Manuscript: bg-2015-62

Title: Seasonal variation in vegetation water content estimated from proximal sensing and MODIS time series in a Mediterranean Fluxnet site

Note to reviewers:

We would like to thank both reviewers for their comments and valuable suggestions that help us to improve the clarity of the manuscript. We have followed the recommendations of the referees and made changes accordingly. Changes can be seen colored in the new manuscript version. In red the parts that have been removed from the previous version and in green the new text that has been included. Detailed answers to each of the comments of the referees can be found below.

Comments to reviewer 1:

The discussion of results would benefit by extending statistical relations with more explicit references to biophysical processes, such as relations of water stress to LAI chlorophyll reduction, which is particularly evident in the case of grasslands.

- We agree in this comment with the reviewer. Is something that we tried to improve now in the new version. We followed the recommendation of the reviewer and included in the text explicit references the relationships between water stress and LAI, and chlorophyll. As example we have included in the discussion.
- Page 16, lines 11-19.*"The relationship between these indices and water metric is indirect, since none of them include spectral bands in the SWIR region where water absorption is strong. However, there is a strong link between grassland water content, chlorophyll activity and LAI in this ecosystem. During wet periods the grassland grows very rapidly, increasing the LAI, biomass and chlorophyll content, but as soon as the dry season starts with high temperatures and low rainfall the grassland becomes cured rapidly losing all chlorophyll and quickly decreasing the LAI and biomass..."*

The conclusions drawn by the authors are very much related to grasslands physiology, but it would not hold for other vegetation types, such as trees or shrubs. For this reason, indices that are not directly linked to water content (such as NDVI or EVI) provide high explicative power. The authors should state this clearly in both the abstract and the conclusions. For this reason, I strongly recommend using grasslands instead of vegetation throughout the paper, including the title and the abstract, as they cannot extend their conclusions to other vegetation types other that what they actually sampled.

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- We definitely agree with the reviewer that the conclusions from this study cannot be extended to other type of vegetation that is not grasslands. Therefore we have changed the title to better adapt to the paper contents to. "Seasonal variation in grass water content estimated from proximal sensing and MODIS time series in a Mediterranean Fluxnet site". Following reviewer´s

recommendations we have added some additional sentences to both the abstract and the conclusions to clarify this point.

- Grass was also used instead of vegetation all over the manuscript where suitable.

Another issue is to better explain why certain indices provide higher explanation than others, and first test whether those R2 or RMS values are statistically significant or not. To explain these differences, proximal sensing measures only grasslands at nadir view angle, but MODIS includes also trees, their shades, and other artifacts at up to 20_ view angle.

- In the new version we have included two figures, one for R2 and a second for RRMSE. In this figure we show the confidence interval for each of the parameters. Since we used bootstrap, we considered more adequate presenting this rather than the significance.

1. Introduction. Include formulas of all referred terms

- Following the suggestion of the referee, we have included in the introduction section the formulas of all referred terms

2. For this introductory section, you may gain by reading the Yebra et al.'s (2013) review.

- Thanks for the recommendation. We have incorporated some of the valuable information in Yebra et al.'s 2013 in the introduction.

3. Page 5505:5: "These indices monitor the vegetation water content by indirectly relating it to another biophysical parameter that is used as a proxy of water stress. This is the case of the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979)". I think this is a misleading sentence, as NDVI has very little relation to plant water content, and therefore it should never be used as a proxy of water stress. It can eventually estimate indirect effects of changes in water content, particularly when reaching stress conditions, such as reductions in chlorophyll or LAI, which is a different issue.

- We removed that sentence and rephrase:
- Page 5, line 7: "In the case of grasslands the relationship with bands in the Visible (VIS) and Near Infrared (NIR) spectral region, has shown a close relationship between vegetation biomass, chlorophyll and water content…"

4. Avoid using qualitative terms in the description of results. Correlations are not better or worse, but higher or lower.

- As recommended, qualitative terms have been avoided in the new version of the manuscript.

5. You compare empirical models with RTM models. It is not clear whether the RTM models used were the originals developed by Jurdao et al. (which did not intend to estimate CWC but only FMC), or do you parameterize them somehow. In this case, please include technical details. Otherwise, state why.

- Following the referee recommendation we have included in the manuscript a section describing the approaches used in the study to estimate FMC and CWC from RTMs. CWC was estimated following Trombetti et al 2008 while for FMC we followed Yebra et al 2008 and 2009 and Jurdao et al 2013 models.
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- 6. page 5517/5: "Therefore, the strategy to capture better the variability of vegetation water content in this ecosystem should be to sample more times but fewer plots". Check grammar.

    - We have changed the sentence:
    - Page 15, line 10-line 13. "Therefore, the strategy to better capture the variability of grassland water content in this ecosystem should consist in increasing the number of samples in time and but sampling less number of plots per day".

7. page 5517/17: "CWC depends on LAI which is even higher correlated than those two variables". Several studies have shown that LAI contribution to total reflectance variability is much higher than water. You may refer to (Bowyer and Danson 2004). For this reason also, CWC should provide more accurate retrievals than FMC, as it depends on LAI, which is highly correlated to the spectral indices

- We changed that sentence to: "CWC depends on LAI which is showing higher correlation values to the empirical models than other metrics such as FMC or EWT. Some studies have shown that LAI contributions to total reflectance variability is much higher than water (Bowyer and Danson, 2004) this would explain that CWC provides more accurate retrievals than FMC or EWT."
- Page 15, lines 27-31

8. Conclusions. "Results indicated that FMC and EWT showed lower spatial variation than CWC". This is pretty obvious, as CWC includes another factor which also varies throughout time.

- We have removed the sentence from the manuscript.

Figure 4 is too complex. Think about alternative ways or restrict the information you consider relevant for displaying. From comparison with Figure 5 is very difficult to extract any conclusion. Why figure 8 is not in color?

- We have simplified figures 4 and 5. Now only the results regarding the R2 (Figure 4) and the RRMSE (Figure 5) is displayed in the figures. We have included in these two figures the confidence interval of the parameters.
- Figure 8 now is displayed with colors.

Comments to reviewer 2:

The abstract does not give a concise summary of the paper. It only covers methods and results but the authors should clearly state why they are doing these analysis and presenting these results as well as the implications of her conclusions and findings.

- Following the recommendation from the reviewer, we have modified the abstract clarifying paper´s objectives and remarking the implications of the results found.

2. The introduction does not clearly state the original contribution of this work. Does this paper builds on previous key work? Which are the knowledge gaps it is trying to fill in?

- We have rewritten the introduction stressing the gaps our work is trying to fill in. In our work we aim to compare three different metrics of vegetation water content. Each of the compared metrics offer information at different level, and therefore the spectral relationships might vary. To make the results comparable we considered that samples should be collected simultaneously to remove part of the uncertainty, per se imposed in field data collection. In the study we also compared different protocols to collect the samples. Even this decision made the reading of the paper a bit more complex, we considered that it is important to evaluate different protocols to ensure the consistency of the measurements taken in the field. We also used new subscripts to designate the different samples collected in the field and aiming making the reading of the paper easier.
- Regarding the remote sensing part, we compared empirically derived models based on spectral indices with other methods based on RTM inversion.

3. The methods section lack on detail/justification in some aspects:
a. Why do the authors compute FMC/EWT from a subsample and the quadrat? What do the authors want to prove with this? Is this important? Again, the research question is not clear. This distinction between quadrat and subsample add complexity to the paper so it should be clearly justified.

- In the new version of the manuscript we have added information trying to clary the use of different protocols used in the field data collection. As there is not a consensus in this issue, we found it interesting to test the effect of two different field protocols in the results when comparing field and proximal/remote sensing data. As far as we know, no previous works have intended this exercise.
- New text included in Page 4, line 11 to Page 4, line 21.

b. The authors should explain more in detail the methodologies from Trombetti and Jurdao they are applying and presenting in this paper. For example, Jurdao et al 2013 derived FMC in woodlands in the Mediterranean and Eurosiberian region using two different Look up Tables (LUT). The authors do not specify which LUT they are using (I assume they are using the LUT developed for the Mediterranean region?). Also, the authors must justify the selection of those methods. Why did you select Jurdao's method that was developed for closed woodlands and nor other more suitable for dehesa type ecosystem? This is definitely something that should be discussed in the discussion section. The apparent worst performance of the RTM models in comparison to the empirical equations may be related to this.

- The reviewer is totally correct. In the case of Jurdao we used the LUT developed for the Mediterranean region. As far as we know there is no method specifically designed for dehesa, as in principle is similar to a Wooded grassland ecosystem. Dehesa can vary in density of tree and therefore that's why we considered appropriated to use this LUT. In addition this LUT was calibrated in Spain, but not using any sample from our study site. In the new version we have included a new section to explain the RTM based estimates. Page 10, line 11 to Page 11, line 11 and discussed deeper in the discussion section in Page 17, line 12 -21.
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- c. The authors should explicitly present in the results section the equations they derive for the empirical models.
- Following reviewer´s recommendation empirical fitting equations are now presented in table 2.
- Page 25.

4. Results do not appear to be well discussed in relation to previous published works (e.g. how the author's findings may contribute to clarified/complement previous findings) and are difficult to follow because the research questions is not clearly identified in the introduction and the implications of their findings are barely discussed. The results presented around FMC/CWC derived using the quadrat/subsample samples are difficult to follow and not well justified. Are the authors trying to conclude which is the better methodology in order to propose a standard sampling protocol? The authors Should also improve the description of the results and avoid qualitative or vague terms (see specific comments)

- Following previous comment the introduction has been modified to better identify the research question addressed in this work. We have also rewritten the discussion section in order to better state the implications of the results found.
- We have reviewed the results section avoiding qualitative terms, as recommended

5. Figures do not have clear captions. The authors should carefully work on figures caption so they are self-contained. Figures 2, 4 and 5 are difficult to read. I would suggest the authors to increase the size of figure 2 and simplify figures 4 and 5. Is it important to include here the results from the quadrat and the subsample? The authors should only consider only the most relevant information.
- We followed the recommendations of the reviewer and modified the figures captions. In order to improve readability, figure 2 has been enlarged. In figure 4 and 5 we removed the non-relevant information and now in the case of figure 5 we only display the information regarding the R^2 between the field metrics and the models generated using the spectral indices from MODIS and proximal sensing. In figure 6 similar information is plotted, but instead of R2 we showed the RRMSE values. In both cases as the results obtained after bootstrap we have included the confidence interval.

Specific comments: The line and page numbers refer to those provided in the printerfriendly version that I downloaded from the website.

Page. 5505 Line 6. Include "a" before "Mediterranean"
- Done.

Page. 5505 Line 12. "Due to the high seasonal Dm variability..." This sentence seems to be out of context.

- We have rephrased the sentence. In the new version the sentence is as follows: “Dm variability was high which demonstrate that a constant annual Dm value should not be used to predict EWT from FMC as other previous studies did.”
- Page 2, line 14- 15

Page. 5505 Line 14 onwards. GEMI, GVMI, etc. need to be defined.

- Acronyms have been defined.

Page 5508. Line 4. “Secondly, the model performance...”. Which models do the authors refer to? They have not presented any model yet.

- We tried to say in this sentence that we compared the performance of the different empirical fitting equations used in the empirical calibration. We have changed part of the text in the paragraph to clarify this.
- Page 6, line 5- 7.

Page 5509 Line 20.” Each EWTsample and a sub-sample from each quadrat ...” This is confusing. My understanding is that EWT sample refers to the EWT derived from the sub-sample? Why do the authors then write here EWTsample and a sub-sample from each quadrat, isn’t that the same?

- As explained in page 5509-line 15 we used a 25x 25 cm quadrant to collect vegetation samples. As we need to obtain the Leaf Area, one of the parameters necessary to calculate EWT we made the decision of trying to different sampling strategies, one was to use a sub-sample from the total sample collected within the quadrant and the other was to collect only a small sample nearby the quadrant. Even with a small quadrant as the one used in our field campaign, it is extremely difficult to scan the entire sample collected so we wanted to know the impact of using two different approaches to select the small sampled to be used for the estimation of leaf area. We have included in the manuscript some additional text to clarify and simplify this point. We have use now new nomenclature to designate the different samples out of quadrant (OQ_{Sample}) and inside quadrant (IQ_{Sample}) Page 7 lines 15 to page 8, line 18.
- A diagram to help understanding the new names and where and how the samples are treated in the laboratory is now included in figure 2. Page 27

Page 5510, Line 14. “ where LAI is the leaf...and EWT is obtained from eq (2). Again I am confused. Do the authors refer to EWTsample.

- The equation in the manuscript has been corrected. In the first approach the CWC was obtained from EWT sample (as in equation 2).
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$$CWC_E\ (g/cm^2) = EWT \cdot LAI$$

Page 5511. Lines 24-26 and Page 5512 Lines 1-8. The description of the indices and the comparison with the RTM models do not belong to the “Field sampling “ section. These should be moved to data analysis. The same applies to Page 5512 Lines 26-28 in MODIS data section.

- In the new version of the manuscript we have included a specific section with the description of the spectral indices and RTM models. Page 10, line 5 to page 10, line 10

Page 5513. Lines 23-25. “As recommended in Steyerberg...” should be moved to line 20 before defining the RMSE.

- We moved the reference. Page 11, line 31 to page 12 to line 2.

Page 5515. Line 1. “...comparison between the spectral indices...”. Spectra indices should be replaced by empirical approach (along the manuscript) since Jurdao and Trombetti also used spectral indices in their RTM modelling.

- We fully agree with the reviewer. We have substituted spectral indices all over the text when necessary to avoid misunderstandings.

Page 5515. Lines 27. “EVI performed better”. Do the authors mean that EVI was the index with the highest correlation coefficient with FMCe and FMCq when using the reflectance form MODIS?

- That’s it. That is what we meant to say. We have corrected the text in the manuscript.
- Page 13 Line 30-31

Page 5516. Lines11-12. “RTM was closer to the empirical models” Do the authors mean that RTM performed similarly to the empirical models?

- Yes, we do. We have rewritten the sentence to clarify this. Page 14, lines 16 to18

Page 5516. Line16. Figure 6 should be Figure 8.

- Corrected in the manuscript

Page 5517. Lines17. “....LAI which is eve higher correlated than those...”. Higher correlated to what?

- We meant correlated to spectral information. We have rewritten this sentence to clarify this point. Page 15, line 27-31

Line 5518. Lines 22-23. “RTM only overcomes empirical approaches when structural information constrains the model inversion)”. I agree however I do not think this statement justify the worst performance of RTM in comparison to the empirical models in your study since the method the authors used (Jurdao et al 2013) includes such structural information. I suspect that Jurdao/Trombetti methods did not work well in this study because they were not designed to be apply in Mediterranean dehesas).

- We did not intend to justify with this sentence that this is the reason why the RTM based estimates perform worse than the empirical models. We included some lines to better explain. Pages 17, lines 12-21.
- The other statement was very strong and might not be true in all cases as the empirical methods also depend on the number of samples etc. so we removed it.

- Empirical models have the great advantage of being calibrated with the data collected in situ, and therefore was expected this results. Jurdao includes some structural information based on GEOSAIL, but this information is used in the generation of the LUT. To obtain FMC what the method does briefly is to comparing the reflectance values against the generated LUT. The one that is more similar based on a merit function is used to assign the FMC value. Among the advantages of using this technique is that it can be easily run without too much computation time after the LUT was generated and therefore offers the possibility of run it at large scales.
- We believe that there is still a lot place for improvement, not just in FMC but also in CWC. Testing other inversion techniques, using multiple observations or using more robust algorithms not based on LUT such as optimization algorithms might help to improve the estimates, however, these methods are usually computing expensive and therefore they lack sometimes in operability.

Table 1. I suggest the authors to improve the caption of the figure so the reader can quickier understand what does Bx mean. The authors should also explain what does NIRREC and SWIRRec stands for.

- As the referee suggests, the changes have been implemented in the table. In the caption information has been added about what Bx mean. We have also included a note explaining what NIR_{REC} stands for and removed $SWIR_{REC}$ as was a typing error in the formula. In the note it is also mentioned the bands used for NIR_{REC} and SWIR.

Figure 6. The authors should also explain what does RTM FMC (Grassland and oak) mean and why is it different from RTM (grassland).

- As the referee suggests, an explanation on the difference between the RTM FMC (Grassland and oak) and (grassland) has been included in the figure caption.

Seasonal variation in ~~vegetation~~grass water content estimated from proximal sensing and MODIS time series in a Mediterranean Fluxnet site

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Abstract

This study evaluates three different metrics of ~~vegetation~~ water content ~~estimated~~ ~~in~~ of an herbaceous cover in a Mediterranean wooded grassland (*dehesa*) ecosystem. ~~from proximal sensing and MODIS satellite imagery:~~ Fuel Moisture Content (FMC), Equivalent Water Thickness (EWT) and Canopy Water Content (CWC) were estimated from proximal sensing and MODIS satellite imagery. Dry matter (Dm) and Leaf area Index (LAI) connect the three metrics and were also analyzed. ~~in order to connect FMC with EWT and EWT with CWC,~~

~~respectively. This research took place in a Fluxnet site located in a Mediterranean wooded grassland (dehesa) ecosystem in Las Majadas del Tietar (Spain).~~ Metrics were derived from field sampling of grass cover within a 500 m MODIS pixel. Hand held hyperspectral measurements and MODIS images were simultaneously acquired and predictive empirical models were parametrized. Two methods of estimating FMC and CWC using different field protocols were tested in order to evaluate the consistency of the metrics and the relationships with the predictive empirical models. In addition, Radiative Transfer Models (RTM) were used to produce estimates of CWC and FMC, which were compared with the empirical ones.

~~The results indicated that FMC and EWT showed lower spatial variation than CWC.~~ Results revealed that, for all metrics spatial ~~variation~~variability was significantly lower than temporal~~.~~ ~~within the MODIS pixel~~ Thus we concluded that experimental design should prioritize sampling frequency rather than sample size.~~ was not as critical as its temporal trend, so to capture better the variability, fewer plots should be sampled but more times. Due to the high seasonal~~ Dm variability was high which demonstrate that a constant annual Dm value ~~would not work to~~ should not be used to predict EWT from FMC as other previous studies did. Relative root mean square error (RRMSE) evaluated the performance of nine spectral indices to compute each variable. Visible Atmospherically Resistant Index (VARI) provided the ~~worst~~ lowest explicative power ~~results~~ in all cases. For proximal sensing, Global Environment Monitoring Index (GEMI) ~~worked best~~showed higher statistical relationships ~~for~~ both for FMC (RRMSE = 34.5%) and EWT (RRMSE = 27.43%) while Normalized Difference Infrared Index (NDII) and Global Vegetation Monitoring Index (GVMI) ~~performed best~~ for CWC (RRMSE =30.27% and 31.58% respectively). When MODIS data was used, results ~~were a bit better with~~showed and increase in R^2 and Enhanced Vegetation Index (EVI) as the best predictor for FMC (RRMSE=33.81%) and CWC (RRMSE=27.56%) and GEMI for EWT (RRMSE=24.6%). ~~To explain these differences, proximal sensing measures only grasslands at nadir view angle, but MODIS includes also trees, their shades, and other artifacts at up to 20° view angle~~Differences in the viewing geometry of the platforms can explain these differences as the portion of vegetation observed by MODIS is larger than when using proximal sensing including the spectral response from scattered trees and its shadows. CWC was better predicted than the other two water content ~~variables~~metrics, probably because CWC depends on LAI, that shows a notable seasonal variation in this ecosystem. Strong statistical relationship was found between empirical models using indices sensible to chlorophyll activity (NDVI or EVI which are not directly related to water content) due to the close relationship between LAI, water content and chlorophyll activity in grassland cover, which is not true for other types of vegetation such as forest or shrubs. ~~which is highly correlated to the spectral indices~~. ~~Finally,~~ These empirical methods tested outperformed FMC and CWC products based on radiative transfer model inversion.

1 Introduction

Water in leaves is a limiting factor for different physiological processes of vegetation and its deficit causes malfunctioning of different cellular processes. Water is involved in the thermal regulation of plant trough transpiration and also becomes crucial in the uptake of CO_2 for photosynthesis (Chaves et al., 2003). It is also fundamental to maintain turgor pressure, which controls different functional processes of plants like cell enlargement or gas exchange (Taiz and Zeiger, 2010).

Different metrics quantify vegetation water content. Fuel Moisture Content (FMC) (Desbois et al., 1997), defined as the mass of water per unit mass of vegetation,

$$\mathrm{FMC}\ (\%) = \frac{W_{Fresh} - W_{Dry}}{W_{Dry}} * 100 \qquad (1)$$

where W_{Fresh} is the fresh weight of the sample measured in the field and W_{Dry} is the oven dried weight. FMC has been extensively used to estimate ~~the~~ fire risk ~~occurrence~~ and fire propagation (García et al., 2008;Yebra et al., 2008b). Equivalent Water Thickness (EWT) or Leaf Water Content (LWC), defined as the mass of water per leaf area, measures the thickness of the water layer with the same leaf area (Danson et al., 1992)

$$\mathrm{EWT}\left(g/cm^2\right) = \frac{W_{Fresh} - W_{Dry}}{Area_{Leaf}} \qquad (2)$$

where $Area_{Leaf}$ is the leaf area.

Several studies showed that EWT can be retrieved from spectral information at leaf level as it is directly related to the water absorption depth of leaves (Ceccato et al., 2001;Datt, 1999). FMC and EWT are related each other since:

$$\mathrm{EWT}\left(g/cm^2\right) = \left(\frac{\mathrm{FMC} \cdot \mathrm{Dm}}{100}\right) \qquad (3)$$

where Dm is defined as the ratio of leaf dry weight and leaf area:

$$Dm\ \left(g/cm^2\right) = \frac{W_{Dry}}{Area_{Leaf}} \qquad (4)$$

~~EWT can be expressed as FMC multiplied by the dry matter (Dm) and divided by 100.~~ Finally, another metric is the Canopy Water Content (CWC), the mass of water in the canopy per ground area (Cheng et al., 2008;Trombetti et al., 2008). CWC represent the product of EWT and Leaf Area Index (LAI), offering information on vegetation water content at canopy level and can be expressed as:

$$CWC\ \left(g/cm^2\right) = EWT \cdot LAI \qquad (45)$$

or

$$CWC\left(g/cm^2\right) = \frac{W_{Fresh} - W_{Dry}}{Area} \qquad (6)$$

where Area denotes for the area of the spatial unit used to collect the sample.

~~Field sampling of~~ FMC, EWT or CWC ~~relies~~ are usually estimated from vegetation samples using ~~on~~ gravitational methods. ~~but this method is quite limited for estimates at regional to global spatial scales, since it requires interpolation to bridge the gaps in both time and space.~~ Different field and laboratory protocols are used, despite of the need for standardization (Yebra et al., 2013). In several studies FMC is sampled using a bag were 100-200g of the fresh sample are introduced and considered as representative (Verbesselt et al., 2007;Chuvieco et al., 2003). In other studies vegetation is sampled within a quadrant whose area is used as reference (Sims and Gamon, 2003). However, uncertainties introduced by the different protocols and therefore their comparability are unknown. The three metrics can be used to measure water content, but relationships existing among them remains also unknown. No comparative studies for grasslands have been reported.

Moreover, field sampling is limited and cannot provide estimates at regional or global scales, since it requires interpolation to bridge the gaps in both time and space. Remote sensing is a powerful alternative data source to provide information on vegetation water content as it fills such temporal and spatial gaps. Monitoring vegetation water content with remote sensing benefits agriculture, to control crop production and prevent stress in plants (Peñuelas et al., 1992;Sepulcre-Cantó et al., 2006) and forestry, to assess fire danger associated with vegetation water conditions (Chuvieco et al., 2003;Chuvieco et al., 2004;García et al., 2008;Yebra et al., 2008b).

To estimate plant water content with remote sensing, vegetation spectral reflectance has been primarily related to specific water absorption bands in the Short Wave Infrared region (SWIR, 1300-2500 nm) (Ceccato et al., 2001;Zarco-Tejada et al., 2003). Other studies related vegetation water content to spectral indices that do not include SWIR ~~data~~ bands~~. These indices monitor the vegetation water content by indirectly relating it to another biophysical parameter that is used as a proxy of water stress. This is the case of the Normalized Difference Vegetation Index (NDVI) (Tucker, 1979),~~ In the case of grass the relationship with bands in the Visible (VIS) and Near Infrared (NIR) spectral region, ~~that~~ has shown a close relationship between vegetation biomass, chlorophyll and water content ~~in grasslands~~ (Chuvieco et al., 2003;Chuvieco et al., 2004;García et al., 2008;Yebra et al., 2008b) as water stress produces changes in the chlorophyll activity and biomass of the plant. Least squares regression models have served to empirically relate observed measurements of vegetation water content to spectral indices. These models ~~have their weakest point of being~~ are site dependent, requiring long datasets for calibration (Chuvieco et al., 2009) and showing different results when the models are extrapolated to other sites using different data sets, making difficult their applicability (Riaño et al., 2005;Yebra et al., 2008a).

Radiative Transfer Models (RTM) simulate vegetation spectra and are a sound alternative to empirical modeling. They can be applied to different locations to estimate different vegetation parameters, as long as the RTM is a true representation of the vegetation canopy. For example, Trombetti et al (2008) predicted CWC for the continental US using RTM PROSAILH (Jacquemoud et al., 1995) simulations. Their model was calibrated with CWC from Airborne Visible / Infrared Imaging Spectrometrer (AVIRIS) hyperspectral water absorption bands. Yebra et al. (2008b) used also PROSAILH to quantify FMC, and more recently, ~~Another example is~~ Jurdao et al (2013) ~~who~~ inverted the RTM GEOSAIL (Huemmrich, 2001) combined with PROSAILH to estimate FMC. The estimations were ~~that was~~ validated with extensive field sampling data in Spain. RTM estimates are based on a physical principle, and one of the advantages is that are not constrained to local conditions as is the case of empirically derived relationships. Therefore, in theory they can be extensively applied at different locations with good results (Yebra et al., 2008a;Yebra et al., 2008b). This study compares the ~~model~~performance of the different empirically derived models and RTM based estimates models. The former were created ~~using~~ stablishing empirical relationships between three different metrics of vegetation water content measured simultaneously in the field (FMC, EWT, CWC) and nine spectral indices calculated at two scales, from ~~both~~

proximal sensing and MODIS spectral data. In addition Dm and LAI were also analyzed in order to connect ~~FMC with EWT and EWT with CWC, respectively~~ metrics which estimates water content at leaf and canopy level. Firstly, an analysis of the temporal and spatial variability of the different ~~measurements~~ vegetation samples collected in the field was conducted to evaluate which biophysical parameter offers more information. Secondly, ~~the model performance was~~the performance statistics of the fitting equations were evaluated to select the most accurate empirical models. Finally, these ~~this strategy gave us the empirical~~ models were compared to ~~two~~ three RTM based ~~models~~ estimates, proposed in the literature to derive ~~one~~ two ~~to derive~~ FMC (Jurdao et al., 2013;Yebra et al., 2008b) and the other for CWC (Trombetti et al., 2008).

2 Methods

2.1 Site description

The study site is located at Las Majadas del Tiétar (Spain) FLUXNET site (http://fluxnet.ornl.gov/site/440, last accessed 2014/06/05) (Fig. 1). The area is a *dehesa*, a typical Mediterranean wooded grassland, ~~which is an~~ ecosystem that occupies about 4% (2.5 Mha) of the Iberian Peninsula (Castro, 1997). Common tree species are different varieties of oaks, here mostly *Quercus ilex* subsp. *ballota* (L.), whose acorns and leaves are mainly used as forage for pigs and cows, respectively. The scattered oak trees have a 9 m mean height and 6 m mean crown diameter. Due to its deep and wide root system, this species is resistant to long drought periods (Camarero et al., 2012). Short grassland covers 86% of the area that is managed for cow shepherding. It is mainly composed by *Rumex acetosella,* L., *Plantago carinata Schrad, Trifolium subterraneum* L., *Cynodon dactylon* (L.) Pers., *Taraxacum dens - leonis* Desf. and *Vulpia myuros* (L.) C. C. Gmel. During the summer, grass dries out rapidly and turns into dead matter. Summers are hot and dry, with 30 °C daily average temperature and only 67 mm total precipitation, which are not representative of mean annual 16.7 °C and 572 mm. The average altitude is 256 m above mean sea level. Soils are lixisols with an average thickness of 80 cm. Due to the presence of a clay layer in some of the areas, small water pools may appear in winter after rainy periods. The occurrence of this type of ecosystem in Mediterranean areas worldwide, the need to track the responses to water stress conditions, together with the presence of a FLUXNET eddy covariance flux tower (http://fluxnet.ornl.gov/site/440) justifies the selection of this site.

2.2 Field ~~sampling~~ data

2.2.1 Vegetation sampling

Grass water status was estimated through destructively ~~sampled~~ sampling every two weeks from April 2009 to April 2011. Sampling was performed assuring no rain occurred in the two previous days to avoid sampling superficial water on the leaves. During the 2009 summer, when grass became completely dry, ~~and~~ samples were not collected ~~in 2009~~. However, to ensure the time series continuity of at least one phenological cycle, sampling was restated throughout the summer of 2010. This sampling strategy leaded to a total of 21 valid sampling days for the whole study period.

Six 25 x 25 m plots were randomly located within the 500 m MODIS pixel that contained the eddy covariance flux tower that was stablished as the center of the study site (Fig. 1). Three grass samples were collected from ~~three~~ 25 x 25 cm^2 quadrants randomly positioned within each plot. All rooted grasses were collected inside the quadrant using clippers (IQ_{Sample} hereafter). Additionally, a different sampling strategy was tested and a smaller sample was collected outside of the quadrant but nearby ~~to estimate EWT -EWT_{Sample} hereafter- in a cost-effective way~~, containing a representative proportion of surrounding species (OQ_{Sample} hereafter) (Fig. 2). All samples were placed in sealed plastic bags, weighed on a scale with 0.01 g precision and then transported in a cooler to the laboratory. Every OQ_{Sample} ~~Each EWT_{Sample}~~ and a sub-sample from each IQ_{Sample} were scanned at 150 pixels per inch (ppi) in an Epson Perfection V30 color scanner (Epson American Inc., Long Beach, CA, USA). Leaf area was calculated automatically from the scanned images using the unsupervised classification algorithm ISOCLUS with 16 iterations in PCI Geomatica (PCI Geomatics, Richmond Hill, Ontario, Canada). All samples were then placed in an oven for 48 hours at a constant temperature of 60°C to obtain their dry weigh. Five biophysical variables were obtained from the collected vegetation samples: FMC, EWT, Dm, CWC and LAI.

FMC was determined from the fresh and dry weights of both the IQ_{Sample} (FMC_{IQ}) and the OQ_{Sample} (FMC_{OQ}) according to Eq. 1. The OQ_{sample} permitted to calculate both, EWT and Dm using Eq. ~~2~~2 and Eq. 4 respectively, since fresh/dry weight and leaf area were measured. The IQ_{sample} was not used in this case as it was unfeasible to obtain the area of the total sample collected inside the quadrant and neither the fresh weight of a sub-sample. ~~FMC was determined from the fresh and dry weights of both the whole quadrant sample (FMC_Q) and the EWT_{Sample} (FMC_E) according to Eq. 1 The EWT_{Sample} permitted to calculate both, EWT and Dm, since fresh/dry weight and leaf area were all measured) of the EWT_{Sample}.~~

CWC was calculated from two different approaches. In the first one, information corresponding to the ~~quadrant and EWT_{Sample}~~ IQ_{sample} and OQ_{sample} were combined using ~~the following expression (~~Eq. 5~~4where LAI is the leaf area index of the grass within the quadrant and EWT is obtained from Eq 2.~~

The grass height was very short due to cow shepherding during some periods, so the only feasible technique to estimate LAI, ~~rather than optically estimated, was measured with~~ was using gravitational methods (He et al., 2007). The biomass to leaf area ratio of a sub-sample inside the IQ_{Sample} to the total quadrant's biomass provided LAI using the following expression (Eq ~~5~~7):

$$LAI\left(cm^2/cm^2\right) = \frac{\frac{W_{Dry}}{W_{Dry}^{Sub}} Area_{Leaf}^{Sub}}{Area} \qquad (7)$$

where W_{Dry} is the total dry weight of the whole sample inside the ~~quadrant~~ IQ_{Sample}, W_{Dry}^{Sub} is the dry weight of a sub-sample of W_{Dry}, $Area_{Leaf}^{Sub}$ is the sub-sample leaf area and Area is the total area of the quadrant. The second approach measured CWC from the fresh and dry weight difference of the IQ_{Sample} as in (Eq. 6).

~~The second approach measured CWC from the fresh and dry weight difference inside the quadrant (CWC_Q in Eq. 6):~~

2.2.2 Proximal sensing

Simultaneously to vegetation sampling, proximal sensing data were acquired using an ASD FieldSpec® 3 spectroradiometer (http://www.asdi.com/) along NE-SW and NW-SE transects in each 25x25 m plot. This instrument measures Hemispherical-Conical Reflectance Factor (HCRF) ~~reflectance~~ from 350 to 2500 nm. Before measuring along each transect, dark current was recorded, instrument settings were optimized and reference spectra were acquired using a Spectralon® 99% reflective reference panel (Labsphere Inc., North Sutton, NH, USA). All measurements were taken under clear sky within about ±2 hours from local solar noon, to guarantee homogeneous illumination and maximum solar irradiance. Sky conditions were recorded in the field logs, and a quality control check removed the spectra where illumination changes may have occurred after calibration. The ASD was handled using bare fiber~~. without fiber optics to reduce the directional effects on the spectroradiometer's fiber bundle field of view (FOV) (MacArthur et al., 2012)~~. Spectra were acquired at approximately 1.2 m height, rendering a sensor footprint diameter of about 53 cm, since nominal FOV is 25º.

An average of approximately 10 spectral measurements was calculated for each transect and ~~then~~ this information was spectrally resampled to MODIS bands using ITT ENVI 4.7. (EXELIS, Boulder CO, USA).~~(Paltridge and Barber, 1988;Yebra et al., 2008b). Finally, two RTM based algorithms were run to compare with these spectral indices. GEOSAIL RTM model inversion estimated FMC testing two different look up tables that constrained the simulations to either a grassland or a mixed tree-grassland cover based on Jurdao et al. (2013). PROSAILH RTM model inversion predicted CWC assuming a pure grassland cover following Trombetti et al. (2008). This model applies the same look up table to all land covers but different calibration coefficients which will render the same R^2 independently of the land cover considered.~~

2.2.3 MODIS ~~data~~ images

MODIS Terra daily surface reflectance (MOD09GA) data from April 1st, 2009 to April 15th, 2011 were downloaded from NASA Land Processes Distributed Active Archive Center (LP DAAC) at the USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, USA. This product includes the reflectance of bands 1 to 7, from 469 to 2130 nm at 500 m spatial resolution, as well as sensor and solar observation angles and quality flags at 1 km. A script programmed in Matlab (Mathworks, Batick, Massachusetts, USA) extracted the MODIS pixel value of our study site from all the images to build the time series. The impact of angular effects on reflectance was reduced by removing images with sensor zenith angles wider than 20°, which also assures the accuracy of the geometrical location of the pixel (Wolfe et al., 2002). In addition, the quality flag layer eliminated images under clouds, cloud shadows and/or with high atmospheric aerosol content. The algorithm selected the closest valid MODIS image to the field sampling day within ±~~+~~ 5 days window, or the MODIS image acquired before the sampling day in case they were equal. Minimal time lag between sensor and field data reduces the chances of discrepancy, as grassland grazing could affect LAI in a short period of time. This leaded to a total of 14 days of MODIS data with coincident proximal sensing measurements and field data.

~~Similarly to proximal sensing, MODIS estimated the biophysical variables from the spectral indices in Table 1 and from the RTM model inversions.~~

2.3 Vegetation indices

~~These~~ For the study 9 spectral indices were calculated from proximal and MODIS reflectance data according to the equations in Table 1. The indices selected to estimate the biophysical variables included bands in the water absorption SWIR region (Faurtyot and Baret, 1997) and bands sensitive to vegetation greenness and structure in the NIR region (Paltridge and Barber, 1988;Yebra et al., 2008b).

2.4 RTM based water metrics estimates

In order to compare performance with the empirical derived models, three RTM based models were used to estimate CWC (Trombetti et al., 2008) and FMC (Yebra et al. (2008b);Jurdao et al. (2013)). As for the empirical models, the spectral information used to run the RTMs was the one obtained using proximal sensing and MODIS data.

2.4.1 CWC

CWC was estimated in the study site following Trombetti et al. (2008). This method uses PROSAILH RTM (Jacquemoud and Baret, 1990;Jacquemoud et al., 1995) and Artificial Neural Networks (ANN) to estimate CWC. Trombetti et al. (2008) trained their model by using MODIS synthetic spectra based on a set of empirical relationships. Different MODIS spectra combinations and vegetation indices were later used as input variables to train a neural network and obtaining as outputs CWC, leaf water content, and LAI. The outputs were validated against AVIRIS CWC and MODIS MOD15A2 LAI product. ~~At the end, a~~ Multiple linear regression approach is later used to establish the equations for each landcover type. In our case we used the original calibration from Trombetti et al. (2008) for grassland.

Further details on this method can be found in Trombetti et al. (2008).

2.4.2 FMC

The FMC estimates are based on Look Up Table (LUT) inversion technique. This technique compares each observed spectra against previously generated spectra stored in a LUT. In this study two LUTs were tested. One specifically designated for grassland based on the study of Yebra et al. (2008b) and that was generated using PROSAILH (Jacquemoud and Baret, 1990). The second LUT was generated using a link between PROSAILH (Jacquemoud and Baret, 1990) at leaf level and GEOSAIL RTM (Huemmrich, 2001) at canopy level and originally proposed to estimate FMC in a mixed-oak-tree-grassland cover (Jurdao et al., 2013). This model includes some additional parameters that allow to account for shadows, especially important in areas with disperse tree coverage as is the case in our study site.

Further details on these methods can be found in Yebra et al. (2008b) and Jurdao et al. (2013).

2.5 ~~Data analysis~~ Empirical models fitting

Intra-group, inter-group and overall R^2 values between FMC_{IQ}, FMC_{OQ}, EWT, CWC_{IQ}, CWC_{OQ} or LAI, and each of the proximal sensing spectral indices were calculated to investigate their variability within the 500 m MODIS pixel. More specifically, the intra-group R^2 offers information about the spatial variability, due to the collection of samples ~~at~~ from different plots within the MODIS pixel. A linear regression model was created for each sampling day where the biophysical variable and the spectral index were the dependent and the independent variable, respectively. The average R^2 of all the regression models for each day provided the intra-group R^2. Instead, the inter-group R^2 explains the temporal variability due to the collection of the samples on different days. In this case, the biophysical variable and the spectral index for all plots were averaged for each sampling day. The linear regression model of these averaged values determined the inter-group R^2. To explain temporal and spatial variability together, the overall R^2 fitted in a single regression model including all plots and sampling days for each spectral index and biophysical variable.

Later, using the mean values of each biophysical variable and the proximal sensing spectral indices, a univariate linear regression model was applied. The same procedure was repeated for MODIS data. Bootstrapping techniques evaluated the empirical model robustness, which is a valid alternative to traditional leave-one-out methods to validate regression models predictability according to Richter et al. (2012) and following Steyerberg et al. (2001) that recommends two hundred simulations. Later the median value of each statistics was used as indicative of its performance. Root Mean Square Error (RMSE), Relative Root Mean Square Error (RRMSE), ~~Nash-Sutcliffe Efficiency index (NSE),~~ determination coefficient (R^2) and Taylor's diagrams evaluated the models' performance. ~~As recommended in Steyerberg et al. (2001), two hundred bootstrap model simulations were run for each model and the median value of each statistics represented its performance.~~ The RMSE measured the error in the estimation of the biophysical variable by each model:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(V_{est}^{i} - V_{obs}^{i}\right)} \qquad (8)$$

Where V_{est}^{i} is the estimated variable and V_{obs}^{i} is its observed field measurement. RMSE cannot compare the error of different variables with different units. To address this limitation in order to compare the model performances between different variables, RRMSE divides RMSE by the average of the observed values $\overline{V}_{obs}$ (Richter et al., 2012):

$$\mathrm{RRMSE} = 100\frac{\mathrm{RMSE}}{\overline{V}_{obs}} \qquad (9)$$

~~The NSE indicates the model predictive power which ranges from −∞ to the best predictive power value of 1 (Richter et al., 2012). It establishes if the model performs at least as accurate as the average of observed values through the following expression:~~

$$\cancel{\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(V_{est}^{i} - V_{obs}^{i}\right)^2}{\sum_{i=1}^{n}\left(V_{obs}^{i} - \overline{V}_{obs}^{i}\right)^2} \qquad (9)}$$

The R^2 measures the proportion of variance explained by the model and is calculated as:

$$R^2 = 1 - \frac{\sigma_r^2}{\sigma^2} \qquad (10)$$

where σ_r^2 represents the residual variance and σ^2 is the variance of the dependent variable.

2.6 Comparing performance between empirical and RTM based estimates

Taylor diagrams allowed the comparison between the ~~spectral indices~~ FMC and CWC predicted by empirical models fit and the RTM inversion estimates ~~based algorithms of~~

~~Jurdao et al. (2013) and Trombetti et al. (2008) for FMC and CWC, respectively~~. In these plots the observed variable and its standard deviation (*SD*) are plotted in the x-axes. RMSE is represented as semicircles centered at the observed data. The correlation coefficient (*r*) is displayed in the azimuthal position. Best models are closer in the plot to the observed measurement; therefore they will have a high r, a low RMSE and a SD similar to the observed values.

3 Results

3.1 Empirical models fitting

All variables showed similar temporal evolution, a strong variability controlled by the meteorological conditions with a peak in spring and second minor peak in the ~~fall~~ winter except Dm (Fig. 3). Dm fluctuated throughout the year and exhibited its highest values in the summer. The 47% Coefficient of Variation (CV) for Dm was less than for CWC_{IQ} (CV= 95%), CWC_{OQ} (CV=0.95%), FMC_{IQ} (CV= 60%) and FMC_{OQ} (CV= 56%), but higher than for EWT (CV= 38%). A higher precipitation in the spring of 2010 ~~versus the previous year~~ compared to previous year translated into higher FMC, CWC and LAI values. FMC_{OQ} and CWC_{OQ}, calculated from the ~~EWT_{Sample}~~ OQ_{Sample}, presented similar trends but in some cases higher values than FMC_{IQ} and CWC_{IQ}, calculated from the ~~quadrant sample~~ IQ_{Sample}.

A low intra-group R^2 for all the variables indicates a low spatial variability between plots (Fig. 4). Contrary, the high inter-group R^2 also for all variables points to the high temporal variability between sampling dates. The main differences between variables occurred for overall R^2. Similar overall and inter-group R^2 values for CWC_{OQ} and FMC_{OQ} indicated that the combination of the temporal and spatial factors matched in importance each factor on its own. Instead, overall R^2 for CWC_{IQ} and FMC_{IQ} laid in between the inter-group and the intra-group R^2 underling the temporal factor as the main source of variation. GEMI offers the best R^2 for all variables while VARI had the weakest R^2.

The ~~most accurate univariate~~ explicative ~~empirical bootstrap~~ model with the highest R^2 to retrieve each variable differed ~~from~~ between proximal sensing and MODIS (Fig. 5) ~~to MODIS (Fig. 5)~~. FMC_{OQ} and FMC_{IQ} showed the best correlations with GEMI from proximal sensing data but EVI ~~performed better~~was the index that presented the highest R^2 when using ~~from~~ MODIS images. EWT offered the poorest adjustments among all variables analyzed both for proximal sensing and MODIS data. In this case GEMI was the best predictor.~~was more accurately estimated with GEMI from either sensor but presented the lowest R^2 and NSE of all the biophysical variables~~. NDII and GVMI were the most accurate predictors for LAI, CWC_{OQ} and CWC_{IQ} with proximal sensing. When using MODIS, the most accurate results for LAI were achieved with NDII and GVMI, but EVI did so for CWC_{OQ} and CWC_{IQ}. When the ~~quadrant sample~~ IQs_{ample} was used instead of the ~~EWT_{Sample}~~ OQs_{ample}, both FMC and CWC showed ~~more accurate~~ higher R^2 results (Fig. 5) with lower RRMSE ~~and higher NSE and R^2~~, although the RRMSE results obtained presented small differences (Fig. 6).

Smaller confidence intervals of R^2 were observed when proximal sensing reflectance was used with the exception of EWT in which MODIS presented smaller intervals.

3.2 Comparing performance between empirical based and RTM estimates

Taylor diagrams in Figs. 7 and 8 compare FMC and CWC estimates using spectral indices and RTM ~~using the Taylor diagrams~~. In the case of FMC_{IQ} from proximal sensing (Fig. 7 left), RTMs are distant from empirical index-based models. They presented higher RMSE and lower r than the spectral indices whereas RTM SD was more similar to the observed values. In the case of FMC_{IQ} estimated from MODIS (Fig. 7 right), RTMs ~~was~~ were closer to the empirical models in the Taylor diagram and therefore perform more similar to those. For CWC_{IQ} (Fig. 8), the differences between the empirical and RTMs are larger. Using ~~from~~ proximal sensing data (Fig. 8 left), RTM overestimated the SD of the observed CWC_{IQ}. ~~At~~ Using MODIS ~~scale~~ (Fig. 8 right), RTM showed a very high overestimation of the CWC_{IQ}.

Temporal evolution of the biophysical variables estimated using the most ~~accurate~~explicative model for proximal sensing and MODIS in Fig. 5 and 6 are shown in Fig. 9. Fitting equations for the different variables are shown in Table 2. Both sensors predicted well EWT, FMC_{IQ} and FMC_{OQ} but showed an overestimation, especially during the dry season. Contrary, the models for LAI, CWC_{OQ} and CWC_{IQ} adjusted well even during the dry season.

4 Discussion

Results revealed that Dm varies significantly throughout the year (CV=47 %) with high values in the summer. These changes could be related to the temporal variation in plant community structure, species composition and diversity in this ecosystem (Casado et al., 1986). Summer should be the best time of the year to invert RTM and predict Dm, since leaves are drier and therefore EWT does mask the Dm spectral absorption signal (Riaño et al., 2005). Casas et al. (2014) applied a constant annual Dm value from the literature to successfully predict seasonal variations in EWT and CWC. However, our study suggests that, due to the high seasonal variation in Dm, a constant annual value would not be recommended ~~here~~ in grassland ecosystems as the one analyzed in this work.

The high inter-group and low intra-group R^2 implies that the temporal trend is much more critical than the spatial variation within the MODIS pixel (Fig. 4). ~~Therefore, the strategy to capture better the variability of vegetation water content in this ecosystem should be to sample more times but fewer plots.~~ Therefore, the strategy to better capture the variability of grass water content in this ecosystem should consist in increasing the number of samples in time and but sampling less number of plots per day. In addition, CWC_{IQ} and FMC_{IQ}, generated from larger sample sizes than CWC_{OQ} and FMC_{OQ}, presented higher inter-group R^2 values, which indicate a better characterization of the temporal variability. Even though similar conclusions were obtained using the two strategies the results in this study showed that the higher R^2 are found in the case of the IQ_{Sample}. Using the quadrant also presented some advantages as it allows not just the retrieval of FMC but also CWC (as in Eq. 6) without going through the time consuming leaf scanning process to retrieve leaf area needed to estimate EWT. This suggests the need to standardize sampling protocols for the estimation of vegetation biophysical parameters to ensure data quality, repeatability and to facilitate accurate cross comparison from different studies. Some initiatives already exist to facilitate this standardization, as the Global Terrestrial Carbon System (GTOS) guidelines in support of carbon cycle science (Law et al., 2008). However, currently there is no international backbone that ensures this and an agreement in the protocols is needed in order to validate remote sensing products.

CWC was better predicted than the other two water content ~~variables~~ metrics, FMC and EWT (Fig. 4). CWC depends on LAI which is ~~even higher correlated~~showing higher correlation values to the empirical models than ~~those two variables~~ other metrics such as FMC or EWT. Some studies have shown that LAI contributions to total reflectance variability is much higher than water (Bowyer and Danson, 2004) for this reason also, CWC should provide more accurate retrievals than FMC or EWT. It is possible to have the same FMC and EWT for different LAI and hence different CWC and amount of soil background, which will change its reflectance. Yebra et al. (2013) demonstrated through PROSAILH simulations how a very different CWC for the same EWT based on changes of LAI translates into a ~~huge~~ large range of NDII values. Our results confirm this theoretical assumption described in Yebra et al. (2013). This issue is especially critical over areas like ~~this one~~ the one analyzed in this work with an herbaceous cover exhibiting large dynamic annual growth. Very low R^2 values were obtained in this study regarding the EWT. More research needs to be done in this line as EWT is a key input parameter in many RTM.

The empirical methods estimated FMC and CWC with slightly different results for proximal sensing and MODIS (Figs. 5 and 6). While GEMI and NDII were the most accurate for FMC and CWC respectively from proximal sensing in our study; EVI was the most ~~accurate~~ explicative estimator of both variables from MODIS. The relationship between these indices and water metric is indirect, since none of them include spectral bands in the SWIR region where water absorption is strong. However, there is a strong link between grass water content, chlorophyll activity and LAI in this ecosystem. During wet periods the grass grows very rapidly, increasing the LAI, biomass and chlorophyll content, but as soon as the dry season starts with high temperatures and low rainfall the grass becomes cured rapidly losing all chlorophyll and quickly decreasing the LAI and biomass. This explains the empirical relationships with high R^2 between water metrics and indices sensible to chlorophyll activity, or those more sensible to water in the SWIR region. In addition, it is remarkable that MODIS estimations ~~were more accurate~~presented higher R^2 than proximal sensing. Bootstrap confidence intervals indicated that R^2 and RRMSE presented large intervals, larger when using MODIS images. Roberts et al. (2006) also observed different correlations between indices and platforms and the discrepancies here need further investigation. The difference in the confidence interval amplitude between proximal sensing and MODIS can be explained because the ~~MODIS~~ pixel included not only grass but also trees, their shades, and other marginal covers like bare soil and a water pond (Fig. 1), and its view angle could be up to 20° whilst p~~P~~roximal sensing measures only two transects within each of the six plots and provides only nadiral measurements of herbaceous cover which could be more affected by the soil signal.

Similarly to this study, Casas et al. (2014) reliably predicted water content variables in California (USA) from GEMI, NDII and EVI using simulated MODIS spectral response from airborne hyperspectral AVIRIS instrument. In their case, it was actually VARI the most accurate for grasslands (FMC and CWC), chaparral (EWT, FMC and CWC) and a Mediterranean oak forest (EWT). Contrary, VARI showed very poor accuracies in our case to estimate FMC, EWT and CWC, but was still capable of capturing the variability in LAI (Fig. 4). This fact also contradicts other studies that predicted FMC from VARI on chaparral (Peterson et al., 2008;Roberts et al., 2006;Stow et al., 2005, 2006). VARI was developed to detect vegetation fraction in homogenous wheat crops (Gitelson et al., 2002b), but Gitelson et al. (2002a) nor the above studies have tested this spectral index to detect vegetation water content on sites like ours, with strong seasonal changes in species composition and LAI.

The empirical methods calibrated for this specific site outperformed the physical RTM estimates for CWC and FMC (Figs. ~~4~~ 7 and ~~5~~8). This confirms the results in Casas et al. (2014) where the CWC algorithm based on RTM inversion developed by Trombetti et al. (2008) also failed to improve results from empirical estimates. Regarding the RTM-based-FMC estimates, considering that the FMC inversion models were not calibrated with any data from the field campaign and that the results were similar to those obtained using empirical approach (Fig. 7) we believe that the models can be applied in other similar areas. ~~RTM only overcome when structural information constrains the model inversion (Yebra et al., 2008b; Casas et al., 2014). Such ancillary information is key to successfully extrapolate a RTM inversion at broader scale.~~

Future work in this line can still be done, testing other inversion techniques, using multiple observations or other optimization algorithms might help to improve the performance of physical based estimates of biophysical variables of vegetation.

5 Conclusions

This work showed a complete analysis of three metrics, EWT, FMC and CWC, to measure ~~vegetation~~ grass water content at two different spatial scales by using proximal sensing from a field spectroradiometer and MODIS images. The temporal changes in these metrics are more critical than their spatial variation within the MODIS pixel. Results indicated that larger samples collected using quadrants as spatial reference sampling units are more representative than ~~the~~ small ~~EWT$_{Sample}$~~ samples in order to follow the temporal trends in FMC and CWC.~~.~~ Protocol standardization ~~in order to make different datasets comparable~~ should be considered to make different dataset comparable both spatially and temporally. Due to the high seasonal Dm variability, a constant annual value should not be used to estimate EWT from FMC in this ecosystem. The dependence of CWC on LAI makes this vegetation water content variable easier to predict than FMC or EWT in grasslands due to the strong existing link between LAI, water content and chlorophyll activity.

GEMI, NDII and EVI reliably predicted vegetation water content. The best empirical estimator differed between sensors. Empirical models based on vegetation indices ~~Results were a bit better~~showed higher R^2 for MODIS than from proximal sensing, probably due to differences induced by observation geometry and canopy observed ~~in view angles, sampling strategy and canopy observed~~. These empirical methods still exceed RTM inversions developed for other sites to predict FMC (Jurdao et al., 2013;Yebra et al., 2008b) and CWC (Trombetti et al., 2008). Conclusions from this study are much related to grassland physiology and cannot be extended to other vegetation types such as forest or shrubs.

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Table 1: Spectral indices calculated using field ~~reflectance~~ HCRF measurements and MODIS data. B_x designates the band number corresponding to the MOD09GA product surface reflectance product.

Index	Formula	Reference
Normalized difference vegetation index (NDVI)	$NDVI = \frac{B_2 - B_1}{B_2 + B_1}$	(Rouse et al., 1973)
Enhanced Vegetation Index (EVI)	$EVI = 2.5 \cdot \left(\frac{B_2 - B_1}{B_2 + 6 \cdot B_1 - 7.5 \cdot B_3} \right)$	(Huete et al., 2002)
Normalized Difference Water Index (NDWI)	$NDWI = \frac{B_2 - B_5}{B_2 + B_5}$	(Gao, 1996)
Normalized Difference Infrared Index (NDII)	$NDII = \frac{B_2 - B_6}{B_2 + B_6}$	(Hardisky et al., 1983)
Simple Ratio Water Index (SRWI)	$SRWI = \frac{B_2}{B_5}$	(Zarco-Tejada et al., 2003)
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \left(\frac{B_2 - B_1}{B_2 + B_1 + L} \right) \cdot (1 + L)$ Where L= 0.5	(Huete, 1988)
Global Environment Monitoring Index (GEMI)	$GEMI = \eta \cdot (1 - 0.25\eta) - \frac{B_1 - 0.125}{1 - B_1}$ where $\eta = \frac{2 \cdot (B_2^2 - B_1^2) + 1.5 \cdot B_2 + 0.5 \cdot B_2}{B_2 + B_1 + 0.5}$	(Pinty and Verstraete, 1992)
Visible Atmospherically Resistant Index (VARI)	$VARI = \frac{B_4 - B_1}{B_4 + B_1 - B_3}$.	(Gitelson et al., 2002a)

Global Vegetation Monitoring Index (GVMI)	$GVMI = \frac{\left(NIR_{REC}^{*} + 0.1\right) - \left(SWIR - 0.02\right)}{\left(NIR_{REC}^{*} + 0.1\right) + \left(SWIR - 0.02\right)}$	(Ceccato et al., 2002)
Central band wavelength	B1= 645.5 nm, B2= 856.5 nm, B3= 465.6 nm, B4= 553.6 nm, B5= 1241.6 nm, B6= 1629.1 nm, B7= 2114.1 nm	

- NIR_{REC} stands for the information in the Near Infra Red rectified as the index was designed for SPOT-VEGETATION (Ceccato et al., 2002). In this study the index was calculated using the spectral bands from MODIS corresponding to that B2 for the NIR and B5 for the SWIR regions

Table 2: Empirical fitting equations obtained after bootstrap.

Fitting equation Proximal Sensing	Fitting equation MODIS
$FMC_{OQ} = (1184.400 \cdot GEMI) - 734.405$	$FMC_{OQ} = (1727.326 \cdot EVI) - 216.433$
$FMC_{IQ} = (999.707 \cdot GEMI) - 626.932$	$FMC_{IQ} = (1398.385 \cdot EVI) - 173.518$
$EWT = (0.029 \cdot EVI) + 0.011$	$EWT = (0.059 \cdot EVI) + 0.003$
$LAI = (2.621 \cdot NDII) + 1.268$	$LAI = (3.524 \cdot NDII) + 1.189$
$CWC_{OQ} = (0.075 \cdot NDII) + 0.029$	$CWC_{OQ} = (0.195 \cdot EVI) - 0.032$
$CWC_{IQ} = (0.063 \cdot NDII) + 0.023$	$CWC_{IQ} = (0.157 \cdot EVI) - 0.026$

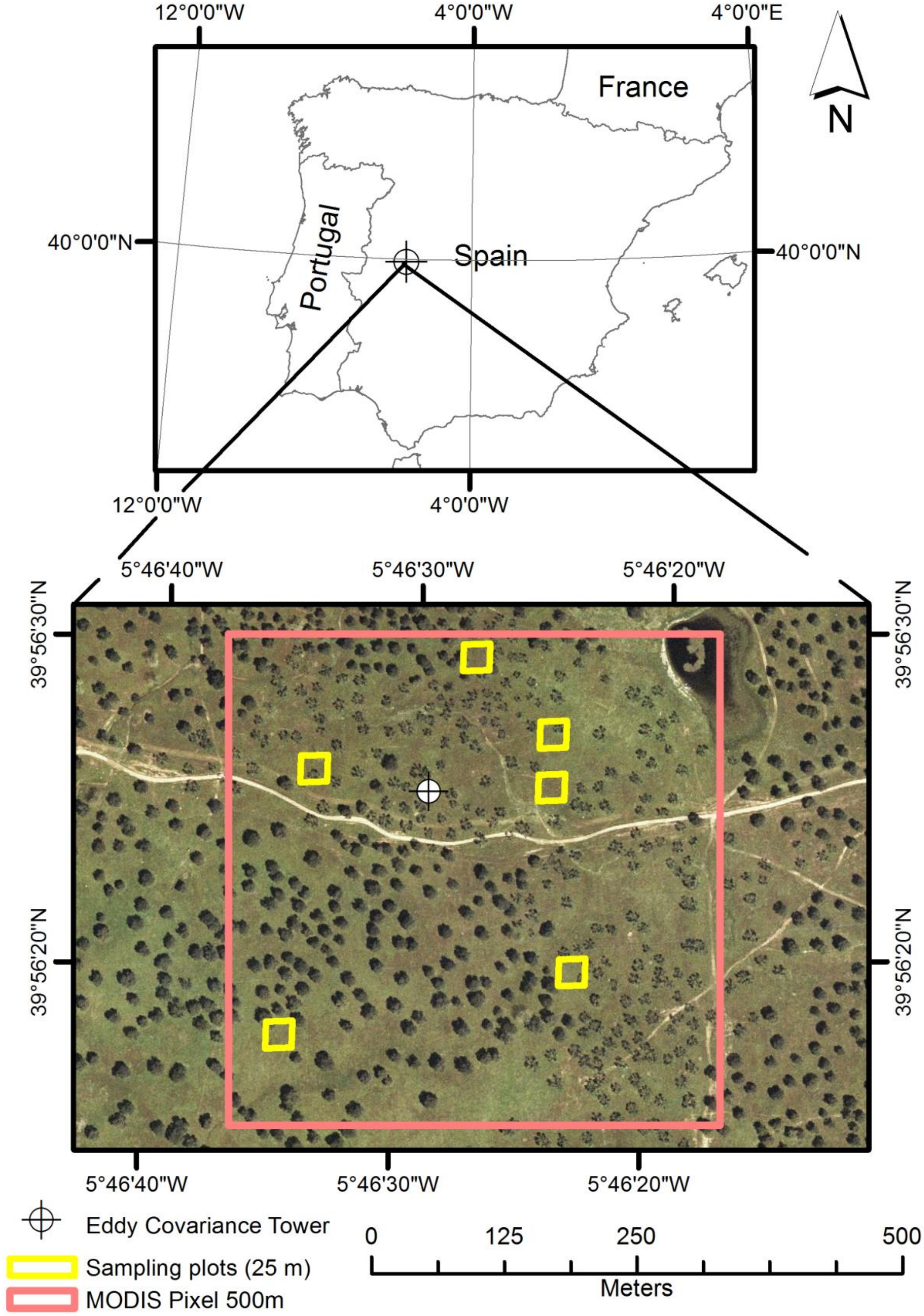

Figure 1. Plots sampled near the FLUXNET tower within the 500 m MODIS pixel at Las Majadas del Tiétar (Spain) study site.

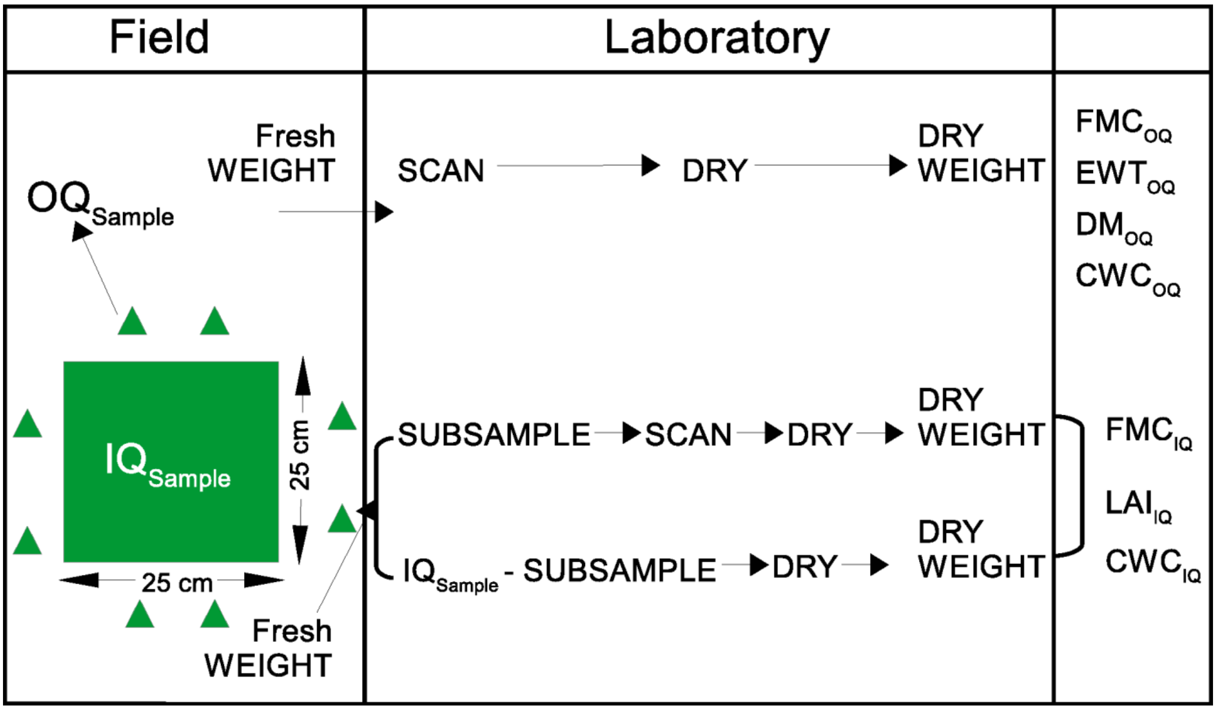

Figure 2. Scheme showing the different samples collected in the field and how they are processed in the laboratory. Metrics obtained as results are also indicated in the last column.

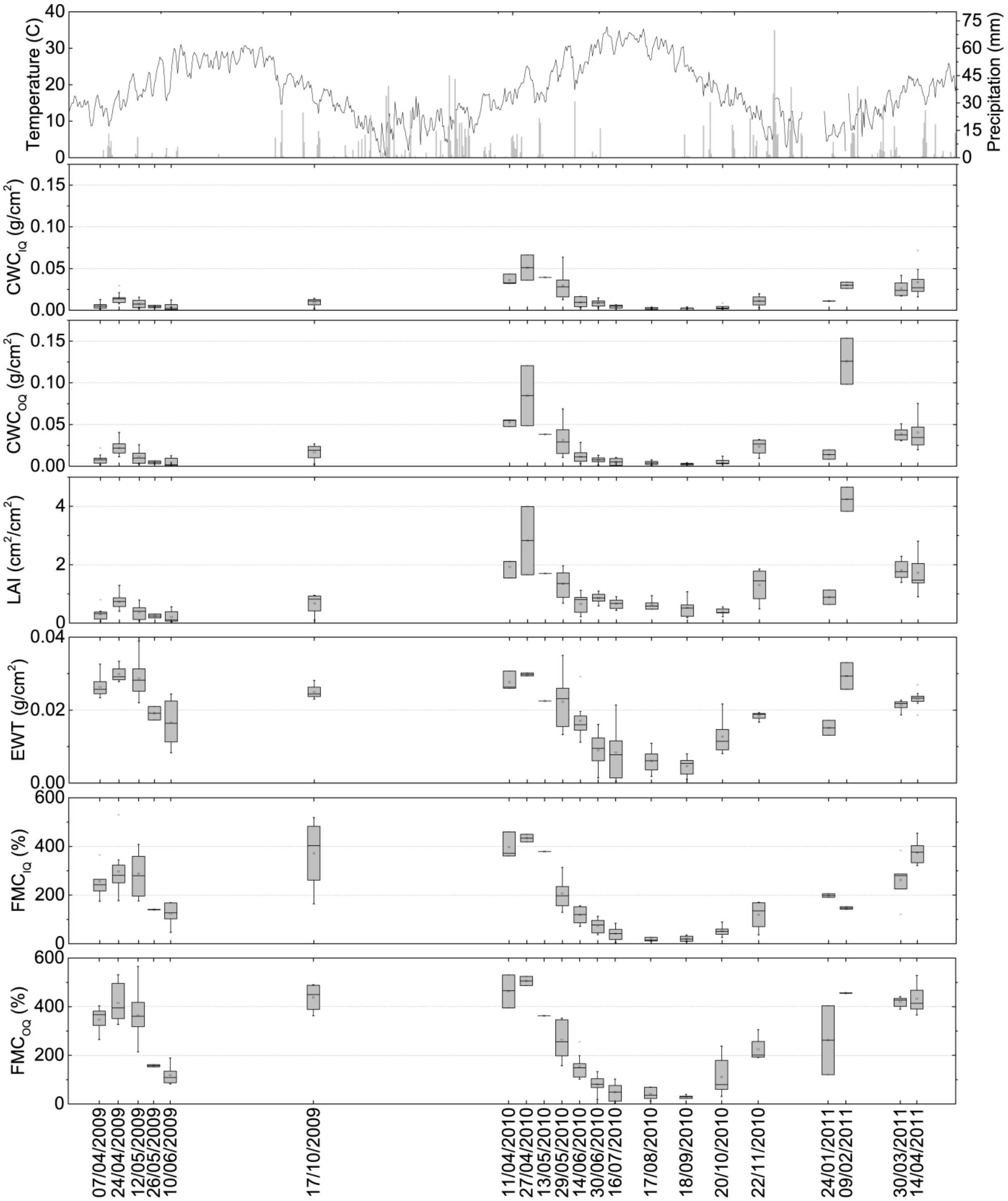

Figure 3. Box plot showing the temporal evolution of field biophysical variables measured. Filled points represent the median of the daily measurements, the boxes indicate the position of the 1st and 3rd quartile, lines delimit the maximum and minimum values~~,~~ and empty points are outliers. Line inside the boxes showed the median value of the day and the point the mean value. Precipitation is represented using bars and temperature is represented with a solid line

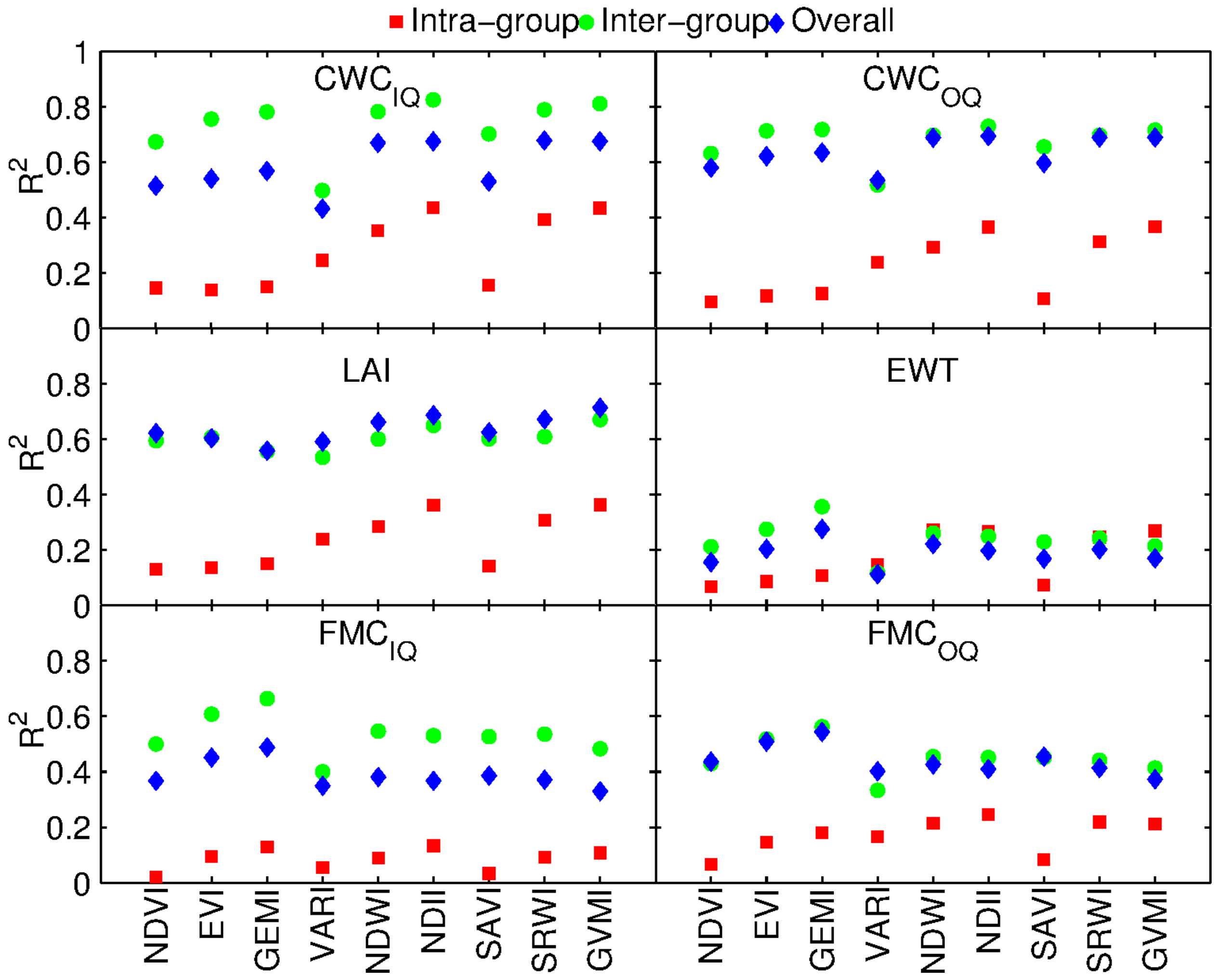

Figure 4. Intra-group, inter-group and overall R^2 values between proximal sensing spectral indexes and biophysical variables measured in the field.

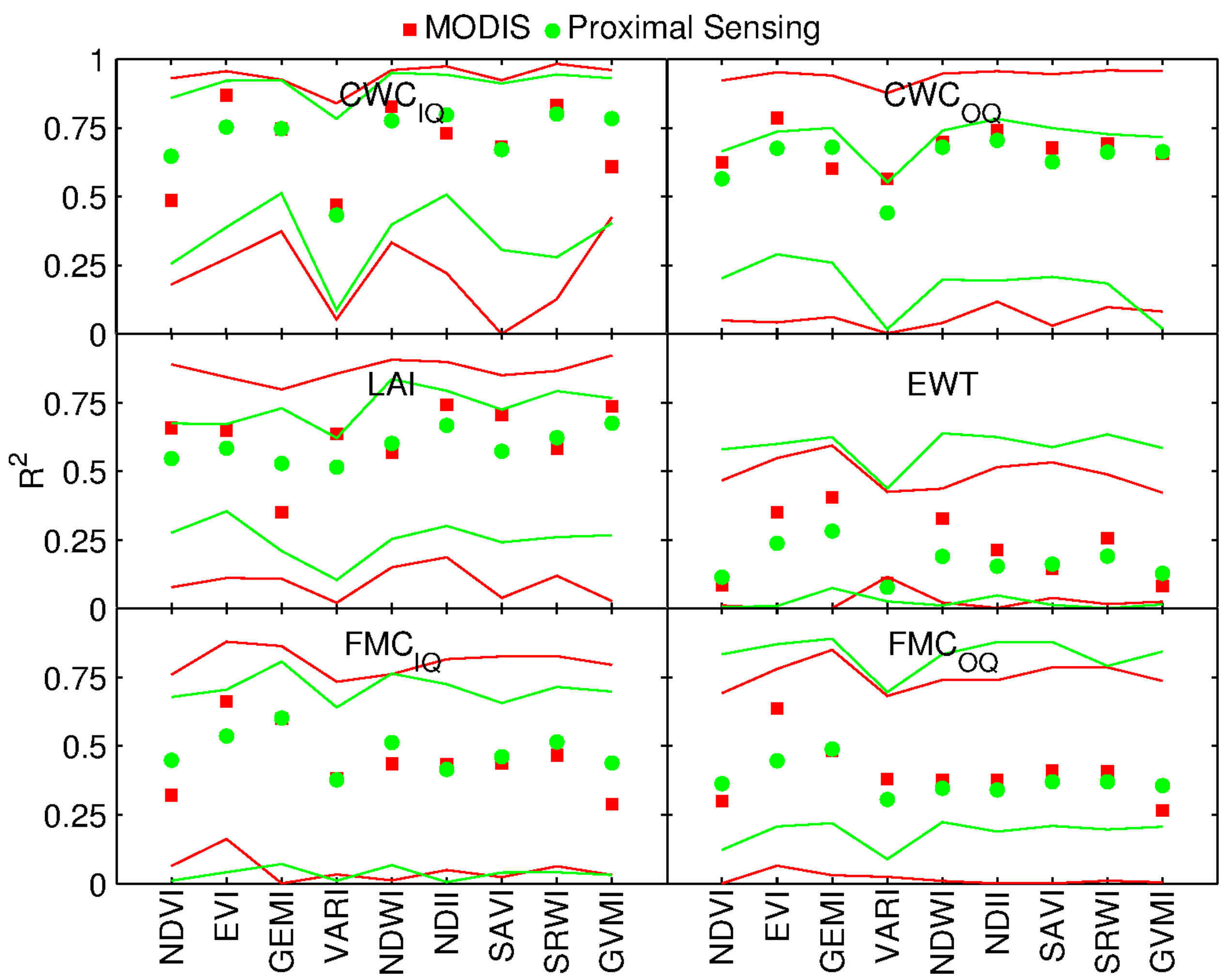

Figure 5. D~~Model performance statistics for all the spectral indices calculated using proximal sensing.~~etermination coefficient for proximal (green circles) and MODIS (red squares) empirical models after bootstrap. Upper and lower limits of the confidence intervals for MODIS and proximal sensing are presented.

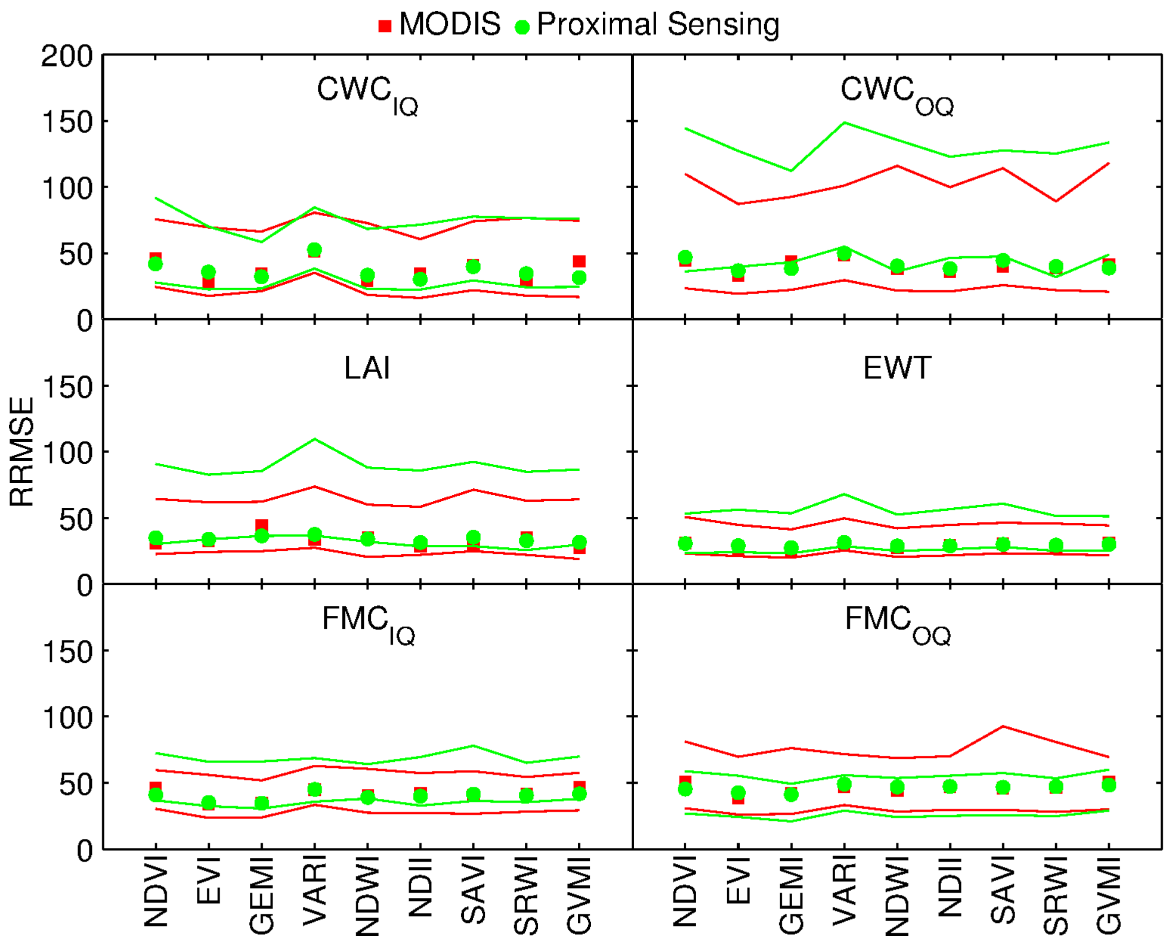

Figure 6. Relative root mean square error for proximal (green circles) and MODIS (red squares) empirical models after bootstrap. Upper and lower limits of the confidence intervals for MODIS and Proximal sensing are presented. ~~Model performance statistics for all the spectral indices calculated using MODIS data.~~

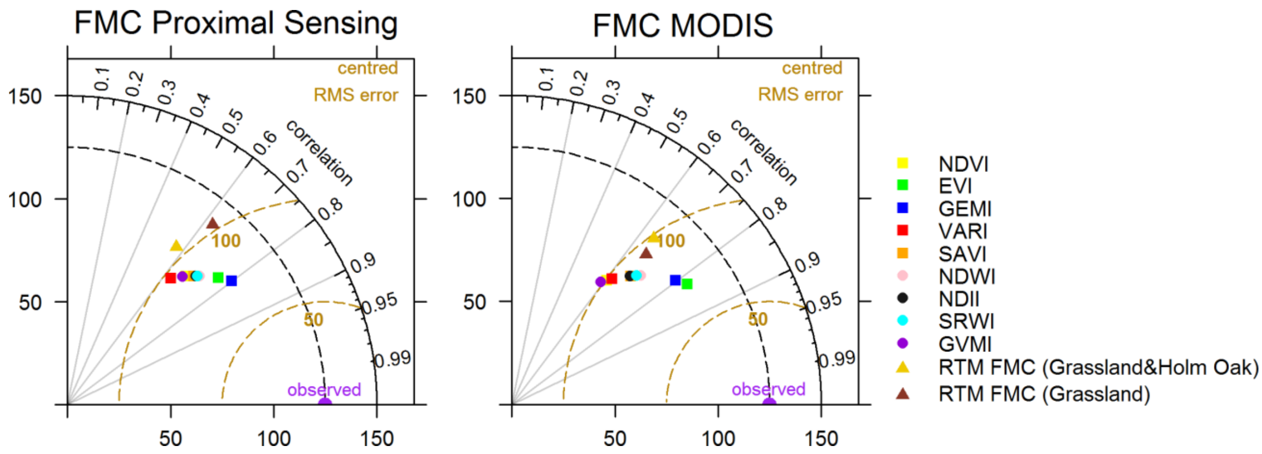

Figure 7. Comparison of empirical vs RTM models to estimate FMC with proximal sensing (left) and MODIS (right). RTM FMC (Grassland) obtained from the LUT proposed by (Yebra et al., 2008b). RTM FMC (Grassland& Holm Oak) obtained from the LUT proposed by Jurdao et al. (2013).

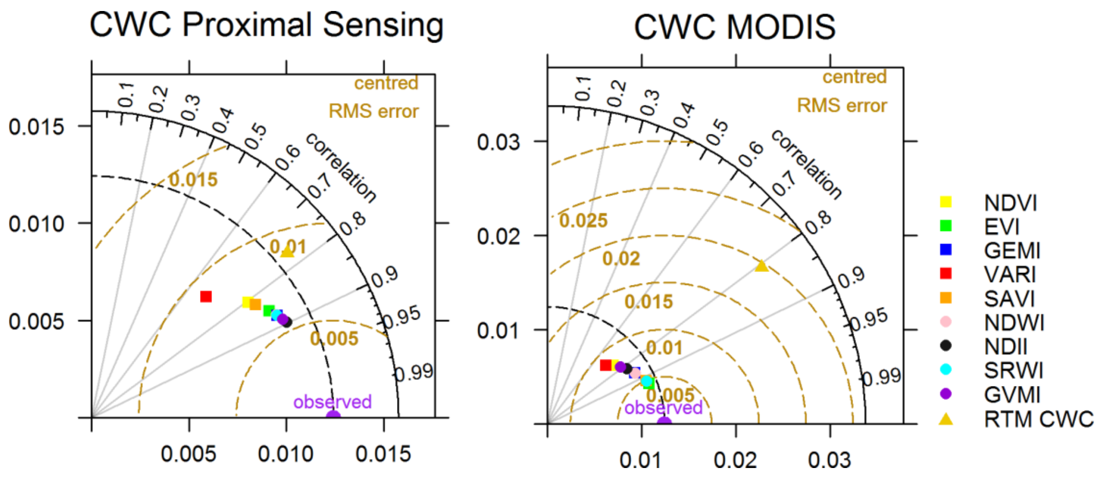

Figure 8. Comparison of empirical vs RTM models to estimate CWC with proximal sensing (left) and MODIS (right). RTM CWC is based on Trombetti et al. (2008).

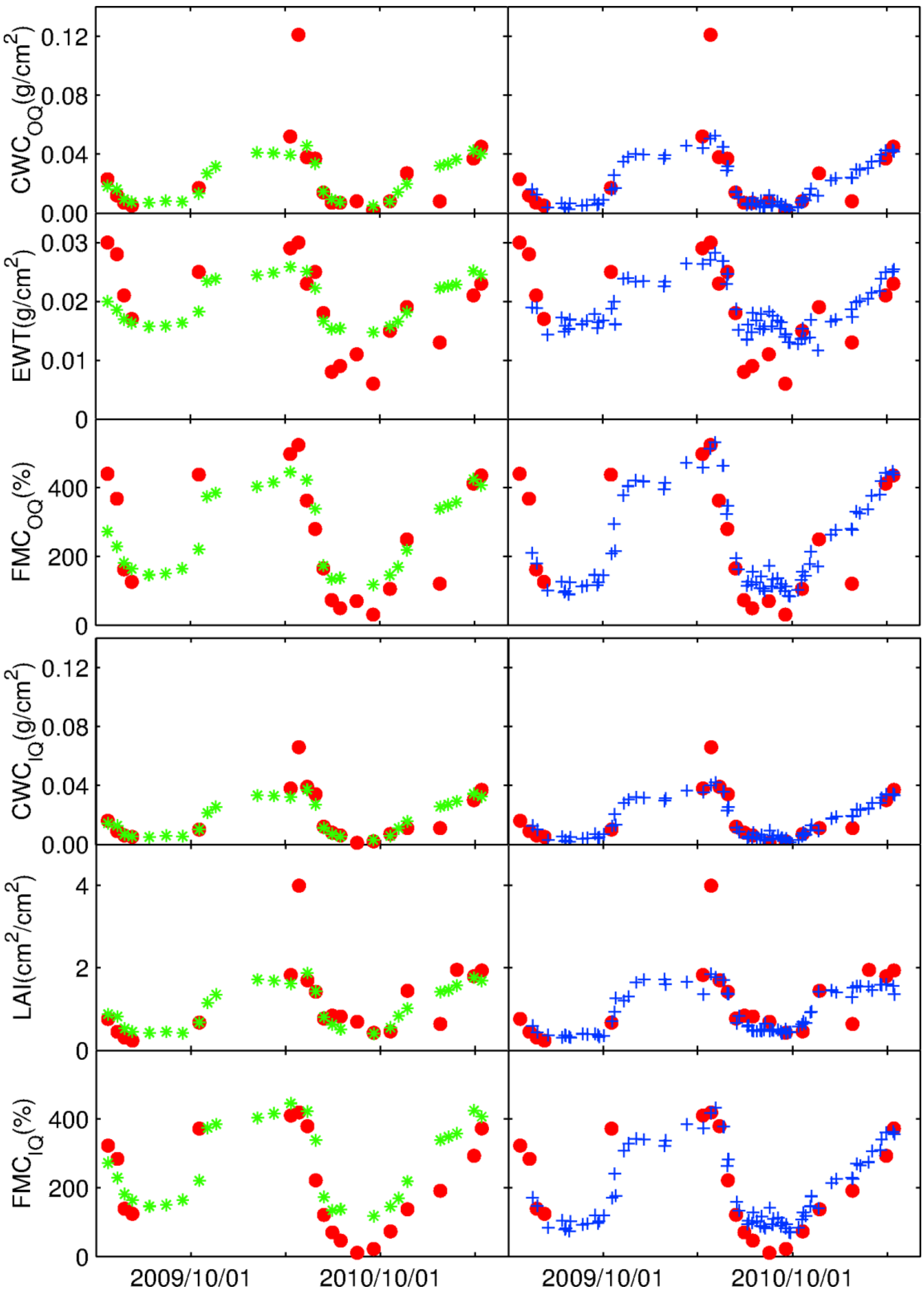

Figure 9. Temporal evolution of the observed (red circles) and estimated FMC_{OQ}, FMC_{IQ}, EWT, LAI, CWC_{OQ} and CWC_{IQ} obtained for proximal sensing (green asterisks) and MODIS (blue crosses). Fitting equations are presented in Table 2.