Monitoring Vegetation Moisture Using Passive Microwave and Optical Indices in the Dry Chaco Forest, Argentina

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***Abstract*—Information about daily variations of vegetation moisture is of widespread interest to monitor vegetation stress and as a proxy to evapotranspiration. In this context, we evaluated optical and passive microwave remote sensing indices for estimating vegetation moisture content in the Dry Chaco Forest, Argentina. The three optical indices analyzed were the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI) and the Normalized Difference Infrared Index (NDII) and, for the microwave region the Frequency Index (FI). All these indices are mainly sensitive to leaf area index (LAI), but NDWI and NDII, and FI are also sensitive to leaf water content (LWC) and Canopy Water Content (CWC) respectively. Using optical and microwave radiative transfer models for the vegetation canopy, we estimated the range of values of LAI, LWC and CWC that can explain both NDWI/NDII and FI observations. Using a combination of simulations and microwave and optical observations, we proposed a two step approach to estimate leaf and canopy moisture content from NDWI, NDII and FI. We found that the short variation of LWC estimated from NDWI and NDII present a dynamic range of values which is difficult to explain from the biophysical point of view, and it is partially related to atmosphere contamination and canopy radiative transfer model limitations. Furthermore, the observed FI short-term variations (∼8 days) cannot be explained unless significant CWC variations are assumed. The CWC values estimated from FI present a short-term variations possibly related to vegetation hydric stress.**

***Index Terms*—Microwave index, optical indices, vegetation water status.**

I. Introduction

THE knowledge of temporal and spatial variability of vegetation moisture is critical to understand plant physiological properties [1], to provide useful information in agriculture for drought assessment [2] and to determining fire susceptibility in forests [3]. Several indices related to vegetation moisture have been proposed as remote sensing proxies to estimate forest evapotranspiration [4]–[6].

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Historically, the estimations of foliar water content have been based on optical systems. Several studies based on the relationship between foliar and vegetation water content and spectral reflectances have been conducted [7]–[9]. Liquid water in leaves has strong absorption features at shortwave infrared (SWIR) wavelengths, which can be used to determine leaf water content (LWC, leaf H2O [g]/leaf fresh weight [g]). Therefore, Normalized Difference Vegetation Index (NDVI) has limited capability for estimation of LWC, because it does not include reflectance information corresponding to the SWIR channels [10], [11]. On the contrary, it has been shown [10], [12], [13] that the reflectance ratio SWIR/NIR is related to the amount of water per leaf area (equivalent water thickness, EWT, g/cm^2). A SWIR channel is critical to estimate EWT and a NIR channel is needed to account for variation of leaf internal structure and dry matter content variations [11], [14]. In particular, Normalized Difference Infrared Index (NDII), which uses 1.65 μm and 0.85 μm channels, was successfully related to leaf water content in specific ecosystems [15]. NDII has been studied by several authors under different names (i.e. Land Surface Water Index (LSWI) using MODIS bands 2 and 6 for paddy rice landcover mapping) [7], [16], [17]. Finally, in [8] the Normalized Difference Water Index (NDWI) was developed using 1.24 μm and 0.85 μm channels. Both vegetation water optical indices present some sensitivity to EWT at leaf scale [5], [8]. These experimental evidences were backed using leaf and canopy radiative transfer interaction models, which demonstrated the theoretical basis behind the relationship between LWC and canopy reflectance in the near-infrared spectral region [18], [19].

However, SWIR/NIR infrared indices are not a general solution to estimate overall vegetation water content (VWC, (include moisture from leaf, branch and stem) H2O [kg/m^2],) [20]. Although there is sensitivity to estimated VWC in herbaceous vegetation, but this sensitivity is very low for complex vegetation architectures. The overall VWC includes two components, one related to branches and steam, and a seasonal component due to leaves. In crops areas the first component can be consider constant, and VWC can be estimated using allometric equations [21]. For trees this approach is more difficult to implement, since the annual xylem growth may supply water to the foliage, and cannot be consider as a constant component [22].

In this context, passive microwave data becomes interesting as a complementary source of information. Passive microwave vegetation indices (such as Frequency Index (FI) and Emissivity Difference Vegetation Index (EDVI) [4]) are also sensitive to vegetation properties [23]. Although characterized by coarser spatial resolutions, passive microwave sensors present shorter revisit times and are less affected than optical systems by atmospheric conditions. In particular, both FI and EDVI are known to be sensitive to vegetation moisture and structure. Moreover, EDVI was found to be sensitive to evapotranspiration fraction under all-sky conditions [4]. This day-to-day analysis of vegetation moisture variations during growing season is particularly relevant, because it is mainly related to plant water stress due to environmental factors.

In this study, we evaluated the potential of passive microwave and optical remote sensing for estimating weekly variation of vegetation moisture (expressed as fraction of water by weight (in g/g)) in an open dry forest in Argentina. In particular, the LWC (defined as g H20/g fresh leaves weight) and Canopy Water Content (CWC, defined as g H20/g fresh weight branches and leaves) are monitored with optical and microwave indices using a two-step procedure. First, we estimated LAI as a function of NDVI using PROSAILH simulations [24] and MODIS LAI product. Second, given LAI values obtained previously, we estimated LWC from both NDWI and NDII (optical estimation) and CWC from FI (microwave estimation), using PROSAILH and a microwave interaction model [23] respectively. In this way, we compared optical and microwave estimations of vegetation moisture, and weighted the utility of these indices.

II. Methodology

A. Study Area

The studied region is the Bermejo River Basin in Argentina (22–27° S, and 58–66° W). This Basin includes the Chaco Plain, which is a dry forest phytogeographic region. Fig. 1 reports a map of this area, which is mainly an open dry forest [25], with mean annual temperatures between 20 and 22° C, mean summer temperatures between 24 and 27° C, and minimum annual rainfall (500 mm). The dominant species of Chaco forest is Quebracho (*Schinopsisi lorentzeii* and *Aspidosperma quebracho-blanco*), and it is accompanied by *Bulnesia sarmientoi*, *Prosopis spp.*, and *Ziziphus mistol*. The study area has several important characteristics for microwave signal analysis: large homogeneous sites covered by forest with biomass values that vary between 70–110 Mg/ha. This region was mentioned as an environmental hot spot of landcover change by [26].

B. Data Sets

Radiometric measurements were collected by AMSR-E from 2007 to 2008 [27]. In this study, we have used L2 A data of the ascending orbits that cover this area, which contain values of brightness temperature at vertical (V) and horizontal (H) polarizations. The temporal resolution is 3 days. Optical measurements were obtained from Aqua's 8-days composition MODIS land surface reflectance product at 500 m spatial resolution (MYD09A1), acquired from February 2007 to December 2008. The data were downloaded from the National Aeronautics and Space Administration (NASA) site http://reverb.echo.nasa.gov/.

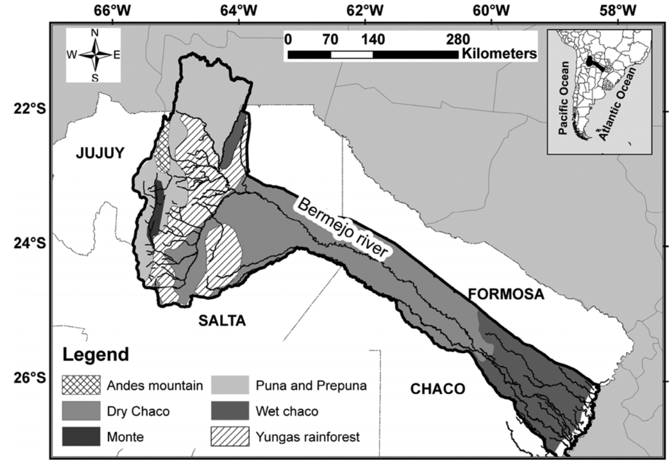

Fig. 1. Ecoregion of Bermejo River Basin. The study area is the Dry Chaco plain.

TABLE I
Spectral Indices Calculated From MODIS and AMSR-E Including Their Shortened Acronym, Mathematical Formulation and References

Index	Formulation	Reference
Frequency index	$FI = \frac{Tbv\ (Ka\ band) - Tbv\ (Xband)}{Tbv\ (Ka\ band) + Tbv\ (Xband)} * 2$	[23]
Normalized difference vegetation index	$NDVI = \frac{\rho 2 - \rho 1}{\rho 2 + \rho 1}$	[32]
Normalized difference infrared index	$NDII = \frac{\rho 2 - \rho 6}{\rho 2 + \rho 6}$	[15]
Normalized difference water index	$NDWI = \frac{\rho 2 - \rho 5}{\rho 2 + \rho 5}$	[8]

ρ_x is the reflectance in MODIS band x (1 to 7), TB is the brightness temperature, and v means vertical polarization.

C. Microwave and Optical Indices

Microwave measurements are affected by the absorption and scattering properties of vegetation elements, which can be characterized by total amount of biomass, its distribution among trunks, branches and leaves, and vegetation moisture [23]. FI was calculated using the brightness temperatures at 37 GHz (Ka Band) and 10.6 GHz (X band) AMSR-E channels at vertical polarization (see Table I). As shown by [4], for forest areas the FI calculated at vertical polarization has a higher correlation with vegetation state than the horizontal component. In addition, frequencies were selected after analyzing and comparing several combinations discussed in a previous study [28]. As an example, [29] showed that plant water status can be monitored using X and Ka bands data. In order to better compare with optical indices, the 8-day mean value of FI was calculated.

There are three main physical processes which could influence FI: 1) yearly cycle of leaves, 2) rainfall during acquisition, and 3) variations of soil moisture [23]. For this area, soil moisture has a small effect on FI due to relatively high crown attenuation (at least at X and Ka bands). On the other hand, rainfall events can strongly affect the emission at Ka band, because the contribution of cold raindrops to the overall emissivity is important. During rain events, FI is strongly reduced, and can become negative. This was checked by comparing FI trends with *in situ* precipitation data. Using this information, negative values of FI were excluded from the analysis.

MODIS 8-day composition of the land surface reflectance product was used to derive NDVI, NDWI, and NDII (see Table I). We projected these indices into the AMSR-E spatial grid for comparison. In general, optical remote sensing measurements are influenced by atmospheric effects, clouds, and viewing geometry [30]. Using the information contained in the Quality Assessment band (QA), we excluded data of lower or bad quality, with partial or complete cloud cover [31].

D. PROSAILH: Optical Radiative Transfer Model

PROSAILH is a combination of SAILH and PROSPECT model [24], [33], [34]. The SAILH canopy reflectance model is a one dimensional bidirectional turbid medium radiative transfer model that has been later modified to take into account the hot spot effect in plant canopy reflectance [34], [35]. SAILH requires input parameters to produce the top of canopy bidirectional reflectance (sun zenith angle (ts), sensor viewing angle (to) and azimuth angle (ps)). PROSPECT model calculates the leaf hemispherical transmittance and reflectance as a function of four input parameters [33]: leaf structural parameter (N), leaf chlorophyll a + b concentration (Ca+b), the dry matter content (DMC), and the equivalent water thickness (EWT).

A simulation approach was conducted to study the capability of MODIS for retrieving EWT and leaf area index (LAI, m^2/m^2) in the Dry Chaco Forest area. EWT (g/cm^2), LWC (g H2O/g fresh weight) and DMC (g/cm^2) for the model are defined as:

$$EWT = \frac{FW - DW}{A} \tag{1}$$

$$DMC = \frac{DW}{A} \tag{2}$$

$$LWC = \frac{FW - DW}{FW} \tag{3}$$

$$LWC = \frac{\left(\frac{EWT}{DMC}\right)}{(EWT/DMC + 1)} \tag{4}$$

where FW is the fresh weight, DW is the dry weight, and A is the leaf area. Equation (4) shows the relation between EWT and LWC.

Using the PROSAILH model [24], we generated synthetic canopy reflectance in the 400–2500 nm range, using input variables that are site specific for Dry Chaco Forest (see Table II). Since the study area is large and mostly inaccessible, input parameters for the models were derived from specific field sampling and a comprehensive literature review. Viewing geometry parameters sun angle (ts), view angle (tv), and relative azimuth angle (ps) from land surface reflectance product were extracted for every pixel in the image from MODIS metadata. The range of variation for viewing geometry of all MODIS reflectance products was 17°–52° for ts, 10°–59° for tv, and −67°–169° for ps. As far as vegetation parameter is concerned, we adopted the usual range of values for N for dicotyledons, (1.25–2.5) [36], [37]. The magnitude of the hot spot size-parameter was estimated with the general rule of thumb defining it as the ratio of leaf width to canopy height [38]. For these data, we estimated the MODIS-equivalent reflectance using the sensor spectral bandwidth: bands centered at 645 nm, 858 nm, 1240 nm, and 1640 nm with 50 nm, 35 nm, 20 nm, and 24 nm bandwidth respectively. From this synthetic MODIS-equivalent signature, we calculated MODIS NDVI, NDWI, and NDII.

TABLE II
SUMMARY OF MAIN AVAILABLE MEASUREMENTS OF FOREST VARIABLES [25], [44]

VARIABLE	VALUE		MODEL
Mean basal area (sum of trunk sections at 1.3 m height) [m^2/ha]	Fixed to 10.55		*Microwave radiative transfer model (MRTM)*
Tree density [1/ha]-subdivided into classes of DBH (Diameter at Breast Height, [cm])	DBH [cm]	tree density by classes [1/ha]	*MRTM*
	5 - 10	390 ±70	
	10 - 30	103 ± 37	
	30 - 50	41 ± 15	
	50 - 70	7 ± 4	
	70 - 100	1	
	> 100	0	
Mean Above-Ground Biomass [Mg/ha]	100 ± 12.7		*MRTM*
Average leaf angle	erectophile		PROSAILH
LAI	1-3 (mean LAI is equal to 1.5, according to ECOCLIMAP)		PROSAILH-MRTM
Ca+b	20-60 [μg/cm^2]		PROSAILH
DMC	Fixed to 0.023 [g/cm^2]		PROSAILH
N	1.25-2.5		PROSAILH
ts	17-52°		PROSAILH
tv	10-59°		PROSAILH
ps	67- 169 °		PROSAILH

E. Forest Microwave Interaction Model

In order to interpret the observed trends in FI, the discrete forest model described in [23] and modified in [39] has been used to simulate the variations of FI as a function of CWC in Dry Chaco Forest area. The model developed at the University of Rome "Tor Vergata" uses the radiative transfer formulation to describe the interaction between the incoming electromagnetic wave and the vegetation [23]. It can compute the emissivity [23] by using the energy conservation law. To represent the vegetation geometry, a discrete approach is adopted, and dielectric bodies with suitable shapes are used to describe the geometric properties. The model includes the multiple interactions among the different dielectric bodies which compose the vegetation and the soil. The model was previously tested using both

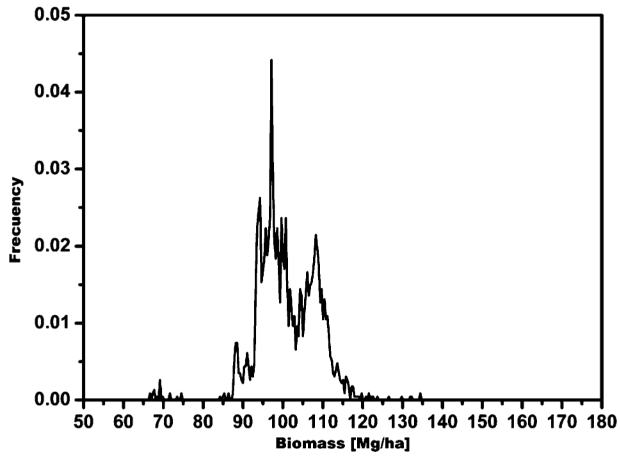

Fig. 2. Ground biomass histogram extracted from [44].

ground based and airborne radiometers, over agricultural fields and forest [40]–[43].

For the simulation we have used all the available information about forest structure in the study area: biomass, dry matter density, gravimetric moisture content of woody matter and diameter at 1.3-m height (DBH) distribution [25], [44] (see Table II). It is important to note that most of the trees in the area belong to species characterized by high-density wood, such as *Aspidosperma quebracho-blanco*, *Schinopsis lorentzii*, and *Bulnesia sarmientoi*. For *Aspidosperma quebracho-blanco*, the following densities (weights over fresh volume) are given: fresh matter of 1100 kg/m^3 and dry matter of 875 kg/m^3. The mean size of the leaves is 5 cm length and 2 cm wide, with a mean leaf thickness of 0.02 cm. We have used these values for the whole forest, since other dominant species show very similar values. Using given data, the other canopy variables required by the model as input have been derived according to the procedure specified in [39].

F. Available Ground Measurements

A summary of the average available data of the selected forest area used for both models is presented in Table II. This includes the distribution of DBH which will be used in the simulations of Section II-B. Additional ancillary information was extracted from an above ground biomass (AGB) map, derived from MODIS [44]. This AGB was estimated using the Random Forest algorithm and the vegetation indices of MODIS. The resulting product was validated using independent biomass measurements. In this validation, a mean relative error of 3% and a maximum relative error of 15% were found [44]. Fig. 2 gives the characteristic biomass distribution extracted from the AGB map. In order to use updated land cover categories, a land cover maps of the area provided by the Argentinean National Forest Monitoring System (UMSEF) [25] and from [31] were utilized.

G. Vegetation Water Content Estimation

The vegetation moisture estimation methodology developed in this work is a two step procedure, based on several assumptions (Fig. 3). In general, the vegetation indices values depend on several canopy variables (LAI, LWC, CWC, chlorophyll content, leaf internal structure, and others [24]), which are known to change throughout the year. Nevertheless, at first order we will assume that the annual cycle of all the studied vegetation indices (NDWI, NDII, and FI) depends on LAI, LWC, and CWC. However, the observed rapid variations of vegetation indices are mainly related to vegetation moisture changes, not LAI changes [45], [46] Therefore, it is mandatory to know LAI to robustly estimate LWC from observations. This can be accomplished using the MODIS LAI product [47] or by using NDVI, which is mainly sensitive to LAI (at least for low values of LAI [48]) and presents a moderate dependence on LWC. Once LAI is obtained, we can use the estimated LAI to retrieve LWC from optical (NDWI and NDII) and microwave (FI) indices. For both steps, interaction models were used.

In order to retrieve a value of a biophysical variable for every acquisition, a minimization procedure was implemented. The iterative technique consists of building the cost function with the observed and modeled values of the index as

$$\Delta = [index_o - index_m(L)]^2 \tag{5}$$

where $index_o$ and $index_m$ are the observed and modeled value of the index respectively, and L is the retrieved biophysical variable (LAI, LWC for theoretical indices and CWC for the microwave indices). Minimizations are performed for every 8-day period independently (temporal unconstrained minimization). However, if some temporal correlation of the estimated variable is expected, it is possible to increase the robustness of the analysis by including temporal constraints to the solution. For example, abrupt changes (spikes) in NDVI can correspond to abrupt changes in LAI and/or cloud contamination and composite algorithm noise [28], [31]. Nevertheless, spikes in the LAI trend are not biophysically sound for the vegetation in our study area [31]. In this cases, it is possible to constraint the solutions by forcing the Fourier spectrum of the solution to only a given set of harmonics (Harmonic Analysis of Time-Series (HANTs) method [49]). In this way, it is possible to filter the solutions which present a given range in frequency harmonics in an estimated variable (Fig. 3). The accuracy of the observed and simulated index values was determined from the determination coefficient (r^2) and the root mean square error (RMSE).

H. Estimation of LAI

The first step is to estimate LAI using MODIS LAI product or MODIS NDVI time series and PROSAILH model with the input parameters of Table II, assuming a constant value of EWT for the whole year. Since NDVI is almost insensitive to EWT, this assumption is reasonable for estimating LAI. For this case, (5) is written as

$$\Delta = [NDVI_o - NDVI_m(LAI)]^2 \tag{6}$$

where the estimated value of LAI corresponds to the minimum value of Δ.

I. Estimation of LWC and CWC

After LAI is estimated, LWC is calculated as a function of NDWI and NDII and CWC as a function of FI with a similar procedure as in Section II-G, but using the estimated LAI time series as input. For example,

$$\Delta = [FI_o - FI_m(CWC)]^2 . \tag{7}$$

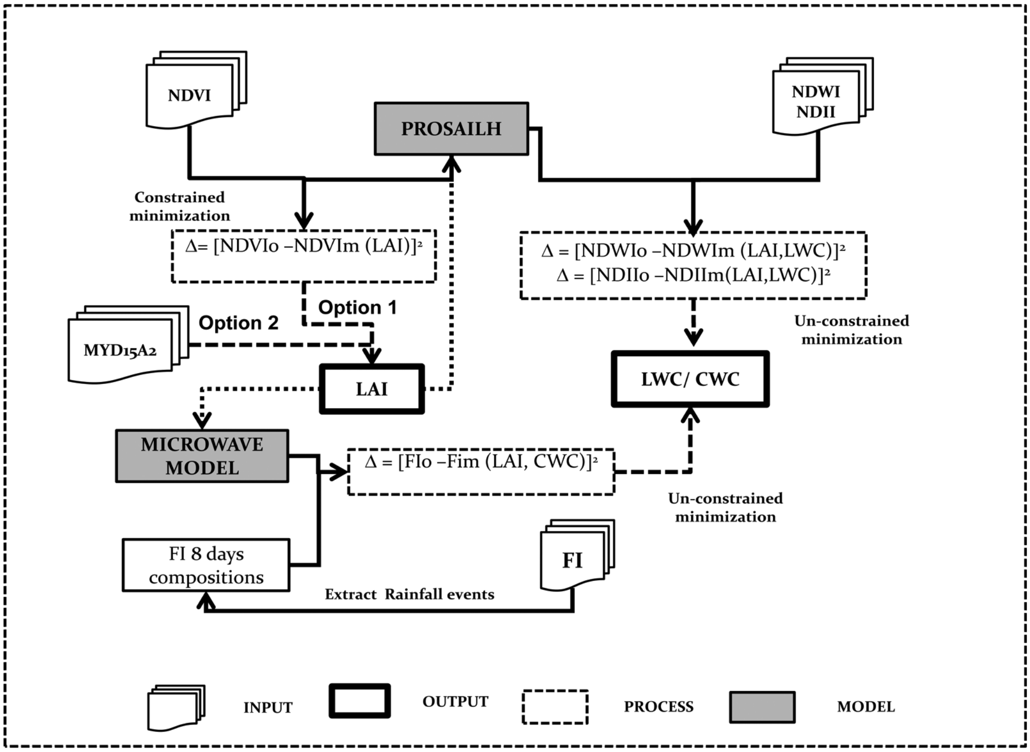

Fig. 3. Methodological flowchart. MODIS land surface reflectance product (MYD09A1) was used to calculate NDVI, NDWI, and NDII, and AMSR-E Level-2A brightness temperatures product (AE_L2A) was used to calculated the FI index. The radiative transfer models used were the Microwave model from [23], and the PROSAILH model from [24]. LAI could be estimated using two options: MODIS LAI product (MYD15A2) or NDVI and PROSAILH model. References: *LAI* is leaf area index, *LWC* is leaf water content, *CWC* is canopy water content, o is observed and m is modeled, and Δ is the cost function.

In this way, the LAI-dependent seasonality is removed in the indices, and the remaining signal is interpreted as changes in LWC or CWC.

III. Results

A. Vegetation Indices Time Series Analysis

Fig. 4 reports the trends of NDVI, NDII, NDWI, and FI as a function of time for the 2007–2008 growing season, expressed as days from July 1, 2007. The starting period for each year is taking at the start of winter, so it includes the complete vegetation cycle. NDVI, NDII, NDWI, and FI time series present an evident annual pattern, related to the phenological cycle.

NDVI trend correlates with annual phenology events such as onset greenness, peak greenness and senescence period. Using the TIMESAT approach [50] with a Savitzky-Golay filtering, we estimated the spring onset and end of growing season days for the vegetation in our study area, which are ~80 and ~300 days from July 1st for the period 2007–2008 (starting in the austral winter). This is in agreement with bibliography in which the mean growing season period has been estimated between March and October [51]. NDWI and NDII time series also present an annual cycle, with higher values in summer and lower values in winter. The main annual behavior of FI shows a decrease in summer and an increase in winter. This is related to the fact that, at microwave frequencies, leaf growth tends to increase the emissivity at the lower frequencies (X band), but an opposite effect can be obtained at Ka band, due to leaf scattering occurring when the leaf becomes large versus wavelength [23].

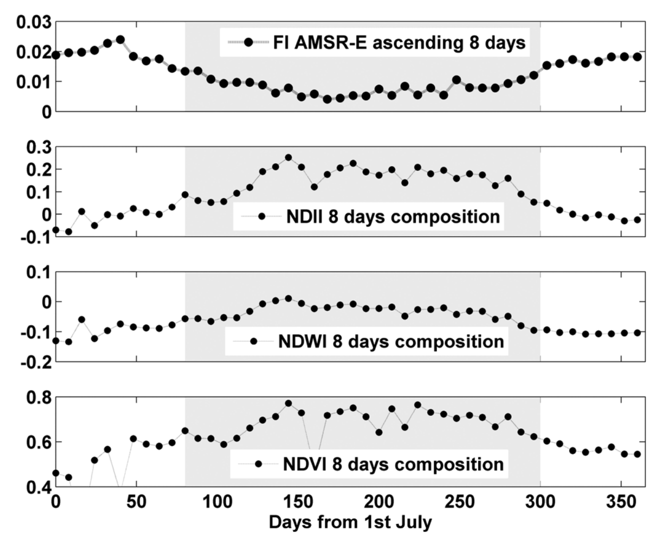

Fig. 4. Representative examples of FI, NDII, NDWI, and NDVI time series data for 2007–2008. Dark box corresponds to the growing season period.

The correlation between water indices (NDWI and NDII) during growing season is 0.87 $(\mathrm{p} < 0.01)$. The correspondence between FI and water indices during this season is consistent, with statistically significant correlation coefficients $(\mathrm{p} < 0.01)$ of -0.72 and -076 respectively. As expected, these indices were inversely related, since a peak of leaf development corresponds to a minimum in FI. There is a low significant correlation $(\mathrm{r} = -0.45)$ between NDVI and FI during the growing season $(\mathrm{p} < 0.05)$. For the same period the correlation values between

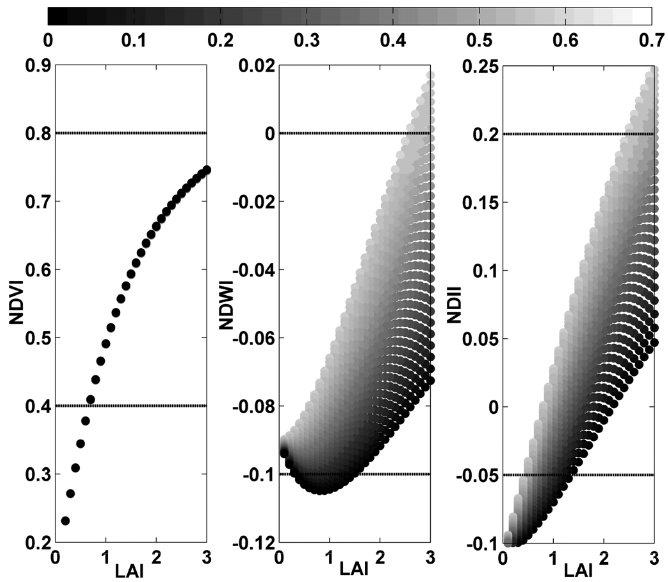

Fig. 5. NDVI, NDWI, and NDIII as a function of LAI, simulated for different LWC values at fixed sun angle (ts), view angle (tv), and relative azimuth angle (ps). Dashed lines represent the range of observed values. Color bar represents a gradient of LWC values.

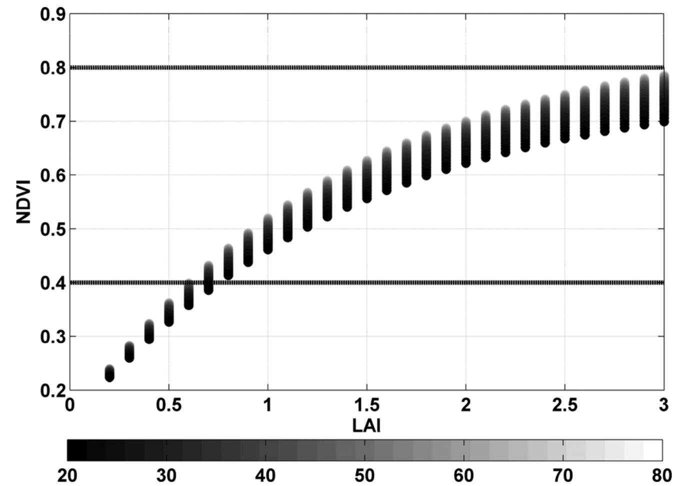

Fig. 6. NDVI as a function of LAI, simulated for different Ca+b values at fixed sun angle (ts), view angle (tv), and relative azimuth angle (ps). Dashed lines represent the range of observed values. Color bar represents a gradient of Ca+b values.

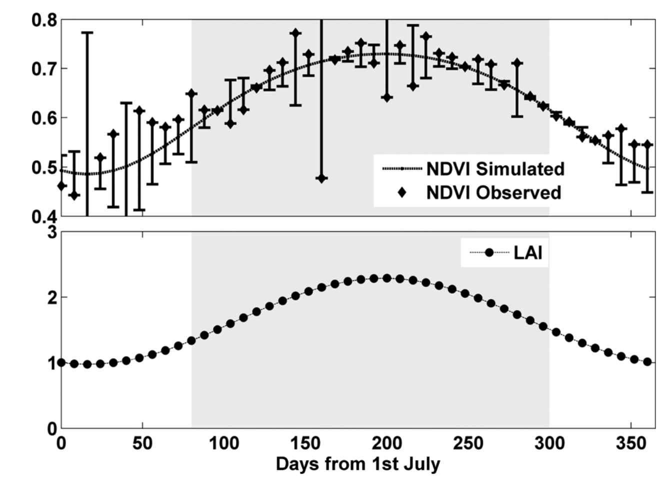

Fig. 7. LAI estimated from NDVI using PROSAILH model [24]. Dark box corresponds to the growing season period.

NDVI and NDWI and is 0.87 and between NDVI and NDII is 0.79 (both $p < 0.01$).

B. Estimation of LAI and LWC

The effects of leaf variables on canopy VNIR and SWIR reflectances were studied in order to test our work hypothesis, using high, medium, and low values of LAI and LWC. Simulation results show the theoretical sensitivity of NDVI, NDWI, and NDII to LAI and LWC for Chaco forest as predicted by PROSAILH (Fig. 5). As expected, NDVI presents high sensitivity to LAI and negligible sensitivity to LWC (although NDVI also presents some sensitivity to changing chlorophyll concentrations (Ca+b) (Fig. 6). Moreover, NDWI and NDII show sensitivity to LAI, but also present a significant sensitivity to LWC (Fig. 5). This means that, according to simulations, NDWI and NDII should be partially correlated to LWC. A number of researchers reported similar results, highlighting how NDWI and NDII are related to LWC [21], [45], [52]. It is important to note that in principle, there is no general direct physiological correlation between LWC and chlorophyll content for the forest in the study area [11], [14].

Estimation of LAI: Since our main objective is to estimate LWC and CWC, to de-trend optical and microwave indices time series we could use MODIS LAI product [47] or NDVI-derived LAI (using PROSAILH). We evaluated both LAI estimations for two reasons: 1) MODIS reflectance product and MODIS LAI product differed in the spatial resolution (500 m and 1 km, respectively); and 2) independent evaluations of the previous Collection 4 MODIS LAI data product arrived at absolute values of LAI error greater than 1.0 [53]–[55]. In this context, we first used a constrained minimization approach to retrieve LAI as a function of NDVI observations and PROSAILH simulations, assuming a constant mean value of LWC = 0.43 g/g corresponding to the mean LWC of the dominant tree species present in the study area (Fig. 7). We implemented the constraint minimization since optical products are strongly affected by atmospheric effects in our study area. Therefore, NDVI presents abrupt changes which cannot be related to rapid changes in LAI or chlorophyll content. As observed in Fig. 7, the estimated LAI presents a maximum in austral summer and a minimum in austral winter.

In order to check for product robustness, in Fig. 8 a comparison between LAI estimations and MYD15A2 product (MODIS global Leaf Area Index and Fraction of Photosynthetically Active Radiation (FPAR) product) is presented [47]. As expected, MODIS LAI product and estimated LAI present a very good correlation but a small offset ($r^2 = 0.99$, RMSE = 0.11). This offset could be a consequence of the differences between product scales of the NDVI and the MODIS LAI product (500 m vs. 1 km). The accuracy between both LAI estimations are good, therefore we concluded that both options are good to be used as input for leaf and canopy water content estimations. In

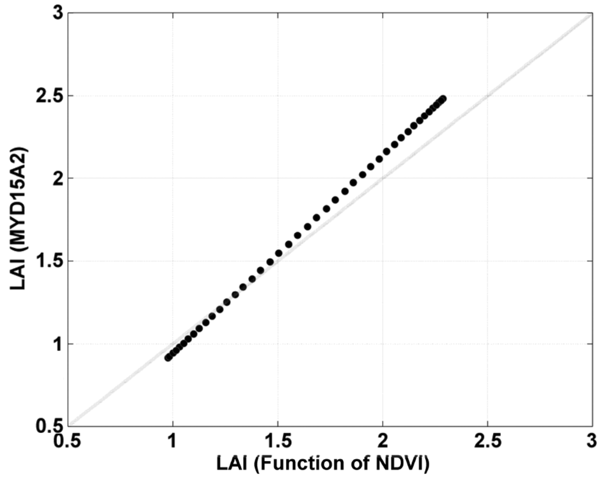

Fig. 8. Scatter-plot between MODIS LAI product (MYD15A2) and LAI estimations from NDVI.

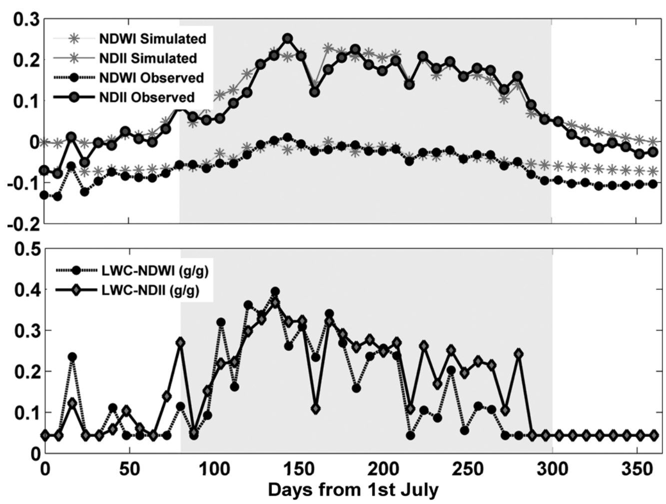

Fig. 9. LWC estimated from NDII and NDWI using PROSAILH model [24] for the 2007–2008 period. Dark box corresponds to the growing season period.

the following sections we used our NDVI-based LAI estimations.

Estimation of LWC Using NDWI/NDII: Using the previously estimated LAI time series and the parameters of Table II, we estimated LWC using the observed values of NDWI, NDII, and PROSAILH simulations. As described before, estimation consisted in determining by exhaustive iteration the LWC value which minimizes the cost function within the range of operation (5). No temporal constraint was used, since abrupt changes in LWC may also be observed in the study area.

The mean value of the LWC estimated using NDWI and NDII for 2007–2008 is shown in Fig. 9. The estimated value of LWC presents a mean value of 0.22 g/g for the growing season, which is low even for dry forests. Moreover, LWC presents abrupt changes, which after investigation were found to be related to minor cloud contamination. In general, LWC values estimated from NDII are higher than the ones estimated from NDWI. Overall, these results indicate that, at least in the growing season, the observed values of vegetation water indices cannot be solely explained by changes in LAI or chlorophyll content.

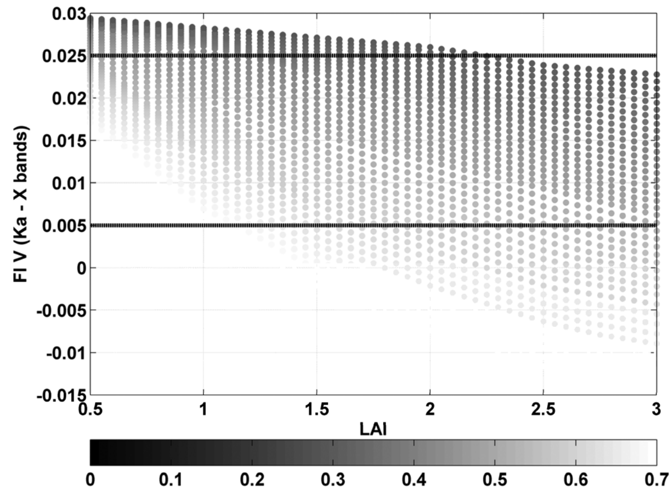

Fig. 10. Relation between FI derived from model [23] (line) and AMSR-E observations at different LAI and CWC. Dashed lines represent the range of observed values. Color bar represents a gradient of CWC values.

It is important to note that these results are valid only during the growing season. In this time of the year, NDII ($r^2 = 0.90$, RMSE = 0.025), and NDWI estimations ($r^2 = 0.82$, RMSE = 0.014) presented better accuracy with observed values than in other seasons (NDII $r^2 = 0.7$, RMSE = 0.032; NDWI $r^2 = 0.53$, RMSE = 0.037). These low values in the other seasons are probably related to complex canopy structure. PROSAILH model is best adapted for use in homogeneous vegetation canopies [56], [57]. Unfortunately, the turbid medium assumption used in this model does not account for heterogeneities in the canopies (e.g., multiple leaf layers having different optical characteristics), like the ones found in Chaco forest outside the growing season. In addition to this, the parameters used for the simulations were measured during summer time (higher LAI values).

Estimation of CWC Using FI: To understand the relation between FI and canopy variables, we used the model described in Section II-E. Fig. 10 shows the simulated trends of FI at a fixed soil moisture value (soil moisture = 0.2 g/g), computed using 37 GHz and 10.6 GHz AMSR-E channels, as a function of CWC and LAI. As expected, FI decreases with LAI, due to the increase in canopy X band emissivity with increasing leaf biomass [23], [29]. Moreover, FI decreases with increasing canopy moisture [23].

Using the estimated LAI time series and the parameters of Table II, we estimated CWC using the observed values of FI and the microwave model simulations in an unconstrained minimization scheme (Fig. 11). As observed, the measured and simulated FI values are in the same range ($\sim$0.005–0.025) ($r^2 = 0.99$, RMSE=2.094 e^{-006}). Similarly to NDWI/NDII, the variations observed in FI could not be explained considering only LAI changes. Estimated CWC presents a non-constant trend with a mean value of $\sim$0.56 g/g. For the growing season, the observed variations in CWC are of the order of 0.05 g/g.

IV. Discussion and Conclusion

In this paper, several estimations of vegetation moisture (LWC and CWC) from remote sensing data were presented. Methodologically, all the estimations were based on interaction models and minimization techniques, where the value of the

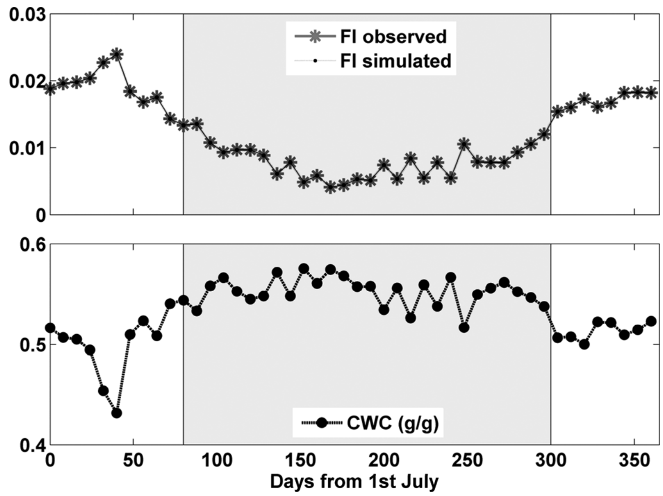

Fig. 11. CWC estimated from FI using the model of [23] for the 2007–2008 period. Dark box corresponds to the growing season period.

biophysical variables which minimizes the difference between data and model simulations was chosen as the best estimate. Both radiative transfer models (PROSAILH [24] and Tor Vergata [23]) were run with all the available ground information of the study area. Three optical (NDVI, NDWI, and NDII) indices and one microwave (FI at Ka and X band) index were tested in order to evaluate their potential to estimate leaf moisture in Dry Chaco Forest.

A direct comparison of land retrievals with *in situ* data would be required for a complete validation. In the case of the current application (estimation of changes in vegetation moisture at regional scale), it is desirable to use spatially representative regional estimations based on *in situ* sensor networks or intensive field campaigns over large areas. However, collecting large-scale ground truth data is quite challenging and costly in areas like Chaco forest. This is mostly due to the large footprints involved ($\sim$50 km $\times$50 km) and logistic matters. Therefore, it is also important to validate large-scale vegetation moisture retrievals through cross-sensor comparisons, model comparisons and ancillary data. In this framework, a methodology was proposed and the consistency that it provides between satellite data and interaction models was studied.

After evaluating indices' seasonal trends using simulations, it was shown that NDWI, NDII and FI seasonal cycles cannot be solely explained by LAI variations at least during the growing season. Moreover, indices sensitivity to LWC and CWC were confirmed by both radiative transfer models. Short 8-day variations of optical indices could not be univocally related to leaf moisture variation, due to the presence of cloud contamination. Nevertheless, the small 8-day variations in FI cannot be explained unless an 8-day change in vegetation moisture is assumed. This cannot be related to atmospheric effects or sensor artifacts, since AMSR-E is an instrument of a very low noise ($\sim$1 K), and the study area presents low standard deviation of brightness temperature (standard deviation (SD) < 0.4 K). This result is particularly relevant, since short-term variations in CWC could be caused by synoptic scale weather variations and can be used to monitor quick changes of environmental factors, including water vapor deficit [5], [58]. According to our results for the growing season analyzed, there are several events where the estimated CWC mean value is reduced about 0.05 g H2O/g. This reduction, although small, could have implications in the surface water flux in Chaco, where most of the above ground water is in the vegetation due to the large evapotranspirations rates. Moreover, it is important to remark that these small changes cannot be explained by sensor errors, atmospheric noise or target heterogeneities. In this context, as was discussed and validated in Harvard forest by [5], [46], and [58], microwave indices may be used to estimate evapotranspiration using the principle of surface energy balance.

Despite not being able to make a direct comparison with field data, it is relevant to mention that the average values of LWC for the main species of the study area, *Aspidosperma quebracho-blanco* (mean LWC 0.43 g/g [53]), *Prosopis Flexuosa* (mean LWC 0.60 g/g [59]), *Zizyphus mistol* (mean LWC 0.54 g/g [59]) are all higher than LWC estimated from optical data. These low estimations of LWC ($\sim$0.20 g/g, calculated without including cloud contaminated data) and its low dynamic range (0.17–0.39 g/g), seem to be related to problems in the PROSPECT model for the Chaco area. This result suggests that the PROSPECT model is not well suited for heterogeneous canopies, as shown in several previous studies [59]. The inversion of PROSAILH under such conditions leads to a bias in the retrieval of biophysical parameters [56], [60].

It is relevant to compare LWC and CWC estimations. In general, it is assumed that tree wood volume and leaf area have strong allometric relationships with tree diameter [61] so a relationship between leaf and overall canopy moisture was expected. Nevertheless, no significant relation was found. This was observed before [22], where it is shown how LWC is a small fraction of the total CWC, so in some cases there are no ability to predict CWC from optical indices (mainly related to LWC). One possible explanation is based on tree physiology. In some forests, xylem growth in several past years may supply water to the foliage [22], effectively decoupling LWC and CWC. On the contrary, for annual crops increases in xylem and leaf area are highly related [21].

It is also interesting to compare inherent virtues and weaknesses of optical and microwave approaches to vegetation moisture estimation. First, SWIR and NIR wavelengths are sensitive to the first layer of the canopy. Furthermore, NDWI/NDII can only be retrieved under clear cloud conditions. On the other hand, FI can be obtained in all-sky conditions, with the exception of rain events. In addition to this, microwave radiation has much more penetration in vegetated areas than optical wavelengths. The microwave emission of a canopy is an integration of microwave radiation from the whole canopy's vertical profile weighted by its transmission [4], [58]. Although microwave measurements have lower spatial resolution than SWIR and VNIR observations, its temporal resolution is much better (3 days maximum). Moreover, as shown in [5], hourly observations from several satellites provide the opportunity to monitor repetitive diurnal variations of passive microwave observations, which can account for diurnal changes in vegetation moisture. Diurnal variation of vegetation moisture cannot be detectable from MODIS, since Terra and Aqua MODIS daytime overpasses are 11.30 and 14.30 local time, respectively, and are relative close to the solar noon.

Further work is needed in order to validate the exact relation between canopy moisture and microwave indices, and the capability to use FI as a short-term proxy of evapotranspiration. As future work, we are planning to validate these hypotheses in other dry forest areas, which present a long history of ground truth (Australia).

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Mercedes Salvia, biography not available at the time of publication.

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