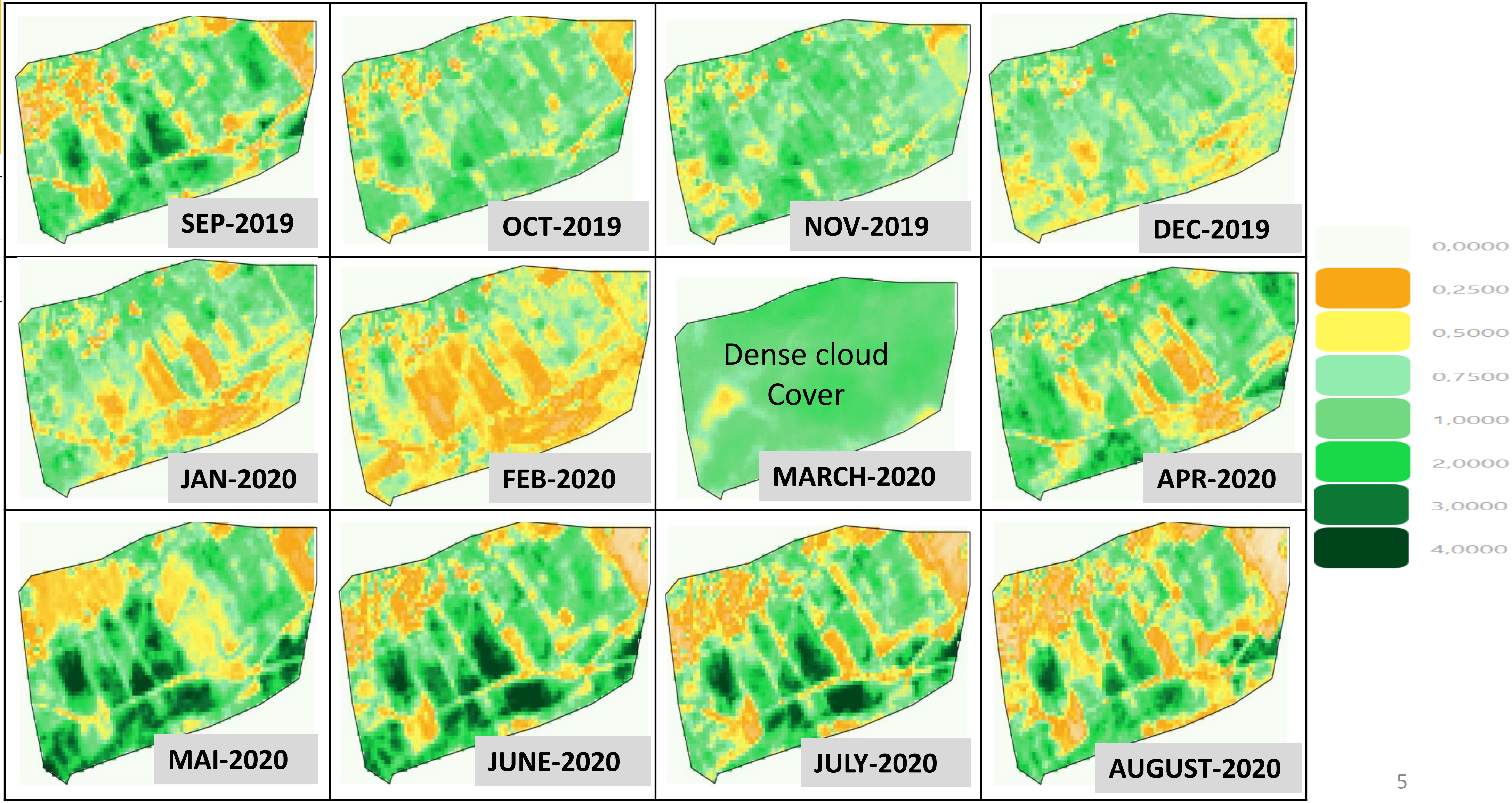
**Case of Dkhila PDI:** *LAI* maps 2019-2020 from SENTINEL 2 (10 m resolution) using ESA SNAP software with sky cover <20%

https://earth.esa.int/eogateway/tools/snap

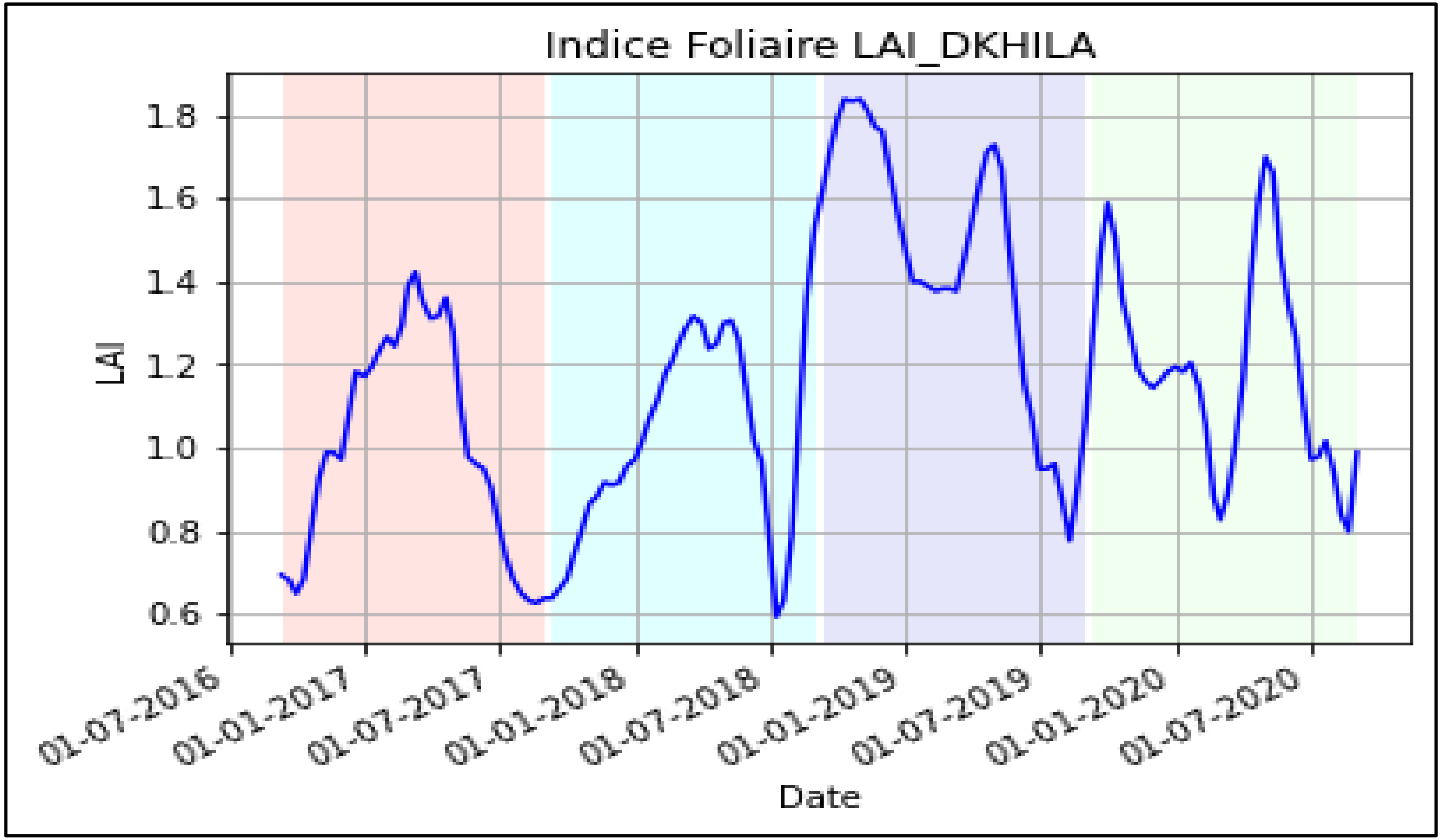
Pump station's monthly energy consumption (Kwh)



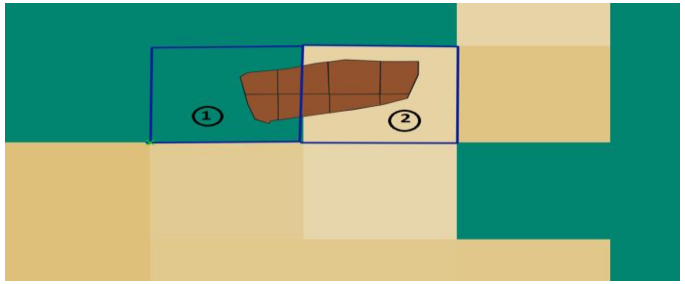

Coherency between vegetation development (as indicated through LAI) and energy consumption



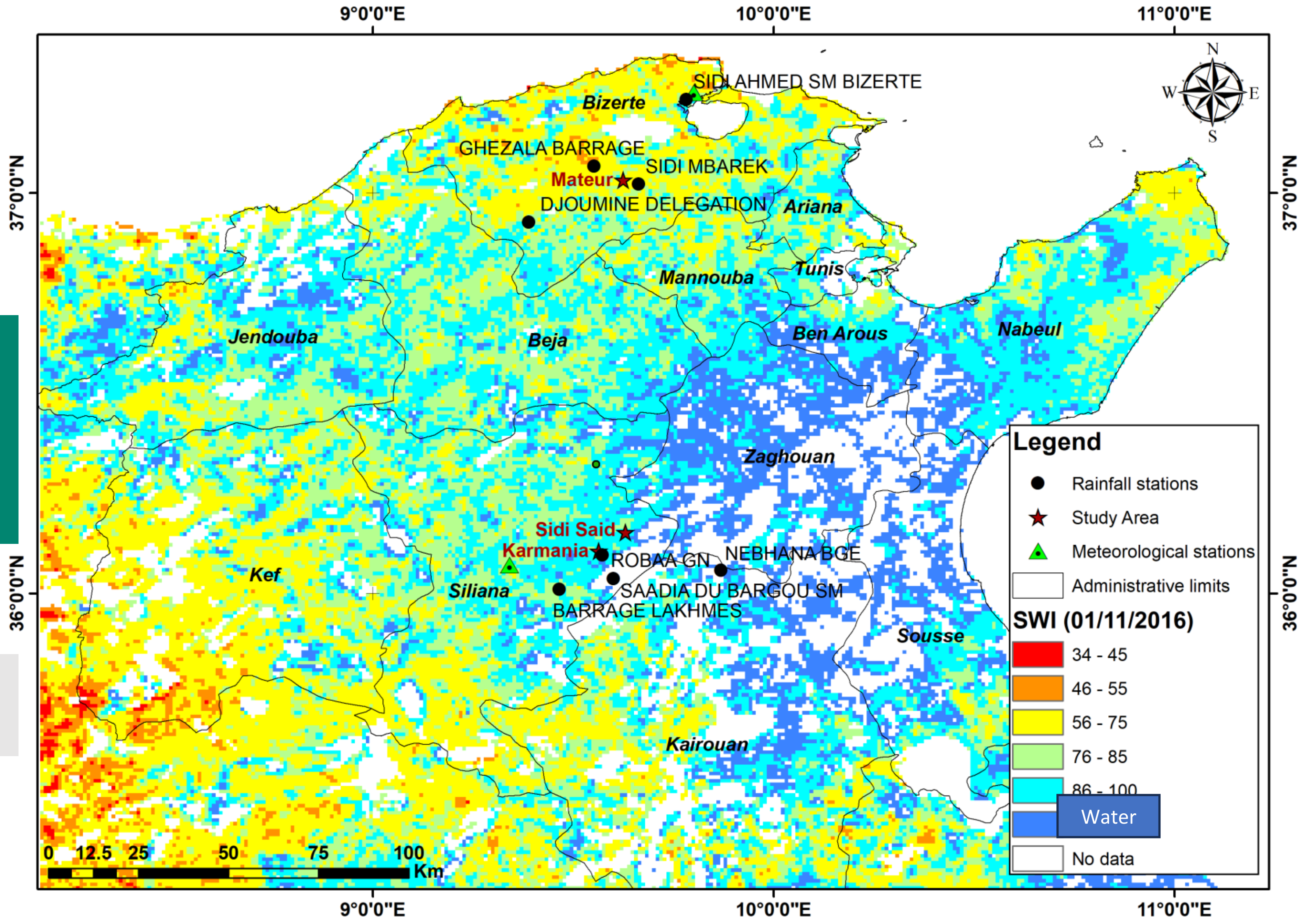
# Case of Dkhila PDI: mean spatial LAI, daily, from September 2016 to August 2020, **resolution 300m**



# SWI maps (%); example of 1/11/2016 (1km resolution)




Dkhila PID is not entirely covered by $SWI$ data. No data for Part 1



# Changes operated in the BBH model of Kobayashi et al., 2001

- The model simulates daily soil moisture content, daily actual evapotranspiration $AET$ and daily runoff $R_s$ as well as daily leakage and capillary rise $G_d$ representing hydrological responses to changes in meteorological conditions and to irrigation inputs.
- It is assumed that percolation corresponds to $G_d$>0 and capillary rise to $G_d$ <0.
- For changes it is focused on the term of actual evapotranspiration $AET$
- The new feature of the model is achieved by
  - (i) introducing the Tanner and Fuchs model for assessing the ratio of $AET$ to $PET$
  - (ii) adopting a model inspired from Jarvis for approximating stomatal conductance using LAI information and soil pressure.
  - Using reference evapotranspiration ET0
  - we adopt a linear empirical relation between $K_c$ and $LAI$ and estimate $PET$ using Penman Monteith equation
- The improvement reformulates the model using meteorological data $T_{max}$ Maximum daily temperature, $T_{min}$ Minimum daily temperature , $e_a$ water vapor pressure at dew point temperature, $VPD$ vapor pressure deficit, $R_g$ Global solar radiation, $u$ wind velocity as well as and vegetation information ($LAI$) and soil texture information (Sfc, Ks, p, $SWC_{\text{wilting point}}$).

# Processing the new version of BBH model

-Processing of mean daily rainfall and meteorological data);

-Processing soil texture information

- Estimation of daily reference evapotranspiration $ET_0$
- Estimation of potential evapotranspiration using Turc as well as Priestly and Taylor model as basis to fit linear regression between cultural coefficient and LAI data
- Estimation model parameters p, $Sf_c$, $K_s$ , $S_{wp}$using soil texture map

-Processing of Leaf Area Index and NDVI data (downloading, mean spatial value, control and gap filling of LAI series)

-Processing of SWI data

-Fitting linear regression between cultural coefficient and LAI data and estimation of (A, B') coefficients using Riou and Priestley and Taylor PET models

-Estimation of potential evapotranspiration based on LAI observations

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-Calibration of the new BBH version and fitting of the model parameter $LAI_0$

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- Implementation of the new evapotranspiration sub-model
- Selecting the stomatal conductance sub-model
- Selecting model criteria (Nash, RMSE, correlation coefficient) linked to the model error in estimating SWI
- Study of model sensitivity using AIC

# Soil moisture satellite data

- Microwave remote sensing estimation of soil moisture in relation with the important variation of **the dielectric constant of the soil** with volumetric water content
- Radar backscatter response is affected by soil moisture, surface roughness, topography and vegetation cover.
- Satellite soil moisture data were evaluated with respect to in-situ soil moisture measurements.
    - soil Moisture Active Passive SMAP (12 days, 3 km resolution),
    - ESA CCI (spatial resolution 0.25, daily temporal scale),
    - Advance Microwave Scanning Radiometer (AMSR) with (10 km, daily)
    - ASCAT product (12.5 km, 1.5 day)
- Surface soil moisture is expressed in
    - degree of saturation (ranges between 0 and 1) within ASCAT product
    - volumetric terms ($m^3/m^3$) or ($g/m^3$) in AMSR-E product
- Surface soil moisture observations are generally rescaled to range between 0 and 1 using respectively the minimum and maximum values observed during the studied period.

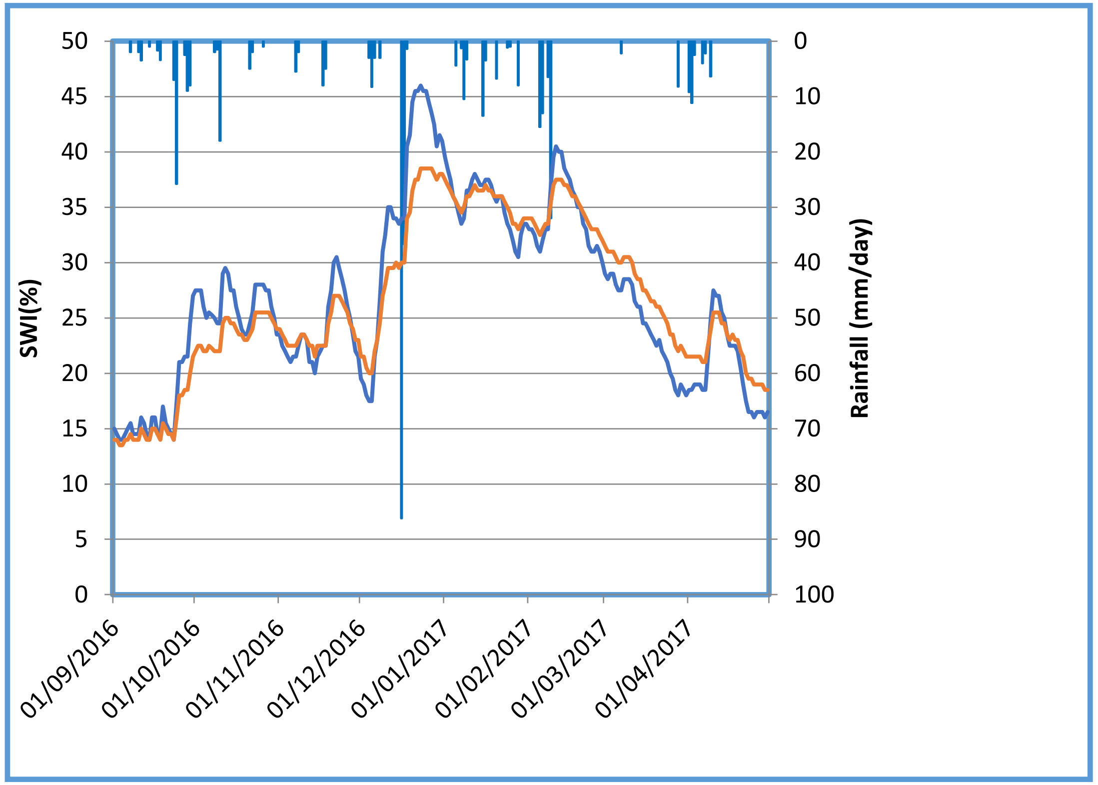
# Estimation of SWI (Wagner et al. 1999)

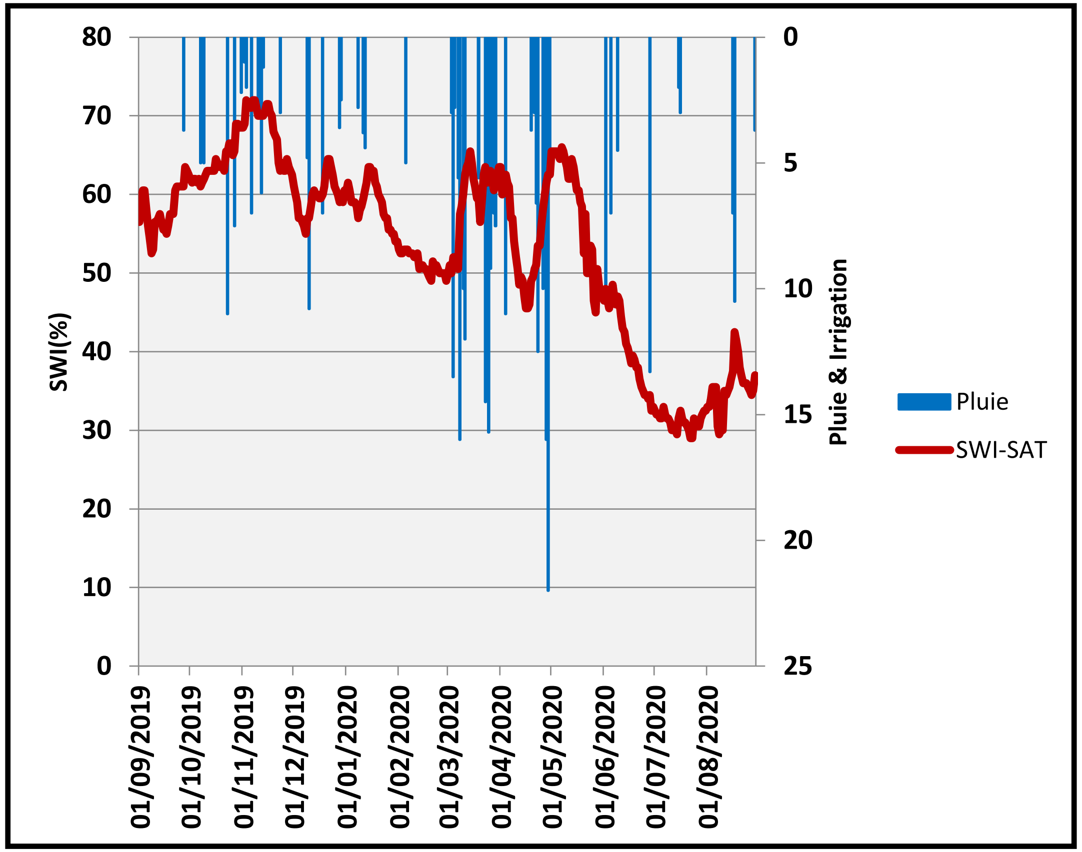
- The surface soil moisture observed by the satellite ($m_s$) is equivalent to the degree of saturation in relative units (between 0 and 1).
- Profile average degree of saturation, corresponding to active soil layer, was estimated from the surface measurements $m_s$using a semi-empirical method assuming a linear exponential filter in the time domain. A fitted parameter representing a characteristic time. **For a given soil texture the deeper the soil horizon, the greater T. T=20 is the most assumed value in the literature.**
- The scale **T** is introduced. e filtered value is called Soil Water index ($SWI$), a non dimensionless index ranging between 0 and 1 where zero corresponds to completely dry conditions and unity to soil saturation.
- Auxiliary soil data for filtering : field capacity, wilting level and porosity
- This approach was validated by Wagner et al., 1999) in comparison to gravimetric soil moisture measurements with an extensive spatial cover, in Ukrania.
- For the hydrological model HBV (and for other models) simulated soil moisture was scaled by the field capacity to be compared to satellite $SWI$.

# Evolution of mean spatial SWI of Dkhila PID comparatively to the nearest station rainfall Ain Boussaadia

SWI 12.5 km, T=10 and T=20

SWI 1 km, T=20




See the effect of the assumption on T paramter (T=10 in blue, T=20 in red)

SWI's dynamics is in coherency with rainfall time variability

# Model assessment

(a)Nash- Sutcliffe Efficiency of SWI. Solutions with highest $NSE$ are the most satisfactory

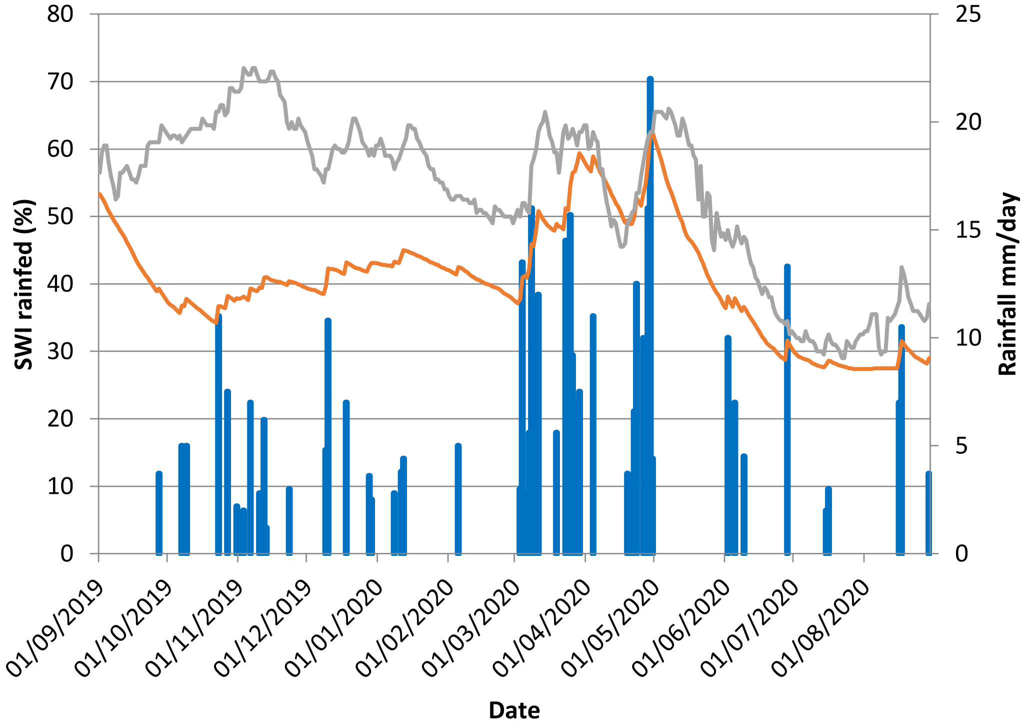
(b)Root Mean Square error$RMSE$ of SWI. Solutions with lowest $RMSE$ are the most satisfactory.

(c)Correlation coefficient $r_I$for SWI. Solutions with highest $r$ are the most acceptable.

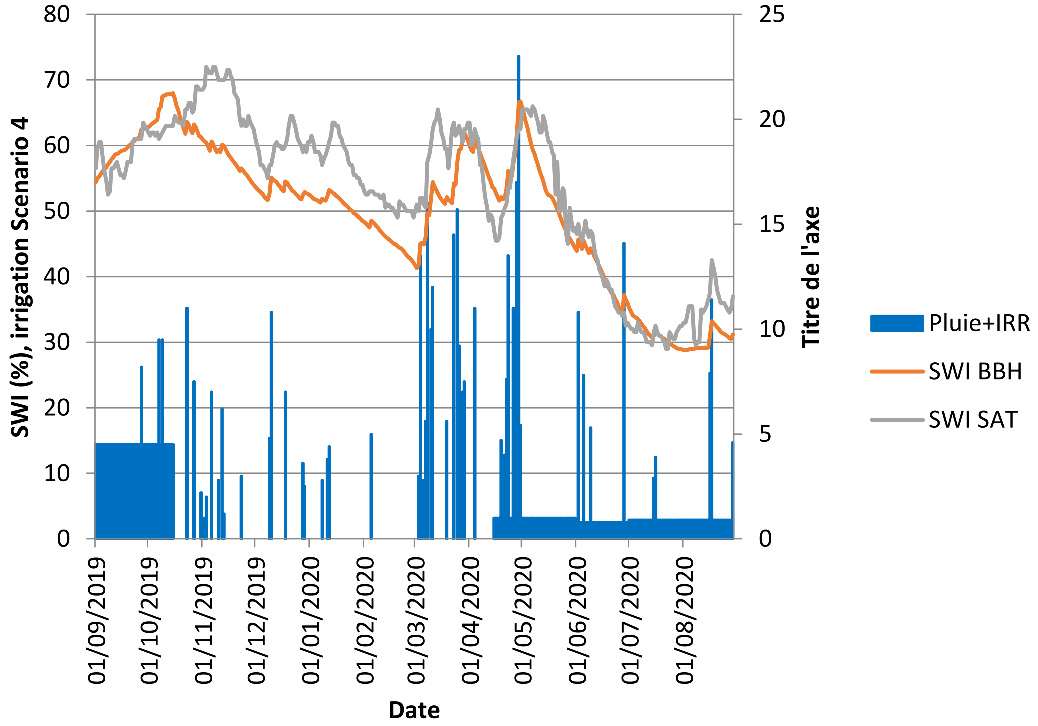
- We retain every candidate solution that results in $NSE_{SWI} > 0.5$.
- We also use $AIC$ which is generally recommended to compare models and select the best model (lowest $AIC$ score). $AIC$ penalizes the increasing of the number of model parameters. With $AIC$ there is a compromise between increasing the value of the fitting criterion and overfitting

# Simulation results for rainfed assumption and one irrigation scenario assumption

## Rainfed simulations (P=386 mm); PET=1180 mm; $AET_{BBH}$=565 mm




## Irrigated simulations (P+I=713 mm); $AET_{BBH}$=710 mm (Scenario 4)



# Estimation of WATer use efficiency under hypothetical irrigation volumes 2019-2020

## Model performance to retrieve SWI

| Input info | RMSE | $R^2$ | NASH | PET mm/y | AET mm/y | AET/PET |
|---|---|---|---|---|---|---|
| Scenario 3 | 5,21 | 0,92 | 0,80 | 1180 | 711 | 0,60 |
| Scenario 4 | 5,89 | 0,92 | 0,75 | 1180 | 712 | 0,60 |
| Scenario 5 | 4,82 | 0,93 | 0,83 | 1180 | 718 | 0,61 |
| Rainfed | | | | 1180 | 565 | 0,48 |

## Estimation of Water use efficiency

| Biomass hyp | A T/ha | 20 | Area ha | 47 | Production T | 940 | Trees per ha | 400 |
|---|---|---|---|---|---|---|---|---|
| Input info | WUE with (P+I) kg/m³ | WUE with AET kg/m³ | l/kg with P+I | l/kg with AET | | | kg/tree | 50 |
| Irrigation hyopthesis 3 | **2,4** | 2,8 | 412 | 355,3 | | | | |
| Irrigation hyopthesis 4 | **2,8** | 2,8 | 357 | 355,3 | | | | |
| Irrigation hyopthesis 5 | **2,5** | 2,8 | 408 | 359 | | | | |
| Rainfed | 5,2 | 3,5 | 193 | 282 | | | | |

website: fr.statistica.com Average apple consumption 822 l / kg
For Dkhila PID, range of l/kg after the hypothesis on irrigation volumes is 377-434 l/kg
In the literature, mean crop production per ha varies between 10 and 80 T/ha depending on the variety

# Conclusions

- A series of 25 years of June NDVI data (30 m resolution) was analyzed for Sodga Publuc irrigation district (PID)
  - Agriculture practices such as tree cutting and replanting were identifiable from the series (minimum local points)
  - The growth of orchards was seen throught the increasing trend of NDVI curve within time
- A series of LAI with 10 m resolution was analyzed for a year period. Growth of LAI was in accordance to water use as represented by pumping energy consimption
- A series of LAI data of 300 m resolution was drawn for Sodga PID within a series of 4 years.
- It was implemented in the modified water balance model BBH to estimate actual evapotranspiration and the other water balance components.
- An estimation of a continuous series of irrigation amounts was obtained using sparse irrigation volumes observations. Three scenarios resulting in accepted Nash coefficients to retrieve SWI were analyzed to estimate water use efficiency
- Water use efficiency varies between 2.4 and 2.8 kg/$m^3$ whitch corresponds to 377-434 l/kg of Apple. The mean value assumed according to the literature is 822 l / kg.
- Conversely, the apple production of Dkhila PDI is 20 T/ha which is  relatively low in comparison to the literature