Response to Editor and Reviewers

[1] We thank the editor and two reviewers for their comments and suggestions. We have made several revisions accordingly, which we explain below. The line numbers refer to the annotated m/s version with changes marked.

Response to Editor

I have read the very detailed comments from both reviewers, as well as the detailed responses you have provided to each of these comments. It strikes me that the points raised primarily require clarification, as they stem from confusion on the part of the reviewer.

You have made several clear comments on how you propose to update the manuscript to help clarify the points raised. Mostly your suggestions are clear. However, in several cases you leave it as reply to the comment. I would encourage you to consider adding one or two words/phrases to help clarify the confusion. This is useful for those readers who may be equally confused but are not inclined to go through all the interactive comments and replies (which I would suspect to be the majority).

[2] Agreed. We have made textual changes to pre-empt similar questions or issues wherever we saw an opportunity, as explained in our responses below.

Response to Reviewer #1

I think the comment on WR3A models is different should be addressed in the manuscript, as you are not clear if you will do this. It is I think important to point out that the structure of the model is important in being able to apply the approach presented, which precludes other perhaps simpler water balance type models.

[3] Agreed, we have added such a sentence (see response [11]).

On the flow diagram. This may indeed be useful, but as it primarily has the purpose to clarify, you may consider including it in the supplementary material.

[4] We have made and included such a flow diagram. In revising we initially included it in the supplement, but it seemed a bit out of place there and so we moved it into the main text. We would gladly take advice, however.

Response to Reviewer #2

I agree that it is not necessarily beneficial to the readability of the manuscript if all the details on model formulations are included in the main manuscript. In fact this may even be detrimental. The suggestion to include these in the supplementary material is I think a good one, but I would also restrict that to not overburden these, as references are indeed given to more complete descriptions. I trust the authors can assess what additional information is useful here. The authors should of course clearly refer the reader to the supplementary material as appropriate in the main manuscript to ensure the link can be made where it is required. Perhaps that would also have helped this reviewer find the relevant detail.

[5] In response to the reviewer comments we moved a description of the forcing and downscaling to the main text. With that gone, it appeared that the information that was previously in the Appendix could instead be provided in the main text without too much additional text, so we did that. We provided some more textual detail on the process descriptions. Including all energy balance equations would have to be added as a supplement, which did not seem to make much sense as the model equations are already documented online, as the editor points out.

It may be worth considering including the figure providing comparison against FLUXNET values in the supplementary material, in support of the comments in the main text. However, I would include in the main text a comment that you do not consider these as true validation I presume due to the issue of representation. This is commented on but maybe useful to add that additional sentence to clarify. Also, what is mean by N=16-168. Is this a typo?
Agreed, we have taken the editor’s advice and included more detail in the supplement, and also added an explicit statement along the lines suggested. We agreed the $N=16-168$ was confusing and changed it. It was not a typo as such, $N=16$ was for the study of Yeabra, and $N=168$ for our unpublished analysis, which is now in the supplement (in revising this number increased to $N=169$ due to an additional site).

On the discussion on “before reaching ocean”, and the need for better maps of closed basins. I would add to this that the reaching of the ocean is often also influence by evaporation (and the increase of evaporation due to irrigation). So while the DEM may indicate the river reaches the ocean, water in the river in fact does not. You could consider that not reaching the ocean is due to either being a closed basin or due to anthropogenic influences.

I would like to suggest the authors update the manuscript based on the comments and the suggestions they have made in response. In that update please clearly outline the changes.

Thank you. Below we outline the changes made. We also provide a copy of the m/s with the changes marked for the convenience of editor and reviewers.

Response to Reviewer #1

We thank the reviewer for their comments and are glad that they enjoyed the m/s. We are also grateful for the editorial corrections and suggestions. Below we address the issues raised.

“The authors mention how all kind of modelling efforts will not produce independent and accurate estimates of irrigation water demand, but after the reading the objective I can only conclude that they will themselves do modelling as well. I think it would be good to refocus the introduction and state that models can have a valuable contribution but have their limitations and highlight how the authors would like to resolve these limitations.”

It is certainly true that our approach requires a model to assimilate the satellite observations into, and it is also true that additional assumptions are needed to translate water use estimates to irrigation water demand. We meant to emphasise that our method differs from existing methods in that it does not require mapping of the area irrigated or the extent of wetlands to estimate secondary evaporation. In revising, we added:

“Such an approach still involves modelling and the assumptions inherent to it, but the greater use of observations should mitigate against errors arising from the modelling.” (l. 94-95)

“I do not fully understand why this model is different from the other global water balance models out there. They authors should do a better job to highlight this, to emphasize why this model is better suited for this excursive than others”

The overall approach is different from existing models in that secondary evaporation is constrained by the satellite observations, rather than the result of simulation. If the reviewer refers to the W3RA model used in assimilation, then we believe a similar approach could be applied to other models, provided they have a coupled water and energy balance model and provided they are extended for data assimilation in the way described. We added:

“The W3RA model used here it not the only suitable modelling framework for the approach described. A similar method could be applied with other local or global models. The main requirements are that the model has a coupled water and energy balance model that simulates LST, and that it is amenable to data assimilation.” (l. 168-171)

“The quality of the forcing data is really low, how do the authors think this will impact the simulations and consequently the evaporation estimates?”

This question does not have a simple answer. The model takes several forcing data as input, the evaporation estimates are not equally sensitive to all of them, and the quality of forcing data also varies spatially and temporally.
seasonally as well as at longer time scales due to advances in satellite sensors). Hence it is impossible to give a quantitative answer to the question, but with regards to evaporation (only), one observed issue is that of heterogeneous biases in air temperature in regions with strong relief. Fortunately, secondary losses occur mostly in areas with low relief (see original text). To emphasise this more, we have added:

“A systematic bias in the global estimates of governing variables (radiation, air temperature and humidity, wind speed) are likely to be less problematic than spatially variable bias in these low-relief areas.” (l. 596-598)

“Line 184-185 and Figure 1, I have the strong feeling that the model is biased in its estimates of E. Therefore, this would violate the basic assumption of a normal distribution with a mean of 0 around the observations. In addition, the authors cut-off the E’ updates, which is in my opinion another violation of the EnKF. I feel the others should make sure that the model is bias free before implementing a DA technique like the EnKF. Otherwise, they can show the global biases to convince the reader that this is only the case for Figure 1, but I have to strong suspicion that it is also a problem for other regions (as for most models). I think the authors should address this large limitation in their discussion or somewhere else in the manuscript.”

[13] Does the reviewer mean the model is biased in the absence of secondary evaporation (i.e. in drylands)? We do not have evidence for that. We have evaluated the (“offline” or background) model against evaporation rates reported by the global Fluxnet network for non-irrigated environments and did not find any bias, which is not surprising given the model was partly trained on those same data. We added the details of the evaluation, previously described as “unpublished”, in a new supplement.

[14] The reviewer suggests showing global biases, but there are no global ET observations (other than Fluxnet) to calculate those from. However, we do compare with estimates from other models and find that ours are well within that range (see discussion in original text).

[15] We did not use EnKF but nudging based on energy balance model inversion.

[16] The reviewer is correct that we did cut off the E’ updates. This was necessary to maintain internal physical consistency, but it is true that it may have introduced bias, particularly if the real E was consistently higher than the available energy, for example due to biases in meteorological forcing data. In revising the m/s, we have added:

“Values of the updated λE’ were constrained to positive values below or equal to potential evaporation E0, and therefore any gross underestimation of E0 by the model due to errors in meteorological forcing data would have resulted in an underestimation of the true evaporation rate.” (l. 588-591)

“The manuscript could significantly benefit from a flowchart describing the full updating, calibration, nudging and assimilation procedure. Which variable are subject to what and where and how? The manuscript is difficult to follow without.”

[17] Thank you for the suggestion. Data assimilation procedures are often difficult and tedious to explain but we have added a flow diagram to attempt to illustrate it better, and added the following explanation:

The methodology of our experiment includes two mostly separate components (Figure 1). The assimilation component integrates various MODIS products into the global hydrological model to estimate the dryland water balance and secondary evaporation. Subsequently, in an offline analysis the estimates of secondary evaporation were combined with mapping of irrigated crops to estimate a minimum irrigation requirement. Below follow details on the model, the data assimilation procedure, estimation of irrigation water use, and the different ways in which the results were evaluated. Details on the data used in the analysis can be found in the supplement to this article.
Figure 1. Illustration showing the processing steps and data used in each step. Acronyms relate to input data that are described in the text.

(l. 112-121)

“Line 253-254 Why is the increase in the estimation evaporation not from missing model processes? Incorrect vegetation parameterization or something else. This assumption is vital for the manuscript and is not really supported by argument on the model’s quality to estimate evaporation in general. Has the model been validated against independent evaporation estimates?”

[18] This was discussed in the original m/s (l. 558-567 in the annotated revised m/s): the assimilation of satellite vegetation observations goes some way to address errors in vegetation parameterization. However, the (necessary) assumption that the assimilation increment is due to irrigation has uncertainty associated with if (but only if) most of a grid cell is occupied by non-irrigated land. Hence also the recommendation that our approach should work better at higher resolution, which we hope to pursue.

[19] Regards validation: see response [13].

“In addition, to the previous comment, the authors have not mention other forms of water use. I see no inclusion of domestic or industrial water use in the model nor in the estimates? Maybe these abstractions cause the errors in water basin closures.”

[20] Domestic and industrial water use are not considered because these are typically non-consumptive uses (i.e., the water is returned to the environment after use). Possibly the main exception to this would be irrigation in urban landscapes, which the irrigation mapping does not capture well or at all. If those uses lead to surface cooling then the LST data assimilation will still have increased E estimates and so they are implicitly accounted for. In practice,
consumptive urban or industrial water uses are unlikely to have a meaningful impact on the water balance of large basins. We added:

“Domestic and industrial withdrawals are not considered here as a large fraction of these withdrawals is not evaporated but returned to the environment.” (l. 391-393)

“Line 129-134 are the calibrated parameter spatially consistent or are they really tuned to the individual basins?”

[21] Neither, they vary spatially as a function of climate aridity and land cover using predictive relationships derived from model calibration to evaporation, soil moisture and streamflow from a very large number of sites and small and unregulated catchments, respectively. This was described in the original m/s, but we added a bit more detail in l. 155-162.

“Line 134-135 Does the model have any lateral flow simulations of groundwater or surface water?”

[22] No, only grid-based routing.

“Line 150 a nudging factor of 0.99 is rather high, does this mean that the model is almost always wrong?”

[23] Poor at predicting highly dynamic surface water extent, one could say, yes. (Like all global models, to the best of our knowledge.) We added:

“(reflecting the low skill in the model to accurate predict surface water extent at 0.05° resolution)” (l. 184-185)

“Line 156-159 what is the spatial resolution of the Tair forcing, since it is very important for the LST simulations”

[24] We agree that correct Tair is important, although the median bias correction step reduces most of the systematic difference, which we would argue is one of the novel aspects of our approach and one reason for its apparent success. These details were in the appendix, but we agree that they are probably important enough to be explained in the main text. Therefore we added:

“Monthly precipitation and air temperature climatology data at 30″ from the WorldClim dataset (Hijmans et al., 2005) were resampled to 0.05° and 0.25°; subsequently, the ratio and difference, respectively, between the data at the finer and coarser resolution were applied to the forcing data.” (l. 145-150)

“Line 177 15degree, does this mean that the LST is spatially average over a 1500 by 1500km area???”

[25] A 15x15° region is indeed about that size at lower latitudes. Note that this does not imply that LST is assumed homogenous across the area. This calculation is to remove the mean bias between daytime LST and time-of-overpass LST. We added “to remove systematic bias” (l. 213)

“Line 508-510 the true error can also be larger. . . It is not said that it will be smaller due to the representativeness error.”

[26] In theory, yes, although given the rather large sample such a statistical accident would be unlikely. Nonetheless we removed this statement, for the more important reason that the relatively large uncertainty in Fluxnet energy balance terms means that they do not provide a very reliable assessment of possible bias in our model estimates (see new supplement).

“Line 581-583 As far as I understand most other models use sub-grid parameterization, which would allow for a partial coverage of the grid cell by irrigation areas. This statement is therefore potentially incorrect and should be removed to avoid misinforming the reader”

[27] We respectfully disagree. The MIRCA2000 mapping suggests the grid cell is 100% equipped for irrigation. To our knowledge the published models assume that the entire equipped area is irrigated so the statement holds. Of course that assumption could be changed for another.
Page 619-623 I feel the units are incorrect, I guess the first estimates should be 75.5 \times 10^{12} \text{Km}^3 \text{y}^{-1} (as well as for the other estimates from this study, which are now 1000 times lower than other studies) 

[28] The units are correct. We could have written 75,500 \text{Km}^3 \text{y}^{-1} but felt using base units (m) was more appropriate, as neither unit is easily imagined.

Response to Reviewer 2

[29] We thank the reviewer for their positive and constructive comments. Below we respond to the issues raised.

First of all, I find the manuscript a bit unbalanced in terms of contents. There is a lot of focus on methods and equations (esp. for irrigation), but relatively a few figures for results. This makes the manuscript very tedious to read with a lot of text and information. At the same time, some information that are critical to assess the results are either missing or in the appendix. For example, forcings and their spatial disaggregation, model formulations of LE and H, etc.”

[30] We are sorry the m/s was tedious to read. We appreciate that the technical detail of the modelling and data assimilation can be a bit tedious, which is why we tried to minimise that aspect in the body text by transferring some of the material to the appendix and referring to existing studies where possible. We have added 2 figures: one illustrating the workflow, and one with some new analysis suggested by the reviewer. We hope this has made the m/s less tedious.

[31] The referee also asks for additional material to be included and we therefore made some additions. We have added further details on “forcings and their spatial disaggregation” in the main text (see response [24]). The “model formulations of LE and H” were described in the methods section. The energy balance equation is the main model component of relevance here, but it is in essence a conventional implementation of the Penman-Monteith equation, which is well-known and the detail of the implementation is readily available online already. We did some additional text to explaining the approach however:

“The surface energy and water balance is simulated using the Penman-Monteith model. The evaporative fluxes from transpiration, unsaturated soil, saturated soil and surface water are simulated subject to the overall constraint of potential evaporation \(E_0\) within the same Penman-Monteith framework. Wet canopy evaporation is simulated outside this constraint, for reasons described in Van Dijk et al. (2015), using a dynamic-canopy version of the event-based Gash model (Van Dijk and Bruijnzeel, 2001; Wallace et al., 2013).” (l. 133-138)

Definition of the secondary evaporation: There is no description on how groundwater’s contribution to LE/ET is a secondary source. In an idealistic theoretical situation, the capillary flux from groundwater will replenish soil moisture (at some point when the soil moisture is drying up), which would eventually increase LE. It is not clear if the model considers such capillary flux processes explicitly. I am curious about what fraction of ‘other’ sources is actually coming from groundwater-soil-LE pathway, and not groundwater-baseflow-surface water-LE pathway. The first one may have a critical influence on vegetation and carbon cycle processes.”

[32] The model does consider capillary fluxes, but in the offline model those are ultimately constrained by longer-term local rainfall, and therefore do not constitute secondary evaporation (i.e., it is derived from locally recharged, unconfined groundwater rather than lateral groundwater inflows). As our study demonstrates, data assimilation helps to estimate secondary evaporation from non-local water sources, but does not directly attribute it to a water source – that requires ancillary data. In some cases, the secondary evaporation may be from irrigation with water pumped from confined aquifers (which bypasses the capillary rise pathway). In other cases, it is possible that secondary evaporation is inferred, e.g. because rainfall is underestimated, capillary rise or deep root water uptake is more important than predicted by the background model (e.g., because the vegetation is more deeply rooted or groundwater is closer to the surface than assumed). There is obviously much more to be done to understand the global water balance in full detail. Our data provide a means of prioritising regions where there appears to be
hydrological behaviour that is not easily explained by the background model, and therefore is worthy of further investigation. To make clear that capillary rise is possible within the model, we added the following words:

“[The soil column is conceptualised as a three-layer unsaturated zone overlaying an unconfined groundwater store], from which capillary rise can occur.” (l. 130-131)

# “Assimilation of LST into model: In the assimilation of LST into model, the basic assumption is that the model-simulated partitioning of the energy fluxes (H and E) are correct. The corrections or ‘nudges’ for LST are back-calculated from the modelled H, and these are propagated through spatial patterns of observed LST. But, there is no explanation of how ‘background’ H and LE are calculated in the model. Perhaps, these may be inferred from previous papers/reports on the model (?), but they are so critical for this study and results presented herein, they deserve to be in this manuscript.”

[33] The basic assumption is actually not that the partitioning of H and LE is correct, but rather, that the estimated total available energy (A=H+LE) is correct. Data assimilation may change the estimate of H, and through that LE=A-H. To make this clear we added:

“A fundamental assumption in this approach is that the partitioning between λE and H can be improved with information on LST, but that the estimate of available energy A is correct.” (l. 224-226)

[34] The background H and LE are estimated using the conventional Penman-Monteith approach. We have added new details on that in the model description section (see [31]).

# “One information that is imperative is whether the parameters of the modelled LE and H were optimized or not. If not, are the used parameter values are reasonable for a global-scale application?”

[35] The most important parameter overall, surface conductance, was predicted from satellite-observed surface reflectances following Yebra et al. (2013) and tuned using a large data base of evaporation measurements (FLUXNET). Another important parameter, vegetation height (affecting aerodynamic conductance) was derived from remote sensing by Simard et al. (2011). We have added a few additional words to hopefully make the approach clearer:

“Global datasets were also used to parameterise the distribution of different land surface types (Bicheron et al., 2008) and the properties of vegetation (Simard et al., 2011), soil (Shangguan et al., 2014), and aquifers (Gleeson et al., 2014; Beck et al., 2015).” (l. 150-152)

and

“(Five model parameters that were both relatively uncertain and influential were calibrated and regionalised) by climate and land cover type class, [using large global data sets of site measurements evaporation and near-surface soil moisture, and a global dataset of catchment streamflow records (the parameters represent proportional adjustments to initial estimates of, respectively, maximum canopy conductance, relative canopy rainfall evaporation rate, soil evaporation, saturated soil conductivity, and soil conductivity decay with depth).]” (l. 1487-153)

# “Related to the above point, validation for model simulated LE and H is not shown or discussed. There are references to a previous study or an unpublished work but the findings of this study also warrant a section on evaluations at the global scale. I am aware that observed global ET and H data are not available, but a comparison with either FLUXNET observations (for sites) or other satellite-based ET products can provide a valuable benchmark.”

[36] In response, we have summarised the result of the unpublished evaluation and included it as a new supplement. We believe putting it in the main text would be misleading readers into thinking it constitutes an assessment of the performance in estimating secondary evaporation, which it does not: the vast majority of flux towers are in environments without secondary evaporation. This was also the reason we initially did not think it a good idea to include it, but we can see that a reader might want to see anything that is referred to and that “unpublished’
therefore might not cut it. As the supplement makes clear, the flux tower observations also suffer from the energy balance closure problem which makes evaluation more ambiguous.

[37] A comparison with other global ET products was discussed in the original m/s.

**# “Estimation of irrigation water use: Assumption of rooting depth: The parameter smax is dependent on the assumed rooting depth. The manuscript would benefit from a discussion on how these parameters vary globally, and to what extent do this variation affects the estimation of secondary evaporation from irrigated area.”**

[38] We follow the published methodology of Siebert and Döll (2010). The assumptions made here do not affect the estimation of secondary evaporation. They do affect the calculated irrigation efficiency and therefore the estimate of irrigation water use. This is a perhaps subtle, but important distinction. We added additional text in to places to make sure this is clear:

“The assimilation component integrates various MODIS products into the global hydrological model to estimate the dryland water balance and secondary evaporation. Subsequently, in an offline analysis the estimates of secondary evaporation were combined with mapping of irrigated crops to estimate a minimum irrigation requirement.” (l. 112-116)

and

“The estimation of l₀ was done after, and entirely separate from, the data assimilation process, and therefore what follows had no bearing on the estimation of secondary evaporation.” (l. 267-269)

**# “Evaluation against discharge observations: In my subjective judgment, the improvement in the basins with discharge < 300 mm/y is mostly driven by Paraná because it has discharge with the largest magnitude. In reality, the river basins with large irrigation water withdrawal/use are also equipped with dams and are not of run-of-river type (with no reservoir). The secondary evaporation from these ‘dammed’ rivers also comprise of evaporation from reservoirs. So, in my opinion, it would be helpful to include the information of reservoir volume (e.g., from GranD database) in the analysis or the figure. This is important because the water evaporated from the reservoirs might actually be significant, especially because the irrigation requirement/use from this study is much lower than previous estimates.”**

[39] Actually, it is also due to the improved water budget for closed basins (dots on the vertical axis) and several other basins (e.g., Indus). Our methodology does use remotely sensed water extent, and that would include reservoir surface area, so evaporation from reservoir surfaces is included in the estimates.

**# “Comparison with previous estimates: The manuscript addresses the minimum irrigation water requirement, which I understood as the actual gross irrigation water use (gross because it has both bare soil evaporation in irrigated areas+transpiration by crops). In most previous modeling studies, difference between PET and ET is used to calculate irrigation water requirement (and withdrawal). Current manuscript rightly points that there are several limitation to ET from irrigated areas. Despite that, it would make sense to compare the difference between PET and ET (Priestley Taylor is already used in the current study) with the bias of l₀ against withdrawal.”**

[40] Unfortunately we did not grasp the analysis the reviewer proposes. In the original m/s, we did compare l₀ to reported withdrawals in Fig 5 and l. 435-449, and this does provide some useful insights, discussed in l. 561-599. We could compare irrigation area ET to PET (as done for example in Fig. 2e in the revised m/s) but are not sure how to summarise such a comparison globally or what it would demonstrate.

**# “Forcing variables: The results of this study are extremely dependent on the biases in the WFD forcing data as well as the spatial patterns of HYDROCLIM data. It is not clear from the current analysis if the biases in secondary evaporation are related to WFD magnitude (over a half degree grid) or the spatial patterns of HYDROCLIM (over 0.05 deg grids).”**

[41] The term ‘extremely’ is subjective, but given the Penman-Monteith energy balance approach used, the evaporation estimates will depend on the meteorological forcing data, as does any method to estimate evaporation.
We used the relative spatial patterns in the high-resolution, station-based WorldClim dataset to downscale air temperature only (see [24]). Because we only assimilated satellite LST in areas with modest relief, we do not expect that the downscaling will have had much effect on secondary evaporation estimates. We also suspect that biases in air temperature in the WFD forcing data may in fact be less important than uncertainties in the radiation balance, wind speed, and perhaps specific humidity. Because we have not separately investigated or quantified these uncertainty sources, we prefer not to speculate and leave such interpretations to the reader. Nevertheless, in the revised m/s we acknowledge that uncertainties in the forcing data could have an impact on the results (l. 558).

# “Temporal variation of secondary evaporation: I would have really learnt a lot on what is drivin

We thank the reviewer for the suggestion and have performed some additional analysis. We have added the following results:

“There is a pronounced seasonal cycle in secondary evaporation at global scale (Figure 11). The rate of secondary evaporation is more than two times higher in northern summer than in northern winter. This is primarily due to the greater rate of evaporation from the many surface water bodies in formerly glaciated regions, including the American Great Lakes, as well as a higher rate of evaporation from the Caspian Sea. By contrast, secondary evaporation in regions located wholly or partially in the southern hemisphere show a much less pronounced seasonal cycle and a greater influence of water availability. Averaged over time, each of the regions considered makes a similarly sized contribution to secondary evaporation globally (10–24%) with the exception of Antarctica (0.4%).

We are not sure whether these findings are very relevant from a global water cycle or climate system perspective, but if the reviewer finds them interesting then perhaps they satisfy a certain curiosity in other readers as well. The main driver of the seasonality is ultimately due to the legacy of glaciation, and so we have added the following to the discussion:

Figure 11. Average (2001—2012) seasonal cycle of secondary evaporation at global scale (black line) and the contribution from different regions (colours corresponding to the map). All rates are expressed in mm d⁻¹ for the global land area.” (l. 535-543)
“There is a strong seasonal cycle in secondary evaporation at global scale, driven by evaporation from extensive surface water bodies in formerly glaciated regions in the northern hemisphere. This illustrates the profound impact that glaciation has had on regional landscape hydrology, and its influence at global scale.” (l. 696-699).

“Evaporation larger than precipitation in southern Africa and Yucatan: The discussion focuses on the biases in the precipitation. If total E (primary + secondary) were correct, the signal should appear in the water storage changes. In that case, GRACE satellite measurements should show a declining terrestrial water storage. A comparison on loss of storage in the study period and the total E – P would provide a great motivation for future studies on what are driving such changes. Essentially, this would already help in refining the potential causes of the negative water budget.”

[43] Again we thank the reviewer for the suggestion. Some knowledge of GRACE based trends was on our mind in interpreting the results, but we did not make this explicit. A previous GRACE model-data assimilation study some of the authors were involved in inferred that water storage did decrease slightly over the Yucatan peninsula between 2003 and 2012 but increased quite strongly in southern Africa. Neither trend was predicted by an ensemble of hydrological models (particularly not for the African case), which led us to suspect deficiencies in the rainfall estimates driving those models. We expanded the discussion as follows.

“We analysed global water cycle reanalysis data that integrated GRACE gravity observations in an earlier study (Van Dijk et al., 2014) for a largely overlapping period (2003–2012) to test this. For the African Southern Interior, the reanalysis demonstrated a clear increasing trend in subsurface storage (+12.3 mm y\(^{-1}\)) that was not reproduced by an ensemble of models (+2.0 mm y\(^{-1}\)). This suggests that the global precipitation estimates used by models were indeed too low for this period, as also concluded by Van Dijk et al. (2014). For the Yucatan peninsula, a slight storage decrease (-3.3 mm y\(^{-1}\)) was inferred from the reanalysis, whereas the model ensemble suggested a slight increase (2.7 mm y\(^{-1}\)). This does not suggest any underestimation of precipitation. A net use of groundwater does appear plausible in this case, though likely not enough to explain the secondary evaporation rates estimated here” (l. 622-632)

Editorial Comments:

# “Line 1: In my opinion, ‘estimates’ should be replaced by ‘simulations’. Essentially, the results are dependent on hydrological model simulations.”

[44] We respectfully disagree. Satellite observations were assimilated to make the results less dependent on model simulations.

# “Line 232: i=1,26 can be replaced by just 26.”

[45] We used this notation to make the meaning of i in Ai in the same sentence clear.

# “Line 259: There is no description for what Pg is. I assumed that it is precipitation for the grid cell.”

[46] Apologies, this should have read \( P_{ir} \). We corrected this.

# “Figures 6-9: I recommend using the same color maps and scales in these figures. It is a bit confusing because the same color ‘blue’ means a different value in different figures.”

[47] Thank you, we made this change.

# “Table 1: Just curious that observed discharge in Nile is 0. Fascinating that no water from such large river basin reaches the ocean.”


# “Line 534: can have affected \(\rightarrow\) can affect or could have affected”

[49] Agreed, thank you.
Agreed, thank you.

Before reaching the ocean is misleading because a fraction of the open water evaporation is from rivers which do not drain to ocean (e.g., inland lakes).

For clarification, we changed this to:

"Around 16% of globally generated water resources evaporate before reaching the oceans or from closed basins, enhancing total terrestrial evaporation by 8.8%.” (l. 752-754)

We do not consider the statement to have been misleading, however. Our phrasing was chosen for pragmatic reasons, although there is also a conceptual argument. The pragmatic reason was that, in identifying closed basins, we found it challenging to separate “truly” closed basins from basins that DEM analysis suggested were closed but which actually did appear to have an overflows according to independent reports. Surprisingly, it appears that there is no reliable global map of closed basins, and it took background research to identify the basins shown in Fig. 3. There were many other basins that the DEM suggested were closed but where we were not able to confirm that, meaning we ultimately did not identify all closed basins and therefore cannot make the distinction between secondary evaporation from (all) closed basins and all ocean reaching rivers.

The conceptual reason is that the referee’s argument can in fact be turned around: those rivers in ‘closed basins’ do not drain to the ocean because evaporation is so high. The difference between closed and ocean-draining basins is a threshold (lake) level, and some basins currently switch between these states depending on the difference between rainfall and evaporation, many others did in the past. We do accept that there are closed basins that would require a very large increase in rainfall indeed (or decrease in evaporation) to top the overflow threshold and start draining to the ocean, but it does mean that there is no fundamental difference between ‘closed’ and ‘open’ basins.

We do believe that a map of all (currently) closed basins would be a valuable information source for water balance studies, and are currently looking into producing one using DEM data of higher accuracy and resolution, but early indications are that it requires intensive quality control. If it had existed, we would have made the distinction.

We are not entirely sure how to interpret this question. In case it answers the question, we did add:

"[The soil column is conceptualised as a three-layer unsaturated zone overlaying an unconfined groundwater store], from which capillary rise can occur.” (l. 130-131)

Thus, the primary evaporation estimates by the model do include the effect of capillary rise. However, if the primary evaporation estimates are too low data assimilation increases those estimates, and the difference will be (perhaps partly or wholly incorrectly) ascribed to secondary evaporation from lateral inflows. We discussed this in l. 501-504 of the original m/s.
Global 5-km resolution estimates of secondary evaporation including irrigation through satellite data assimilation

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Abstract

A portion of globally generated surface and groundwater resources evaporates from wetlands, water bodies and irrigated areas. This secondary evaporation of ‘blue’ water directly affects the remaining water resources available for ecosystems and human use. At the global scale, a lack of detailed water balance studies and direct observations limits our understanding of the magnitude and spatial and temporal distribution of secondary evaporation. Here, we propose a methodology to assimilate satellite-derived information into the landscape hydrological model W3 at an unprecedented 0.05° or c. 5 km resolution globally. The assimilated data are all derived from MODIS observations, including surface water extent, surface albedo, vegetation cover, leaf area index, canopy conductance, and land surface temperature (LST). The information from these products is imparted on the model in a simple but efficient manner, through a combination of direct insertion of surface water extent, evaporation flux adjustment based on LST, and parameter nudging for the other observations. The resulting water balance estimates were evaluated against river basin discharge records and the water balance of closed basins and demonstrably improved water balance estimates compared to ignoring secondary evaporation (e.g., bias improved from +38 mm/d to +2 mm/d). The evaporation estimates derived from assimilation were combined with global mapping of irrigation crops to derive a minimum estimate of irrigation water requirements ($I_0$), representative of optimal irrigation efficiency. Our $I_0$ estimates were lower than published country-level estimates of irrigation water use produced by alternative estimation methods, for reasons that are discussed. We estimate that 16% of globally generated water resources evaporate before reaching the oceans, enhancing total terrestrial evaporation by $6.1 \times 10^{12}$ m$^3$ y$^{-1}$ or 8.8%. Of this volume, 5% is evaporated from irrigation areas, 58% from terrestrial water bodies and 37% from other surfaces. Model-data assimilation at even higher spatial resolutions can achieve a further reduction in uncertainty but will require more accurate and detailed mapping of surface water dynamics and areas equipped for irrigation.
Introduction

The generation of surface and groundwater resources is commonly conceptualised one-dimensionally as the net difference between precipitation, evaporation (including transpiration) and soil storage change. However, some part of the generated ‘blue’ water (Falkenmark and Rockström, 2004) subsequently inundates floodplains, accumulates in wetlands and freshwater bodies, or is extracted for irrigation. A fraction of that water will evaporate in this second instance. This ‘secondary evaporation’ directly reduces the remaining blue water resources available for ecosystems and economic uses downstream but also increases the use of water by terrestrial ecosystems before discharging into the oceans. At the global scale, our understanding of the magnitude and spatiotemporal distribution of secondary evaporation is limited by a lack of detailed water balance studies and direct observations. Until recently, land surface models ignore lateral water transport and secondary evaporation altogether or provide a rudimentary description. This is understandable, given the complexity and computational challenge in simulating the lateral redistribution and secondary evaporation of water at the global scale. However, it is increasingly clear that the lateral redistribution of water cannot be ignored in global water resources analyses (Oki and Kanae, 2006; Alcamo et al., 2003), carbon cycle analysis (Melton et al., 2013) and regional and global climate studies (e.g., Thiery et al., 2017).

Even approximate numbers on the importance of secondary evaporation in the global water cycle are not available. Oki and Kanae (2006) derived global bulk estimates of gross evaporation from lakes, wetlands and irrigation (combined $10.1 \times 10^{12} \text{ m}^3 \text{ y}^{-1}$) but their estimate was based on modelling only and included both primary and secondary evaporation. There have been some studies estimating irrigation water requirements at the global scale (Döll and Siebert, 2002; Wada et al., 2014; Siebert and Döll, 2010) but these studies were based on idealised modelling, did not attempt to separate between primary and secondary evaporation, and did not consider other sources of secondary evaporation.

There have been attempts to use satellite observations to estimate the importance of secondary evaporation at a regional scale. For example, Doody et al. (2017) used MODIS-based evaporation estimates (Guerschman et al., 2009) over Australia to delineate areas receiving lateral inflows. They used ancillary data to attribute these to surface water inundation, irrigation, and groundwater-dependent ecosystems, respectively. At the global scale, Wang-Erlandsson et al. (2016) used satellite-based ET estimates from several sources to infer rooting depth, which provided some insights into the spatial distribution of surface- and groundwater dependent ecosystems.

Historically, three contrasting approaches have been followed to estimate evaporation: water balance modelling; inference from land surface temperature (LST) remote sensing; and estimation based on vegetation remote sensing. All three approaches rely on meteorological data and effectively involve a land surface model of some description, albeit of variable complexity. Hybrids between the three approaches have also been developed over time to mitigate respective weaknesses (Glenn et al.,
For example, dynamic simulation of the soil water balance can provide a valuable constraint on satellite-based evaporation estimates in water-limited environments; provided precipitation is the only source of water for evaporation, and accurate precipitation estimates are available (Glenn et al., 2011; Miralles et al., 2016). However, where there are additional sources of water or unexpected soil moisture dynamics, applying this constraint can degrade evaporation estimates.

Beyond dynamic hydrological models, evaporation products based more closely on vegetation remote sensing implicitly account for the effect of lateral water redistribution on transpiration, but often do not account for open water evaporation (Yebra et al., 2013; Zhang et al., 2016), with exceptions (Guerschman et al., 2009; Miralles et al., 2016). Satellite-observed LST has a direct, physical connection to the surface heat balance, and through the overall surface water and energy balance can provide a constraint on evaporation estimates. Several techniques have been developed to infer evaporation from LST, and many successful applications at local scale have been documented (Kalma et al., 2008). Over larger areas, the application of LST-based methods is complicated by the need for time-of-overpass estimates of radiation components, air temperature, and aerodynamic conductance (Kalma et al., 2008; Van Niel et al., 2011). There are promising developments that can overcome some of these challenges (Anderson et al., 2016), although they are yet to be fully evaluated.

Arguably, the most promising approach to evaporation estimation is to combine water balance modelling, LST remote sensing, and vegetation remote sensing within a model-data fusion framework. Such an approach still involves modelling and the assumptions inherent to it, but the greater use of observations should mitigate against errors arising from the modelling. This prospect motivated the present study.

**Aim**

Our objective was to develop a methodology to assimilate optical and thermal observations by the MODIS satellite instruments into a 0.05° resolution global hydrological model to estimate evaporation and to evaluate the quality and quantitative accuracy of the resulting estimates as much as possible. Based on the resulting estimates, we wished to answer the following questions:

- What is the magnitude of secondary evaporation of surface and groundwater resources in the global and regional water cycle?
- What is the magnitude of irrigation evaporation and how does it relate to total agricultural water withdrawals?
- What are the contributions of secondary evaporation from irrigation, permanent water bodies, ephemeral water bodies, and other surfaces?
- Is secondary evaporation likely to have a noticeable impact on the global carbon cycle and climate system?
**Materials and Methods**

The methodology of our experiment includes two mostly separate components (Figure 1). The assimilation component integrates various MODIS products into the global hydrological model to estimate the dryland water balance and secondary evaporation. Subsequently, in an offline analysis the estimates of secondary evaporation were combined with mapping of irrigated crops to estimate a minimum irrigation requirement. Below follow details on the model, the data assimilation procedure, estimation of irrigation water use, and the different ways in which the results were evaluated. Details on the data used in the analysis can be found in the supplement to this article.

![Figure 1. Illustration showing the processing steps and data used in each step. Acronyms relate to input data that are described in the text.](image)

**Global water balance model description**

The World-Wide Water model (W3) version 2 is an evolution of the AWRA-L and W3RA group of models. The AWRA-L model is used operationally for water balance estimation across Australia at 0.05° resolution by the Bureau of Meteorology. An overview of the operational AWRA-L model
(version 5) can be found in Frost et al. (2016b), with details on the scientific basis in Van Dijk (2010). Very briefly, the model operates at daily time step and is grid-based. Each cell is conceptualised to represent several parallel small, identical catchments. The soil column is conceptualised as a threelayer unsaturated zone overlaying an unconfined groundwater store, from which capillary rise can occur. The unsaturated soil water balance and corresponding water and energy fluxes can be simulated separately for hydrological response units (HRUs) that each occupy a fraction of the grid cell. The surface energy and water balance is simulated using the Penman-Monteith model. The evaporative fluxes from transpiration, unsaturated soil, saturated soil and surface water are simulated subject to the overall constraint of potential evaporation $E_0$ within the same Penman-Monteith framework. Wet canopy evaporation is simulated outside this constraint, for reasons described in Van Dijk et al. (2015), using a dynamic-canopy version of the event-based Gash model (Van Dijk and Bruijnzeel, 2001; Wallace et al., 2013). Sub-grid parameterisations are applied to simulate the area fractions with surface water, groundwater saturation and root water access to groundwater dynamically, based on the hypsometric curves (i.e., the cumulative distribution function of elevation) for each grid cell (Peeters et al., 2013).

The W3 (version 2) model is a global implementation of AWRA-L (version 5) at the same 0.05° resolution. Important differences are as follows (details in Appendix A). Separate HRUs were not considered, however, the water balance of permanent water bodies is calculated separately. Global gridded climate time series and surface, vegetation and soil parameterisation data were used. In brief, MSWEP v1.1 (Beck et al., 2017) precipitation estimates and other meteorological data from the WFDEI v1 dataset (Weedon et al., 2014). Monthly precipitation and air temperature climatology data at 30° from the WorldClim dataset (Hijmans et al., 2005) were resampled to 0.05° and 0.25°; subsequently, the ratio and difference, respectively, between the data at the finer and coarser resolution were applied to the forcing data. Global datasets were also used to parameterise the distribution of different land surface types (Bicheron et al., 2008) and the properties of vegetation (Simard et al., 2011), soil (Shangguan et al., 2014), and aquifers (Gleeson et al., 2014; Beck et al., 2015). We used the cumulative distribution function of Height Above Nearest Drainage (HAND; Nobre et al., 2015) for each grid cell instead of hypsometric curves, which we derived from high-resolution global digital elevation models.

Five model parameters that were both relatively uncertain and influential were calibrated and regionalised by climate and land cover type class, using large global data sets of site measurements, evaporation and near-surface soil moisture, and a global dataset of catchment streamflow records (the parameters represent proportional adjustments to initial estimates of, respectively, maximum canopy conductance, relative canopy rainfall evaporation rate, soil evaporation, saturated soil conductivity, and soil conductivity decay with depth). Differences less relevant here include the addition of a snow water balance model with parameters from Beck et al. (2016) and grid-based river routing using a flow direction based on HydroSheds (Lehner et al., 2008) where available and HYDRO 1k elsewhere.
A range of W3-simulated water and energy balance terms has been made publicly available as part of ‘Tier-2’ of the eartH2Observe project (Schellekens et al., 2017). The AWRA-L and W3 models have received extensive evaluation, demonstrating realistic estimates of evaporation, soil moisture, deep drainage, streamflow and total water storage (e.g., for more recent implementations, Tian et al., 2017; Frost et al., 2016a; Beck et al., 2016; Holgate et al., 2016).

The W3RA model used here is not the only suitable modelling framework for the approach described. A similar method could be applied with other local or global models. The main requirements are that the model has a coupled water and energy balance model that simulates LST, and that it is amenable to data assimilation.

Data assimilation

All data assimilated here were derived from NASA’s Moderate Resolution Imaging Spectroradiometer (MODIS) instruments. The data included albedo, reflectance, leaf area index (LAI) and LST (details in Appendix A). We followed the following steps, except for LST. First, the MODIS band reflectances (product MCD43C4.005) were used to estimate vegetation cover fraction and canopy conductance following Yebra et al. (2015; 2013); surface water extent was estimated following Van Dijk et al. (2016); and MODIS albedo (MCD43C3.005), snow cover fraction (MCD43C4.005) and the MODIS GLASS LAI products (product Xiao et al., 2014) were used in their original form. Next, seven model states were updated using a simple nudging scheme. For each state, the observation and model error estimates were based on an assessment of the noise in the observational data, the expected dynamic rate of change, and the expected skill of the model. The resulting ‘gain’ factors (i.e. the relative weight of observations) varied from 0.5 for LAI and snow fraction to 0.99 for surface water fraction (reflecting the low skill in the model to accurately predict surface water extent at 0.05° resolution). The updated states were also used dynamically to update six related parameters of diagnostic model equations, including a parameter relating vegetation cover fraction to canopy conductance, another relating vegetation cover to LAI, and four parameters relating surface state to albedo.

The approach to assimilate LST observations was different. In this case, the dynamic model was run one timestep forward to produce a background estimate of the surface energy balance and evaporation flux. The corresponding average daytime LST ($T_s$, K) was estimated from the average daytime sensible heat flux ($H$, W m$^{-2}$) as

$$T_s = T_a + \frac{H}{\rho_a c_p g_a}$$

(1)

where $T_a$ is air temperature (K), $\rho_a$ air density (kg m$^{-3}$), $c_p$ specific heat capacity (J kg$^{-1}$ K$^{-1}$), and $g_a(u)$ aerodynamic conductance (mm s$^{-1}$). The latter is a function of wind speed scaled by the wind speed measurement and vegetation heights, respectively, following Thom (1975).
Poor characterisation of spatial gradients in radiative exposure, air temperature, and wind speed in areas with relief can cause a poor relationship between observed and modelled LST (Kalma et al., 2008). Fortunately, secondary evaporation primarily occurs in regions with low relief. Therefore, data assimilation was only attempted for areas with an average slope less than 3% (as calculated from the higher resolution DEM, Appendix A). This threshold was empirically found to include a large majority of observed surface water inundation and mapped irrigation areas.

A second challenge relates to the inconsistency between the observation time-of-overpass LST and model-predicted mean daytime LST. We assumed that time-of-overpass and mean daytime LST will have different spatial averages, but share a near-identical spatial pattern of deviations from the spatial averages. This assumption also helps to remove systematic bias, which is the largest source of error in MODIS LST estimates used here (MOD11C1.006; Wan, 2015). Previous assessments report errors in MODIS that are within 0.7 K under conducive atmospheric conditions but can increase to 3 or 4 K due to errors in atmospheric correction that tend to cause similar level of bias over a larger area (Wan et al., 2004; Wan, 2008; Wan and Li, 2008; Hulley et al., 2012).

In the assimilation step, first the median observed and modelled LST were calculated for all low-relief grid cells within a spatial window of 15° latitude and longitude and subtracted from the respective gridded LST values to remove systematic bias. Subsequently, we calculated the difference between resulting observed and modelled LST values. The calculated difference was reduced by up to 1 K to conservatively allow for uncertainty in the assumptions and errors in the observations. Next, the model LST was updated with the remaining difference towards the MODIS-observed LST. An updated latent heat flux ($\lambda E'$ in W m$^{-2}$; the prime indicating the updated variable) can be calculated from the inverted version of the energy balance equation as

$$\lambda E' = A - H' = A - \rho_a c_p g_a(T_s - T_a)$$ (2)

where $A$ is available energy (W m$^{-2}$). To ensure physical consistency within the model context, $\lambda E'$ was constrained to positive values below or equal to potential evaporation $E_{dp}$ calculated following Penman-Monteith theory (details in Van Dijk, 2010). Temporal consistency was ensured by recording the ratio $\lambda E'/\lambda E$ and using it to adjust simulated $\lambda E$ for subsequent days until a new LST observation was available. Finally, $E$ was calculated through division by the latent heat of vaporisation $\lambda$. A fundamental assumption in this approach is that the partitioning between $\lambda E$ and $H$ can be improved with information on LST, but that the estimate of available energy $A$ is correct.

To illustrate the data assimilation, time series of observations and model results for one 0.05° grid cell in the Nile delta in Egypt are shown in Figure 1 and Figure 2. This grid cell was chosen because it represents one of comparatively few grid cells worldwide deemed to be 100% equipped for irrigation in global mapping (although annual maximum NDVI derived from Landsat suggests that only 80–81% of the area is in fact irrigated; Figure 1a). The processing steps are illustrated by a comparison of observed, background and analysis LST estimates for the year 2002 (Figure 1).
234 2b), and the resulting sensible heat flux (Figure 1, Figure 2c) and daily evaporation (Figure 1, Figure 2d). Corresponding temporal patterns in the evaporative fraction ($E/E_0$) show that data assimilation brings the temporal pattern of evaporative fraction in close agreement with satellite-observed vegetation cover fraction (Figure 1, Figure 2e), which provides as a largely independent consistency test.

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![Figure 1 Figure 2](image)

240 Figure 1-2. Illustration of method to assimilation MODIS land surface temperature observations. Data shown are for 2002, for 0.05° grid cell in the Nile River delta, Egypt (centred 31.075°N, 30.325°E). (a) Maximum normalised difference vegetation index (NDVI) derived from Landsat imagery provided by Google.
Earth Engine, suggesting that effectively 81% and 80% of the grid cell was cropped in 1998 and 2014, respectively. (b) Land surface temperature: background ($T_s$, grey line), observed ($T_{\text{s,obs}}$, circles) and analysis ($T'_s$, red line) estimates for the grid cell with average bias across the 15° window removed. (c) Sensible heat flux: background ($H$, grey) and analysis ($H'$, red) estimates along with net radiation ($R_n$, blue). (d) Evaporation: background ($E$, grey) and analysis ($E'$, red) estimates along with potential evaporation ($E_0$, blue). (e) Evaporative fraction: background ($E/E_0$, grey) and analysis ($E'/E_0$, red) along with vegetation cover fraction derived from MODIS NDVI ($f_{\text{eg}}$, green).

Irrigation water use estimation

For irrigated areas, the long-term average difference between precipitation and total evaporation derived from data assimilation provides an estimate of the importance of additional water inputs. However, it cannot be interpreted directly as an estimate of irrigation water requirements, much less as an estimate of water withdrawals. This is because precipitation and crop water requirements are both unevenly distributed in time, and there is limited water storage capacity in the crop root zone. Additional water is lost from the root zone through drainage and runoff, which will need to be compensated by additional irrigation inputs. This field-level irrigation inefficiency does not necessarily change the long-term net water balance: provided total precipitation and evaporation do not change, the additional inputs will equal the additional runoff and drainage. However, such inefficiencies do need to be accounted for when estimating the total amount of irrigation water required (Siebert and Döll, 2010).

Estimating total field-level irrigation water requirements is sensitive to assumptions about the capacity for added water to remain stored in the root zone irrigation and about strategies (e.g., pursuing a stable low or high soil moisture or paddy water level, suboptimal or soil moisture deficit irrigation, flood irrigation or partial drip irrigation, and so on). Here, we estimated a minimum field-level irrigation requirement ($I_o$ in mm), which can be taken as a conservatively low estimate of irrigation that represents highly efficient irrigation practices. The estimation of $I_o$ was done after, and entirely separate from, the data assimilation process, and therefore what follows had no bearing on the estimation of secondary evaporation.

We used global mapping by crop type to estimate $I_o$ using a plausible range of published assumptions about water storage capacity. It was assumed that irrigation is just sufficient to replenish lost water without any direct drainage or runoff losses; that is, losses only occur when precipitation exceeds available storage capacity. Following Siebert and Döll (2010), we estimate the available root zone storage capacity ($S_{\text{max, i}}$, in mm) for $i=1...26$ irrigated crop types based on the estimated harvested area ($A_i$, in ha) of each as contained in the MIRCA2000 dataset (Portmann et al., 2010). These numbers are combined with assumed rooting depth ($z_i$) and the allowable fraction of depletion of available soil water ($p_i$ (Allen et al., 1998) for each crop type as proposed by Siebert and Döll (2010). The plant available water content ($\theta_a$) was estimated using global soil property data (Shangguan et al., 2014, see Appendix A), calculated as the difference between $\theta$ at field capacity and...
permanent wilting point, assumed to correspond to water potential values of -3.3 and -150 m, respectively. In formula:

\[ S_{\text{max}} = \frac{\sum A_i z_i \theta_i}{\sum A_i} f_{\text{irr}} \]  

(3)

where \( f_{\text{irr}} \) is the fraction of the grid cell area that is equipped for irrigation (Portmann et al., 2010). This method produced a global average root zone storage of 51 mm per unit of irrigated land, with 90% of values between 10–85 mm, with values depending primarily on the value of \( z_i \).

Because we have observation-based estimates of evaporation, we do not simulate the influence of soil water status on evaporation, but instead, propagate a simple water balance model forced with evaporation estimates. In words, the change in soil moisture storage from one day \( S_t \) to the next \( S_{t+1} \) is the net result of gross rainfall onto the irrigated area \( P_{\text{irr}} \), evaporation from the irrigated area \( E_{\text{irr}} \), the minimum irrigation water application required \( I_0 \) and drainage \( D \), with storage and cumulative fluxes (all in mm):

\[ S_{t+1} = S_t + P_{\text{irr}} - E_{\text{irr}} + I_0 - D \]  

(4a)

Partial rainfall \( P_{\text{irr}} \) is proportional to the irrigation fraction and grid cell rainfall \( P \):

\[ P_{\text{irr}} = f_{\text{irr}} P \]  

(4b)

It is assumed that any increase in the estimate of evaporation \( E' - E \) from data assimilation is due to irrigation, where this occurs, and therefore \( E_{\text{irr}} \) is given by:

\[ E_{\text{irr}} = f_{\text{irr}} E + (E' - E) \]  

(4c)

Any soil water additions more than maximum storage capacity \( S_{\text{max}} \) are assumed to become drainage, and irrigation is assumed to be just enough to prevent \( S<0 \):

\[ I_0 = \max(E_t - P_{\text{irr}} - S_t, 0) \]  

(4d)

\[ D = \max(S_t + P_{\text{irr}} - E_t - S_{\text{max}}, 0) \]  

(4e)

Rainfall interception losses are included in \( E \). Surface runoff and residual drainage are assumed negligible when \( S<S_{\text{max}} \). This is an important simplification, but consistent with the definition of a minimum irrigation requirement estimate that reflects optimal efficiency. The daily water balance model was evaluated with an initial state of \( S=S_{\text{max}} \) and propagated from 2000–2014. The first year was not used in subsequent calculations to allow for artefacts from the initial state chosen.

Evaluation of basin water balance

One test of the accuracy of secondary evaporation estimates is to evaluate whether their inclusion in the basin water balance improves agreement with observations. The difference between \( E' \) derived from data assimilation and the background estimate \( E \) is interpreted to be derived from lateral inflows.
\[ E_{lat} = E' - E \]  
(5a)

For any basin, the total net amount of discharge from the basin \((Q_n)\) is the result of the gross amount of streamflow generated in all tributaries \((Q_g)\) minus secondary evaporation of flows downstream \((E_{lat})\) and the change in storage derived from those flows \((\Delta S_{lat})\):

\[ Q_n = Q_g - E_{lat} - \Delta S_{lat} \]  
(5b)

Natural storage variations in soil and groundwater and river channel storage are explicitly simulated by the model and not included in \(\Delta S_{lat}\). Storage changes in other surface water bodies (e.g., lakes and reservoirs), river-groundwater exchanges, and induced soil or groundwater storage changes directly related to inundation or irrigation (including pumping) would affect \(\Delta S_{lat}\). It is assumed here that the magnitude of \(\Delta S_{lat}\) is negligible compared to the other terms if fluxes are averaged over the period 2001–2014. This needs to be considered when interpreting results for individual basins.

We used discharge data for large basins to evaluate whether our estimates of \(E_{lat}\) improved the overall agreement between modelled and observed \(Q_n\). The river discharge data used were drawn from the global database of end-of-river discharge records compiled by Dai et al. (2009). This includes data for 925 rivers worldwide. Out of these, we considered only basins for which more than five years of data were available during 1995–2014. This longer period was adopted because few basins had sufficient measurements after 2000. To avoid errors arising from differences in the delineation of basins, we rejected basins with a catchment area less than 100,000 km\(^2\) and those with a reported drainage area that was more than 25\% different from the DEM-derived basin area at the river mouth. For the remaining 38 large basins, the temporal and area-average discharge was calculated and compared to the modelled \(Q_n\) and \(Q_g\) (all in mm y\(^{-1}\)).

Closed or endorheic basins represent a special case where \(Q_n=0\) and can also be used to construct a water balance. The 0.05° flow direction grid was used to delineate all internally draining basins located between 72°N and 60°S (further poleward the DEM is affected by land ice). Adjoining endorheic basins were merged into contiguous regions to avoid incorrect basin delineation. From the resulting regions, all those with a surface area greater than 50,000 km\(^2\) were extracted, resulting in 13 contiguous regions. For these regions, Eq. (5b) was evaluated and compared to the expected \(Q_n=0\).

The LST data assimilation changes evaporation without adjusting other water balance terms and hence does not conserve mass balance. In both open and closed basins, this can produce a positive or negative \(Q_n\) from Eq. (5b). A difference between estimated and observed \(Q_n\) can occur for any of four reasons: \(Q_g\) is underestimated, \(E_{lat}\) overestimated, \(\Delta S_{lat}\) is non-negligible, or (for discharging basins only) recorded \(Q_n\) is in error.

**Evaluation of apparent irrigation water use**

Evaluating estimates of secondary evaporation due to irrigation is challenging. Direct observations of evaporation from irrigated land are not widely available, represent point observations, and include
primary evaporation. At basin or country level, estimates of irrigation water use can be categorised as ‘bottom-up’ or 'top-down’ estimates. Bottom-up estimates require scaling of estimated crop water use to field-level irrigation requirements. Top-down estimates involve estimating large-scale withdrawals (e.g., by differencing of discharge measurements along a river reach or measured bulk diversions) and accounting for “project” or scheme losses along the distribution network (Bos and Nugteren, 1990).

Both approaches have large uncertainties but provide estimates of the order of magnitude of irrigation water use.

Bottom-up estimates of irrigation water use at the global scale and for individual countries are available from previous studies (Siebert et al., 2010; Wada et al., 2014; Siebert and Döll, 2010). They involve soil-vegetation water balance modelling. Similar to the approach used here, these methods require assumptions about root zone storage capacity, the rate of drainage of water from the root zone, the permissible range of root zone soil moisture, and the efficiency of irrigation. Unlike the approach used here, they furthermore require assumptions about evaporation, usually following FAO’s crop factor approach (Allen et al., 1998) to model crop water use. The resulting one-dimensional irrigation water requirement estimates are subsequently extrapolated spatially using mapping of areas equipped for irrigation (e.g., Portmann et al., 2010), using assumptions about the number of crop rotations and the area factually irrigated. Each of these assumptions introduces errors and uncertainties.

Nonetheless, a comparison with these studies should provide insight into the method developed here.

An important source of uncertainty in our estimation of large-scale $I_o$ is due to the diffuse spatial distribution of irrigated areas, which is further amplified in current mapping products. The mapping of areas equipped for irrigation contained in the MIRCA2000 dataset (Portmann et al., 2010) was done at 0.08° grid resolution and linearly interpolated to 0.05° resolution in this study. Even at this high resolution, a large proportion of total irrigable land occupies only a small fraction of a grid cell (Figure 2, Figure 3).
Figure 2. Cumulative distribution curve or quantile plot describing the degree to which the global irrigable area is concentrated. It shows that, at 0.05° grid resolution, almost half of the total global irrigable area occupies less than 25% of a grid cell.

The degree of concentration differs between countries for two reasons. Firstly, the true distribution of irrigation land varies; for example, irrigation tends to be highly concentrated in large surface water irrigation schemes (e.g., the Nile delta and Indus floodplains) but can be highly distributed where supplementary irrigation water is drawn from unregulated streams or groundwater. Secondly, the quality, resolution and predictive value of information related to irrigation area varies widely, which affects the accuracy of mapping (Portmann et al., 2010). The distribution of irrigation land introduces uncertainty in the attribution of $E'$ in grid cells with small fractions of irrigated land. We expect that the fraction of a grid cell that needs to be irrigated to create a measurable LST signal may be around 10% but will vary spatially depending on the LST contrast between irrigated and non-irrigated land.

To account for this uncertainty, we calculated the mean $I_o$ (Eq. 4) per unit irrigation area for all grid cells with more than, respectively, 1, 2, 5, 10 and 25% of the area equipped for irrigation. These estimates were subsequently multiplied with the total area equipped for irrigation in each country. The coefficient of variation among the five estimates was calculated as a measure of estimation uncertainty.

The AQUASTAT database (FAO, 2017) provides country-level estimates of agricultural water withdrawal ($W$ in km$^3$ y$^{-1}$) from surface and groundwater. (Domestic and industrial withdrawals are not considered because a large fraction of these withdrawals is not evaporated but returned to the environment.) The estimates are derived by different methods for different countries, and likely include both bottom-up and top-down techniques. Estimates also relate to different periods or years. Despite these uncertainties, they currently represent official international statistics for each country.
Any comparison of field-level irrigation water application ($I_0$) and large-scale water withdrawal ($W$) needs to account for inefficiencies in the entire water distribution network. These include evaporation, leakage and return flow on- and off-farm. ‘Project efficiencies’ that express the ratio of $I_0$ over $W$ can be estimated in principle, but this requires detailed ancillary data (Bos and Nugteren, 1990). In their global modelling study, Siebert and Döll (2010) proposed ratios range from 0.25 for irrigation dominated by paddy rice to 0.70 for efficient crop irrigation methods in Canada, Northern Africa and Oceania. We did not assume values but instead calculated an ‘apparent’ bulk project efficiency for each country, by dividing the ratio of modelled $I_0$ over $W$ reported in AQUASTAT. The credibility of the resulting values was subsequently interpreted within the framework developed by Bos and Nugteren (1990).

**Secondary evaporation and the global water cycle**

Total secondary evaporation was estimated as the sum of open water evaporation plus the difference $E'-E$, representing the difference between modelled primary evaporation $E$ for a situation where precipitation is the only source of water (the background estimate) and total evaporation $E'$ resulting from LST assimilation (the analysis estimate). The resulting estimate of total secondary evaporation is a hypothetical and model-based quantity. Evaporation in the absence of lateral flows is counterfactual and not necessarily accurately estimated by the model, particularly in humid environments. Furthermore, all open water evaporation was included in secondary evaporation; we did not attempt to estimate the evaporation that might have occurred from the surface had it not been covered by water.

The difference $E'-E$ was distributed dynamically in proportion to the magnitude of each of the three evaporation terms (i.e., transpiration, soil evaporation, and open water evaporation; wet canopy evaporation was left unchanged). A component of secondary evaporation was attributed to irrigation following the method described earlier. The remainder could be attributed to permanent water bodies, ephemeral water bodies, and a residual component that includes any evaporation from replenished wetlands and floodplains, as well as any use of groundwater sources beyond that simulated by the model to occur from shallow groundwater (Peeters et al., 2013).

**Results**

**Basin water balance**

The combined surface area of the 51 basins used in evaluation (38 ocean-draining and 13 closed basins) was 63 million km$^2$ or 47% of the ice-free land surface area (Figure 3, Figure 4). For each region, the period-average measured discharge (zero in the case of closed basins) was compared with modelled $Q_s$ and $Q_n$ (Figure 4, Figure 5, Table 1). Overall, accounting for secondary evaporation produced a very small improvement in the correlation between observed and estimated discharge (Figure 4, Figure 5a). However, the largest error contribution was from basins with high discharge.
rates, where secondary evaporation represents a small fraction of $Q_s$. A clearer improvement in the
agreement was found for basins with less than 300 mm y\(^{-1}\) net discharge (Figure 4Figure 5cd). The
explained variance ($R^2$) increased from 0.67 to 0.71, and there was a reduction of the bias from +38 to
+2 mm y\(^{-1}\). Water balance estimates were improved considerably for several basins, including the
Indus River (‘I’ in Figure 4Figure 5cd), Nile River, the Great Basin in the USA, and the African Rift
Valley (Table 1). The agreement could not improve where $Q_s$ estimates were already lower than
observed, such as the Paraná and Fitzroy Rivers (‘P’ and ‘F’ in Figure 4Figure 5cd). Water balance
estimates for some closed basins were also degraded, evident from negative $Q_n$ values (e.g., the South
Interior and Rukwa basins in Southern Africa), implying that $Q_s$ was underestimated, secondary
evaporation overestimated, or both (Table 1).
Figure 3 and Figure 4. Extent and area-average annual discharge for the 38 ocean-draining (orange to blue) and 13 closed basins (dark orange) used in the evaluation. The two darkest blue colours indicate a discharge in excess of 300 mm y\(^{-1}\).
Figure 4. Comparison of observed basin-average discharge (mm y$^{-1}$) for large basins that are internally draining (i.e., zero discharge) or have adequate station discharge data with model estimates of (a) net discharge ($Q_n$), that is, gross discharge ($Q_g$) minus secondary evaporation, and (b) $Q_g$ only. (c) and (d) data for discharge below 300 mm y$^{-1}$ only (cf. Table 1). Letters indicate Indus (I), Paraná (P), and Fitzroy (F) River.
Table 1. Area-average discharge (mm y\(^{-1}\)) for selected basins as observed and estimated by the model in the presence \(Q_n\) and absence \(Q_g\) of secondary evaporation, respectively. Listed data for basins with discharge less than 300 mm y\(^{-1}\) only (cf. Figure 4Figure 5cd).

| Area-average basin discharge (mm y\(^{-1}\)) | estimated | Observed |  \\
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Closed river basins</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Great Basin, US</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td>Guzman, North America</td>
<td>-</td>
<td>-6</td>
</tr>
<tr>
<td>Mairan-Viesca, Mexico</td>
<td>-</td>
<td>-15</td>
</tr>
<tr>
<td>Patagonia, South America</td>
<td>-</td>
<td>5</td>
</tr>
<tr>
<td>Titicaca-Chiquita, South America</td>
<td>-</td>
<td>-19</td>
</tr>
<tr>
<td>North Interior, Africa</td>
<td>-</td>
<td>-4</td>
</tr>
<tr>
<td>South Interior, Africa</td>
<td>-</td>
<td>-71</td>
</tr>
<tr>
<td>Rukwa, Africa</td>
<td>-</td>
<td>-56</td>
</tr>
<tr>
<td>Rift Valley, Africa</td>
<td>-</td>
<td>35</td>
</tr>
<tr>
<td>Jordan</td>
<td>-</td>
<td>-1</td>
</tr>
<tr>
<td>Arabian peninsula</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>Central Asia</td>
<td>-</td>
<td>57</td>
</tr>
<tr>
<td>Central Australia</td>
<td>-</td>
<td>-20</td>
</tr>
<tr>
<td><strong>Ocean-reaching rivers</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nile, Africa</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>Murray, Australia</td>
<td>1</td>
<td>-5</td>
</tr>
<tr>
<td>Orange/Senqu, Africa</td>
<td>7</td>
<td>-9</td>
</tr>
<tr>
<td>Colorado, US</td>
<td>23</td>
<td>33</td>
</tr>
<tr>
<td>Huanghe, China</td>
<td>24</td>
<td>61</td>
</tr>
<tr>
<td>Burdekin, Australia</td>
<td>48</td>
<td>70</td>
</tr>
<tr>
<td>Parnaiba, Brazil</td>
<td>76</td>
<td>94</td>
</tr>
<tr>
<td>Brazos, US</td>
<td>57</td>
<td>64</td>
</tr>
<tr>
<td>Fitzroy, Australia</td>
<td>54</td>
<td>6</td>
</tr>
<tr>
<td>Indus, Asia</td>
<td>58</td>
<td>172</td>
</tr>
<tr>
<td>Sao Francisco, Brazil</td>
<td>105</td>
<td>97</td>
</tr>
<tr>
<td>Niger/Issa Ber, Africa</td>
<td>88</td>
<td>78</td>
</tr>
<tr>
<td>Nelson, Canada</td>
<td>85</td>
<td>52</td>
</tr>
<tr>
<td>Paraná, South America</td>
<td>255</td>
<td>163</td>
</tr>
<tr>
<td>Elbe/Labe, Europe</td>
<td>172</td>
<td>224</td>
</tr>
<tr>
<td>Mississippi, US</td>
<td>204</td>
<td>198</td>
</tr>
</tbody>
</table>
Irrigation water requirements

Spatiotemporal estimates of \(I_0\) at 0.05° and daily time step were aggregated to country-level estimates in km\(^3\) y\(^{-1}\) (Table 2). Also calculated were the coefficient of variation in \(I_0\) estimates (\(CV_{I0}\)) caused by the treatment of ‘mixed pixels’ in irrigation mapping, FAO-reported annual \(W\), and the apparent project irrigation efficiency. Global \(I_0\) for 2001–2014 was 680 km\(^3\) y\(^{-1}\) (standard deviation 110 km\(^3\) y\(^{-1}\)). This value is lower than estimates of contemporary irrigation water use reported in the literature of 1092 km\(^3\) y\(^{-1}\) (Döll and Siebert, 2002), 1180 km\(^3\) y\(^{-1}\) (Siebert and Döll, 2010) and 994–1179 km\(^3\) y\(^{-1}\) (Wada et al., 2014). Estimates of \(I_0\) listed for seven countries by Döll and Siebert (2002) were all higher than those found here (Table 2), and even more than double for the USA (112 vs. 48 km\(^3\) y\(^{-1}\)) and Spain (21 vs 5.1 km\(^3\) y\(^{-1}\)). Quoted independent estimates were 113 km\(^3\) y\(^{-1}\) for the USA (Solley et al., 1998) and 15 km\(^3\) y\(^{-1}\) for Spain (J.A. Ortiz cited in Döll and Siebert, 2002).

Table 2. Irrigation water withdrawal (\(W\)) as reported to FAO for the 20 countries with largest agricultural withdrawals, along with the estimated minimum field-level irrigation requirement (\(I_0\)), the coefficient of variation in \(I_0\) estimates (\(CV_{I0}\)) and the apparent project efficiency (\(I_0/W\)).

<table>
<thead>
<tr>
<th>Country</th>
<th>(W)</th>
<th>(I_0)</th>
<th>(CV_{I0})</th>
<th>(I_0/W)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>km(^3) y(^{-1})</td>
<td>km(^3) y(^{-1})</td>
<td></td>
<td></td>
</tr>
<tr>
<td>India</td>
<td>688</td>
<td>152</td>
<td>0.07</td>
<td>0.22</td>
</tr>
<tr>
<td>China</td>
<td>392</td>
<td>105</td>
<td>0.13</td>
<td>0.27</td>
</tr>
<tr>
<td>United States of America</td>
<td>175</td>
<td>48</td>
<td>0.20</td>
<td>0.27</td>
</tr>
<tr>
<td>Pakistan</td>
<td>172</td>
<td>49</td>
<td>0.01</td>
<td>0.28</td>
</tr>
<tr>
<td>Indonesia</td>
<td>93</td>
<td>14</td>
<td>0.10</td>
<td>0.15</td>
</tr>
<tr>
<td>Iran</td>
<td>86</td>
<td>5</td>
<td>0.22</td>
<td>0.06</td>
</tr>
<tr>
<td>Viet Nam</td>
<td>78</td>
<td>15</td>
<td>0.05</td>
<td>0.19</td>
</tr>
<tr>
<td>Philippines</td>
<td>67</td>
<td>5</td>
<td>0.16</td>
<td>0.07</td>
</tr>
<tr>
<td>Egypt</td>
<td>67</td>
<td>30</td>
<td>0.02</td>
<td>0.44</td>
</tr>
<tr>
<td>Mexico</td>
<td>62</td>
<td>19</td>
<td>0.22</td>
<td>0.31</td>
</tr>
<tr>
<td>Japan</td>
<td>54</td>
<td>4</td>
<td>0.23</td>
<td>0.07</td>
</tr>
<tr>
<td>Iraq</td>
<td>52</td>
<td>5</td>
<td>0.19</td>
<td>0.10</td>
</tr>
<tr>
<td>Thailand</td>
<td>52</td>
<td>16</td>
<td>0.09</td>
<td>0.32</td>
</tr>
<tr>
<td>Uzbekistan</td>
<td>50</td>
<td>11</td>
<td>0.02</td>
<td>0.21</td>
</tr>
<tr>
<td>Brazil</td>
<td>45</td>
<td>16</td>
<td>0.39</td>
<td>0.36</td>
</tr>
<tr>
<td>Turkey</td>
<td>34</td>
<td>6</td>
<td>0.36</td>
<td>0.16</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>32</td>
<td>20</td>
<td>0.08</td>
<td>0.63</td>
</tr>
<tr>
<td>Burma</td>
<td>30</td>
<td>13</td>
<td>0.21</td>
<td>0.43</td>
</tr>
<tr>
<td>Chile</td>
<td>29</td>
<td>2</td>
<td>0.22</td>
<td>0.07</td>
</tr>
<tr>
<td>Argentina</td>
<td>28</td>
<td>5</td>
<td>0.47</td>
<td>0.17</td>
</tr>
<tr>
<td>Global</td>
<td>2,767</td>
<td>680</td>
<td>0.16</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Figure 5. Figure 6. Comparison of country-level agricultural water withdrawal (W) (FAO, 2017) and estimated minimum irrigation requirement ($I_0$) expressed as (a) total volume, and (b) depth per unit area of area equipped for irrigation for countries with $>1$ km$^3$ y$^{-1}$ withdrawals ($N=91$). Dotted lines show apparent project efficiencies between the two quantities. Countries indicated are (in a) Egypt (EG), Pakistan (PK), United States (US), China (CN) and India (IN), and (in b) Cambodia (KH), Senegal (SN), Mauritania (MR), United Arab Emirates (AE), Chile (CL), and the Philippines (PH).

The $I_0$ explains 96% in the variance in W by country (Figure 5), but total variance is dominated by only four countries, and the area equipped for irrigation explains already explains 86% of the variance. Volumes were divided by the total area equipped for irrigation to normalise for these effects. Normalised $I_0$ explained 38% of the variance in normalised W (Figure 6). A high correlation between the two is not necessarily to be expected, as country-average project efficiencies will vary (represented by the lines in Figure 6b). For example, a low efficiency is inferred and would be expected in the Philippines, where irrigation is dominated by paddy rice agriculture, whereas higher efficiencies would be expected in large schemes in arid countries such as Egypt and Mauritania. Nonetheless, apparent efficiencies are generally lower than would be expected based on benchmark estimates provided by Bos and Nugteren (1990). For example, using global volumes of $I_0$ and W, a project efficiency of 0.25 is calculated. This is lower than estimates of 0.36–0.43 assumed in previous studies (Döll and Siebert, 2002; Wada et al., 2014; Siebert and Döll, 2010). Physically impossible or implausible project efficiencies were also calculated for some countries, including Cambodia ($I_0/W > 1$), and the United Arab Emirates and Chile ($I_0/W < 0.1$) (Figure 6b). Possible explanations for this will be discussed.
Secondary evaporation and the global water cycle

We estimate that secondary evaporation contributed 41.2 mm y\(^{-1}\) or 8.1% to total evaporation from the global land area during 2001–2014 (Table 3), equivalent to 5.4% of terrestrial precipitation (759 mm y\(^{-1}\)) and 16% of generated streamflow (258 mm y\(^{-1}\)). Globally, only a very small percentage of all secondary evaporation (5%) was due to irrigation. Overall more important pathways for secondary evaporation were evaporation from permanent water bodies (48%), enhanced transpiration associated with wetland vegetation or greater-than-predicted groundwater uptake (27%), enhanced soil evaporation (11%), and evaporation from ephemeral water bodies (10%). Surface and groundwater inputs enhance global plant transpiration by an estimated 12.1 mm y\(^{-1}\), representing a 4.4% increase. Of this increase, 10% can be attributed to irrigation.

Table 3. Estimates of annual primary and secondary evaporation (\(E\) in mm y\(^{-1}\)) components for 2001–2014 expressed as water depths across the global terrestrial area (149·10\(^6\) km\(^2\)).

<table>
<thead>
<tr>
<th>Component</th>
<th>Primary E</th>
<th>Secondary E</th>
<th>Total</th>
<th>Irrigation only</th>
</tr>
</thead>
<tbody>
<tr>
<td>wet canopy E</td>
<td>81.3</td>
<td>–</td>
<td>81.3</td>
<td>–</td>
</tr>
<tr>
<td>transpiration</td>
<td>278.7</td>
<td>12.1</td>
<td>290.8</td>
<td>1.2</td>
</tr>
<tr>
<td>soil E</td>
<td>107.0</td>
<td>4.9</td>
<td>111.9</td>
<td>0.5</td>
</tr>
<tr>
<td>E from ephemeral water</td>
<td>–</td>
<td>4.6</td>
<td>4.6</td>
<td>0.3</td>
</tr>
<tr>
<td>E from permanent water</td>
<td>–</td>
<td>19.6</td>
<td>19.6</td>
<td>–</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>467.0</strong></td>
<td><strong>41.2</strong></td>
<td><strong>508.2</strong></td>
<td><strong>2.0</strong></td>
</tr>
</tbody>
</table>

The spatial distribution of evaporation from irrigation areas (Figure 6, Figure 7a) and permanent water bodies (Figure 6, Figure 7b) largely reflects the irrigation and water mapping input data, respectively. The spatial distribution of other sources of secondary evaporation provides some new insights (Figure 6, Figure 7c). Globally, some areas with the greatest secondary evaporation volumes include receiving floodplains in tropical monsoonal regions. The main regions in South America include the Gran Chaco and Pantanal plains and Amazon floodplains (Figure 7, Figure 8). The main regions in Africa the Southern Interior basin in Botswana and surrounding countries (including the Okavango Delta and other wetlands), and the floodplains of the White Nile River in South Sudan and the Inner Niger Delta (Figure 8, Figure 9). Other areas with high secondary evaporation rates include the Yucatan peninsula in Mexico (Figure 7, Figure 8), the boreal wetlands and ephemeral lakes of Canada and Scandinavia (Figure 7, Figure 8 and Figure 8, Figure 9, respectively), and the salt lakes and floodplains of inland Australia (Figure 9, Figure 10).
Figure 6. Spatial distribution of estimated secondary evaporation losses derived from (a) irrigation, (b) permanent water bodies, and (c) other sources, including wetlands and floodplains.
Figure 7. Spatial distribution of secondary evaporation losses in the Americas.

Figure 8. Spatial distribution of secondary evaporation losses in the Americas.
Figure 8. Spatial distribution of secondary evaporation losses in Eurasia and Africa.

Figure 9. Spatial distribution of secondary evaporation losses in Africa.
Figure 9. Figure 10. Spatial distribution of secondary evaporation losses in Eastern Asia and Oceania.
There is a pronounced seasonal cycle in secondary evaporation at global scale (Figure 11). The rate of secondary evaporation is more than two times higher in northern summer than in northern winter. This is primarily due to the greater rate of evaporation from the many surface water bodies in formerly glaciated regions, including the American Great Lakes, as well as a higher rate of evaporation from the Caspian Sea. By contrast, secondary evaporation in regions located wholly or partially in the southern hemisphere show a much less pronounced seasonal cycle and a greater influence of water availability. Averaged over time, each of the regions considered makes a similarly sized contribution to secondary evaporation globally (10–24%) with the exception of Antarctica (0.4%).

Discussion

Uncertainties in evaporation estimation

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Figure 11. Average (2001–2012) seasonal cycle of secondary evaporation at global scale (black line) and the contribution from different regions (colours corresponding to the map). All rates are expressed in mm d\(^{-1}\) for the global land area.
The uncertainty in estimates of secondary evaporation arises from three main sources: (1) estimation of ‘background’ evaporation $E$; (2) estimation of surface water evaporation; and (3) estimation of total evaporation $E'$ by LST assimilation. A formal assessment of error in each of these terms is not possible for lack of observations and will vary in space and time. Below we discuss what we expect to be the main sources of uncertainty in each component.

An error in background model $E$ may be compensated by data assimilation, but still leads to an error in the estimated secondary evaporation, calculated as $E' - E$. The main sources of error in $E$ vary as a function of environmental conditions and the quality and density of the measurement network on which the meteorological forcing data are based. In water-limited environments, the most likely sources of error in $E$ are errors in precipitation estimates and the simulation of water availability in the root zone. The quality of precipitation estimates is relatively poor in many of the world’s dry regions (Beck et al., 2017). Information on the ability of vegetation to access deeper soil moisture and groundwater is important, particularly in ephemerally wet systems, but is not available at the global scale. In humid environments, the most likely sources of error in $E$ are in the estimation of rainfall interception losses, the net available energy for evaporation, and surface conductance. As part of earlier model development, background $E$ was compared with estimates derived from flux tower observations and compared with alternative ET estimation methods (Yebra et al., 2013; Van Dijk, unpublished and supplement to this article). These evaluations showed little if any no systematic bias in $E$ and a standard difference of 135–168 mm y$^{-1}$ across sites ($N=16–168$). This total difference also includes errors in the flux tower-derived estimates (e.g., due to a lack of energy balance closure) and differences arising because the tower footprint is not representative of the grid cell. Therefore the true error in our estimates will be lower.

Observation-based estimates of large-area evaporation from water bodies, wetlands and irrigated areas (i.e. $>0.05^\circ$) are scarce. Some site measurements of wetland and irrigation evaporation have been published (e.g., Guerschman et al., 2009) but typically reflect an environment with very high spatial variation and therefore often cannot easily be compared to estimates at 0.05$^\circ$. A coordinated effort that collates observations of secondary evaporation and combines these with historical time series remote sensing imagery (cf. Figure 1a) to generate estimates at a more representative spatial scale would appear necessary and valuable.

Errors in the estimation of surface water evaporation are the combined result of errors in the estimation of open water evaporation rate and the mapping of surface water extent. Open water evaporation rate was estimated using the Priestley and Taylor (1972) approach. An important uncertainty in this approach is that it does not account for strong contrasts in near-surface water temperature. Surface water extent was mapped using 8-day MODIS shortwave infrared (SWIR) reflectance composites (Van Dijk et al., 2016). Systematic overestimation of water extent can occur in low relief regions with very low SWIR reflectance (e.g., lava outflows), whereas underestimation can occur in regions with a dense elevated canopy that prevents water detection (e.g.,
floodplain forests or mature flooded crops). Values of the updated $\lambda E'$ were constrained to positive values below or equal to potential evaporation $E_0$, and therefore any gross underestimation of $E_0$ by the model due to errors in meteorological forcing data would have resulted in an underestimation of the true evaporation rate.

The LST assimilation mitigates estimation errors in background and open water evaporation but is also subject to uncertainties of its own. The technique developed here relies on the assumption that there is a perfect correlation between spatial LST anomalies at the time-of-overpass (around 10 am local time) and daytime (sunrise-sunset) average values, or at least for the low-relief areas where LST was assimilated. A systematic bias in the global estimates of governing variables (radiation, air temperature and humidity, wind speed) are likely to be less problematic than spatially variable differences in those low-relief areas. In reality, there can be spatial differences in the temporal rate of LST change, for example, as a function of spatial differences in heat storage capacity and aerodynamic conductance (Kalma et al., 2008). Furthermore, we assumed a constant, maximum bias-adjusted error of 1 K in the difference between observed and model background LST. Each of these choices can-could have affected the efficacy of the assimilation.

Nonetheless, assessment of temporal patterns in $E'$ (such as in Figure 1c) and the spatial patterns in secondary evaporation (Figures 6–9) agree with known areas receiving lateral inflows (e.g., wetlands) or irrigation. Less expected were the widespread high secondary evaporation rates in the northern Yucatan peninsula in Mexico and the Southern Interior in Southern Africa. The northern Yucatan peninsula is a low lying region with karst geology and forest are known to access shallow groundwater (Bauer-Gottwein et al., 2011). The Southern Interior includes several terminal wetlands (e.g., the Okavango Delta) and has unconsolidated alluvial deposits that contain productive aquifers (MacDonald et al., 2012) and it is plausible that at least some of the vegetation has access to deeper soil moisture or groundwater. In both cases, the background evaporation estimate ($E$) is constrained by precipitation and the corresponding simulated presence of soil- and groundwater within the root zone ($E$). Any underestimation of $E$ leads to an increased estimate $E' - E$ and therefore an increased estimate of secondary evaporation, without necessarily implying that all the water involved is derived from later inflows. An alternative measure of the importance of secondary evaporation is $E' - P$ (Figure 4011). These results suggest that period-average $E'$ exceeds $P$ by in the order of 100 to 200 mm y$^{-1}$.

For the Southern Interior basin, we found an apparent overestimation of c. 72 mm y$^{-1}$ (Table 1) which suggests that at least some of this difference is realistic. Underestimation of precipitation may also go some way towards explaining these differences: both regions are in transitional climates with a relatively strong, non- orographic precipitation gradient of 900–1400 mm y$^{-1}$ (Yucatan) and 400–1100 mm y$^{-1}$ (Southern Interior), respectively. Combined with a low density of rainfall gauges (Hijmans et al., 2005), these gradients make a systematic bias in rainfall estimates more plausible. We analysed global water cycle reanalysis data that integrated GRACE gravity observations in an earlier study (Van Dijk et al., 2014) for a largely overlapping period (2003–2012) to test this.
Southern Interior, the reanalysis demonstrated a clear increasing trend in subsurface storage (+12.3 mm y\(^{-1}\)) that was not reproduced by an ensemble of models (+2.0 mm y\(^{-1}\)). This suggests that the global precipitation estimates used by models were indeed too low for this period, as also concluded by Van Dijk et al. (2014). For the Yucatan peninsula, a slight storage decrease (-3.3 mm y\(^{-1}\)) was inferred from the reanalysis, whereas the model ensemble suggested a slight increase (2.7 mm y\(^{-1}\)). This does not suggest any underestimation of precipitation. A net use of groundwater does appear plausible in this case, though likely not enough to explain the secondary evaporation rates estimated here.

**Figure 12.** Mean difference between total evaporation and precipitation for 2001–2014 for (a) Botswana and (b) the Yucatan peninsula, and surrounding areas.

**Uncertainty in irrigation water requirement estimation**

The total estimate of minimum irrigation water requirement \(I_0\) at the global scale was about a third lower than previous model-based estimates (Siebert et al., 2010; Wada et al., 2014; Siebert and Döll, 2010). There are some likely explanations for this. Firstly, the diffuse distribution of areas equipped for irrigation (Figure 2) means that the LST signal from irrigation will likely have been too small to estimate the associated \(I_0\) correctly everywhere. An insufficient LST signal is most likely for grid cells and countries with a temperate and humid climate and highly distributed irrigation, such as the US, where our estimate of \(I_0\) was twice smaller than published previously. Conversely, irrigation evaporation estimates should be more accurate in hot, arid regions with large and concentrated irrigation, such as Egypt’s Nile Delta (Figure 1). The temporal pattern of the evaporative fraction for this grid cell corresponds well with that of vegetation cover (Figure 1e) and assumes values that
appear realistic, even more so when considering that only around 80% of the grid cell was irrigated (Figure 1a).

Second, previous studies have estimated crop water use (and from that, \( I_0 \)) using the FAO method of Allen et al. (1998). This method assumes a well-growing crop not affected by ineffective or insufficient irrigation, unfavourable weather, nutrition or soil, pests and diseases, or other growth-limiting factors. The resulting crop water use estimates are likely to represent idealised conditions and may be higher than actual water use.

Third, errors in irrigation area mapping are also likely to have played a role. It is noteworthy that the MIRCA2000 mapping used here (Portmann et al., 2010) indicated that 100% of the grid cell in Figure 1a was equipped for irrigation. This is not the case: most unirrigated areas are settlements. Previous studies will have assumed the entire area was available for irrigation and this difference alone would cause their \( I_0 \) estimates for this particular grid cell to be 25% higher. While these numbers relate to just a single grid cell, it serves to demonstrate that incorrect mapping of irrigation areas can have considerable impact on our \( I_0 \) estimates. As another example, any irrigation outside the grid cells indicated to have at least some irrigable area in the MIRCA2000 mapping would be wholly attributed to non-irrigation forms of secondary evaporation.

Despite these caveats, it is highly likely that true irrigation water application is greater than our estimate \( I_0 \), as it was defined as a hypothetical quantity that might occur under conditions of optimally efficient irrigation. Previous studies have made similar assumptions. In reality, field-level irrigation efficiency is reduced by additional drainage below the root zone and any surface runoff that may occur. Further uncertainties are introduced through the necessary assumptions about rooting depth and root zone storage capacity. The comparison with FAO-reported \( W \) estimates suggests project efficiencies that are lower than those assumed in previous studies, but the overall correlation between country \( I_0 \) and \( W \) volumes was high, and could not solely be attributed to differences in irrigated area (Figure 6). A comparison of country \( I_0 \) and \( W \) expressed as area-average rates indicates contrasts in project efficiency that are expected in several cases. In other cases, values are outside a plausible range. At least some of these poor estimates are likely related to the mentioned inaccuracies in irrigation mapping (e.g., Chile and the United Arab Emirates in Figure 6b).

Overall, the method developed here shows a promising approach to estimate irrigation water use. Estimation at an even higher spatial resolution should help to detect the LST signal more accurately where irrigation areas are dispersed and so produce better estimates of \( E' \). This provides a powerful argument in support of ‘hyper-resolution’ water balance observation and modelling (Wood et al., 2011). All satellite-derived inputs are available at a resolution that is about an order of magnitude finer (500–1000 m) than used here, and computationally data assimilation at this resolution is also already feasible. The main impediment is the resolution and quality of irrigation area mapping, which is required to attribute secondary evaporation to irrigation and other sources. The \( E' \) estimates
themselves may assist in mapping, along with information on temporal vegetation patterns, open water mapping and relief, among others. This is an avenue we hope to pursue in future.

**Importance of secondary evaporation in the global water cycle**

Our analysis suggests that secondary evaporation makes a meaningful contribution to global evaporation (8.1%) and reduces the amount of discharge to the oceans by c. 16%. At the global scale, irrigation is responsible for only a small fraction of this reduction (c. 5%), with the remainder occurring from water bodies and wetlands. These global averages hide significant regional variation. For example, irrigation plays an important role in the evaporation of river flows in the Nile, Indus and Murray-Darling basins, where most of the discharge is evaporated before reaching the ocean. About half of total global secondary evaporation is from permanent freshwater bodies, including from some very large water bodies such as the Caspian Sea, the Great Lakes, and the African Rift Valley Lakes.

There is a strong seasonal cycle in secondary evaporation at global scale, driven by evaporation from extensive surface water bodies in formerly glaciated regions in the northern hemisphere. This illustrates the profound impact that glaciation has had on regional landscape hydrology, and its influence at global scale.

We estimated global terrestrial evaporation to be 508 mm y\(^{-1}\) per unit land area or 75.5·10\(^{12}\) m\(^3\) y\(^{-1}\) total for 2001–2014, made up of 467 mm y\(^{-1}\) or 69.6·10\(^{12}\) m\(^3\) y\(^{-1}\) primary evaporation and 41.2 mm y\(^{-1}\) or 6.1·10\(^{12}\) km\(^3\) y\(^{-1}\) secondary evaporation. This is close to estimates derived from previous studies. For example, Miralles et al. (2016) reported 13 estimates of terrestrial \(E\), derived from a variable combination of satellite observations and modelling, with an average value of 69.2·10\(^{12}\) km\(^3\) y\(^{-1}\) and coefficient of variation (CV) of ±10%. Schellekens et al. (2017) reported a mean of 74.5·10\(^{12}\) km\(^3\) y\(^{-1}\) (CV of ±6%) for an ensemble of 10 state-of-the-art global hydrological models and land surface models. Some of these differences are attributable to the differences in total area and period considered, but the different datasets also includes secondary evaporation losses to different degrees. Given these represent 8% of total evaporation, such inconsistencies help to explain differences between estimates.

The partitioning between primary evaporation components is within the range of recently published estimates, though noting that those ranges are broad (Table 4). Secondary evaporation is fully responsible for open water evaporation and has no impact on wet canopy evaporation; both are a logical consequence of the way these terms are conceptualised. It is estimated that global transpiration and soil evaporation are both enhanced by about 4.5% due to secondary evaporation of surface and groundwater resources. Irrigation is responsible for a tenth of this increase, with the remainder due to natural processes. Because of the coupling between transpiration and carbon uptake, it can be assumed that these enhancements will increase global carbon uptake by a similar proportion. Once again these small contributions apply at global scale, but there are strong differences locally and regionally.
Table 4. Estimated percentage of total (or, between brackets, primary) terrestrial evaporation ($E$) contributed by different pathways, compared with estimates from two recent studies.

<table>
<thead>
<tr>
<th>Percent of total $E$</th>
<th>this study</th>
<th>Zhang et al. (2016)</th>
<th>Miralles et al. (2016)</th>
</tr>
</thead>
<tbody>
<tr>
<td>wet canopy $E$</td>
<td>16 (17)</td>
<td>10</td>
<td>10-24</td>
</tr>
<tr>
<td>transpiration</td>
<td>57 (60)</td>
<td>65</td>
<td>24-76</td>
</tr>
<tr>
<td>soil $E$</td>
<td>21 (23)</td>
<td>25</td>
<td>14-52</td>
</tr>
<tr>
<td>open water $E$</td>
<td>4 (0)</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Thiery et al. (2017) simulated the global impact of irrigation using coupled land surface and atmosphere models. They estimated an evaporation increase from irrigation of 418 km$^3$ y$^{-1}$; of similar magnitude to the 300 km$^3$ y$^{-1}$ we found. Despite this small contribution to total global evaporation, their modelling did predict small but meaningful reductions in high-temperature extremes over and near large irrigation areas; irrigation rates tend to be highest during hot and dry conditions. To the best of our knowledge, there have been no studies on the impact of wetlands and water bodies on regional and global climate so far. Given that we estimate these other forms of secondary evaporation to be twenty times greater than from irrigation, their impact on the atmosphere should be significant.

Conclusions

We presented a methodology to assimilate thermal satellite observations into a global hydrological model W3 at a resolution of 0.05° to estimate secondary evaporation of surface and groundwater resources. In addition, we used a simple irrigation water balance model to estimate minimum irrigation requirement ($I_0$) globally. Our main conclusions are as follows.

1. The method developed produces realistic temporal and spatial patterns in secondary evaporation. Accounting for secondary evaporation measurably improved water balance estimates for large closed and open basins, reducing bias in the overall water balance closure from +38 to +2 mm y$^{-1}$.

2. Our $I_0$ estimates were lower than country-level estimates of irrigation water use produced by other model estimation methods, for three reasons. Firstly, at the 0.05° resolution, much of global irrigated land occupies only a small part of individual grid cells and may not reduce LST sufficiently to be accurately estimated. Second, our $I_0$ estimates reflect actual evaporation, which can be lower than idealised crop water use estimates used in previous studies. Third, spatial errors in irrigation area mapping directly affect the attribution of secondary evaporation to irrigation. Overall, actual irrigation application will most likely be higher than estimated here but possibly lower than reported previously.
The role of irrigation water use in secondary evaporation is minor at the global scale, accounting for 5% of total secondary evaporation and 0.4% of total terrestrial evaporation. Nonetheless, water withdrawals and irrigation evaporation are an important part of the water balance in some regions.

(4) Around 16% of globally generated water resources evaporate before reaching the oceans or from closed basins, enhancing total terrestrial evaporation by 8.8%. Of this secondary evaporation, 5% is evaporated from irrigation areas, 58% from water bodies, and 37% from other surfaces.

(5) Lateral inflows of surface and water resources were estimated to increase global plant transpiration by c. 4.5%. The impact on global carbon uptake would be expected to be of similar magnitude. Previous studies have predicted that irrigation evaporation affects regional and global climate. Given evaporation from wetlands and permanent water bodies is an order of magnitude larger, their impact on the climate system should be pronounced.

There is scope for further improvement in accounting for natural and anthropogenic secondary losses by applying the model-data assimilation approach developed here at higher resolution. This is conceptually straightforward and computationally achievable. Key developments required include more accurate and detailed dynamic observational data on surface water dynamics and more accurate mapping of areas equipped for irrigation.

Data availability

The 5-km water balance estimates presented here are available via http://www.wenfo.org/wald/data-software/.

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Author contribution

AVD conceptualised the study. JS, HB, AW and GD developed global input data for the modelling. MY developed the remote sensing evaporation scheme. LR assisted in the development of the data assimilation approach. AVD carried out the analysis and wrote the first draft manuscript. All other authors contributed to the analysis, interpretation and writing.
References


