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# Synergetic use of Sentinel-1 and 2 to improve agro-hydrological modeling

## Preliminary results on Rice paddy detection in South-India

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### ABSTRACT

In the context of global changes and population growth, agricultural activities are a growing factor influencing water resources availability in term of quantity and quality. Water management strategies have to be analyzed at a regional catchment scales. Yet, agricultural practices, crop water and nutrient consumption that drive the main water and nutrient fluxes at the catchment scale have to be monitored at a high spatial (crop extension) and temporal resolution (crop growth period). This proceeding describes some advances in the framework of a co-funded ESA Living Planet Fellowship project, called “agro-hydrology from space”, which aims at demonstrating the improvement brought by synergetic observations of Sentinel-1 (S1) and Sentinel-2 (S2) satellite mission in agro-hydrological studies. Geo-information time-series of vegetation and water index with multi-spectral optical detection S2 together with surface roughness time series with C-band radar detection S1 are used to re-set soil water holding capacity parameters (depth, porosity) and agricultural practices (sowing date, irrigated area extent)

of a crop model coupled with a hydrological model in two contrasted water management issues: stream water nitrate pollution in Gascogne region in south-west of France and groundwater depletion and shortages for irrigation in Deccan Plateau, in south-India.

### 1. General context

#### Why and how to evaluate agricultural impacts on water resources at a regional scale?

Agricultural activities are highly hinging on **good quality** of natural resources (**soil** structure, **water** resource quality/quantity) and are also impacting the environment quality (soil degradation, water contamination and scarcity). Nowadays, intensive and food-producing agricultures are both challenging:

- an increase of **competing demand for land** (Urban expansion, bio-fuel or cash crop) and **water** (industries, domestic requirements)
- natural **hazards** related to **global changes** (climate changes, socio-economic changes)
- increasing **food demand** of the worldwide market.

In Europe, public environmental policies target the good environmental status of water resources and soon soil resources. In the developing world, food security and socio-economical changes are mainly driving the agricultural and environmental policies and/or mutations. The global trend of the last decades has been a conversion of 35% of ice free continental surfaces into agricultural areas [1], this conversion is part of the most significant global changes [2], with a rate that is recognized as non sustainable [3].

Irrigated areas have been multiplied by 6 during the last century and concerns 24% of the worldwide cultivated areas. They are mainly located in drought prone semi-arid or arid areas [4]. The recent increase of this proportion during the end of the last century has been mainly sustained by the apportionment of groundwater. Nevertheless, the global decline of these resources coming with the lack of appropriate assessment and management is threatening the nowadays agricultural production that sustain economy and subsistence of local populations [4], [5]. Recent investigation from the GRACE mission data estimated a decline of Groundwater stock in the Gangus basin, India [6], in Iran [7], and others authors estimate worldwide the role of agriculture in these trends [5].

Water bodies' contamination by nitrate is, as well, and despite constraining laws in developed countries, not contained. Best agricultural practices solutions costs are difficult to compare with environmental quality benefits from an ecological, political, sociological and economical point of view. This contamination is becoming alarmingly common not only in western Europe and northern America, but also in eastern Mediterranean and Africa waterways where it has more than doubled [8]. In India and Africa, 20-50% of wells contain high levels of nitrate concentration. In India, new elements confirm the role of high pumping rates of groundwater for irrigation that increases the groundwater contamination through contaminated return flow from irrigated field [9].

### **1.1. Agricultural impact assessment for appropriate water resources management policies**

To be efficient, environmental decisions should be based on evidence and facts, being used to build fair and efficient environmental policies. This target supposes to build tools to understand, quantify and predict the agricultural impacts on water resources. Understanding supposes to multiply environmental observations of agro-hydro system dynamics; quantifying and predicting supposes to build numerical representation of the cascade of processes and retroactions between climate, soil, water resources and agricultural practices: cultivation of land, fertilization, irrigation.

In its broadest concept, **AGRO-HYDROLOGY**, as a scientific discipline, is a study of interactions, to evaluate not only the influence of available water on

agricultural production but also the influences of the cultivation of land and its agricultural practices on the resources availability [10]. These retroactions are studied in space and time using numerical modelling approaches. These models represent the main processes involved in the crop growth and water and nutrient transfer within catchments: soil water and nutrient uptake, drainage and transfers to aquifer and rivers, as a function of crop calendar, rotation, fertilisation, irrigation, tillage [11]–[16]. These modelling objectives require spatially distributed models, where information of soil-crop location within slopes as well as hydrological settings (topography, groundwater storage, reservoir location or irrigation pumping) are included to provide spatially explicit information: fertilisation and crop growth parameters [17], soil and groundwater stock and irrigation pumping for instance [15].

It pictures the situation of **water resources** under **human activities**, test the efficiency of designed water/agricultural **management options** [18] and is used to project the nowadays water consumption under future climate or socio-economical situations [19].

### **1.2. Limitations: the lack of spatial information**

This spatially distributed agro-hydrological models are simulating a cascade of many processes, involving numerous parameters to represent the spatial and temporal dynamic of water, nutrient cycle, crop growth, which are calibrated on available observations: water and nutrients stream fluxes at the outlet of a catchment, average yield [17], [20], aquifer recharge [15] or satellite based evapotranspiration (MODIS products, 500 meters resolution [21]). The lack of observation of soil, crop, climatic variables and parameters lead to a lack of spatial processes calibration which may lead to equifinality problems, e.g. more than one parameter set leading to similar results [22] or compensation between processes leading to similar stream water fluxes [17]. Uncertainties raised by these modelling approaches at the watershed level are mainly related to the lack of agricultural operations data and soil-crop conditions encountered within the catchment, i.e. saturated conditions within slopes and their feedback on crop productivity. For instance, the timing of fields operations (first fertilization and sowing date) has a strong impact on the winter wheat growth in Europe [23]. These data are crucial input parameters to accurately simulate crop growth dynamics and interaction with water resources and not available at the large spatial extent appropriate for water management.

### **1.3. Contribution of Sentinel-2 to agro-hydrology**

Recent studies have demonstrated the benefit of the capacities of Sentinel-2 mission to provide such information of field operation and crop growth to reset agro-hydrological model parameters. The infra-monthly detection of biophysical variables such as Leaf Area

Index (LAI) for selected areas from optical acquisition of Sentinel-2 at 10 meters resolution [24], [25] enable to detect the crop emergence and refine the sowing dates from a time series of 105 cloud free images at 8m resolution [26]. A delay of few weeks in the sowing date of winter wheat (from October to November) could lead to postpone the emergence date to few months (3 months in the case of the year 2010), whereas emergence date of sunflower follows directly the sowing dates in spring when cumulative daily temperature threshold are reached in few days. The winter wheat simulated growth and biomass is then highly impacting the total nitrogen and water uptake between “a-priori” and optimized situations. Both effects have significant impact on in-stream nitrogen fluxes rather than discharge (<1% of annual discharge modification) but an important effect on monthly soil water content dynamic: the early detection of crop emergence from remote sensing time series enable 1-to accurately simulate the soil water uptake by crop transpiration during spring and 2-to better account for soil drought conditions that can occur in summer and affect crop productivity [27]. Another use of these time series of LAI derived from Sentinel-2 is to retrieve soil water holding capacity parameters of an agro-hydrological model at the image pixel level (10 meters). The interpolation of LAI in time is done to estimate the maximum of LAI (LAX) reached for a growing season in each pixel of the image. The heterogeneity of this LAX is used to optimize a set of two soil parameters of an agro-hydrological model (soil depth and retention porosity) that both define the soil water holding capacity. A spatial distribution of optimal soil parameters is then obtained for several years. It allows to simulate the within field spatial heterogeneity of crop growth observed by Sentinel-2 [28]. Authors emphasize the importance to derive the soil moisture from Sentinel-1 observations, as saturated conditions could affect the crop growth and so the optimization parameters. These previous experiments show the strong interest of Sentinel-1&2 observations to improve the representation of agro-hydrological processes dynamics to study critical moment (drought periods) and the spatial heterogeneity of within field physical properties.

## 2. Synergetic use of Sentinel-1 and Sentinel-2 to detect crop dynamics and agricultural practices

We present here an example of the synergetic use of Sentinel-1 and 2 to monitor the small irrigated area extents in south-India, a first step to estimate the seasonal groundwater extraction for irrigation using an agro-hydrological modelling approach.

Indian agricultures represented 89% of water consumption in 2000, of which 39% came from groundwater. In South India, this contribution rise to

90%. To cope with the recurrent groundwater shortages coming with dry monsoon and overexploitation, local farmers modulate their consumption by limiting the irrigated area extent (from 2 to 8 % for rice for instance). They also manage traditional rainWater Harvesting System (WHS) composed by small water reservoirs spread along the drainage network, to capture runoff and increase groundwater recharge (see black surfaces shown in Fig. 1). Reference [15] was the first to quantify the apportionment of WHS to groundwater recharge during the monsoon period at an experimental catchment scale, the Gajwel catchment (grey area in Fig. 1), by monitoring the surface water fluctuation in the WHS together with the estimate of groundwater extraction and recharge from both irrigated area extent surveys and groundwater table fluctuation monitoring. Both two surface variables -1 irrigated area extent and 2- surface water dynamic - are key drivers to estimate the 1- groundwater extraction demand and 2- the groundwater recharge from WHS. Both variables can be easily detected from systematic remote sensing acquisitions.

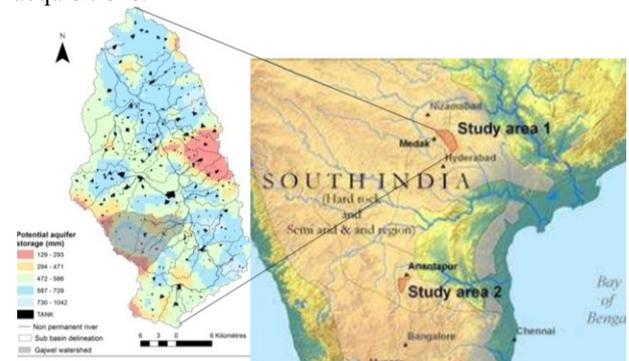


Figure 1. Kudaliar study site location (1000 km<sup>2</sup>), near Hyderabad. The potential aquifer storage estimated by reference [29] shows the heterogeneity of groundwater resource. The black areas correspond to the network of tanks composing the Water Harvesting System maintained by farmers to catch the monsoon runoff.

The groundwater budget was previously simulated with the Soil Water Assessment Tool (SWAT) for the period 2002-2012 in reference [19]. The main limitation of this application was that the irrigated area extent was estimated from remote sensing using only few images of monsoon 2009 and dry period 2010 and used to force the groundwater extraction for the whole period (10 years). This is far from realistic as the irrigated area extent can vary from 2 to 8% depending on the groundwater availability and monsoon intensity.

We intend to take the advantage of revisit frequency of both Sentinel 1&2 to make a clear distinction between water surfaces in tank, rice inundated areas, as well as vegetables and orchards irrigated area during the dry period of 2016 (Dec. 2015 to March 2016) using the set of exiting cloud free Sentinel-2 and Sentinel-1-IW.

## 2.1. Land cover survey (January to March 2016)

A survey of land cover have been carried out in February and March 2016 (fig. 2), corresponding to 600 plots of natural vegetation cover, dry rainfed or bareground areas, agro-forestry plots (eucalyptus and Teak), irrigated orchards (mainly mango trees), irrigated crop areas (vegetables) and inundated crop areas (rice). In this last category, more than 100 rice paddies (few acres each) have been identified during both field trips. The dataset was especially scrutinized for rice crop checking accordance with the NDVI time series, due to the small extent of each rice paddies and the operator's imprecision in delineating them.

## 2.2. Sentinel-2 derived NDVI and NDWI time series

The dry, cloudless season (December to April), is appropriate for optical acquisitions of Sentinel-2 observations. The Kudaliar catchment where the Gajwel catchment is embedded (respectively delineated in black and filled in grey in fig. 1) has been used to set up a first evaluation of Sentinel-2 and Sentinel-1 classification potential of irrigated area extents in this context. Acquisitions dates are summarized in Tab. 1.

Table 1: Sentinel-1 and 2 (cloud free) acquisition dates

	Sentinel-1	Sentinel-2
November 2015	17 <sup>th</sup> and 29 <sup>th</sup>	clouds
December 2015	23 <sup>rd</sup>	31 <sup>st</sup>
January 2016	04 <sup>th</sup> and 16 <sup>th</sup>	10 <sup>th</sup> and 30 <sup>th</sup>
February 2016	21 <sup>st</sup>	09 <sup>th</sup> and 19 <sup>th</sup>
March 2016	04 <sup>th</sup>	10 <sup>th</sup>

Normalized Difference Vegetation Index (NDVI) has been extensively used to monitor vegetation dynamics as it is easy to compute from most of remote sensing sensors. It is a robust integrator of crop development. NDVI has also some drawbacks like for example it is soil dependant in lower values and it saturates at higher values. That's the reason why other indicators have been proposed like SAVI or EVI [30]. The Normalized Difference Wetness Index (NDWI, [31]), has been used either for water detection or well-watered areas. As irrigated soils are generally wetter than non irrigated soils, especially in semi-arid areas, NDWI can be a good indicator of irrigation if the image frequency allows seeing the impact of water added by irrigation. It has been previously successfully used in the identification of irrigated areas [32].

NDVI (eq. 1) was computed at 10 meters resolution while NDWI (eq.2) was resampled from 20 meters to 10 meters using the bicubic method. We used the following Sentinel-2 bands 3, 4, 8 and 11 (respectively the green (560 nm), red (665 nm), near infra red (842 nm) and shortwave infrared (1610 nm) after the optical correction using Sen2cor (version 2.2.1, released on

May the 4<sup>th</sup>), as proposed in [33].

$$NDVI_{10m} = \frac{B_8 - B_4}{B_8 + B_4} \quad (\text{eq. 1})$$

$$NDWI_{20m} = \frac{B_3 - B_{11}}{B_3 + B_{11}} \quad (\text{eq. 2})$$

## 2.3. Sentinel-1 VH radar backscatter time series

We have as well extracted the Sentinel-1 acquisition on the study site using the Google Earth Engine application (GEE - [34]). The Sentinel-1 observation strategy defines the Interferometric Wideswath (IW) mode as the pre-defined mode over land. This mode provides dual-polarisation (VV and VH) imagery, at a resolution of 10 meters, with a swath of 250km.

The data provided by GEE is the Ground Range Detected (GRD) Level-1 products. They consist of focused SAR that has been detected, multi-looked and projected to ground-range using an Earth ellipsoid model. The Sentinel-1 data have been first calibrated (<https://sentinel.esa.int/documents/247904/685163/S1-Radiometric-Calibration-V1.0.pdf>). We additionally multi-looked the data (window size of 2x2) to reduce the speckle noise effect, reaching a spatial resolution of 20m. Then, terrain correction was applied to adjust the images by correcting SAR geometric distortions (foreshortening, layover and shadow) using a digital elevation model (DEM), producing map projected images. A speckle filter [35] was applied to further reduce the speckle effect while preserving the spatial resolution and the fine structure of the image. The method used produces images with reduced speckle effects from multi-temporal (10 dates) and multi-polarized (VH and VV) images. The speckle filter is expressed as follows:

$$J_k(v) = \frac{I_k(v)}{N} \sum_{i=1}^N \frac{I_i(v)}{\langle I_i(v) \rangle} \quad \text{with } k=1, \dots, N \quad (\text{eq. 3})$$

where  $J_k(v)$  is the radar intensity of the output image  $k$  at pixel position  $v$ ,  $I_i(v)$  is the radar intensity of the input image  $i$ ,  $\langle I_i(v) \rangle$  is the local average intensity of the input image  $k$  (window size of 7x7) and  $N$  is the number of images.

The resulting theoretical number of looks is 58.

## 2.4. Classification methods

A cross comparison of a supervised classification method and a threshold method with different input data is done focusing only on the rice crop (80% of the groundwater consumption). The advantage of the threshold method is that it does not need a training dataset. The drawback is that the parameters may vary from one year to another depending mainly on climatic

conditions. The Random Forest algorithm [36] is an automatic classification tree method that has the advantage to be fast and to explore automatically and randomly the different spaces of data. In this study, we used the implementation of the scikit-learn python package (<http://scikit-learn.org>). The threshold algorithm was designed to discriminate rice fields based on the supposed temporal behavior of the crop development and soil wetness of rice fields. The algorithm identifies the rice from other perennial or irrigated seasonal crops by defining high differences between minimum and maximum value of NDVI detected during the growing season, together with a low value of NDWI maintained during the period due to daily inundation of rice. After an *a priori* approximation, the parameters of the algorithm, the threshold of NDVI and NDWI, were optimized using the Nelder-Mead method [37]. Finally, the performances of the classifiers are compared using the Cohen's kappa [38].

### 3. Results and discussion

Fig. 2 shows the results of one of the tested method for the whole Kudaliar watershed. It illustrates the main

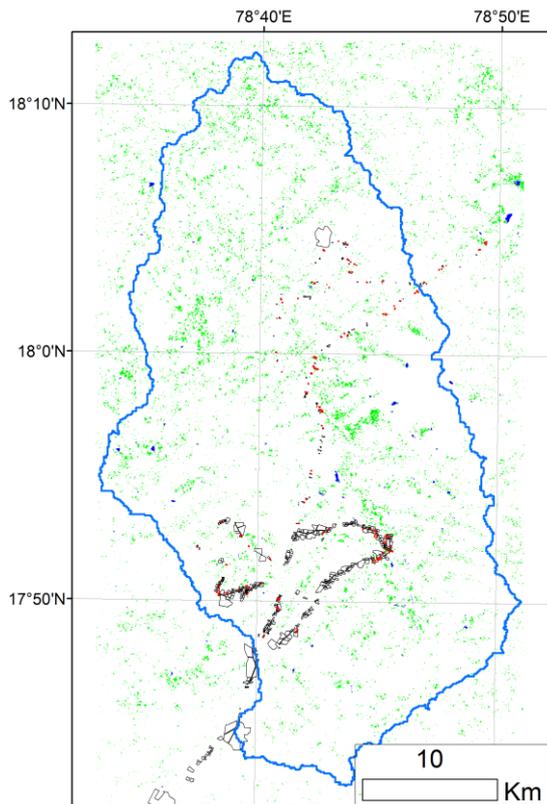


Figure 2: Rice paddy area extent (green) during the December-March 2016 season derived from the thresholding method in the Kudaliar watershed (blue). The training areas (red=rice, black=others) corresponding to the field surveys are also shown.

challenge of estimating rice area extent in this region: rice paddies are composed by very small plots (few acres each) grouped around a pumping borewell, themselves disseminated in the landscape. The high resolution of Sentinel is essential. Fig. 3 shows a zoom in the center of the watershed to illustrate the differences between the three methods. Tab. 2 shows the kappa and also the percentage of good classification (rice pixels identified as rice fields during the field campaign) and the percentage of erroneous classification (rice pixels identified as another crop).

Table 2: Cross tabulated results

		NDVI & NDWI	NDVI & NDWI & BS VH
Thresholding	Kappa	0.81	-
	% rice in watershed	3.7	
	% Good detection	79.2	-
	% Bad detection	16.3	-
Random Forest	Kappa	0.44	0.6
	% rice in watershed	2.41	2.04
	% Good detection	46.34	50.26
	% Bad detection	56.33	24.43

#### 3.1. Optical detection only

Accurate detection of irrigated area extents are obtained with the thresholding method based on optical indices, with a kappa of 0.81, almost 80% of good detection and 16% of mislead detection. We had poor performance with the Random Forest method (kappa=0.44). In particular, the output showed a lot of confusion with the rainfed cotton (mainly dry since December) and agroforestry which will be explored in future studies.

#### 3.2. Synergetic radar and optical detection

Optical detection was possible thanks to the low cloud coverage during the dry season, but it is expected that cloud free optical acquisitions will be infrequent during the monsoon season. The radar detection is then the best option during these periods. Tab. 1 shows that integrating backscattering in VH polarization from the Sentinel-1 time series improves the Random Forest algorithm prediction, increasing the Kappa from 0.44 to 0.60, which is very encouraging. Yet, we suspect that the low performances of the Random Forest algorithm are due to both confusions affecting the land cover survey (geographical locations, crop identification) and the few number of certain crop type sampled while water shortages could create a high heterogeneity of

spectral reflectance for a same crop type.

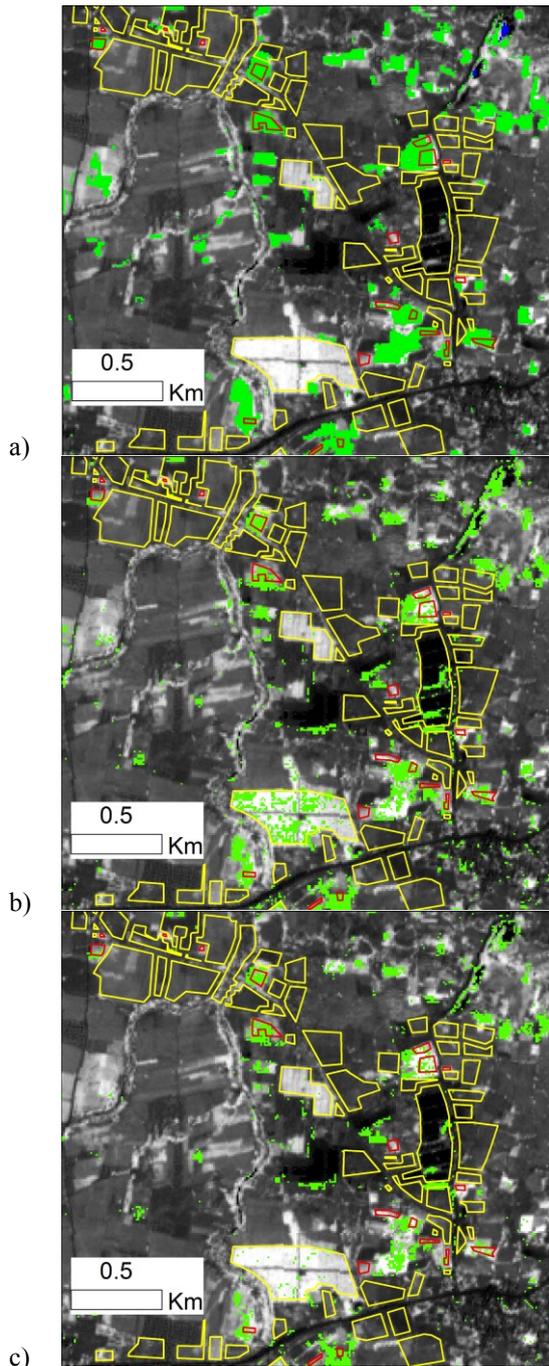


Figure 3: Zoom with the three method (a: Thresholding with NDVI and NDWI, b: Random Forest with NDVI and NDWI, c: Random Forest with NDVI, NDWI and VH backscattering). The red plots are rice paddies, the yellow plots are other crops. The NDVI of February 2016 is used as background image.

A higher acquisition frequency of S1 data should allow detecting not only the vegetation as the main driver of backscattering, but also changes in surface roughness

and soil wetness due to tillage and irrigation.

### 3.3. Rice area extent uncertainties and groundwater extraction estimates

The range of rice detected area extent between each method varies from 2.04 to 3.7% of the total area, but with more confidence in that late proportion. Based on the previous agro-hydrological modelling [15], [19], these irrigated area extent correspond to respectively 28 and 51 mm of irrigated water demand. In 2015, the monsoon rainfall accounted for 756 mm and recharge has been estimated to 174.4 mm using the water table fluctuation method (non published data from the Indo-French Center for Groundwater Research, Hyderabad), method described in reference [39], in a nearby and similar experimental watershed. The temporal variability of monsoon rainfall and subsequent groundwater recharge is presented in Fig. 4.

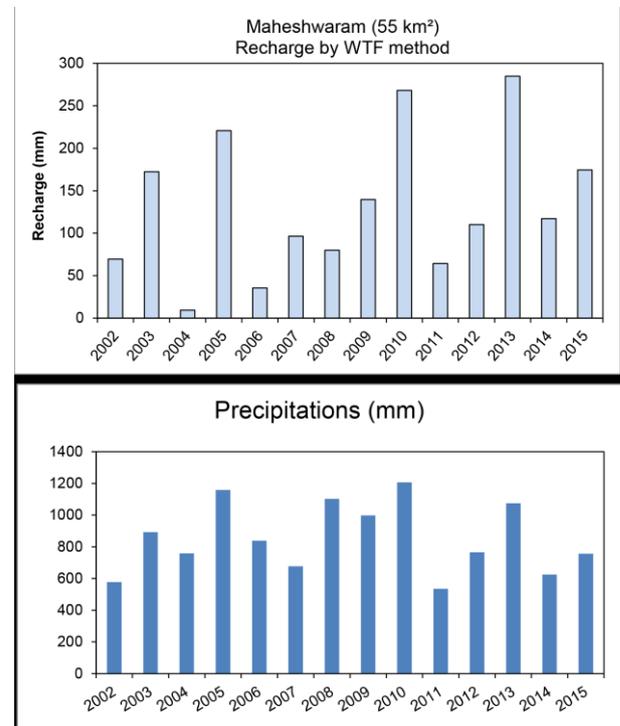


Figure 4: Temporal variability of monsoon (down) and recharge (up) estimated in the study region (source IFCGR-BRGM for the Maheshwaram watershed, from [39])

### 4. Perspectives

The systematic detection of rice and irrigated area extent with Sentinel-1&2 are foreseen to provide accurate quantifications of seasonal Irrigation Water Demand (IWD), as defined in the reference [19]. This amount was directly linked to the surface extent of each irrigated crop, associated to observed irrigation practices. For instance, the land cover of the dry season 2010 in the catchment (Fig. 1) was composed by 6.96%

of rice (70.6 km<sup>2</sup>), 6.79% of vegetables (68.9 km<sup>2</sup>), accounting for 93.44 mm and 15.59 mm of groundwater extraction respectively [19]. This high amount extracted during the dry season (January to March 2010) relied on relatively high groundwater level at this time. The estimated amount of 50 mm of irrigated water needed for the rice in the dry season 2016 depicts a shortage situation: the average 130 mm of annual recharge observed since 2002 (Fig. 4) could not sustain the irrigation water demand of two growing season as observed during the year 2009-2010 [19]. Farmers coping strategy consist mainly in limiting their rice production to the extent observed in dry season 2016. In this region, nowadays shortages of groundwater are explained by both climatic drought since 2013 and overexploitation of the groundwater for rice irrigation mainly.

Sentinel-1&2 high spatial resolutions are essential for an accurate estimates of irrigated area extent. The multi-spectral data of Sentinel-2 allows detecting both vegetation and water presence. SAR detection allows improving automatic optical images classification based on Random Forest algorithm, but Sentinel-1 detection suffers in this study from a lack of acquisition dates to demonstrate its determinant contribution in dry season.

Finally, the water detection from both Sentinel-1&2 is crucial to monitor the water dynamic in the WHS, to better constrain by modelling the groundwater recharge from these installation that covers whole Deccan plateau. Surface water detection Algorithms will be set up to monitor the filling and draining period between respectively June to October and November to February.

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