Estimation of the FAO-56 crop coefficient of winter wheat from radar Sentine-1 data

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Abstract

Estimating crop evapotranspiration (ETc) is of primary importance for irrigation management. The model commonly used for this purpose is the FAO-56 approach which consists of accurately estimating the basal crop coefficient K_{cb}. Historically, K_{cb} is derived from optical indices, primarily NDVI. Since optical data are disturbed by the presence of clouds, the use of radar data seems more advantageous. In this context, this study is devoted to derive K_{cb} from Sentinl-1 C-band data for the first time in the literature. The data are collected from a winter wheat field in Morocco monitored during two agricultural seasons 2016-2017 and 2017-2018. The field is equipped with an eddy covariance station allowing the estimation of ETc every 30 minutes. Sentinel-1 data are processed to compute the backscattering coefficient and the interferometric coherence (ρ). The results show the existence of exponential relationships between K_{cb} and the polarization ratio (PR) and ρ, in particular R = 0.76 and RMSE = 0.18 between K_{cb} and ρ have been found. These statics are close to those obtained between K_{cb} and NDVI. Application of these relationships provides a good estimate of ETc with R = 0.7 and RMSE = 0.75 mm/day.

1. Introduction

Estimating evapotranspiration (ET) is fundamental for monitoring vegetation water requirements, an important component of agricultural water use management. It is often estimated using two methods: (i) in situ measurements that are local and expansive; or (ii) using land surface models [1]. The most common model in the literature is the FAO-56 [2]. It requires the computation of the reference evapotranspiration (ET0), which represents the atmospheric evaporative demand, and a crop coefficient K_c that describes the actual condition of the crop under consideration. Because K_c is related to vegetation development, it is variable throughout the agricultural season [3]. Historically, K_c is a trapezoidal shape constructed by three values corresponding to the main growth stages [2]. These values are estimated using in situ measurements by eddy covariance stations and lysimeters or sap flow systems [4], [5]. However, these methods require costly and time-consuming facilities.

Remote sensing data are a relevant tool that provides frequent large-scale data. They allow a global, practical and operational application to derive K_c and consequently ET. Indeed, several studies have derived K_c from optical data taking advantage of the strong correlations of reflectance in the visible to mid-infrared range with the development of the targeted vegetation via its biophysical variables such as cover fraction and leaf area index [3], [5]. Among several indices, the most widely used relationship is that between K_c and NDVI [5], [6], [7]. Nevertheless, the use of optical data is hampered by atmospheric conditions, such as in cloudy regions or during winter. In this context, the objective of this work is to investigate the potential of Sentinel-1 C-band data to derive K_c in a continuous manner. In particular, strong relationships have been found between the polarization ratio (PR) and the interferometric coherence (ρ), on one hand, and several vegetation variables such as biomass and leaf area index on the other hand [8], [9].

The objective of this work is to investigate the relationships between K_c and PR and ρ derived from Sentinel-1 with a revisit cycle of 6 days. The study is conducted on two years of winter wheat in Morocco to (i) investigate the relationship between K_c, PR, and ρ; (ii) estimate K_c from the two radar variables; and (iii) calculate ETc from the estimated K_c and compare it to the eddy covariance measurements.

2. MATERIAL AND METHOD

The present work is conducted near Marrakech city in Morocco. Figure 1 present the location of the study area. The area belongs to the Haouz plain characterized by a semi-arid climate with high annual reference evapotranspiration (1600 mm) against a limited annual precipitation of about 250 mm.

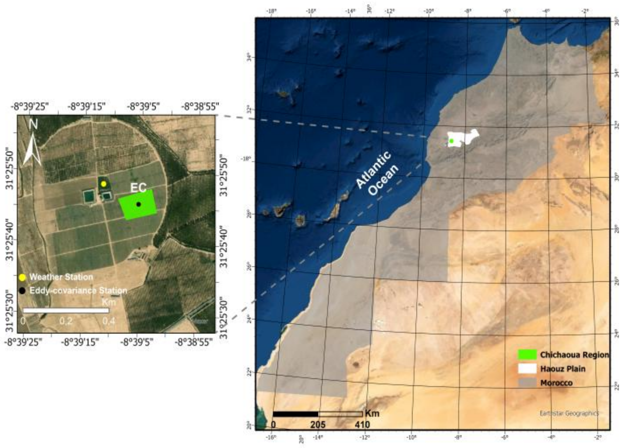

Figure 1. Eddy covariance station location within the wheat field in the Haouz plain in Morocco.

Within the area, an eddy covariance station (EC) is installed over a wheat field irrigated using the drip technique. Sowing took place in November and harvesting in June. The field is monitored during 2016-2017 and 2017-2018 growing season. The row data are processed to obtain the ETc with time step of 30 min. The meteorological variables are also measured every 30 min by a weather station installed near the wheat field as illustrated in Figure 1. The ET0 is computed from the meteorological data using the Penman-Monteith equation [2] and then the K_c is computed as the ratio of ETc to ET0. Data corresponding to water stress or high soil evaporation are eliminated so that K_c=K_{cb}, where K_{cb} is the basal crop coefficient.

The Sentinel-1 products, namely the GRDH and SLC products are processed to compute the backscattering coefficient (σ^0) and the interferometric coherence (ρ) at VV and VH polarizations. Details on the processing can be found in [8]. The polarization ratio (PR) is then computed as the ratio of σ^0 at VH to σ^0 at VV. The NDVI is also computed using Sentinel-2 data.

3. RESULTS ANALYSIS AND DISCUSSION

3.1. Relationships between K_{cb} and satellite data

Figure 2 displays the relationships between K_{cb} in one hand and PR, ρ at VV (ρ_{VV}) and NDVI in the other hand. The data are fitted with an exponential model drawn in black in the figure. The corresponding R and RMSE values are also displayed in each subplot.

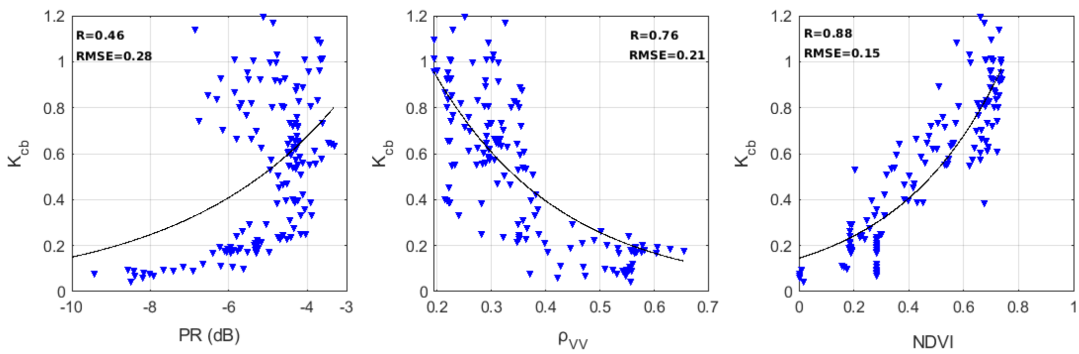

Figure 2. Relationships between K_{cb} and satellite variables including PR, ρ_{VV} and NDVI.

NDVI and PR exhibit a similar increasing trend as K_{cb} over the growing season, while ρ_{VV} decreases, which is demonstrated by the fitting models in Figure 2. The results show that the best fitting is obtained between K_{cb} and NDVI (hereafter named K_{cb}-NDVI) and between K_{cb} and ρ_{VV} (K_{cb}-ρVV). In contrast, the relationships are more scattered between K_{cb} and PR (K_{cb}-PR), potentially due to the rapid saturation of the relationship. Obviously, K_{cb} is better fitted to NDVI with an RMSE limited to 0.15 but the results using ρ_{VV} to estimate K_{cb} are also promising.

3.2. Estimated K_{cb} and ET_c

The relationships between K_{cb} and the satellite variables are calibrated over one agricultural season and then used to estimate K_{cb}, Figure 3 shows the obtained results.

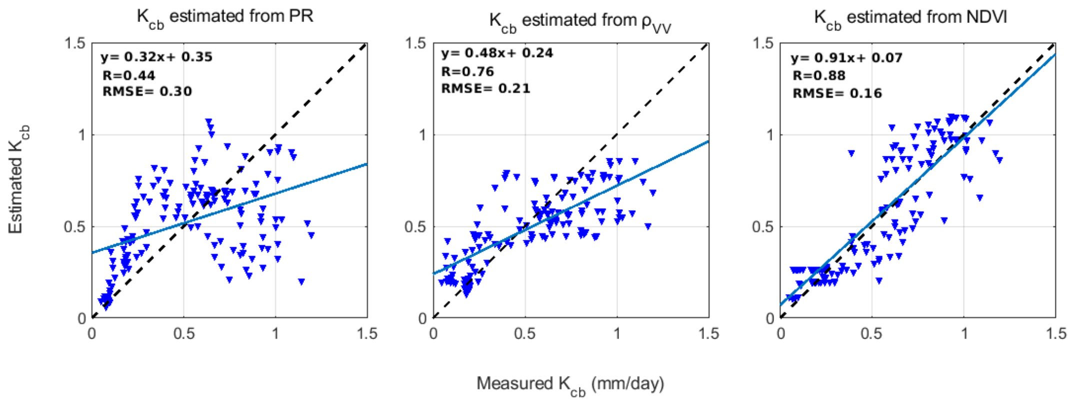

Figure 3. Estimated K_{cb} using the satellite variables including PR, ρ_{VV} and NDVI.

As expected, the best results are obtained with K_{cb}-NDVI and K_{cb}-ρ_{VV}. The inverted K_{cb} from radar data is limited to almost 1 because of the quick saturation of the C-band data. On the other hand, the K_{cb} -NDVI can reach up to 1.2 and thus reproduce well the K_{cb}. This advantage is reflected on the good statics on this field with R = 0.88 and RMSE = 0.16. However, ρ_{VV} also demonstrates a good estimates with R=0.76 and RMSE=0.21. The PR is the least accurate in the estimation of K_{cb} and this is related to the rapid saturation of the relationship as stated in section 3.1.

The estimated K_{cb} from the three variables is used to compute the ETc over the two seasons. The results are presented in Figure 4. The outcomes with K_{cb}-NDVI and K_{cb}-ρ_{VV} are encouraging because of the good estimates of K_{cb} (Figure 3). Consequently, similar comments can be drawn. The K_{cb}-NDVI is the best method to estimate ETc with R = 0.80 and RMSE = 0.65 mm/day. Using ρ_{VV}, good statistics are also obtained with R=0.70 and RMSE=0.75 mm/day.

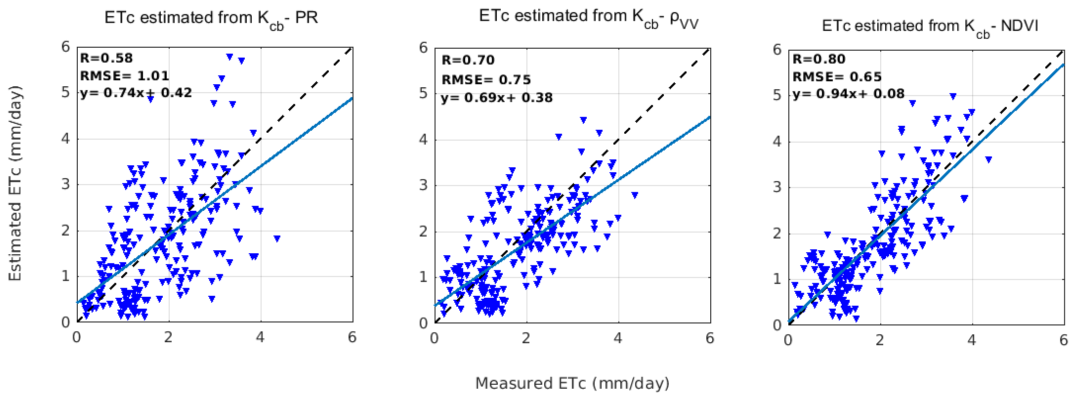

Figure 4. Retrieved ETc using the established relationships between K_{cb} and satellite variables

It is important to note here that the objective of this study is not to show that ρ can outperform NDVI. The objective is to see the potential use of some radar variables, which are directly related to vegetation development, for estimating ETc as a substitute for optical variables and especially when the latter are inoperable. It is possible that NDVI is the best for the estimation of K_{cb} but radar data such as ρ show competitive performance with the advantage of being independent of clouds and time of day and can therefore be used in all regions, including cloudy regions or simply winter months where optical data are not available. However, the database for this study is limited and the study should be extended to other study sites for further investigation.

4. CONCLUSION

The outcomes of this study showed that the variables derived from SAR data can also be successfully used to estimate K_{cb} and ETc, in particular, ETc is estimated using K_{cb}-ρ_{VV} with an RMSE = 0.75 mm/day similar to the RMSE obtained using K_{cb}-NDVI (0.65 mm/day). This study presents the first attempt to estimate K_{cb} and ETc from SAR data, although it has shown encouraging results but further validation is needed as the results presented are for only one field. Extending the approach to a larger database will allow further in-depth investigation of the behavior of the K_{cb}-radar and K_{cb}-optical relationships and their robustness in the estimation of ETc. This will open new perspectives for robust and operational applications at large spatial scales, especially in regions where optical data are inoperable or in winter, when optical images are not available due to clouds.

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6. REFERENCES

[1] A. Subedi, and J.L. Chávez, "Crop Evapotranspiration (ET) Estimation Models: A Review and Discussion of the Applicability and Limitations of ET Methods," . J. Agric. Sci., vol. 7, pp. 50–68, 2015, https://doi.org/10.5539/jas.v7n6p50.

[2] R. G. Allen, L. S. Pereira, D. Raes, and M. Smith, *Crop Evapotranspiration—Guidelines for Computing Crop Water Requirements*. ROME, Italy: FAO, 1998. [Online]. Available: http://academic.uprm.edu/abe/backup2/tomas/fao 56.pdf.

[3] L. S. Pereira, P. Paredes, D. J. Hunsaker, R. López-Urrea, and Z. Mohammadi Shad, "Standard single and basal crop coefficients for field crops. Updates and advances to the FAO56 crop water requirements method," *Agric. Water Manag.*, vol. 243, no. August 2020, p. 106466, 2021, doi: 10.1016/j.agwat.2020.106466.

[4] S. S. Anapalli, D. K. Fisher, S. R. Pinnamaneni, and K. N. Reddy, "Quantifying evapotranspiration and crop coefficients for cotton (Gossypium hirsutum L.) using an eddy covariance approach," *Agric. Water Manag.*, vol. 233, p. 106091, 2020, doi: 10.1016/j.agwat.2020.106091.

[5] S. Er-Raki, J. C. Rodriguez, J. Garatuza-Payan, C. J. Watts, and A. Chehbouni, "Determination of crop evapotranspiration of table grapes in a semi-arid region of Northwest Mexico using multi-spectral vegetation index," *Agric. Water Manag.*, vol. 122, pp. 12–19, 2013, doi: 10.1016/j.agwat.2013.02.007.

[6] I. Pôças, A. Calera, I. Campos, and M. Cunha, "Remote sensing for estimating and mapping single and basal crop coefficientes: A review on spectral vegetation indices approaches," *Agric. Water Manag.*, vol. 233, no. February, p. 106081, 2020, doi: 10.1016/j.agwat.2020.106081.

[7] B. Duchemin *et al.*, "Monitoring wheat phenology and irrigation in Central Morocco : On the use of relationships between evapotranspiration , crops coefficients , leaf area index and remotely-sensed vegetation indices," *Agric. Water Manag.*, vol. 79, no. 1, pp. 1–27, Jan. 2006, doi: 10.1016/j.agwat.2005.02.013.

[8] N. Ouaadi *et al.*, "C-band radar data and in situ measurements for the monitoring of wheat crops in a semi-arid area (center of Morocco)," *Earth Syst. Sci. Data*, vol. 13, pp. 3707–3731, 2021, doi: 10.5194/essd-13-3707-2021

[9] N. Ouaadi *et al.*, "Monitoring of wheat crops using the backscattering coe ffi cient and the interferometric coherence derived from Sentinel-1 in semi-arid areas," *Remote Sens. Environ.*, vol. 251, no. C, p. 112050, 2020, doi: 10.1016/j.rse.2020.112050.