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Hydrology and Earth System Sciences
Discussions

Interactive comment on "Mapping groundwater abstractions from irrigated agriculture: big data, inverse modeling and a satellite-model fusion approac" *by* Oliver Lopez et al.

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We appreciate the reviewer comments and have attempted to improve the description of some of the methodological choices in the paper. In the following responses, we identify parts of the text that we added to address these comments.

Comment 1: Firstly, more details about CABLE model simulation should be given. For example, is there a crop model in it? How was the simulation conducted for different crops (maize-C4 and wheat-C3, and others)? What if there are more than two crop types (if that is possible in this region) within a single field? How was the spin-up conducted? What's the model's performance in simulating ET when giving observed

LAI compared with flux-tower or other ground-based measurements?

Author's response: Our aim was to independently approximate groundwater abstraction for the year 2015 of one of the largest agricultural regions in Saudi Arabia. We selected this year for operational reasons. Unfortunately, sufficient ground-truth data does not exist - and in fact, the motivation for the approach comes from the fact that there is a lack of any independent assessments to compare against. This study initiates the first efforts to provide an approximation of water consumption over a large region with sufficient granularity to compare values between individual fields, which will be refined once relevant ground-based data (slowly) become available (i.e. through on-farm metering) (page 22, lines 6-26).

To do this, we employ the CABLE land surface model (given its application in other dryland environments and as the land surface scheme for regional and global climate models; Zhang et al., 2009; Haverd et al., 2013; Hirsch et al., 2019): but the approach is not limited to any particular scheme. To provide further details on this approach, we have added additional information at the end of section 3.4.2:

"This version of CABLE is also available for offline global simulations using look-up tables for soil classification derived from Zobler (1999), and vegetation types defined by the International Geosphere and Biosphere Program (Loveland et al., 2000). CABLE includes monthly LAI data derived from MODIS data averaged from 2002 to 2009 (Gao et al., 2008; Ganguly et al., 2008), as specified in the CABLE user guide (Srbinovsky et al., 2013). As a first attempt, the default soil texture was used, and assumed as uniform across the studied region. However, LAI data was derived as described in section 3.1, as the coarse-scale MODIS-derived dataset is not representative of the actual crop growing patterns. The possibility of different crops and crop rotation in the same field within the year was considered, as explained in Section 3.3, using the clustering technique based on LAI data. One limitation of the framework is the lack of a crop identification module, which would improve the definition of vegetation characteristics. In this study, vegetation parameters were assigned based on the default CABLE cropland vegetation class, as currently no crop identification strategy was implemented, other than the delineation and clustering technique."

We also added the following text referring to the spin-up of the model, which follows directly after the paragraph added above:

"Under basin-scale water budget studies, a spin-up of the model is generally required to achieve a realistic initial soil moisture state. This is normally done by running a representative year of meteorological data several times, or running several years prior to the start of the study period (Ajami et al., 2014; 2015), and assuming that the spin-up period is representative of the "normal" conditions. This assumption does not hold in our simulations because we are aiming to retrieve irrigated amounts, which could change from one year to the other, as different crops are grown. Therefore, this poses a challenge for how to represent the initial state of irrigated agricultural fields at the start of our simulations. In our study, the spin-up for each field was performed as follows: after estimation of the irrigation amount for one season, the model is run using this irrigation amount, and the final state is saved as the initial state for the next iterative process. However, the problem still lies with the spin-up of the first period. To solve this, we started by first running the groundwater abstraction strategy for a three-month period prior to the start of the study period, thus generating an initial state for the actual period of study."

Ajami, H., Evans, J. P., McCabe, M. F., Stisen, S. (2014). Technical Note: Reducing the spin-up time of integrated surface water–groundwater models. Hydrol. Earth Syst. Sci., 18(12), 5169-5179. doi:10.5194/hess-18-5169-2014

Ajami, H., McCabe, M. F., Evans, J. P. (2015). Impacts of model initialization on an integrated surface water–groundwater model. Hydrological Processes, 29(17), 3790-3801. doi:10.1002/hyp.10478

Ganguly, S., Samanta, A., Schull, M. A., Shabanov, N. V., Milesi, C., Nemani, R. R., . . . Myneni, R. B. (2008). Generating vegetation leaf area index Earth system data

record from multiple sensors. Part 2: Implementation, analysis and validation. Remote Sensing of Environment, 112(12), 4318-4332.

Gao, F., Morisette, J. T., Wolfe, R. E., Ederer, G., Pedelty, J., Masuoka, E., . . . Nightingale, J. (2008). An algorithm to produce temporally and spatially continuous MODIS-LAI time series. IEEE Geoscience and Remote Sensing Letters, 5(1), 60-64.

Haverd, V., Raupach, M., Briggs, P., Canadell, J., Isaac, P., Pickett-Heaps, C., . . . Wang, Z. (2013). Multiple observation types reduce uncertainty in Australia's terrestrial carbon and water cycles. Biogeosciences, 10(3), 2011.

Hirsch, A. L., Kala, J., Carouge, C. C., De Kauwe, M. G., Di Virgilio, G., Ukkola, A. M., . . . Abramowitz, G. (2019). Evaluation of the CABLEv2.3.4 Land Surface Model Coupled to NU-WRFv3.9.1.1 in Simulating Temperature and Precipitation Means and Extremes Over CORDEX AustralAsia Within a WRF Physics Ensemble. Journal of Advances in Modeling Earth Systems, 11(12), 4466-4488. doi:10.1029/2019ms001845

Loveland, T. R., Reed, B. C., Brown, J. F., Ohlen, D. O., Zhu, Z., Yang, L., Merchant, J. W. (2000). Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. International Journal of Remote Sensing, 21(6-7), 1303-1330.

Srbinovsky, J., Law, R., Pak, B. (2013). The Community Atmosphere Biosphere Land Exchange (CABLE) land surface model - User guide for CABLE-2.0. User guide.

Zobler, L. 1999. Global Soil Types, 1-Degree Grid (Zobler). Data set. Available on-line [http://www.daac.ornl.gov] from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, U.S.A. doi:10.3334/ORNLDAAC/418.

Zhang, L., Zhang, H., Li, Y. (2009). Surface energy, water and carbon cycle in China simulated by the Australian community land surface model (CABLE). Theoretical and Applied Climatology, 96(3), 375-394. doi:10.1007/s00704-008-0047-z

Comment 2: Secondly, the only validation reported in this manuscript is in Fig. 6

and 7 showing comparison between the annual/seasonal model estimation and farm reported groundwater abstraction. There is no validation on LAI and ET estimation from the satellite remote sensing. If there is uncertainties, how would they propagate to the final estimation of groundwater abstraction?

Author's response: We have previously addressed both the validation of LAI and ET data in the response to Reviewer 1, and thus here we include similar responses to these two issues: Houborg and McCabe (2018) described an approach for LAI estimation using a combination of physically-based estimates and in situ data. In their study, they showed reasonable LAI estimates for a small-scale (around 40 center-pivot fields) farm. In our study, as no comparable in situ data set exists for the Al Jawf region, we decided that a more physically-based approach was needed. That is why the PROSAIL implementation was explored. While not shown in the manuscript, we have implemented both approaches over the same region as in the Houborg and McCabe (2018) study and found that the second approach produced more reasonable LAI estimates. This provides confidence regarding the application of the second approach in this study. However, further work is needed to explore how the uncertainties in LAI (and other inputs) propagate to the final estimates of groundwater abstraction, a recommendation that we now added to the text (page 21, line 6) as follows: "The goal of this study was to provide a first approximation of regional groundwater abstraction independent from self-reported data, and for this, we have used a specific choice of models (i.e. TSEB and CABLE). Further investigation is required to determine the uncertainties of these models – as well as from other inputs such as LAI – and how they propagate through our groundwater abstraction framework. One approach that could help mitigate biases within specific models is to explore the use of multi-model estimates, which would also help provide ranges of groundwater abstraction."

Furthermore, the potential of TSEB for estimation of ET through remote sensing data has been well documented and validated over irrigated crops in semi-arid and arid regions (e.g. Colaizzi et al., 2012; Zhuang and Wu, 2015; Nieto et al., 2019). However,

validation of evaporative estimates using different remote sensing-based ET models (including TSEB) within the region examined in this study forms part of parallel efforts within our group (Aragon et al., 2019). We have now added a figure showing a comparison of estimated TSEB with in situ data for one of the irrigated fields in our study (Figure S2).

Aragon, B., Malbeteau, Y., Fisher, J. B., McCabe, M. F. (2019). Evaluating the use of thermal imagery in crop water use management. Paper presented at the Geophysical Research Abstracts.

Colaizzi, P. D., Kustas, W. P., Anderson, M. C., Agam, N., Tolk, J. A., Evett, S. R., . . . O'Shaughnessy, S. A. (2012). Two-source energy balance model estimates of evapotranspiration using component and composite surface temperatures. Advances in Water Resources, 50, 134-151. doi:https://doi.org/10.1016/j.advwatres.2012.06.004

Houborg, R., McCabe, M. F. (2018). A hybrid training approach for leaf area index estimation via Cubist and random forests machine-learning. ISPRS Journal of Photogrammetry and Remote Sensing, 135, 173-188. doi:https://doi.org/10.1016/j.isprsjprs.2017.10.004

Nieto, H., Kustas, W. P., Torres-Rúa, A., Alfieri, J. G., Gao, F., Anderson, M. C., . . . McKee, L. G. (2019). Evaluation of TSEB turbulent fluxes using different methods for the retrieval of soil and canopy component temperatures from UAV thermal and multispectral imagery. Irrigation Science, 37(3), 389-406. doi:10.1007/s00271-018-0585-9

Zhuang, Q., Wu, B. (2015). Estimating Evapotranspiration from an Improved Two-Source Energy Balance Model Using ASTER Satellite Imagery. Water, 7(12), 6673-6688.

Comment 3: Thirdly, was the inverse modeling conducted at daily time scale? If it is, are we expecting irrigation every day, which is absolutely not true in the reality? The authors reported the accumulated amount of irrigation water use at monthly and annual time scale. How about irrigation timing and times?

Author's response: Surprisingly, in Saudi Arabia, irrigation is indeed typically applied on a daily and continuous basis for prolonged periods during the crop growth cycle – hence the need to develop an approach that can address this major water use concern. The inverse modelling as applied in this work aimed at retrieving irrigation amounts at longer time scales. However, the frequency of satellite data used for 2015 is simply not sufficient to differentiate irrigation amounts between different crop developmental stages and seasons. Future development will aim at incorporating data form other platforms (Cubesats, Sentinel 2, etc) and determine whether sub-seasonal irrigation amounts can be obtained. However, we don't suspect that irrigation timing and times can be determined – although we are exploring other approaches that can attempt this, including CubeSats and Sentinel-1.

Comment 4: Fourthly, where did the authors assessed the model performance as described in section 3.5?

Author's response: This was done in Section 4.1 (Pivot-based framework performance at the Tawdeehiya Farm). As there is no ground-based data on irrigation applied at the Al Jawf region for the study period, we evaluated the model's performance using data from the smaller Tawdeehiya farm. As we described in the manuscript, this data presented some problems as well, but we obtained a Nash-Sutcliffe efficiency value of 0.38 and R squared value of 0.61 (Figure 6).

Comment 5: Finally, organization of this manuscript can be further improved. For example, Fig. 1 and Fig. 2 can be combined? Descriptions of TSEB and CABLE models can be simplified and details about them can be put into supplementary? Instead, the authors should focus more on simulation protocols there.

Author's response: We believe that the description of CABLE and TSEB were simplified in our manuscript relative to more detailed descriptions found in the literature

(Norman et al., 1995; Colaizzi et al., 2012; Wang et al., 2011; Kowalzcyk et al., 2013). However, based on comment 1, we added two paragraphs that add specific details of our strategy. We agree with the reviewer regarding the combination of figures 1 and 2, and we now have a combined figure (attached Figure 1).

Figure 1 caption: Figure 1: Location of the two study regions. Left: The Tawdeehiya farm in Al Kharj (southeast of Riyadh). A false color Landsat 8 image (2015/06/09) is shown to highlight active center-pivot fields over the desert environment. Right: The Al Jawf agricultural region in the north-west of Saudi Arabia spans two Landsat 8 tiles. Two false color images are shown: 2015/06/09 for path/row 172/39 (left) and 2015/06/19 for path/row 171/39 (right). Center-pivot fields are densely packed and largely uniform in size in the main area (30° N, 38.25° E), while in other areas they are sparser and less uniform (for example, the image on the right).

Colaizzi, P. D., Kustas, W. P., Anderson, M. C., Agam, N., Tolk, J. A., Evett, S. R., . . . O'Shaughnessy, S. A. (2012). Two-source energy balance model estimates of evapotranspiration using component and composite surface temperatures. Advances in Water Resources, 50, 134-151. doi:https://doi.org/10.1016/j.advwatres.2012.06.004

Kowalczyk, E., Stevens, L., Law, R. M., Dix, M., Wang, Y. P., Harman, I. N., Haynes, K., Srbinovsky, J., Pak, B., and Ziehn, T.: The land surface model component of ACCESS: description and impact on the simulated surface climatology, Aust. Meteorol. Ocean., 63, 65–82, 2013.

Norman, J. M., Kustas, W. P., Humes, K. S. (1995). Source approach for estimating soil and vegetation energy fluxes in observations of directional radiometric surface temperature. Agricultural and Forest Meteorology, 77(3), 263-293. doi:https://doi.org/10.1016/0168-1923(95)02265-Y

Wang, Y. P., Kowalczyk, E., Leuning, R., Abramowitz, G., Raupach, M. R., Pak, B., van Gorsel, E., and Luhar, A.: Diagnosing errors in a land surface model (CABLE) in the time and frequency domains, J. Geophys. Res., 116, G01034, doi:10.1029/2010JG001385, 2011.

Please also note the supplement to this comment:
https://www.hydrol-earth-syst-sci-discuss.net/hess-2020-50/hess-2020-50-AC2-supplement.pdf

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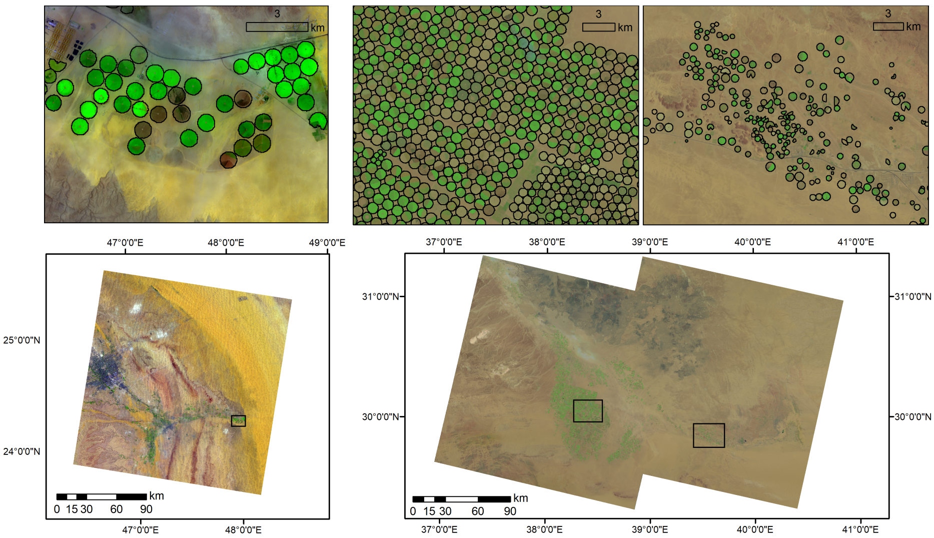

Fig. 1. Revised Figure 1