Dear Editor,

We are grateful to you, the Editor and the Reviewers for the time and effort spent on the review of our manuscript. Our detailed response to the comments raised by the Reviewers is attached. We believe our responses and the revisions made to the manuscript fully address the issues raised by the Reviewers. These revisions have helped clarify important aspects of our work and improve its presentation.

Page/Line numbers given in our response refer to the pages/lines of the ORIOGINAL and the NEW version of the manuscript to allow tracking the answer with respect to the original comments.

Sincerely,

Mireia Fontanet Ambròs on behalf of all co-authors

Legend

Bold: the comments and questions by the editor and the reviewers.

Blue: our answers.

Red: the detailed changes introduced in the manuscript.

Yellow: restructured

Green: rewritten

Response to Reviewer 1:

GENERAL COMMENTS

1) **MAJOR: The text of the manuscript does not read well in many parts. In the specific comments, I added some suggestions for the abstract only. The whole text should be revised avoiding repetitions, improving English writing (but I am not mother-tongue), and taking care to write accurately symbols, equations, acronyms. Being a scientific paper, the structure and the methodology used should be clear to the readerships.**

   - We have completely revised the manuscript to avoid repetitions, clarify some parts of the manuscript and also improve English quality.

   - We have also modified mistakes regarding acronyms and symbols, especially at the abstract.

   - Specific comments have been corrected. Please, see the list of specific comments at the end of this document.

2) **MAJOR: The authors found that 1-km SMOS soil moisture product is not suitable to detect small scale irrigation, even though theorically the 1-km resolution of the product should be suitable for detecting irrigation in the investigated area. The**

authors investigated spatial variability of NDVI and LST and found it is much larger (even if not specified in the text) than the extend of in situ soil moisture measurements, therefore the comparison should not be carried out. Moreover, the problem is not related to the spatial variability of NDVI or LST, but to their capability to detect the irrigation signal. Much better should be to carry put a specific analysis with NDVI and LST to assess if they are able to "see" irrigation.

- The range of a semivariogram is the distance at which spatial correlation vanishes. This geostatistical property is used here to measure the size of independent image details. This is described at page 8 line 4 (new version): "*The distance beyond which $\gamma(h)$ can be considered to be a constant value is known as the range, which represents the transition of the variable to the state of negligible correlation. Thus, the range can ultimately be seen as the size of independent objects in the image.*"
  Of course, if the size of independent information content is too large compared to our field site, the satellite image cannot capture the spatial variation occur at the scale of the field site. This is essentially the same as saying that there is no statistical difference between neighbor pixels.
  To further demonstrate this point, we can complement the geostatistical analysis with a visual comparison of the NDVI and LST pixel data obtained at a certain distance away from the Foradada pixel.

  Page 11 line 12 (new version): We have added this information

  To further corroborate this point, Figure 6 compares the temporal evolution of LST and NDVI obtained from two adjoin MODIS pixels: the Foradada pixel and its North-West neighbour pixel. Note that the neighbor pixel corresponds to a not irrigated area. Data was downloaded using MOD13A2 and MOD11A1 products with Google Earth Engine website, from DOY036 to DOY298. In general, irrigation in an agriculture field site should produce a decrease in LST values and an increase in NDVI. However, Figure 6 shows the same dynamics and similar values in both pixels even when irrigation is applied. Results show that the LST and NDVI information cannot detect neither the sprinkler irrigation nor the crop growth as a consequence of irrigation in this case.

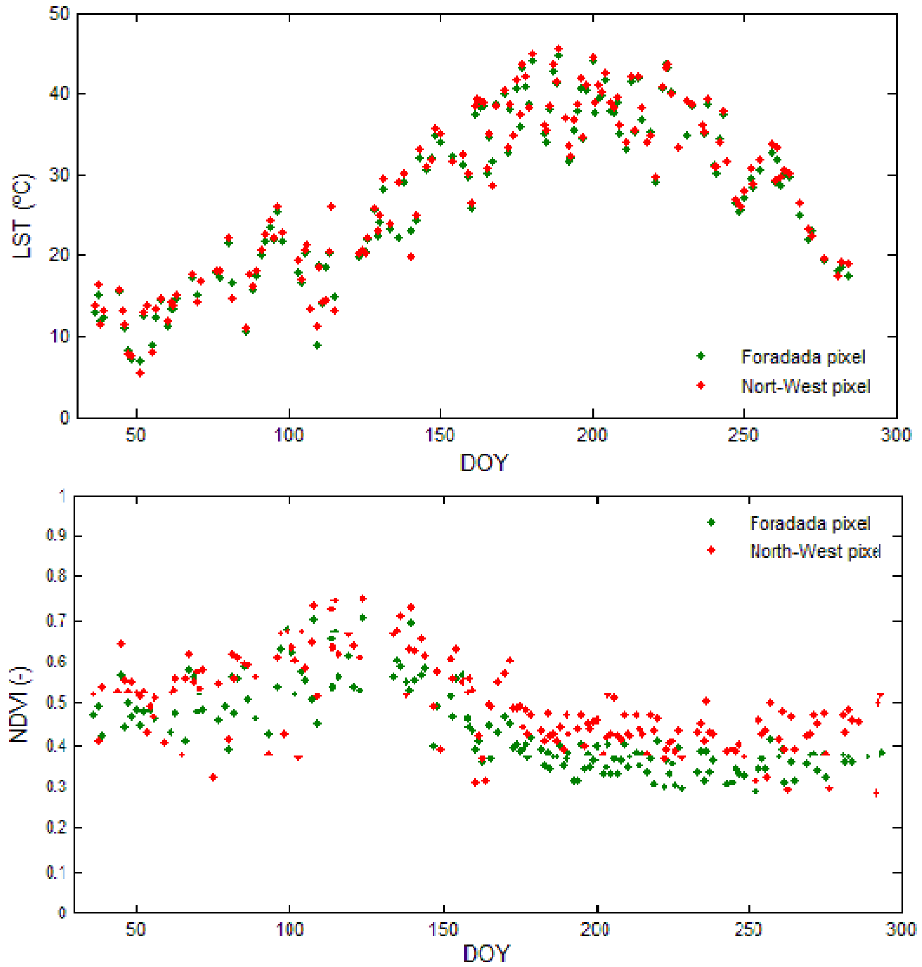

Figure 6. Temporal evolution of LST and NDVI obtained at the Foradada pixel and its neighbour North-West pixel situated 2 kms away.

In our opinion, we think that this extra information clarifies the information in the manuscript.

3) **MAJOR: Related to point (2), I believe that the problem is the strong dependency of the disggregated SMOS 1-km product to SMOS soil moisture product. SMOS has a spatial resolution of around 40 km, therefore it is not sensitive to small scale irrigation in the area. As the 1-km product is strongly dependent on SMOS, it is simply not suitable for detecting irrigation at a field scale (we obtain similar results in scientific analyses we doing). As mentioned above, the analysis of the NDVI and LST signal by MODIS should be carried out, even though the temporal resolution might be not good due to cloud coverage. I believe that if we want to consider a disaggregated soil moisture product for irrigation detection, a different strategy should be implemented.**

- We agree with your comment when you say that a different strategy for measuring soil moisture should be implemented, in fact, this is a part of our conclusions in page 12, line 7 (new version): *"From a different perspective, these results also suggest that irrigation scheduling based on satellite information coupled with the DISPATCH downscaling algorithm can be appropriate in regions of* *the world with extensive irrigation surface coverage, larger than approximately 10 km (e.g., Punjab basin). However, caution should be paid to the direct application of this method as its performance will strongly depend on the spatiotemporal variation of the irrigation within the area. These variations can generate occasional heterogeneity leading to the failure of the soil moisture prediction method."*

We would like to note that the DISPATCH method uses NDVI and LST information from Terra and Aqua satellite data to downscale soil moisture. The NDVI and LST satellite data is supposed to have a spatial resolution of 1 km and therefore one should expect these estimates to be affected by local irrigation at the scale of the given field site (and consequently the DISPATCH product). The point here is that we actually see that the DISPATCH product is not affected, which calls for a reanalysis of the spatial resolution of these input variables. In the revised manuscript, we have added this information for making this discussion clear:

We have added this information Page 10 line 2 (new version):

We seek to answer the important question of why the DISPATCH soil moisture estimates obtained by downscaling satellite information from 40 km to 1 km of resolution are not sensitive to sprinkler irrigation in this case. The following possible sources of discrepancies can be identified: (i) errors associated with the approximations used in the DISPATCH downscaling formulation; (ii) differences in the scale of observations; and (iii) low quality of information associated with DISPATCH input variables. We concentrate the analysis on (ii) and (iii).

MODERATE: As mentioned before, the text should be improved and specifically the structure of the paper. In section 4 "Discussion" the theoretical background of geostatistical analysis is described. It should be moved to the methodology section.

- We have also reorganized the manuscript to improve the structure and flow of the manuscript based on the comments raised by the two reviewers. We have rewritten some parts of the manuscript. In this context, we have added a sub-section entitled "Spatial Resolution and Spatial Variability" in section 2 (i.e., Materials and Methods). This way, the methods used to estimate the spatial resolution of variables (which where before introduced in the discussion section) were moved to the methods section. The new manuscript structure is as follow:
  1. Introduction
     1.1 Study Area
  2. Materials and Methods
     2.1 In Situ Soil Moisture Measurements
     2.2 DISPATCH Soil Moisture Measurements
     2.3 Spatial Resolution and Spatial variability
  3. Results
     3.1 General Observations
     3.2 Analysis and Discussion
  4. Conclusions

  We hope this will largely improve the clarity of the manuscript.

- We have also improved the manuscript in several editing aspects based on the comments raised by the two reviewers: avoiding repetitions, writing symbols, and equations consistently, improve English grammar and clarify confusing aspects about resolution and the use of scales.

SPECIFIC COMMENTS:

Note that the main specific comments are not in the document because we have rewritten the manuscript.

- **Page 1, line 8: Soil moisture data are not really important for climate change studies.**

  We have deleted "climate change studies" and added "hydro-climate approaches".

- **Page 1, line 10: "with both space and time" is not correct, to be revised.**

  We have rewritten this part.

- **Page 1, line 12: Currently we can obtain soil moisture estimated through 1) in situ observation (fixed stations and field measurements), 2) remote sensing (satellite, aire-planes, drones), and 3) modeling (hydrological and/or climate).**

  We have rewritten this part.

- **Page 1, line 13-14: "where soil moisture measurements…" Which measurements?**

  We have rewritten this part.

- **Page 4, line 16: Currently we have Setinel-1 that can provide 1-km soil moisture measurements… and also new techniques (e.g. CYGNSS)**

  Even though Setinel-1and other new techniques, such as CYNSS, provide soil moisture at 1 km resolution, we consider that it is not relevant information for abstract, but, we have added this information at the Introduction section (Page 4, line 6 new version):

  Other satellites, such as Sentinel-1, can estimate NSSM at 1 km resolution (Hornacek et al., 2012; Mattia et al., 2015; Paloscia et al., 2013). Sentinel-1 provides two kinds of products, the first one is Single Look Complex (SLC) and the second one is Ground Range Detected (GRD). The last one can be used for solving a wide range of problems related to Earth surface monitoring, such as soil moisture, but it is not a direct measurement and therefore data treatment is needed. In this case, GRD product is converted into radar backscatter coefficient and then into dB units to estimate soil moisture. Usually, these conversations are cumbersome because these kind of measurements have surface roughness and vegetation influence that affect the signal (Garkusha et al., 2017; Wagner et al., 2010).

- **Page 1, line 19: Acronyms should be defined (SMOS, NDVI, LST…)**

  It is true and we have added acronyms definitions (Page 1, line 14, new version).

  … DISaggregation based on Physical And Theoretical scale CHange algorithm (DISPATCH) has been proposed in the literature to downscale soil moisture satellite data from 40 km to 1 km of resolution by combining the low resolution Soil Moisture Ocean Salinity (SMOS) satellite soil moisture data with the high resolution (Normalized

Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) datasets obtained from a Moderate Resolution Imaging Spectroradiometer (MODIS) sensor.

- **Page 1, line27: "reason for why" remove "for"**
  We have rewritten this part.

Response to Reviewer 2:

GENERAL COMMENTS:

1) **CRITICAL: The manuscript does not read well and it needs to be revised by improving structure, avoiding repetitions, and by writing symbols, equations, acronyms consistently. Being a scientific paper, the structure has to be clear for the readership. I found the introduction doesn't flow and lacks background information. Methods/Results/Discussion sections are confusing; methods are scattered throughout the sections and discussion reveals mainly results. Find comments and suggestions in the document attached.**

   - We have improved the manuscript taking into account your specific comments, avoiding repetitions, writing symbols, and equations consistently. You can see all the corrections in the specific comments section.
   - We have rewritten the abstract:
     Abstract. Soil moisture measurements are needed in a large number of applications such as hydro-climate approaches, watershed water balance management and irrigation scheduling. Nowadays, different kinds of methodologies exist for measuring soil moisture. Direct methods based on gravimetric sampling or Time Domain Reflectometry (TDR) techniques measure soil moisture in a small volume of soil at few particular locations. This typically gives a poor description of the soil moisture spatial distribution in relatively large agriculture fields. Remote sensing of soil moisture provides a large coverage and can overcome this problem but suffers from other problems stemming from its low spatial resolution. In this context, the DISaggregation based on Physical And Theoretical scale CHange algorithm (DISPATCH) has been proposed in the literature to downscale soil moisture satellite data from 40 km to 1 km of resolution by combining the low resolution Soil Moisture Ocean Salinity (SMOS) satellite soil moisture data with the high resolution (Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) datasets obtained from a Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. In this work, DISPATCH estimations are compared with soil moisture sensors and gravimetric measurements to validate the DISPATCH algorithm in an agricultural field during two different hydrologic scenarios; wet conditions driven by rainfall events and local sprinkler irrigation. Results show that the DISPATCH algorithm provides appropriate soil moisture estimates during general rainfall events but not when sprinkler irrigation generates occasional heterogeneity. In order to explain these differences, we have examined the spatial variability scales of NDVI and LST data, which are the input variables involved in the downscaling process. Sample

variograms show that the spatial scales associated with the NDVI and LST properties are too large to represent the variations of the average soil moisture at the site and this could be a reason why the DISPATCH algorithm is not working properly in this field site.

- We have also reorganized the manuscript to improve the structure and flow of the manuscript based on the comments raised by the two reviewers. In this context, we have added a sub-section entitled "Spatial resolution analysis" in section 3 (i.e., Materials and Methods). This way, the methods used to estimate the spatial resolution of variables (which where before introduced in the discussion section) were moved to the methods section. The new manuscript structure is as follow:
  1. Introduction
     1.1 Study Area
  2. Materials and Methods
     2.1 In Situ Soil Moisture Measurements
     2.2 DISPATCH Soil Moisture Measurements
     2.3 Spatial Resolution and Spatial variability
  3. Results
     3.1 General Observations
     3.2 Analysis and Discussion
  4. Conclusions

  We hope this will largely improve the clarity of the manuscript.

2) **CRITICAL: The authors investigated the spatial variability of NSSM, NDVI and LST. Although, the spatial resolution of LST and NDVI is 1 km (using MODIS dataset), the spatial resolution of soil moisture is few centimeters by using gravimetric measurements. Thus, the comparison does not make any sense and the respective discussion is wrong. It would be interesting to explore the value of DisPATCh and LST for different field scales over large areas, such as the SG region. Or you explore LST and NDVI at high spatial resolution using Landsat data. Find comments and suggestions in the document attached.**

- There is some confusion here. The support volume of gravimetric soil moisture punctual measurements is few centimeters but the reviewer should notice that our comparison is not between point measurements and satellite information. The comparison is between the averages of these measurements over the entire field site (very well distributed with more than 100 measurement points) with satellite information. The average of the soil moisture is representative of the entire field site with a support volume of about 25 ha. Consequently, these two variables have similar support scale and therefore are comparable.
  We have rewritten part of the manuscript to clarify this issue, Page 8, Line 23 (new version):
  Figures 3 compares gravimetric and soil moisture sensor measurements with the DISPATCH soil moisture estimates obtained from remote sensing data during the first period of time (without irrigation). We note that the comparison here is not between punctual gravimetric measurements (with support volume of few centimetres) and satellite information (1 km in resolution). We compare the

average of these punctual measurements over the entire field site (very well distributed with more than 100 measurement points) with satellite information. The average of the soil moisture is representative of the entire irrigated area associated with the Foradada field site. Consequently, these two variables have similar support scale and are therefore comparable. Error bars in the gravimetric measurements represent the standard deviation of all the measurements obtained in one day. In addition, the green region in this figure displays the daily minimum and maximum values of soil moisture data obtained from 5 EC-5 sensors.

- Another point along the same line is that soil moisture sensor data is also measured at the centimeter scale. This data is interesting because it shows the daily fluctuations of soil moisture. Sensors are well distributed over the entire field site but in this case we have only 5 sensors. Gravimetric measurements show that the average of soil moisture over the entire field site lays always between the maximum and minimum values of these sensors. Based on this, we have chosen to exhibit the minimum and maximum values of these 5 sensors in the figures. This way, the reader knows that the average soil moisture value lays within this region and can therefore appreciate the differences between the average soil moisture and satellite information in days where only sensor data is available. This point was also not clearly explained in the manuscript and we therefore understand the confusion of the reviewer.

We have now rewritten the manuscript to clarify this point. Page 9, Line 7 (new version):

We note that the average of gravimetric soil moisture data lays always within this region.

- We agree that it would be interesting to explore the value of DisPATCh and LST for different field scales over larger areas, such as the SG region, but the DISPATCH algorithm has been already well validated over large areas (Escorihulea et al. 2016, Malbeteau et al. 2015 2018, Molero et al. 2016) and we thought it is more interesting to analyze this under different conditions, i.e., punctual heterogeneity produced by local irrigation. Note that we already mentioned in the manuscript that the DISPATCH algorithm is capable to detect water bodies such as rivers, floods and large irrigated areas (page 4, line 19, new version).

3) **MAJOR: The authors evaluated DisPATCh NSSM using in situ measurements, however this study needs to be fulfilled by a statistical analysis (Correlation, Bias etc..). The result section would be improved by adding a temporal description/comparison of NSSM.**

- We sincerely do not understand this point; we have done more than this. We have conducted a geostatistical analysis of the key data involved, which is more than a simple statistical analysis. Even the field campaigns were designed to characterize the spatial variability. In the end, we decided to only show the variograms because we think it is the information needed to understand the discrepancy observed between satellite information and measurements. Moreover, the scope of the manuscript is not to report a geostatistical analysis but to understand the worth of satellite information for local irrigation.

4) **MAJOR: I don't think that concluding statement: "DisPATCh algorithm fails to describe the fluctuations in water content caused by irrigation" is correct; the current spatial resolution of DisPATCh might still be too coarse for local irrigation detection. However, DisPATCh succeeded to reveal spatial heterogeneity as rivers, irrigation areas, floods (Escorihuela et al. 2016, Malbeteau et al., 2015 2018, Molero et al., 2016). It would be interesting to discuss the value and the limitation of DisPATCh over irrigated area (from local to large irrigation system). This conclusion needs to be balanced and the limitation of the analysis performed in this study need to be considered.**

- We have changed the sentence "DisPATCh algorithm fails to describe the fluctuations in water content caused by irrigation" with Page 11, Line 25 (new version):
  Results have shown that in this case the downscaled soil moisture estimations are capable of predicting the variations in soil moisture caused by general rainfall events but fail to reproduce the temporal fluctuations of the average water content caused by local irrigation.
- To clarify the advantages of DisPATCh we have added in the introduction section Page 4, Line 18 (new version):
  DISPATCH succeed to reveal spatial heterogeneities as rivers, large irrigation areas and floods (Escorihuela and Quintana-Seguí, 2016; Malbéteau et al., 2015, 2017; Molero et al., 2016) and it has also been validated (Malbéteau et al., 2015; Merlin et al., 2012; Molero et al., 2016) in fairly large and homogeneous irrigation areas, but not in complex settings with spatially changing hydrologic conditions such as those representing a local irrigation field.

MINOR: (1) Figures 1 to 4 need to be improved before publication. I suggest that they can be merged into one figure with two subfigures (figures 2, 3 and 4 into one map + zoon out figure 1 in order to see the coastline and Barcelona). (2) DisPATCh pixels on figure 4 are not squared, any explanation? Is it really 1x1 km?
We think that we can merge Figure 1, 2 and 3 like the figure is shown below (Figure 1), but we think that merge also Figure 4 is too much information in a single figure.

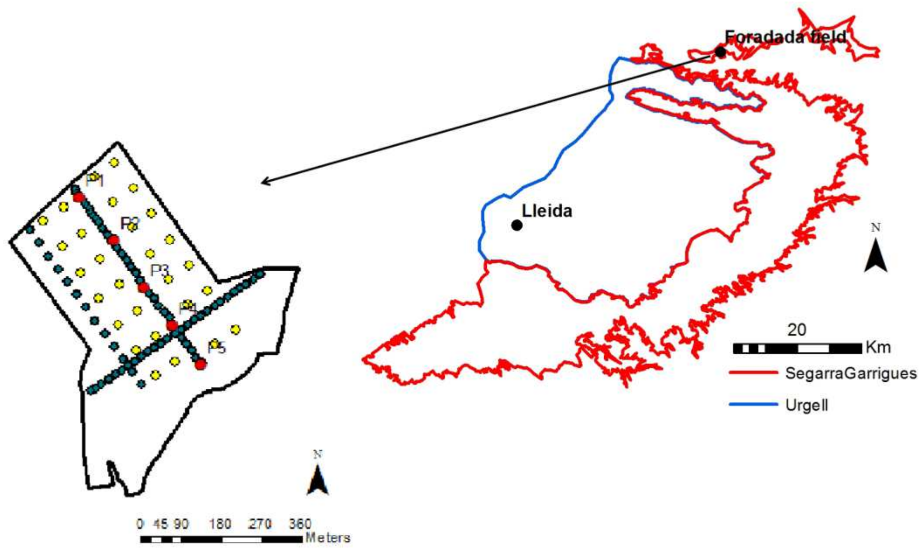

Figure 1. Location of the Foradada field site within the Segarra-Garriga irrigation system and distribution of soil moisture measurement points. Gravimetric measurement points are arranged with cross section points in green and support points in yellow. The location of EC-5 sensors are represented in red.

- It is not exactly 1 x 1 km, it is 0.9 x 1.1 km.

SPECIFIC COMMENTS:

Note that the main specific comments are not in the document because we have rewritten the manuscript.

- **Page 1 line 8:**
  We have deleted “climate change”

- **Page 1 line 12:**

  We have rewritten this part of the abstract.

- **Page 1 line 22:**
  We have rewritten this part of the abstract.

- **Page 1 line 27:**
  We have rewritten this part of the abstract.

- **Page 2 line 12:**
  We have rewritten this part.

- **Page 2 line 1:**

  We have added some information Page 2 line 7 (new version):

  “Here, we highlight that soil moisture measurements from the root zone yields important information for field irrigation scheduling, determining to a great extent the duration and frequency of irrigation needed for plant growth as a function of water availability (Blonquist et al., 2006; Jones, 2004; Campbell, 1982).”

- **Page 2 line 16:**

  we have added Page 2 line 11 (new version): “ and with atmospheric conditions (Koster and Suarez, 2001)”.

- **Page 3 line 7:**

  We have rewritten this part.

- **Page 3 line 25:**

  We have connected better both sentences with. Page 3, Line 8 (new version):

"It has global coverage and a revisit period of 3 days at the equator, giving two soil moisture estimations, the first one taken during the ascending overpass at 6:00 am and the second one during the descending overpass at 6:00 pm local solar time."

- **Page 3 line 16:**

  We have modified the sentence with Page 3, Line 13 (new version):

  "Since SMOS NSSM have been validated on a regular basis since the beginning of its mission (Bitar et al., 2012; Delwart et al., 2008), it is considered suitable for hydro-climate applications (Lievens et al., 2015; Wanders et al., 2014).

- **Page 4 line 7:**

  We have deleted "authors" and added "studies". Page 4 line 2 (new version).

- **Page 4 line 11:**

  Your comment is "This makes it sound like its 'just another algorithm'. Rephrase the sentence in a way that introduces DISPATCH already as a superior method".

  We do not know or we do not have any reference that this algorithm is superior to the other algorithms.

- **Page 4 line 17:**

  Your comment is "Great! But why do we need it validated in irrigation fields? Highlight the importance of having this. Also, was there anywhere a mention between differences in soil moisture in irrigation vs rain fail? That is critical and missing here.

  We think that is necessary validate this algorithm in irrigation fields because one of the aim of this algorithm is monitor soil moisture for irrigation scheduling and management. Thus, this validation is the next step for the algorithm.

  We assume that precipitation and irrigation increase water content in the field and this process is measured by soil moisture sensors, but we consider that there is no difference between them except the scale effect (general rain fall versus local irrigation).

- **Page 4 line 23:**

  We have changed "lot" by "lon". Page 5 line 2 (new version).

- **Page 5 line 5:**

  We have changed "has" by "represents". Page 5 line 11 (new version).

- **Page 6 line 8:**

  We changed the title of the subsection " Remote Sensing Soil Moisture Measurements" by "DISPATCH Soil Moisture Measurements". Page 6 line 13 (new version).

- **Page 6 line 9:**

  We modified the sentence "The main objective of the DISPATCH algorithm is to downscale" by "DISPATCH algorithm aims to downscale". Page 6 line 15 (new version).

- **Page 7 line 7:**

  We have rewritten this part.

- **Page 10 line 18:**

  We have rewritten this part.

- **Page 11 line 14:**

  We have rewritten this part.

The value of satellite remote sensing soil moisture data and the DISPATCH algorithm in irrigation fields

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Abstract. Soil moisture measurements are needed in a large number of applications such as hydro-climate approaches, watershed water balance management and irrigation scheduling. Nowadays, different kinds of methodologies exist for measuring soil moisture. Direct methods based on gravimetric sampling or Time Domain Reflectometry (TDR) techniques measure soil moisture in a small volume of soil at few particular locations. This typically gives a poor description of the soil moisture spatial distribution in relatively large agriculture fields. Remote sensing of soil moisture provides a large coverage and can overcome this problem but suffers from other problems stemming from its low spatial resolution. In this context, the DISaggregation based on Physical And Theoretical scale CHange algorithm (DISPATCH) has been proposed in the literature to downscale soil moisture satellite data from 40 km to 1 km of resolution by combining the low resolution Soil Moisture Ocean Salinity (SMOS) satellite soil moisture data with the high resolution Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) datasets obtained from a Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. In this work, DISPATCH estimations are compared with soil moisture sensors and gravimetric measurements to validate the DISPATCH algorithm in an agricultural field during two different hydrologic scenarios; wet conditions driven by rainfall events and local sprinkler irrigation. Results show that the DISPATCH algorithm provides appropriate soil moisture estimates during general rainfall events but not when sprinkler irrigation generates occasional heterogeneity. In order to explain these differences, we have examined the spatial variability scales of NDVI and LST data, which are the input variables involved in the downscaling process. Sample variograms show that the spatial scales associated with the NDVI and LST properties are too large to represent the variations of the average soil moisture at the site and this could be a reason why the DISPATCH algorithm is not working properly in this field site.

1. Introduction

Soil moisture measurements taken over different spatial and temporal scales are increasingly required in a wide range of environmental applications, which include crop yield forecasting (Holzman et al., 2014), irrigation planning (Vellidis et al., 2016), early warnings for floods and draughts (Koriche and Rientjes, 2016), and weather forecasting (Dillon et al., 2016).

This is mostly due to the fact that soil moisture controls the water and energy exchange between key environmental compartments (atmosphere and earth) and hydrological processes, such as precipitation, evaporation, infiltration, and run-off (Ochsner, 2013; Robock et al., 2000).

There are several applications in which soil moisture measurements have been shown to provide relevant information (Robock et al., 2000). For example, in environmental applications, soil moisture is typically used for defining the water stress occurring in natural and human systems (Irmak et al., 2000) or for quantifying nitrate leaching and drainage quality (Clothier and Green, 1994). Here, we highlight that soil moisture measurements from the root zone yields important information for field irrigation scheduling, determining to a great extent the duration and frequency of irrigation needed for plant growth as a function of water availability (Blonquist et al., 2006; Jones, 2004; Campbell, 1982).

Soil moisture is highly variable in space and time, mainly as a result of the spatial variability in soil properties (Hawley, 1983), topography (Burt and Butcher, 1985), land uses (Fu, 1994), vegetation (Le Roux et al., 1995) and atmospheric conditions (Koster and Suarez, 2001). As a result, soil moisture data exhibits a strong scale effect that can substantially affect the reliability of predictions depending on the method of measurement used. For this reason, it is important to understand how to measure soil moisture for irrigation scheduling in a commercial field site.

Nowadays, available techniques for measuring or estimating soil moisture can provide data on a small or large scale. Gravimetric measurements (Gardner, 1986) estimate soil moisture by the difference between the natural and the dry weight of a given soil sample. They are used as a true value of soil moisture for sensor calibration (Starr and Paltineanu, 2002) or soil moisture validation studies (Bosch et al., 2006; Cosh et al., 2006). The main disadvantage of this method is that these measurements are time-consuming; users have to go to the field to collect soil samples and place them in the oven for a long time. Soil moisture sensors such as Time Domain Reflectometry sensors (Clarke Topp and Reynolds, 1998; Schaap et al., 2003; Topp et al., 1980) or capacitance sensors (Bogena et al., 2007; Dean et al., 1987) are capable of measuring soil moisture continuously using a data logger, thereby enabling the final user to save time. Soil moisture sensors are especially useful for studying processes at a small scale, but suffer from the fact that field data is typically scarce and provides an incomplete picture of a large area (Western et al., 1998). Nevertheless, the use of soil moisture sensors is a common practice for guiding irrigation scheduling in cropping field systems (Fares and Polyakov, 2006; Thompson et al., 2007; Vellidis et al., 2008).

Remote Sensing, can estimate soil moisture continuously over large areas (Jackson et al., 1996). In this case, soil moisture estimations refer to the Near Surface Soil Moisture (NSSM), which represents the first 5 cm of the top soil profile. In recent years, Remote Sensing techniques have been improved and diversified their estimation, making them an interesting tool for monitoring NSSM and other variables such as the Normalized Difference Vegetation Index (NDVI) and the Land Surface Temperature (LST). Different satellites exist that are capable of estimating NSSM, one of them is the Soil Moisture and Ocean Salinity (SMOS) satellite launched in November 2009 (Kerr et al., 2001). It has global coverage and a revisit period of 3 days at the equator, giving two soil moisture estimations, the first one taken during the ascending overpass at 6:00 am and the second one during the descending overpass at 6:00 pm local solar time. SMOS satellite is a passive 2D interferometer operating at L-band (1.4 GHz) (Kerr et al., 2010). The spatial resolution ranges from 35 to 55 km, depending on the incident angle. Its goal is to retrieve NSSM with a target accuracy of a 0.04 m3/m3 (Kerr et al., 2012). Since SMOS NSSM have been validated on a regular basis since the beginning of its mission (Bitar et al., 2012; Delwart et al., 2008), it is considered suitable for hydro-climate applications (Lievens et al., 2015; Wanders et al., 2014).

The relatively large variability of soil moisture compared to the low resolution of SMOS-NSSM data hinders the direct application of this method to irrigation scheduling. However, the need for estimating NSSM with a resolution higher than 35 – 55 km using Remote Sensing has increased for different reasons: 1) This data can be downloaded easily from different web sites; 2) A field installation of soil moisture sensors is not necessary; and 3) No specific maintenance is needed. For these reasons, in the last few years, different algorithms have been developed to downscale Remote Sensing soil moisture data to tens or hundreds of meters.

Chauhan et al., (2003) developed a Polynomial fitting method which estimates soil moisture at 25 km resolution. This method links soil moisture data with surface temperature, vegetation index and albedo. It does not require in situ measurements but cannot be used under cloud coverage conditions. The change in the detection method reported by Narayan et al. (2006) downscales soil moisture at 100 m resolution. This is an optimal resolution for agricultural applications, but the method is highly dependent on the accuracy of its input data. The same problem is attributed to the Baseline algorithm for the Soil Moisture Active Passive (SMAP) satellite (Das and Mohanty, 2006), which downscales soil moisture at 9 km resolution. These algorithms have to be validated using in situ measurements. For this purpose, most studies use soil moisture sensors installed at the top soil profile, i.e., the first 5 cm of soil (Albergel et al., 2011; Cosh et al., 2004; Jackson et al., 2010), while others use gravimetric soil moisture measurements (Merlin et al., 2012) or the combination of both methodologies (Robock et al., 2000).

Other satellites, such as Sentinel-1, can estimate NSSM at 1 km resolution (Hornacek et al., 2012; Mattia et al., 2015; Paloscia et al., 2013). Sentinel-1 provides two kinds of products, the first one is Single Look Complex (SLC) and the second one is Ground Range Detected (GRD). The last one can be used for solving a wide range of problems related to Earth surface monitoring, such as soil moisture, but it is not a direct measurement and therefore data treatment is needed. In this case, GRD product is converted into radar backscatter coefficient and then into dB units to estimate soil moisture. Usually, these conversations are cumbersome because these kind of measurements have surface roughness and vegetation influence that affect the signal (Garkusha et al., 2017; Wagner et al., 2010).

The DISPATCH method (DISaggagregation based on Physical And Theorical CHange) (Merlin et al., 2012; Merlin et al., 2008) is an algorithm that downscales SMOS NSSM data from 40 km (low resolution) to 1 km resolution (high resolution). This algorithm uses Terra and Aqua satellite data to estimate NDVI and LST twice a day using the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. These estimations have 1 km resolution and can be conducted even if there is no cloud coverage. This downscaling process provides the final user with the possibility of estimating NSSM using Remote Sensing techniques at high resolution. DISPATCH succeed to reveal spatial heterogeneities as rivers, large irrigation areas and floods (Escorihuela and Quintana-Seguí, 2016; Malbéteau et al., 2015, 2017; Molero et al., 2016) and it has also been validated (Malbéteau et al., 2015; Merlin et al., 2012; Molero et al., 2016) in fairly large and homogeneous irrigation areas, but not in complex settings with spatially changing hydrologic conditions such as those representing a local irrigation field.

In this work, we evaluate the worth of Remote Sensing in agricultural irrigation scheduling by comparing in situ soil moisture data obtained from gravimetric and soil moisture sensors, with soil moisture data determined by downscaling Remote Sensing information with the DISPATCH algorithm.

1.1. Study Area

The study area shown in Figure 1 is located in the village of Foradada (1.015 lat., 41.866 lon.), in the Segarra – Garrigues (SG) system (Lleida, Catalonia). The SG system is an important hydraulic project currently being carried out in the province of Lleida, Catalonia, which involves converting most of the current dry land fields into irrigated fields. Its construction enables 1000 new hectares with a long agricultural tradition to be irrigated in most of the dry land. To achieve this, an 85 km long channel was constructed to supply water for irrigation. At present, approximately 16000 irrigators are potential beneficiaries of these installations. However, most farmers have not yet installed this irrigation system, which means that the SG systems can still be regarded as dry land.

The Urgell area is located in the west of the SG system. This area has totally different soil moisture conditions, especially during the summer season when the majority of fields are currently irrigated. This gives rise to two clearly distinguishable wet and dry soil moisture conditions. Figure 1 shows the Foradada field, which represents 25 ha of a commercial field irrigated by a solid set sprinkle irrigation system distributed with 18 different irrigation sectors. The soil texture is 65.6% Clay, 17.6% Silt and 16.8 Sand. Every year two different crops are grown, the first one during the winter and spring seasons, when wet conditions are maintained by precipitation, and the second one during the summer and autumn seasons, when wet conditions are maintained by sprinkler irrigation. The Foradada field is thus one of the few irrigated fields located within the SG system. Consequently, this field has soil moisture conditions similar to those in the surrounding area during the winter and spring season, but completely different conditions during the summer and autumn seasons. This makes this site unique for assessing Remote Sensing in a distinct isolated irrigation field.

2. Materials and Methods

2.1. In situ Soil Moisture Measurements

A total of 9 intensive and strategic field campaigns were conducted in the study area during 2016: DOY42, DOY85, DOY102, DOY187, DOY194, DOY200, DOY215, DOY221 and DOY224. During each field campaign, disturbed soil samples were collected from the top soil profile (0-5 cm depth) for measuring gravimetric soil moisture data. A total of 101 measurement points, depicted in Figure 1., were defined around the field. They are divided into two different kinds of points:

1) Cross section points; 75 points defined to represent the spatial variability of soil moisture in different cross sections. In these cross sections, points are separated by 9, 16 and 35 m; 2) Support points; 26 points complement information measured from cross sections, thereby adding and supporting information about field spatial variability. Each soil sample is analyzed using the gravimetric method for measuring gravimetric soil moisture content, which is transformed to volumetric soil moisture content using bulk density measurements (Letelier, 1982). Daily averages and their standard deviations of gravimetric measurements were computed to represent the soil moisture associated with the entire field site.

Soil moisture was also measured using capacitive EC-5 sensors (METER Group, Pullman, WA, USA), previously calibrated in the laboratory (Star and Paltineanu, 2002). As Figure 1 shows, a total of 5 control points were installed across one of the three gravimetric cross sections. Each control point represents a different irrigation sector of the field. Soil moisture sensors were installed at 5 cm depth, taking into account the explore volume of these sensors. Their resolution is ±0.03 cm3·cm-3. They were connected to an EM50G data logger (METER Group, Pullman, WA, USA) that register soil moisture every 5 minutes.

2.2. DISPATCH Soil Moisture Measurements

In this section we briefly describe the DISPATCH algorithm. Further details can be found in Merlin et al. (2013) and references therein. The DISPATCH algorithm aims to downscale NSSM data obtained from SMOS at 40 km resolution to 1 km resolution. The method assumes that NSSM is a linear function of the Soil Evaporative Efficiency (SEE), which can be estimated at high resolution (1 km) from the acquisition of two products obtained from MODIS, i.e., LST and NDVI datasets. This MODIS-derived SEE is further considered as a proxy for the NSSM variability within the SMOS pixel. The estimation of SEE is assumed to be approximately constant during the day given clear sky conditions. The downscaling relationship is given by Eq. (1)

$$\theta_{\mathrm{HR}} = \theta_{\mathrm{SMOS}} + \theta'_{\mathrm{HR}}(\mathrm{SEE}_{\mathrm{SMOS}}) \times (\mathrm{SEE}_{\mathrm{HR}} - \mathrm{SEE}_{\mathrm{SMOS}}), \tag{1}$$

where θ_{SMOS} is the low resolution SMOS soil moisture data, $\mathrm{SEE}_{\mathrm{HR}}$ is the MODIS-derived SEE at a high resolution (1 km), $\mathrm{SEE}_{\mathrm{SMOS}}$ is the average of $\mathrm{SEE}_{\mathrm{HR}}$ within the SMOS pixel at a low resolution (40 km), and $\theta'_{\mathrm{HR}}(\mathrm{SEE}_{\mathrm{SMOS}})$ is the partial derivative of soil moisture with respect to the soil evaporative efficiency at high resolution evaluated at the $\mathrm{SEE}_{\mathrm{SMOS}}$ value.

This partial derivative is typically estimated by using the linear soil evaporative efficiency model of Budyko (1956) and Manabe (1969), which is written by Eq. (2)

$$\theta_{HR} = SEE_{HR} \times \theta_p \quad (2)$$

where θ_{HR} represents the soil moisture of the top soil layer (0-5 cm) at high resolution, and θ_p is an empirical parameter that depends on soil properties and atmospheric conditions. The soil evaporation efficiency at high resolution SEE_{HR} is estimated as a linear function of the soil temperature at high resolution ($T_{s,HR}$), Eq. (3)

$$SEE_{HR} = \frac{T_{s,max} - T_{s,HR}}{T_{s,max} - T_{s,min}}, \quad (3)$$

The soil temperature at high resolution is estimated by partitioning the MODIS surface temperature data (LST) into the soil and the vegetation component according to the trapezoid method of Moran et al. (1994). This also requires an estimation of the fractional vegetation cover, which is calculated from the NDVI data. $T_{s,min}$ and $T_{s,max}$ are the soil temperature end-members (Merlin et al., 2012).

In this work, the DISPATCH algorithm has been executed during period DOY36 and DOY298 to estimate NSSM at 1 km resolution in the Foradada field site. DISPATCH provides a daily NSSM pixel map (regular grid). The Foradada field site is entirely included in one pixel. In this pixel, 51.5% of the total area corresponds to irrigated area. The remaining portion of the pixel corresponds to dry land (shown in Figure 2).

2.3. Image Spatial Resolution and Spatial Variability

The information contained in a satellite image is characterized here by two properties: the spatial resolution and the spatial variability of the image attributes. The spatial resolution of a satellite image is the ground area represented by each pixel, i.e., the raster cell size. It is essentially the representative support volume chosen to describe the variations of the attributes of interest at the ground. This is typically determined based on the type of satellite sensor. Instead, the spatial variability refers to the variations of the attributes presented in the image at the ground surface, e.g., patterns of spatial continuity, size of objects in the scene, and so on. In random field theory and geostatistics, the spatial variability is mainly characterized by the covariance function or by its equivalent, the semivariogram, which is defined by (Journel and Huijbregts, 1978) Eq. (4),

$$\gamma(h) = \frac{1}{2} E\{[Z(x+h) - Z(x)]^2\}, \quad (4)$$

where Z(x) is the random variable at the x position, and E{·} is the expectation operator. Essentially, the semivariogram is a function that measures the variability between pairs of variables separated by a distance h. Very often, the correlation between two variables separated by a certain distance disappears when |h| becomes too large. At this instant, γ(h) approaches a constant value. The distance beyond which γ(h) can be considered to be a constant value is known as the range, which represents the transition of the variable to the state of negligible correlation. Thus, the range can ultimately be seen as the size of independent objects in the image. If the pixel size is smaller than 10 times the minimum range (in the absence of the nugget effect), then neighbour pixels will be alike, containing essentially the same level of information (Journel and Huijbregts, 1978). This will be a critical point in the discussion of the results later on. We finally note that the spatial resolution and the spatial variability are two related concepts. Several authors content that a rational choice of the spatial resolution for remote sensing should be based on the relationship between spatial resolution and spatial dependence. However, since this is not the usual procedure, the spatial resolution can be inappropriate in some cases or provide unnecessary data (Atkinson and Curran, 1997; Woodcock and Strahler, 1987).

3. Results

3.1. General Observations

One of the main advantages of our experiment is that remote sensing soil moisture data is evaluated during two different hydrologic periods of the same year in a given agriculture field site. The first period represents crop growth with soil wet conditions caused by natural rainfall events (without irrigation). This period transpired during the winter and spring season, i.e., from February to June. The following period occurs during the dry season with artificially created soil wet conditions caused by sprinkler irrigation operating upon crop demand during the summer and autumn season, from June to October. In contrast to the rainfall events, sprinkler irrigation creates a local artificial rainfall event using several rotating sprinkler heads. The comparisons of these two hydrologic periods allow us to evaluate the sole effect of local sprinkler irrigation on remote sensing estimates.

Figures 3 compares gravimetric and soil moisture sensor measurements with the DISPATCH soil moisture estimates obtained from remote sensing data during the first period of time (without irrigation). We note that the comparison here is not between punctual gravimetric measurements (with support volume of few centimetres) and satellite information (1 km in resolution). We compare the average of these punctual measurements over the entire field site (very well distributed with more than 100 measurement points) with satellite information. The average of the soil moisture is representative of the entire irrigated area associated with the Foradada field site. Consequently, these two variables have similar support scale and are therefore comparable. Error bars in the gravimetric measurements represent the standard deviation of all the measurements obtained in one day. In addition, the green region in this figure displays the daily minimum and maximum values of soil moisture data obtained from 5 EC-5 sensors. We note that the average of gravimetric soil moisture data lays always within this region. Therefore, this information can be used to complement soil moisture data in days where no gravimetric sampling is available. The error bars associated with DISPATCH data refer to the standard deviation obtained with two daily SMOS estimations and four MODIS data (two at 6:00am and two more at 6:00 pm). To better appreciate tendencies, the same information is also presented as a normalized relative soil moisture, i.e., $(\theta - \theta_{\min})/(\theta_{\max} - \theta_{\min})$, where $\theta_{\min}$ are the minimum and maximum values of all soil moisture measurements. Results show that DISPATCH estimates can properly detect the relative increase in soil moisture estimates caused by general rainfall events. Note for instance that all methods produce a similar relative increase in soil moisture signal after the occurrence of a strong rainfall event. In absolute terms, we see that DISPATCH can slightly underestimate the true value of soil moisture but this could be attributed to small differences between the support volume of the field site and the spatial resolution of the satellite image.

A similar analysis is shown in Figure 4, which compares gravimetric and sensor soil moisture measurements with DISPATCH soil moisture estimations during the second period (soil wet conditions maintained by sprinkler irrigation). In contrast to our previous results, one can see that the DISPATCH dataset is essentially not sensitive to sprinkler irrigation even though they respond properly to sporadic small rainfall events. Likewise, the relative increase in soil moisture measurements also shows that sprinkler irrigation does not affect the DISPATCH estimation. Thus, even though the DISPATCH estimations seems to properly respond to significant rainfall events during the first period, irrigation operating at the Foradada field scale remains undetected during the second period. The DISPATCH dataset disregards irrigation and merely indicates that soil dry conditions exist at a larger picture. We conclude then that the DISPATCH dataset provides representative estimates of soil moisture at a resolution lower than expected.

3.2. Analysis and Discussion

We seek to answer the important question of why the DISPATCH soil moisture estimates obtained by downscaling satellite information from 40 km to 1 km of resolution are not sensitive to sprinkler irrigation in this case. The following possible sources of discrepancies can be identified: (i) errors associated with the approximations used in the DISPATCH downscaling formulation; (ii) differences in the scale of observations; and (iii) low quality of information associated with DISPATCH input variables. We concentrate the analysis on (ii) and (iii). First, we note that the DISPATCH resolution of 1 km is similar to the characteristic scale of the irrigated area at the Foradad field site and therefore a better performance was expected. The extent of the irrigated area in the DISPATCH pixel size of interest is 51.5 % (see Figure 2). Given that soil moisture is a linear property, we content that this cannot explain the almost zero relative increase in soil moisture obtained during irrigation. Then, we examine the semivariograms of the different input variables involved in the downscaling process, i.e., the NDVI and the LST properties provided by the MODIS sensor. The NDVI and LST semivariograms were respectively estimated from the MOD13A2 and MOD11A1 product data, which can be freely downloaded from the Google Earth Engine website (https://earthengine.google.com). We selected a daily representative image of April, June and August. The April image describes a general rainfall event in the region, the June image shows when local irrigation starts in the Foradada field, and finally the August image represents when the crop is well developed and frequent irrigation is needed. Experimental semivariograms have been fitted with a theoretical model (spherical and exponential models for the LST and NDVI, respectively), which can be formally expressed as Eq. 5 and 6,

$$\gamma_{LST}(h) = c_{11}\,\mathrm{Sph}\left(\frac{|h|}{a_{11}}\right) + c_{12}\left[1 - \cos\left(\frac{|h|}{a_{12}}\,\pi\right)\right], \tag{5}$$

$$\gamma_{NDVI}(h) = c_{21}\,\mathrm{Exp}\left(\frac{|h|}{a_{21}}\right) + c_{22}\,\mathrm{Exp}\left(\frac{|h|}{a_{22}}\right) + c_{23}\left[1 - \cos\left(\frac{|h|}{a_{23}}\,\pi\right)\right], \tag{6}$$

where c_{ij} are constant coefficients that represent the contribution of the different standard semivariogram models, and a_{ij} are the corresponding ranges of the different structures. The LST and NDVI experimental and theoretical semivariograms are shown in Figure 5. The parameters adopted in the random function model are summarized in Tables 1 and 2. The analysis determines a nested structure with a positive linear combination between isotropic stationary semivariogram models and the hole effect model. Hole effect structures most often indicate a form of periodicity (Pyrcz and Deutsch, 2003). In our case, this periodicity reflects the presence of areas with different watering and crop growth conditions, i.e., in contrast to the SG area, the Urgell area is based on irrigation.

The spatial variability of NDVI and LST vary with time according to changes in hydrologic conditions. In April, the semivariogram of NDVI displays more variability and less spatial continuity due to the differences in growth rate and crop type conditions existing at the regional scale during the wet season (controlled by rainfall events). On the other hand, the spatial dependence of LST is more significant in August. Importantly, results show that the scale of variability (range) associated with MODIS data during the dry season, when a controlled amount of water by irrigation is applied, ranges between 35 and 36 km for the NDVI and between 22 and 32 km for the LST. Recalling the discussion provided in section 2.3., this means that the size of independent objects in the NDVI and LST images is about 30 kms and that insignificant spatial variations of NDVI and LST values are expected below 1/10 of this size. This suggests that the NDVI and LST products provided by MODIS cannot detect differences between neighbour pixels of size 1 km.

To further corroborate this point, Figure 6 compares the temporal evolution of LST and NDVI obtained from two adjoin MODIS pixels: the Foradada pixel and its North-West neighbour pixel. Note that the neighbour pixel corresponds to a not irrigated area. Data was downloaded using MOD13A2 and MOD11A1 products with Google Earth Engine website, from DOY036 to DOY298. In general, irrigation in an agriculture field site should produce a decrease in LST values and an increase in NDVI. However, Figure 6 shows the same dynamics and similar values in both pixels even when irrigation is applied. Results show that the LST and NDVI information cannot detect neither the sprinkler irrigation nor the crop growth as a consequence of irrigation in this case.

4. Conclusions

We analyze the value of Remote Sensing and the DISPATCH downscaling algorithm for predicting soil moisture variations in an irrigated field site of size close to image resolution. The DISPATCH algorithm based on the NDVI and LST data obtained from the MODIS satellite is used for downscaling the SMOS information and transforming the SMOS soil moisture estimations from a resolution of 40 km to 1 km. These estimates are then compared with average gravimetric and soil moisture sensors measures taken all over the field site. Results have shown that in this case the downscaled soil moisture estimations are capable of predicting the variations in soil moisture caused by general rainfall events but fail to reproduce the temporal fluctuations of the average water content caused by local irrigation. To provide insight into this problem, we examine the spatial variability of the different input variables involved, i.e., the NDVI, the LST. Results indicated that the size of individual objects in the NDVI and LST images is too large to be able to represent adequately the variations of the average water content at the site. This effect is not significant during rainfall events because the typical spatial scale of rainfall events is much larger than the size of the irrigated field site.

From a different perspective, these results also suggest that irrigation scheduling based on satellite information coupled with the DISPATCH downscaling algorithm can be appropriate in regions of the world with extensive irrigation surface coverage, larger than approximately 10 km (e.g., Punjab basin). However, caution should be paid to the direct application of this method as its performance will strongly depend on the spatiotemporal variation of the irrigation within the area. These variations can generate occasional heterogeneity leading to the failure of the soil moisture prediction method.

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Figures

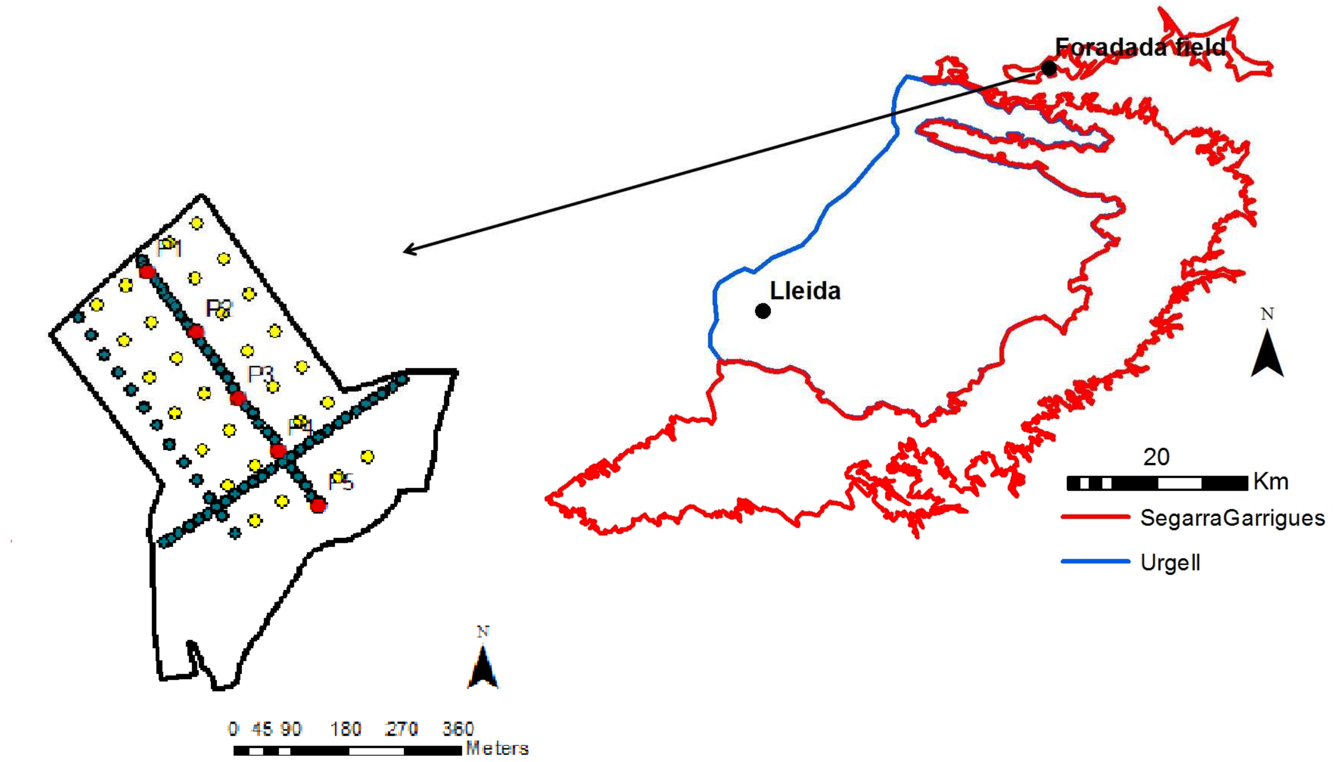

Figure 1. Location of the Foradada field site within the Segarra-Garriga irrigation system and distribution of soil moisture measurement points. Gravimetric measurement points are arranged with cross section points in green and support points in yellow. The location of EC-5 sensors are represented in red.

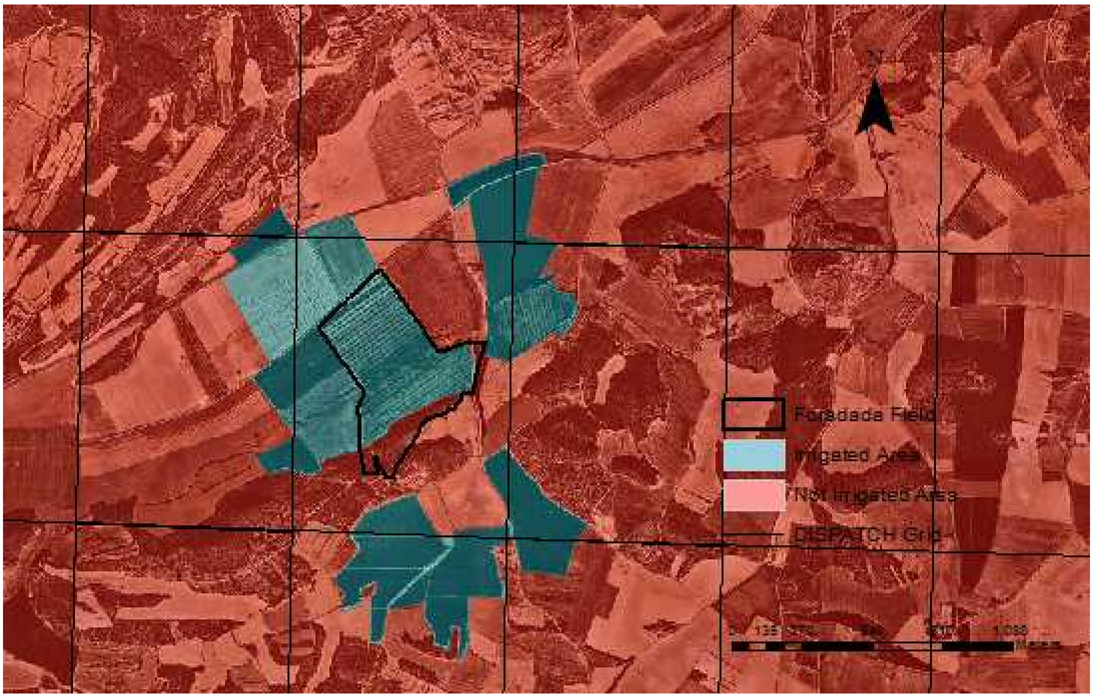

Figure 2. The DISPATCH grid representing the Foradada field, outlined in dark blue; irrigated fields, in light blue; and dry land in light red.

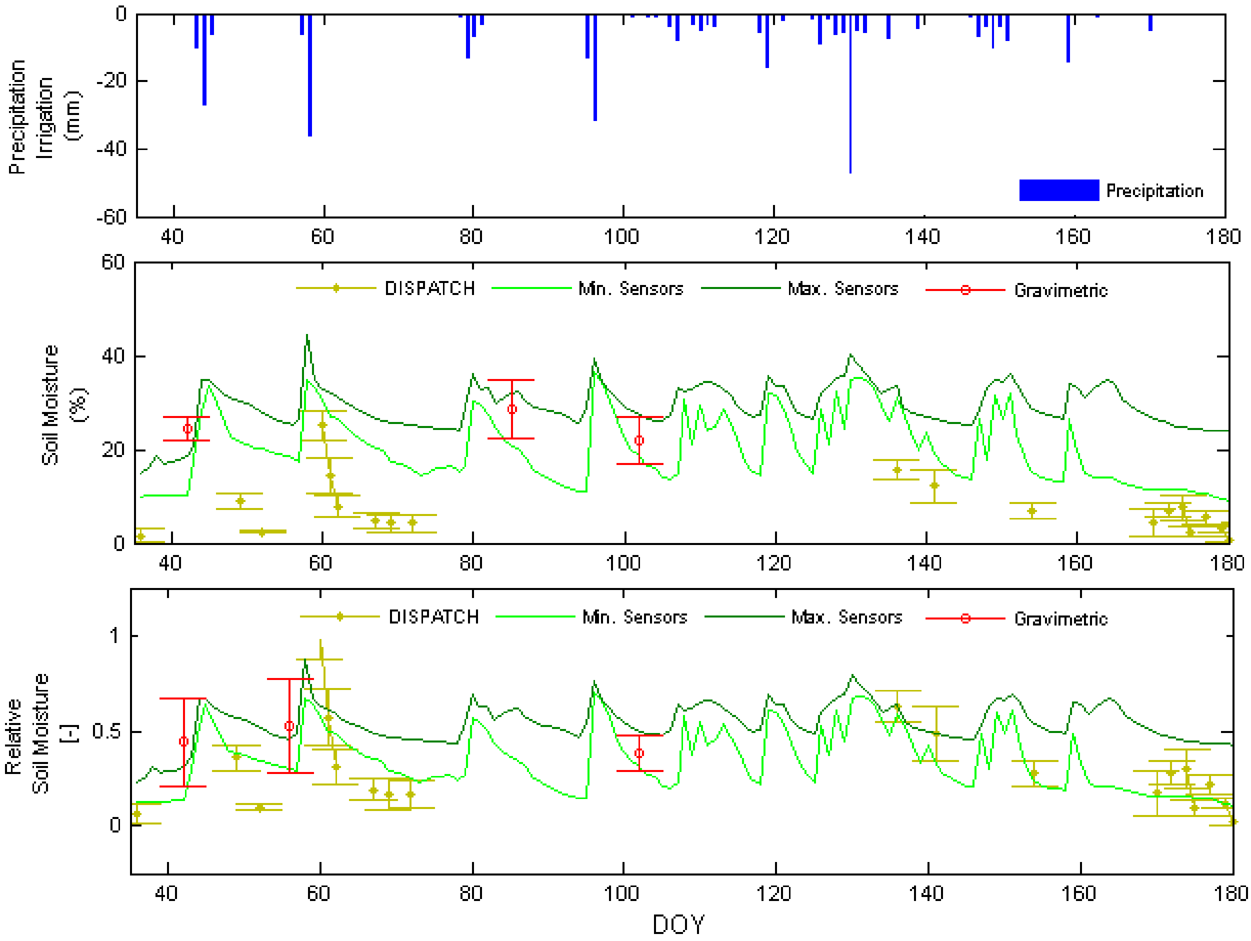

Figure 3. Comparison of average gravimetric soil moisture measurements (red) with the DISPATCH soil moisture estimations (yellow) and the daily maximum and minimum soil moisture sensors measurements (green) during the first hydrologic period (soil wet conditions caused by rainfall events only).

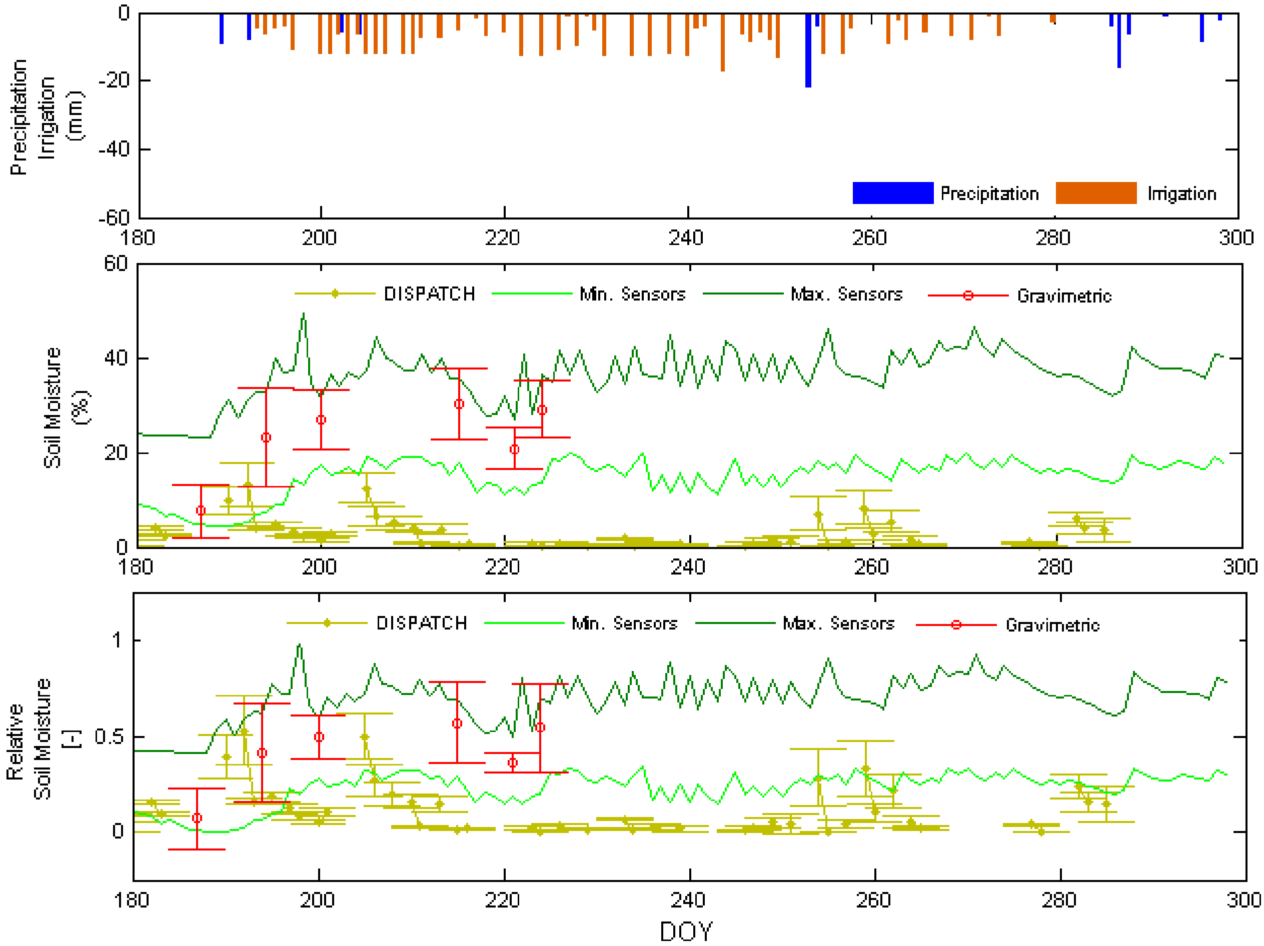

Figure 4. Comparison of average gravimetric soil moisture measurements (red) with the DISPATCH soil moisture estimations (yellow) and the daily maximum and minimum soil moisture sensors measurements (green) during the second hydrologic period (soil wet conditions caused by irrigation). The top figure shows the intensity of precipitation and irrigation.

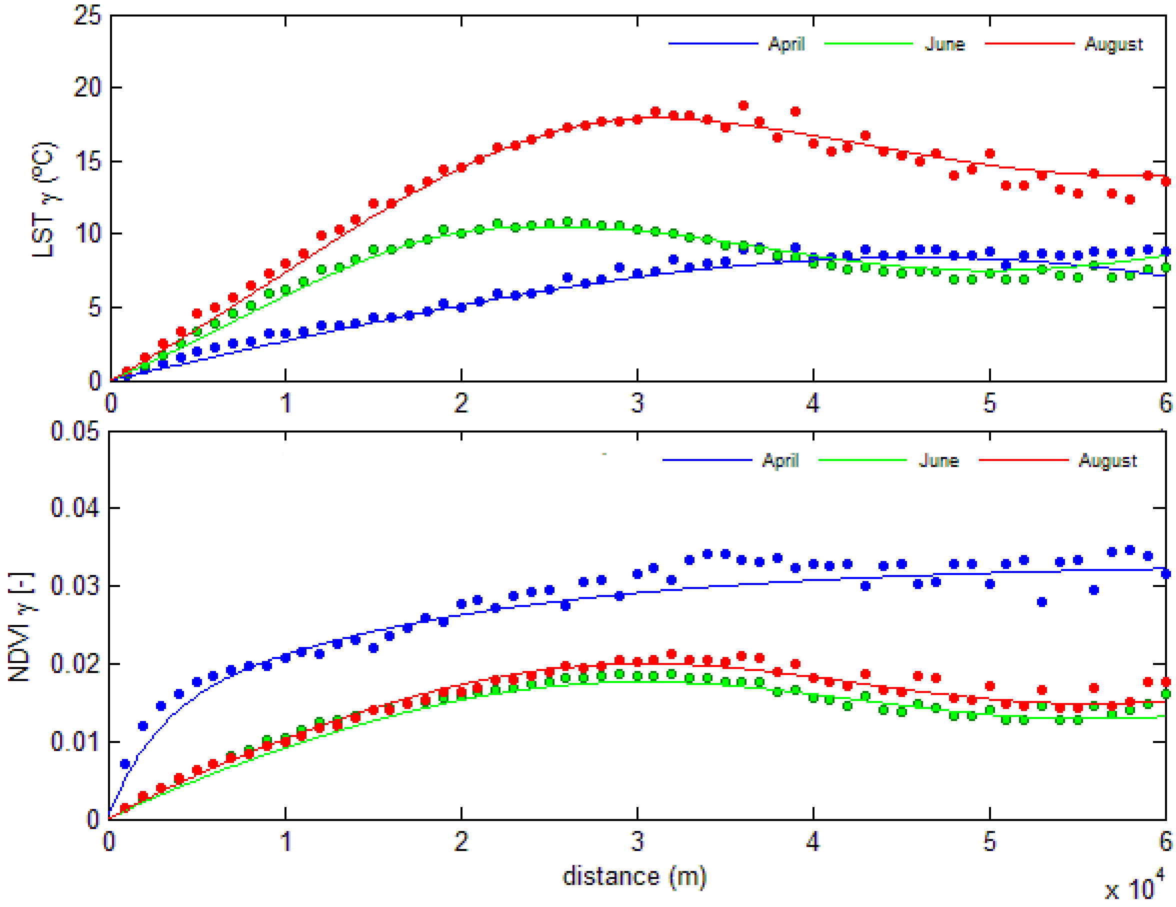

Figure 5. LST and NDVI experimental and theoretical semivariograms associated with April (blue), June (green), and August (red).

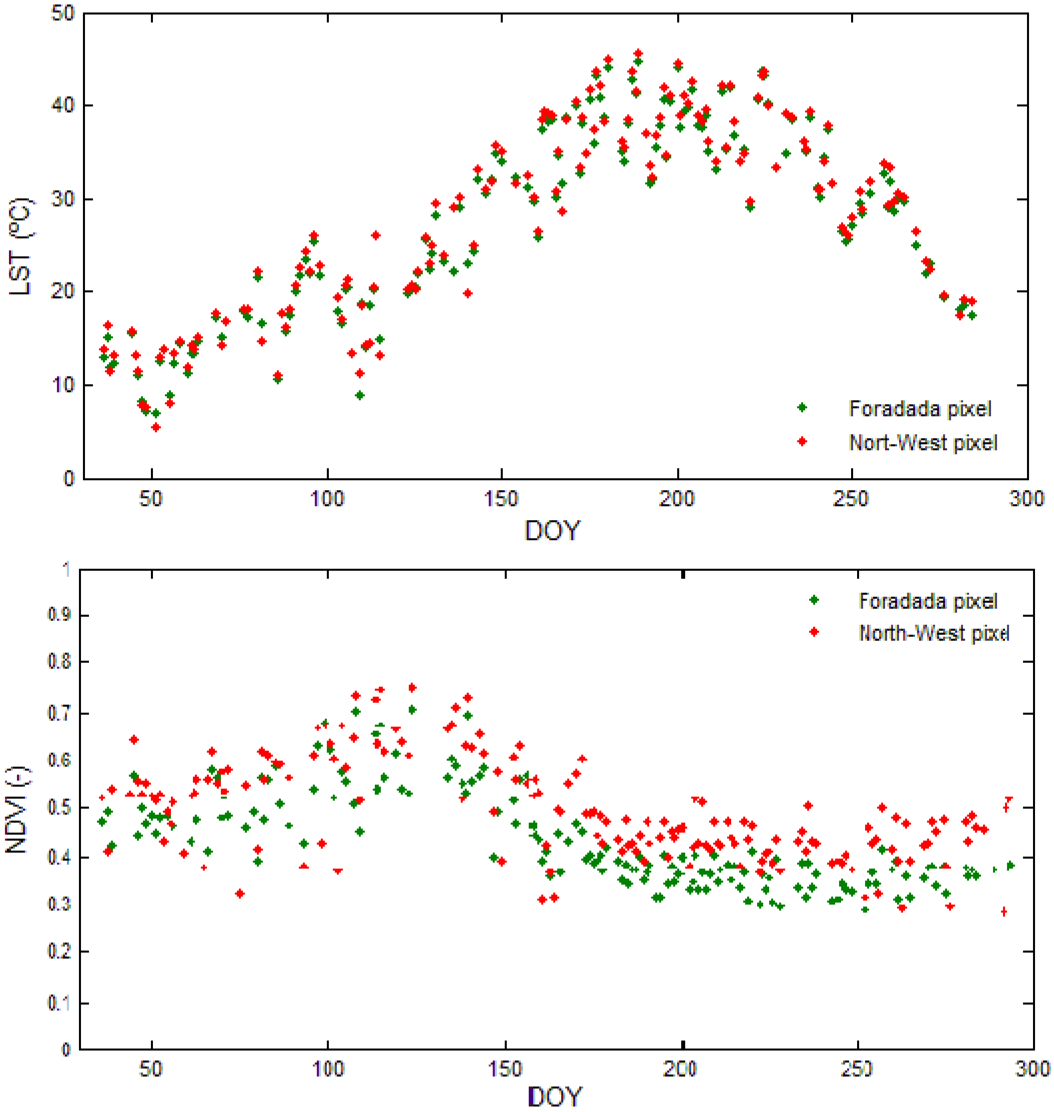

Figure 6. Temporal evolution of LST and NDVI obtained at the Foradada pixel and its neighbour North-West pixel situated 2 kms away.

Tables

LST					
		Variogram		Hole effect	
Month	Model	Sill (c_{11})	Range (a_{11})	Sill (c_{12})	Range (a_{12})
April	Spheric	8.4	46000	-	-
June	Spheric	7.5	22000	1.5	25000
August	Spheric	14	32000	2	29000

Table 1. Randon function model parameters of LST semivariograms.

NDVI							
		Variogram				Hole effect	
Month	Model	Sill (c_{21})	Range (a_{21})	Sill (c_{22})	Range (a_{22})	Sill (c_{23})	Range (a_{23})
April	Exponential	0.013	8000	0.02	55000	-	-
June	Exponential	0.013	35000	-	-	0.22	28000
August	Exponential	0.015	36000	-	-	0.21	28000

Table 2. Random function model parameters of NDVI semivariograms.