Answers to Referee Comment #1

RV#1:
The authors describe the development of a global data set of irrigated land. Irrigation mapping was performed by using such a data set published before (Siebert et al., 2013), remote sensing based vegetation activity and ancillary information such as cropland masks, suitability maps and climate data (Table 1). Better knowledge where and when irrigation is used is very important for many applications, therefore attempts to reduce the present uncertainty are highly welcome. The manuscript is well written and the figures presented in it are of high quality.

Authors:
Thank you for reviewing our manuscript, your valuable and sophisticated comments and your general recognition of the meaning of the topic. In the following we try to address your concerns – please find below our improvements.

RV#1:
1) Title and abstract of the manuscript show that the authors cannot put their contribution into the context of the present knowledge and completely fail to describe the scientific merit and the innovation of their research. Title and abstract suggest that previous attempts to map irrigation were restricted to the use of survey based land use statistics and indicate that using of remote sensing and of suitability maps represents a major innovation. This is definitely wrong

Authors:
We agree that title, abstract and some parts of the methodology leave space for misinterpretation. Accordingly, we revised both, title and abstract completely as well as parts of the methodology to better put our contribution to the scientific context. To address your concerns, we suggest a new title, which goes more into detail of what we did:
"A global approach to estimate irrigated areas – a comparison between different data and statistics"
As you mentioned, the irrigation map by Siebert et al. (2013) allocates irrigation to agricultural land according to statistical data and land use classification data. On the basis of this map we include irrigated areas that are not mapped in the approach by Siebert et al. (2013). We do this by following a decision tree that uses several input data (crop suitability based on topography, soil and climate, multi-temporal NDVI data, land-use classifications). Given the decision tree, we decide that a pixel which is not classified as irrigated in Siebert et al. (2013) must be irrigated or not. Thus, our approach allows allocating more irrigated areas than statistically designated for a specific region. A spatial detection and quantification of these additional irrigated areas seems scientifically important and innovative, since it illustrates a gap between different data from different sources and methods. Analyzing these differences (between the statistically calibrated Siebert et al. (2013) data and our new irrigation map) could be of interest for the scientific community.

RV#1:
At global scale, there are three other data sets of irrigated land which were published before: Thenkabail et al. (2009) used remote sensing and ancillary information to map irrigation but they did not apply survey based land use statistics in their mapping algorithm at all. The same appears for Salmon et al. (2015). Siebert et al. (2013) is the only study that uses survey based land use statistics for mapping irrigated land but in addition they also apply a huge variety of remote sensing based national land cover products and remote sensing imagery as well. Therefore, using remote sensing products and suitability information is certainly not an innovation; it is the present standard in mapping irrigated land.

Authors:
We are aware of these publications and cited all of them. It is well-known that previous approaches already derived irrigated areas from remote sensing products and suitability information. We do not state that just the application of remote sensing data and crop suitability data would be an innovation. Our approach differs from previous studies by using different remote sensing and suitability data as well as a different methodology. In the revised manuscript we will enlarge the description of applied data and methodology so that the difference to other approaches is getting clearer.

RV#1:

2) Developing new methods to combine a variety of different data sets for irrigation mapping is interesting from an academic perspective. However, the major challenge is to show that new methods improve present irrigation maps and reduce the uncertainty with regard to the extent and timing of irrigation. This requires in depth validation of the new data set and comparison to products published before. Unfortunately the validation described in the article is very poor and insufficient. The only data set used for validation are ground observations for Europe but the method used for validation is not appropriate. The authors compare their grid based product to point observations and it remains completely unclear how this can help to validate the accuracy of area estimates. What means an accuracy of 72% in this regard? What can we learn from this about the accuracy of the irrigated area estimate for countries like Spain or Italy where the authors detect more irrigation than in other studies before? The minimum requirement is that the authors present errors of commission and errors of omission for different countries separately. In addition they need to describe how relevant the point estimates contained in the LUCAS sample are for pixels of 1 km2 used in the product developed by the authors.

Authors:

We completely agree with you that the validation of the new irrigation map could be improved. Basically, a validation with national statistics is methodically not appropriate, since we are interested in the differences to the statistics. We agree that the comparison of our data with point observation is not appropriate and revised the validation section completely. We compared our results with existing approaches; we included a statistical comparison of our results with Salmon et al. and Thenkabail et al. on country level and on state or provinces level in case of the regional comparison.

RV#1:

3) Since irrigation is less relevant in Europe as compared to other continents the authors should focus their validation on other regions, in particular those where the new irrigation data set differs considerably from the products published before. For sure this should be India, China and Central Asia. There is a variety of high resolution irrigation data sets available for these countries or regions which could be used as a reference. Ambika et al. (2016) should certainly be used as a reference for India while Zhu et al. (2014) could be used for China. In addition, there are inventories for the US (Ozdogan and Gutman, 2008) and Australia (http://www.agriculture.gov.au/abares/aclump/landuse/ data-download) that could be used to validate the product for these regions. All these data sets were developed by using time series of high resolution remote sensing images and a lot of local background knowledge that the authors of the present article cannot have.

Authors:

We agree that a regional validation should be part of the study. We followed your suggestion to focus the validation on where irrigation is an important part of agriculture. We compared the irrigation map with the publication of Ozdogan and Gutan (2008), Ambika et al. (2016) and Zhu et al. (2014).

RV#1:

4) Based on the validation exercise before the authors should also discuss more critically limitations and constraints of their own approach. A variety of assumptions are made in the classification (e.g. specific thresholds) that have a big impact on the result.

Authors:

The decision tree and the thresholds are a result of a sensitivity analysis and a comparison of different existing studies in the literature (Pervez et al. (2014), Ozdogan & Gutmann (2008), Pervez & Brown (2010), Wardlow & Egbert (2008), Aparicio et al. (2000)). We discussed the difficulty of using NDVI as a vegetation indicator and the risk of over- or underestimation using hard thresholds.

RV#1:

In addition there are limitations because of the spatial, temporal and categorical detail in the input data used by the authors. Ozdogan and Woodcock (2006), for example, describe that in parts of China and Africa even Landsat imagery with a 30 meter resolution might be to coarse for land use classification because field sizes are smaller. The coarse resolution of the imagery used in the present study and the binary (irrigation *yes or no) decision tree could be one reason why in many regions the share of rainfed and irrigated fields cannot be distinguished resulting in considerable over – or underestimate of the irrigation extent.*

Authors:
Land use classifications always have a scaling problem – temporally and spatially. We tried to argue why we chose the size of 30 arc second. The installation of irrigation technique is expensive and for only one field or a small field not economic. For Africa and Asia, field size in general may be much smaller than our resolution, but usually, irrigated fields may be much bigger in size, since irrigation is often applied by large scaled farms with large fields or small fields are agglomerated since irrigation infrastructure and water is available. Accordingly, we assume an agglomerate of fields rather than a single field within a pixel.
The resolution is a source of uncertainty. Salmon et al. (2015) solved this problem with a field size factor. If they had information about field size they recalculated their results, if not, they assumed that only 80 % are in agricultural use (50 % in case of a mosaic class). The global results without the field size factors are very close to our findings: 367,039 mha (see manuscript) and 376,7 mha (Salmon et al.).
We enlarged the explanation and tried to clarify our arguments and discussed the advantages of using field-size factors or not.

RV#1:
Furthermore, the suitability data used by the authors will certainly not reflect the diversity of land use patterns at the ground, in particular for regions with multiple cropping. What about permanent crops like citrus or olives?

Authors:
The agriculture suitability data represents an overall suitability of the 16 most common crops and considers the annual course of the growing period and multiple harvests. One of the main finding was that the NDVI courses indicate double or multiple cropping in regions where only one harvest would be possible without irrigation.
The suitability considers oil palm – as a permanent crop. Olive-, date-, almond- and citrus trees are not considered in the suitability, since their global area is relatively small, but even plants which are used to grow in a dry area need a minimum of water and if the climatic conditions do not provide enough rain the plants have to be irrigated. We improved the description of the suitability data and added these points to the discussion.

RV#1:
What about regions in which irrigation is mainly used for pasture (New Zealand, Australia). There are many sources of uncertainties but little information how the mapping product is impacted by these uncertainties.

Authors:
Most of the irrigation is used for cereals and staple crops, a minor share for vegetables, fruits, oil crops and pasture. In developed countries the share of irrigated pasture or permanent crops may be higher, but in using the existing study of Siebert et al. (2013) as a basis in our approach, the irrigated pastures should be part of the data set and therefore also be part of the new irrigation map, especially as you consider that irrigated pastures are more important in developed countries where the official statistics are less susceptible to inaccuracies and are more reliable.

RV#1:
To my opinion it is not helpful to release products without a proper validation and uncertainty analysis. There is already a lot of confusion in the community caused by poorly validated land use products and for countries like India just the remote sensing based estimates of irrigated land vary between 70 and 220 million hectares. Hydrological modelling has shown that even an extent of 70 million hectares would result in a drastic overuse of water resources so that it is extremely hard to believe that there should even be much more irrigated land at the ground.

We would like to clarify this issue. The paper was not about increasing irrigated area clueless, but to compare existing products with official national statistics. The irrigated areas in India are a good example and shows the wide spread of the results. Our analyses for India show 88.4 million hectares of irrigated

land. This is close to the results of Ambika et al. (74.14 million ha) and are far away from Thenkabail et al. (220.22 million ha).
For ending the confusion between the different data and improving validation and discussing uncertainties, we added a table on total irrigated area for the different global and regional approaches (e.g. Thenkabail, Ambika, Ozdogan, etc.) together with national statistical data for each country worldwide for a detailed comparison between the different irrigation data in a supplement.

RV#1:
To conclude: what is needed is not to publish just some more figures with unknown accuracy but to develop products that are better than the products developed before and to prove this by an appropriate validation.

Authors:
We absolutely agree with your opinion on this and we tried to improve the manuscript implementing suggestions to your comments above.
Again, thank you for your interesting and constructive comments. We hope we could eliminate your major concerns and clear up some misunderstandings. We are very confident that the improvements through your review make the goal and the intention of our study clearer and the methods more understandable and transparent.

References:

Ambika, A. K., Wardlow, B., and Mishra, V.: Remotely sensed high resolution irrigated area mapping in India for 2000 to 2015, Sci Data, 3, 160118, 2016.
Aparicio, N., Villegas, D., Casadesus, J., Araus, J. L., and Royo, C.: Spectral Vegetation Indices as Nondestructive Tools for Determining Durum Wheat Yield, Agronomy Journal, 92, 83-91, 2000.
Ozdogan, M. and Gutman, G.: A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US, Remote Sensing of Environment, 112, 3520-3537, 2008.
Ramankutty, N., Foley, J. A., Norman, J., and McSweeney, K.: The global distribution of cultivable lands: current patterns and sensitivity to possible climate change, Global Ecology and Biogeography, 11, 377-392, 2002.
Salmon, J. M., Friedl, M. A., Frolking, S., Wisser, D., and Douglas, E. M.: Global rain-fed, irrigated, and paddy croplands: A new high resolution map derived from remote sensing, crop inventories and climate data, International Journal of Applied Earth Observation and Geoinformation, 38, 321-334, 2015.
Pervez, M. S. and Brown, J. F.: Mapping Irrigated Lands at 250-m Scale by Merging MODIS Data and National Agricultural Statistics, Remote Sens-Basel, 2, 2388-2412, 2010.
Pervez, M. S., Budde, M., and Rowland, J.: Mapping irrigated areas in Afghanistan over the past decade using MODIS NDVI, Remote Sens Environ, 149, 155-165, 2014.
Siebert, S., Doll, P., Hoogeveen, J., Faures, J. M., Frenken, K., and Feick, S.: Development and validation of the global map of irrigation areas, Hydrology and Earth System Sciences, 9, 535-547, 2005.
Siebert, S., Henrich, V., Frenken, K., and Burke, J.: Update Of The Digital Global Map Of Irrigation Areas to Version 5. Nations, F. a. A. O. o. t. U. and Bonn, U. o. (Eds.), 2013.
Sys, C. O., van Ranst, E., Debaveye, J., and Beernaert, F.: Land Evalutation: Part III Crop Requirements., Agricultural Publications, 1993. 1993.
Thenkabail, P. S., Biradar, C. M., Noojipady, P., Dheeravath, V., Li, Y., Velpuri, M., Gumma, M., Gangalakunta, O. R. P., Turral, H., Cai, X., Vithanage, J., Schull, M. A., and Dutta, R.: Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium, International Journal of Remote Sensing, 30, 3679-3733, 2009.
Wardlow, B. D. and Egbert, S. L.: Large-area crop mapping using time-series MODIS 250 m NDVI data: An assessment for the U.S. Central Great Plains, Remote Sens Environ, 112, 1096-1116, 2008.
Zhu, X., Zhu, W., Zhang, J., and Pan, Y.: Mapping Irrigated Areas in China From Remote Sensing and Statistical Data, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7, 4490-4504, 2014.

Answers to Referee Comment #2

This paper is well-written and understandable for a greater audience. It provides a clear description of the study and outcomes. The authors display relevant knowledge of global data sets for irrigation mapping, using references. The method to combine statistical data and remote sensing data is interesting. The methodology section and the validation sections may require some additional clarification. The following points can be further elaborated or explained.

Authors:
Thank you for reviewing the article and your valuable comments. Please find our suggestions for improvement below.

RV# 2
The different data sets used in this study, cover different time periods (Table 1). For instance the GMIA has a time frame of 2000-2008, and Globcover covers 2004-2006. However, the study provides an irrigation map of 1999-2012. It is unclear how the different data sets from different periods are agglomerated and if any discrepancies can be caused by comparing different years of data. For instance, if a pixel is fallow during the period of Globcover, it will be excluded from the analysis because it was not considered cropland. The GMIA is downscaled using a data set of a different time frame (2004-2006). This might cause some inaccuracies. In addition, it is unclear what the effect is of averaging the NDVI values over 14 years. Several different cropping patterns might exists. Some further explanation will be useful for the reader to understand this part of the methodology.

Authors:
It is correct that the inputs refer to different time periods. Nonetheless, all data focus around the year 2005. Since it is global approach, land use change within +- 3 years is supposed to be relatively small in comparison to uncertainties within the input data. Further, global data often are not available for specific years.
The downscaling of the GMIA was done with a bimonthly-maximum NDVI of the years 2004-2006, more precise November 2004 – June 2006. We chose this time period because it represents, more or less, the center of the covered time period of GMIA. If there is a change in land use during the covered time period the different time periods definitely have an influence on the result – but mainly on the local scale. We will discuss this issue in the revised version of the paper.
In case of different cropping patterns or occasionally fallow field the influence on the NDVI is low. A change of crops or a lower NDVI every few years do not change the averaged NDVI critically. For a better understanding we extended the methodology part with a more detailed description of the chosen input data and provide more transparence for the reader.

RV#2:
The methodology and processing diagram (figure 3) shows that the results are highly sensitive to the accuracy of the land cover map (Globcover or ESA-CCI-LC) and the suitability maps. The author can acknowledge this influence and determine the uncertainty of these data sets. Possibly this can be done by validating these 'intermediate' data sets.

Authors:
We agree, the uncertainty of the input data should be better discussed and questioned critically. We think a regeneration of the validation is not feasible but we will mention the validation results of the applied data sets. We discuss the validation results of the intermediate products. We already mentioned some potential sources of uncertainties within the suitability map, since it only considers 16 crop types and may be inaccurate in some regions due to drought resistant varieties.

RV#2:
The validation paragraph includes a description of the methodology, which is better placed in the methodology section.

Authors:
Thank you for your comment, we changed it.

RV#2:
The validation process can be elaborated by including additional data sets, besides Europe. Also results can be compared with existing regional irrigated areas maps.

Authors:
We compared our data with existing approaches; we included a statistical comparison of our results with Salmon et al. and Thenkabail et al. and added a comparison with existing regional studies of Ozdogan and Gutan (2008) (USA), Ambika et al. (2016) (India) and Zhu et al. (2014) (China).
For improving validation and discussing uncertainties, we added a table on total irrigated area for the different global and regional approaches (e.g. Thenkabail, Ambika, Ozdogan, etc.) together with national statistical data for each country worldwide for a detailed comparison between the different irrigation data in a supplement.

RV#2:
Some minor comments in addition to the points mentioned above are: - The use of the term water use efficiency on p.1 l.34 is confusing because it is interpreted differently by different disciplines. In the referenced paper the term irrigation efficiency is used, which is my suggestion as well.

Authors:
Thank you, we changed it.

RV#2:
The captions of figure 5 and figure 8 can be improved to give a better description of the figure (without needing to read the text).

Authors:
Thank you for this comment we changed following captions:
Figure 4: Global distribution of the irrigated areas identified by different approaches. The blue areas are the downscaled data set of Siebert et al. (2013) which is based only on statistics and provides the basis of this map. Green, red and yellow are the extended areas by the approaches developed in this study.

Figure 5: The results of the new irrigation map (dark) and the downscaled irrigation map of Siebert et al. (2013) (bright). The bar at the right side represents the total sum of the global irrigated area and A, B and C shows the amount of additional irrigated area derived with the developed methods.

RV#2:
- The role of supplemental irrigation, meaning the role of irrigation only during the summer (dry) period, is excluded in this study. Supplemental irrigation is relevant especially for regions having sufficient rainfall during the spring and fall. This might be an explanation for a few of the results.

Authors:
It is correct that supplemental irrigation is difficult to detect just by the combination of suitability and NDVI data. This is the main reason why we based our approach on the Siebert et al (2013) data, where these areas are included in the statistical dataset used for calibration.

RV#2:
Overall, the paper provides good information and an interesting approach. If these parts of the methodology are elaborated it will be more understandable and transparent for the reader. Also being critical of the 'intermediate' products (land suitability and Land cover maps) will improve the paper and give suggestions for future work.

Authors:
Thank you.

References:

Ambika, A. K., Wardlow, B., and Mishra, V.: Remotely sensed high resolution irrigated area mapping in India for 2000 to 2015, Sci Data, 3, 160118, 2016.
Ozdogan, M. and Gutman, G.: A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US, Remote Sensing of Environment, 112, 3520-3537, 2008.
Salmon, J. M., Friedl, M. A., Frolking, S., Wisser, D., and Douglas, E. M.: Global rain-fed, irrigated, and paddy croplands: A new high resolution map derived from remote sensing, crop inventories and climate data, International Journal of Applied Earth Observation and Geoinformation, 38, 321-334, 2015.
Siebert, S., Doll, P., Hoogeveen, J., Faures, J. M., Frenken, K., and Feick, S.: Development and validation of the global map of irrigation areas, Hydrology and Earth System Sciences, 9, 535-547, 2005.
Siebert, S., Henrich, V., Frenken, K., and Burke, J.: Update Of The Digital Global Map Of Irrigation Areas to Version 5. Nations, F. a. A. O. o. t. U. and Bonn, U. o. (Eds.), 2013.
Sys, C. O., van Ranst, E., Debaveye, J., and Beernaert, F.: Land Evalutation: Part III Crop Requirements., Agricultural Publications, 1993. 1993.
Thenkabail, P. S., Biradar, C. M., Noojipady, P., Dheeravath, V., Li, Y., Velpuri, M., Gumma, M., Gangalakunta, O. R. P., Turral, H., Cai, X., Vithanage, J., Schull, M. A., and Dutta, R.: Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium, International Journal of Remote Sensing, 30, 3679-3733, 2009.
Zhu, X., Zhu, W., Zhang, J., and Pan, Y.: Mapping Irrigated Areas in China From Remote Sensing and Statistical Data, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7, 4490-4504, 2014.

A global approach to estimate irrigated areas – a comparison between different data and statistics

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Data are available on request.

Abstract. Agriculture is the largest global consumer of water. Irrigated areas contribute to 40% of the agricultural production. Information on their spatial distribution is highly relevant for regional water management and food security. Spatial information on irrigation is highly important for policy and decision makers who are facing the transition towards a more efficient sustainable agriculture. However, the mapping of irrigated areas still represents a challenge for land use classifications and existing global data sets differ strongly in their results. The following study tests an existing irrigation map based on statistics and extends the irrigated area using ancillary data. The approach processes and analyses multi-temporal NDVI SPOT-VGT data and agricultural suitability data – both at a spatial resolution of 30 arc seconds – incrementally in a multi decision tree. It covers the period from 1999 to 2012. The results globally show 18% more irrigated area than existing approaches based on statistical data. The largest differences compared to the official national statistics are found in Asia and particularly in China and India. The additional areas are mainly identified within already known irrigated regions where irrigation is more dense than previously estimated. The validation with global and regional products shows the large divergence of existing data sets with respect to size and distribution of irrigated areas caused by spatial resolution, the considered time period and the input data and assumption made.

Keywords: Irrigation, Global Irrigated Areas, Global Scale, Resolution, Remote Sensing, Statistics, Land Use Classification, Agriculture, Cropland

1 Introduction

One of the major challenges for the 21st century will be the nourishment of the rising world population (Foley et al., 2011). The consideration of increasing meat consumption and additionally the increased use of biofuel and bio-based materials, lead to estimations that global agricultural production would have to double until 2050 (Alexandratos and Bruinsma, 2012; Godfray et al., 2010; Tilman et al., 2011). Separated by sector, agriculture is the largest consumer of water. 69% of the global water withdrawal from rivers, lakes and groundwater (blue water) is used for agriculture, in some regions the share can be over 90% like in South Asia or in the Middle East (FAO, 2014b). The regional limitation of fresh water availability plays a crucial role for global agricultural production, considering that 40% of the global yields are harvested on irrigated fields (FAO, 2014a). Irrigated areas almost doubled over the last 50 years and contribute to 20% of the global harvested area today (FAO, 2016b). A future expansion of irrigated area and a related increase in water consumption is expected (Neumann et al., 2011). Due to climate change in some parts agricultural water availability is expected to decrease (Strzepek and Boehlert, 2010). The low irrigation efficiency of the common irrigation techniques such as sprinkler and flood irrigation (Evans and Sadler, 2008), the unsustainable usages of limited sources like groundwater (Wada et al., 2014), the changing river regimes (Döll and Schmied, 2012) and the changing supply by snow melt (Mankin et al., 2015; Prasch et al., 2013) underline the need of a transition towards a more sustainable and efficient use of water. The SDG's clearly reflects this need in achieving food security and a sustainable development of land use (UNO, 2016). For a better inventory and investigation of global and regional water cycles and as input for crop models detailed global information on irrigated areas at a high resolution is needed.

Attempts to identify irrigated areas already exist that do not rely on surveys and are independent from statistics (Ozdogan et al., 2010). Remote sensing can be an alternative approach for mapping irrigated areas. Previous studies showed that remote sensing data can be used to detect irrigated areas for small and medium scale analyses (Abuzar et al., 2015; Ambika et al., 2016; Jin et al., 2016; Ozdogan and Gutman, 2008). Vegetation indices (Ozdogan and Gutman, 2008) or climate elements, such as evapotranspiration (Abuzar et al., 2015) derived from satellite information and combined with meteorological data were used to determine irrigated area. Ozdogan et al. (2010) summarised different approaches for mapping irrigated areas from local to global scale.

There are only few studies which identify irrigated areas globally (Salmon et al., 2015; Siebert et al., 2005; Thenkabail et al., 2009a). Land use classification data sets often neglect irrigated area. Some classify irrigated area as a separate class (ESA, 2015; USGS, 2000), but do not focus on irrigated areas.

A common approach to the specific mapping of irrigated area, such as provided by the Global Map of Irrigation Areas (GMIA) (Siebert et al., 2005), distributes statistical data of national and subnational agricultural surveys like AQUASTAT (FAO, 2016a) to the agricultural and other classes of land use classifications. However, approaches that are restricted to statistics alone are hard to verify, since statistics may include errors and multi-scale statistics do hardly exist globally. For instance in some countries in West Africa the informal irrigated areas in urban and peri-urban areas are twice the size of the official irrigated areas for the whole country (Drechsel et al., 2006). Irrigation may increase due to economic growth and a dietary shift from staple crops towards more vegetables and fruits (Molden, 2007). Already 15 years ago the official FAO statistics engendered criticism after comparing national statistics with remote sensed based data (Vorosmarty and Sahagian, 2000). The study of Thenkabail et al. (2009a) globally identified 43% more irrigated areas than reported in official FAO statistics. The discrepancies between those data were explained by the politicized nature of the FAO data reports and different definitions of irrigated area (Vörösmarty, 2002). The Global Irrigated Area Mapping (GIAM) of Thenkabail et al. (2009a) is a combination of meteorological data, land use classification information (forest) and remote sensing data from multiple satellite sensors. It is validated using ground truth data and Google Earth images. Thenkabail et al. (2009a) showed that the global irrigated areas might be underestimated by the official statistics. Another approach to map global irrigated areas was developed by Salmon et al. (2015). They combine statistics, climate- and remote sensing data. The study also shows an underestimation by the national- and subnational statistics – although a small one. Salmon et al. (2015) showed that merging remote sensing data and ancillary data is suitable for irrigation mapping. Thenkabail et al. (2009b) concludes that 'both remote sensing and national statistical approaches require further refinement'.

The aim of this study is to test an existing statistics-based medium-resolution irrigation map (Siebert et al., 2013) with high-resolution data from satellite observations, which are available in the meantime. We study, through extraction of likely irrigated areas from the high spatial resolution data, to what extent and where formally hidden irrigated areas show up. At first we downscale Siebert et al. (2005) statistically based irrigation map using high resolution remote sensing information. In a second step we derive irrigated land from agricultural suitability data combined with remote sensing information consisting of multi-temporal NDVI-profiles at a high spatial resolution. By following a decision tree we identify irrigated areas as showing an active vegetation growth in agricultural unsuitable regions. If these irrigated areas are not reported by the official statistics they are added in the new irrigation map. Hence, the new irrigation map is not restricted to irrigated areas known by official reports and allows for extending these predetermined areas. Finally, we compare our results with existing global approaches as well as with regional analysis (USA, India, China) and investigate the differences with the official national and subnational statistics.

2 Data and Method

The basic idea of our approach is to combine different data sets providing different kind of information. The applied data sets are available at different spatial resolutions (Tab. 1). In a first step the data sets are homogenized to the same spatial resolution. We decided for a high spatial resolution of 30 arc seconds (approx. 1 km² at the equator), since the demand for high resolution global data is increasing in different applications (Deryng et al., 2016; Jägermeyr et al., 2015; Liu et al., 2007; Mauser et al., 2015; Rosenzweig et al., 2014) and the pixel size of approximately 1 km² is already close to large fields (depending on the region) or an agglomeration of smaller irrigated fields. For Africa and Asia, the field size of 1 km² might be too large (Fritz et al., 2015), but usually, irrigated fields may be much bigger in size, since irrigation is often applied by large scaled farms. Small fields are agglomerated since irrigation is usually not practiced on a single field, due to high investment and installation costs of irrigation systems. The resulting data at 30 arc seconds only distinguishes between irrigated and rain-fed and does not contain percentage shares.

The decision tree in Figure 1 shows how the data sets are analysed and formerly not detected irrigated areas are identified. As we mentioned above, the basic idea is to increase the spatial resolution of an existing global irrigation map to 30 arc seconds and to extend the data set by additional identified irrigated areas. The lower grey box in Fig. 1 shows the principal of the downscaling process, where we assign the percentage values of Siebert et al. (2005) to the high-resolution pixels within a medium-resolution pixel which show the highest NDVI values (see section 2.1). The assigned irrigation percentages to the high-resolution pixels form the basis of our new irrigation map. The upper grey box in Fig. 1 shows the processing of the NDVI data, which is only done on agricultural used areas (see section 2.2 and 2.3). The processed NDVI data are compared to a global high-resolution data set on agricultural suitability (see section 2.5 and the right grey box in Fig 1.). The combination of the downscaling and the comparison of NDVI and agricultural suitability results in a global high resolution irrigation map. The development of the map is described more in detail in the following section.

2.1 The downscaling of the statistically based data set

Siebert et al. (2005) distribute statistical data to the Global Map of Irrigated Areas (GMIA). The data set has a resolution of 5 arc minutes and is available in several versions – we applied the version 5.0 (Siebert et al., 2013). To combine the different data sets to a final irrigation map at a resolution of 30 arc seconds, the resolution of GMIA has to increase. For the downscaling process, shown in the lower grey box in Fig. 1, we use global bimonthly maximum MERIS NDVI data (ESA, 2007) at a spatial resolution of 10 arc seconds and calculate the yearly maximum NDVI (Fig. 2). The bimonthly maximum NDVI data covers the period November 2004 – June 2006 and represents more or less the center of the covered time period of the applied GMIA version. After upscaling the yearly maximum NDVI to 30 arc seconds using a majority algorithm, the GMIA data are distributed to the areas with the highest NDVI within a corresponding coarse pixel. To avoid distributions to dense woodlands (closed tree cover >40%), cities and open water, these areas are excluded from the distribution, based on the ESA-CCI-LC data set (ESA, 2015). Pixels with a percentage share of irrigated area below 1% are not considered. The downscaled data set of Siebert et al. (2013) shows the irrigated area at a high spatial resolution of 30 arc seconds and will in the next steps be extended by irrigated area, which are not part of the statistics yet. In the following, the downscaled data set of Siebert et al. (2013) will be named as “downscaled GMIA”.

2.2 Remote sensing data

This part of the decision tree is shown in the upper left grey box in Fig. 1. For the detection of the actual active vegetation we used the NDVI product of ESA-CCI (ESA, 2015). The data provides 7-daily-NDVI means and covers the time period from 1999 to 2012. From this data, we calculated the annual course of NDVI, averaged over the whole time period. Thereof we derived the number of annual NDVI peaks. In order to increase the precision of detecting active vegetation, each pixel is analysed according to a NDVI threshold approach (Ambika et al., 2016; Shahriar Pervez et al., 2014). The chosen thresholds are a result of a comparison of different studies (Ambika et al., 2016; Shahriar Pervez et al., 2014) and the comparison of NDVI values of known irrigated and rain-fed areas. Following criteria need to be fulfilled and are shown in Fig. 3:

- The minimum NDVI has to be below 0.4, while the maximum NDVI has to be over 0.4. Since the NDVI product is a 7-daily mean over 14 years, it is very likely that fields lie fallow within the time period, resulting in lower mean values. Therefore, a NDVI of 0.4 turned out to be a suitable lower threshold. This guarantees clear distinction between non vegetated and vegetated pixels and eliminates evergreen vegetation, such as forests and pasture. Thresholds like minimum and maximum NDVI used in this study have a strong effect on the result. For a global study it is difficult to find universal, transferable thresholds that can be applied globally.
- Minimum and maximum NDVI must at least differ by 0.2 points to identify only pixels with a dynamic annual course that is assumed for agricultural areas.
- NDVI peaks must be at least 12 weeks apart to assign a peak to a specific growing period, assuming that the length of a growing period is 12 weeks in minimum (Sys et al., 1993). Additionally, this allows for separating multiple growing periods within a year. Often, a slight greening right after harvest was observed. This can be explained e.g. through the seeding of legumes for soil treatment, or the development of natural vegetation after harvest, which results in an increase of NDVI.
- In order to avoid classifying multiple peaks as a regular harvest, it turned out that two sequenced peaks must not differ by more than 25%.

The described criteria of minimum, maximum and yearly course of NDVI and the length of growing period turned out as robust to determine the number of crop cycles globally. The chosen criteria are suitable regarding the fact, that we used 7-daily-NDVI-means averaged over 14 years.

2.3 Land use classification products

The extension of irrigation is restricted to agricultural areas. The information on cropland are taken from the ESA-CCI-LC product (cropland rain-fed, cropland irrigated, mosaic cropland > 50%) (ESA, 2015) and from the predecessor GlobCover (ESA, 2010) (Post-flooding or irrigated croplands, rain-fed croplands, mosaic cropland (50-70%)). According to the authors, the 'accuracy associated with the cropland and forest classes' is high 'and therefore a quite good result' (ESA, 2015). The user's accuracies of both data sets are shown in Tab. 2. The classification of cropland depends on the definition of cropland. In both data sets pasture is neither a separate class nor part of the class 'grassland' or 'cropland'. False classification of cropland can therefore lead to false classification of irrigated areas. The combination of both data sets increases the chance to classify irrigated areas only on cropland. Pixels that are classified as mosaic cropland in the underlying land use data sets are weighted by the averaged amount of cropland fraction for the corresponding class. All other cropland pixels are assumed to be 100% cropland.

2.4 Agricultural suitability data

Agricultural suitability data are taken from Zabel et al. (2014). The data describes the suitability for 16 staple, energy and forage crops (Tab. 3) according to climate, soil and topography conditions at a spatial resolution of 30 arc seconds. It determines suitability for crop cultivation and the potential number of crop cycles per year, under the climate for 1981-2010 (Zabel et al., 2014). Soil properties are not considered in this approach, because human activities may alter soil properties e.g. by fertilizer and manure application and soil tillage. The data is available for past and future climate periods as well as for rain-fed and irrigated conditions separately. The data set used in this study represents for each pixel the highest suitability value over all selected crops as well as the annual course of the growing period and the potential number of crop cycles per year.

2.5 High resolution mapping of irrigated areas

The downscaled GMIA data serve as a basis, providing a proven global distribution of irrigated areas. The irrigated areas which are already part of the statistics are extended by additional – until now – not captured irrigated areas. The identification of the additional irrigated areas in the new irrigation map is accomplished using the criteria described above and relationships of the annual temporal NDVI profiles to the agricultural suitability. The general criterion for the identification of unknown irrigated areas is that the land use is already cropland according to ESA-CCI-LC and GlobCover. The restriction to cropland avoids the classification of irrigated areas in other land uses or covers in dry areas with high NDVI values due to lichens or weed, since a low agricultural suitability does not exclude plant growth at all. The upper right grey box in Fig. 1 shows the assumption for irrigated areas using the NDVI and agricultural suitability data:

A. The annual NDVI course clearly suggests a dynamic vegetation growth while the agricultural suitability shows a low value.
B. The number of NDVI peaks is higher than the potential number of crop cycles per year under rain-fed conditions.
C. Land is not suitable but classified as cropland while at the same time NDVI values and yearly courses indicate vegetation.

If one of the criteria is true, we assume the full area of the 30 arc second pixel as being irrigated. As a result, the combination of A, B, and C identify the irrigated pixels, which were not assigned to irrigation areas in the downscaled GMIA irrigation map.

3 Results

3.1 Global analysis

The new global irrigation map shows 18% more irrigated areas than the downscaled GMIA (Fig. 4). Overall, 3,674,478 km² of irrigated areas have been identified, which is an increase of 659,605 km² compared to the downscaled GMIA (Fig. 5). The global result confirms the underestimation of irrigated areas of Thenkabail et al. (2009a) who globally identified 3,985,270 km² irrigated areas by a remote sensing based approach and are significantly higher than the results of Salmon et al. (2015) with 3,141,000 km² and the global estimates of the FAO or of Siebert et al. (2005).

Figure 5 shows the global irrigated area additionally allocated through each of the criteria A, B, and C of section 2.5. The largest amount of additional irrigated area is identified by considering multiple cropping (B). In this case, 493,123 km² are not part of the downscaled GMIA. These areas are mainly found in Asia (Fig. 4), where according to our results, irrigation is often required to allow for multiple cropping. 100,069 km² are additionally identified, because they are not suitable for crop cultivation but are classified as cropland (indicator C). By the use of indicator A, 76,054 km² are additionally allocated.

3.2 Regional analysis

The indicators A, B and C show different amounts of additional irrigated area for different regions. Methods A and C identified irrigated areas mostly in arid and semi-arid regions, by comparing low or no suitability versus high NDVI. Figure 6 shows that additional irrigated areas by using A and C are mainly found in regions with annual precipitation < 500 mm, according to the WorldClim data set for 1961-1990 (Hijmans et al., 2005).

In humid regions, criterion A and C are not sensitive, because agricultural suitability values in humid regions are high since precipitation is not limiting. We found that B extends irrigated areas in regions with low as well as high annual precipitation (Fig. 6), where irrigation is often used to allow for a second harvest. In total, Figure 6 demonstrates that irrigation decreases with increasing precipitation, but irrigation not only takes place in dry regions. The largest amounts of new areas are in countries where irrigation plays an important role for agriculture. Irrigated areas seem to be denser in already irrigated regions.

3.2.1 Asia

The newly identified irrigated areas are mainly found in Asia, particularly in Central and South East Asia. The countries with the largest amount of additional area are India (+267,283 km²) and China (+149,871 km²). In these countries, irrigation plays a dominant role in agriculture, where 40% (India) and 57% (China) of the total cropland is irrigated according to statistics (FAO, 2016b). Nevertheless, statistics seem to largely underestimate irrigated areas, particularly in India. Here, we found on the one hand considerable additional irrigated areas compared to GMIA within regions that are sparsely irrigated, such as the state of Madhya Pradesh (Fig. 7). On the other hand, irrigated areas are additionally identified within regions that already show a high irrigation density, such as Uttar Pradesh along the foothills of the Himalayan Mountains, where the density of irrigated areas even increases in our results (Fig. 7). Particularly in these regions the irrigated areas where detected comparing the potential vegetation cycles to the actual yearly NDVI coarse. Due to the seasonality of the precipitation only one harvest is possible – the second has to be achieved by irrigation. Even legumes, which serve as nitrogen fertilizers, have to be irrigated.

Within Asia, the developed method unveils large previously unknown irrigated areas in Kazakhstan (+30,661 km²), Pakistan (+26,667 km²), Myanmar (+25,212 km²), Uzbekistan (+17,454 km²) and Turkmenistan (+13,483). In Central Asia, particularly the irrigated areas along the rivers are larger than previously reported. The Asian countries with the largest percentage difference compared to FAOSTAT (FAO, 2016b) statistical data (averaged from 1999-2012) are Mongolia (+815%), Kazakhstan (+183%), Myanmar (+119%) and Yemen (+103%).

3.2.2 Africa

Irrigation plays a minor role in the tropical regions of Africa, while there are contiguous irrigated regions along the Nile in Egypt and Sudan, some smaller irrigated areas within the Mediterranean countries and some irrigated areas within Southern Africa. The countries with the largest amount of additional irrigated areas are found in Somalia (+6,427 km²), Egypt (3,867 km²), and Ethiopia (+3,536 km²). The irrigated regions along the Nile Delta are denser and result in an increase of irrigated area of 12% in Egypt. The African continent shows the highest percentage discrepancy when being compared to FAOSTAT (averaged from 1999-2012) (Tab. 4). Countries with the highest percentage difference to statistics are Chad (+500%), Somalia (315%), Kenya (311%) and Cameroon (+243%).

3.2.3 Europe

The discrepancy between the downscaled GMIA and the new irrigation map in Europe is smaller than in the regions mentioned above. The largest differences exist in Italy (+11,059 km²), Spain (+5,270 km²) and Greece (+3,922 km²). While the Po valley, the largest contiguous irrigated region within Europe, does not show significant differences between the downscaled GMIA and our high-resolution irrigation map, many additional areas on Sardinia and Sicily are detected. In Spain, the known irrigated areas near to the Pyrenees are well captured by GMIA but especially the intensely used agricultural area around Valladolid in the North West of Spain shows additional irrigated areas according to our results. The highest percentage difference to FAOSTAT is found for Bosnia and Herzegovina (+500%), Croatia (+220%), Montenegro (+207%) and some other countries in the East Europe. The comparison of FAOSTAT to GMIA in these regions results in similar high differences, since the FAOSTAT data were obviously not used in the GMIA data. The highest percentage difference in Western Europe to FAOSTAT are found in Portugal (+41%), Great Britain (+28%), France (+27%) and Italy (+26%).

3.2.4 America

The position and extent of the large irrigated areas in North America in Fig. 4 are very consistent to the distributed statistics of the downscaled GMIA. Only in the North Western part of the USA our results show significantly more irrigated areas than GMIA. It is notable that additional identified irrigated areas are found next to already detected irrigated areas in California, North West and the Middle West of the USA. Thus, density increases within irrigated agglomeration regions. The percentage difference to FAOSTAT is relatively low compared to the other continents (Tab. 4). The highest percentage difference is found in Chile (+71%), Canada (+41%), Mexico (+12%) and Brazil (+8%).

To demonstrate the effect of the high spatial resolution of the results, Fig. 8 shows the results for a specific extent in the North West of the USA (Oregon). The comparison of the new irrigation map at 30 arc seconds resolution with the GMIA at 5 arc minutes resolution demonstrates the improvement of the data (Fig. 8). The higher resolution allows for a more precise identification of irrigated fields. Further, the additionally recognized irrigated areas that are not included in the GMIA data set match well with the underlying true colour satellite image. In this case it also shows that the resolution of 30 arc seconds degree is suitable for field scale for irrigation mapping in this region.

3.3 Differences between the downscaled GMIA and the original GMIA

The downscaling process leads to differences between the downscaled and the original GMIA data. Since fractions of irrigated areas < 1% are not allocated to the finer resolution, they are neglected within the downscaling process. This leads to a global loss of irrigated area of 46,329 km². If there are no pixels available for distribution, e.g. due to excluded land such as forests, water bodies or urban areas, the irrigated area may not be allocated, which results to a global reduction of 19,780 km². Since we can only distribute integer values we additionally lose 2,442 km² through rounding the floating point numbers of the percentage share of the irrigated areas. Overall, we do not distribute 68,551 km² of irrigated areas, which are 2.28% of the GMIA data set in its original resolution. This small difference in percentages allows us to spatially compare at the same spatial resolution the new irrigation map with the downscaled GMIA, which results from the procedure described above.

4 Validation

The new irrigation map partially shows significant differences to the statistics and the resulting GIAM data set. No final truth exists on the amount and location of global irrigated area. Nevertheless, in order to validate the new high resolution irrigation map we compare our results to existing global and also regional studies. The comparison of ground truth data with the new irrigation map can also be a way to outline the differences between the new map and ground truth data. There are ground truth data available (European Environment Agency, 2014), providing point specific land use information for specific regions, but they are rare and not always tagged with needed land use information like irrigation. Further, there are always scaling issues, concerning the spatial resolution, in comparing point information with spatial information. For the validation we decided to compare our map with the existing global data set IWMI-GIAM (Thenkabail et al. (2009a) and GRIPC (Salmon et al. (2015). Additionally we compare our results with regional studies in the USA (Ozdogan et al., 2010), China (Zhu et al., 2014) and India (Ambika et al., 2016), where we map the highest absolute differences compared to the statistical data and where irrigation is an important practice in agriculture. Regional studies are able to develop approaches which consider local characteristics, while global studies have to transfer their methods to regions with completely different conditions. The global comparison is done on country level and the regional comparison on the level of states or provinces. For each country/state the irrigated area is calculated and compared to other studies.

4.1 Global Validation

The resulting global irrigated area of 3.67 mkm² lie between the results of GRIPC's 3.14 mkm² (Salmon et al., 2015) and IWMI-GIAM's (Thenkabail et al., 2009a) 3.98 mkm² values. All three data sets show more irrigated area than reported by the statistics. Despite the absolute difference our new high-resolution map shows strong correlation with both data sets (IWMI-GIAM r=0.97; GRIPC r=0.99) (Fig. 9) when correlating country values. The irrigated area is weighted with the size of the country area. Thus, the deviations of the countries are comparable with each other. The slope shows a small overestimation of our results compared to GRIPC (1.04) and a larger underestimation of the IWMI-GIAM (0.76). The regression plots also show the range of deviation (Fig. 9). The linear fit is strongly influenced by the high values and shows the underestimation of our results compared to IWMI-GIAM and overestimation compared to GRIPC (Fig. 9). The average difference per country is expressed by the Root-Mean-Squared-Error (RMSE). The RMSE of IWMI-GIAM (3.48%) and GRIPC (3.24%) are quite similar. The results of GRIPC (3.14 mkm²) are very close to the official statistics (3.07 mkm²). GRIPC uses a regionally based field-size factor which weights the size of the pixels. Without the field-size factor the results show remarkably more irrigation (3.76 mkm² instead of 3.14 mkm²). If we apply the GRIPC field-size factor to our results, it changes the amount of irrigated area to 3.05 mkm². The use of field size factors can be a way to adjust regions characterized by small holder farms and heterogeneous landscapes. On the other hand it would have to appropriately be determined and validated and may create another source of uncertainty.

4.2 Regional Validation

The regional data suggest a strong linear correlation between our results and the regional studies described by the correlations coefficient r=0.94 (USA), 0.84 (China) and r=0.92 (India) (Fig. 10). The slope shows an overestimation of our results regarding all compared data sets. The RMSE was weighted with the size of the compared state and shows a small overestimation of our data set compared to the regional studies.

The difference of our result and the irrigated area in the USA given by Ozdogan et al. (2010) can be explained by the statistical acreages that were used to derive our irrigation map. They are 25% larger than the corresponding acreages of Ozdogan et al. (2010). Our map extends this area and results in 28.7% more irrigated area than given by Ozdogan et al. (2010). The regions where our analysis shows more irrigated areas are in the dry regions at the Western USA and in the South (Tab. 7). The largest irrigated areas in the USA are found in California, where we estimate 41,816 km² of irrigated areas. Ozdogan et al. (2010) calculate 26,808 km² of irrigated areas, while the United States Geological Survey (USGS) reports 42,087 km² of irrigated areas for the year 2010 (Maupin et al., 2014). California is a good example for the different information about irrigated areas and the problems of validating irrigation maps. Even the official statistics for the year 2010 has two different values: the USGS states an irrigated area in California of 42,087 km², while the California Department of Water Resources (2010) reports 38,033 km². The example of California shows that the available statistics differ remarkably, which leads to strong impacts on the validation results. The complaints in California against the Water Rights regarding "Unauthorized Diversion" prove the illegal irrigation activities (California Environmental Protection Agency , 2017) which are not part of the official statistics and is not only an issue of small holder farmers or of watering lawns (Bauer et al., 2015). The comparison of our irrigation map with a study of irrigated areas in India shows a smaller relative error compared to the irrigation map of the USA. Overall the results are 138,172 km² higher than the results for India of Ambika et al. (2016). The differences could be caused by the different spatial resolution. The data of Ambika et al. (2016) is applied at a spatial resolution of ~250 m which fits better to the small fields and the heterogeneous landscape of smallholder farms as they occur in India.

Zhu et al. (2014) developed an irrigation map of China. The irrigation map of China (Zhu et al., 2014) represents official statistics downscaled by using NDVI data. The differences to the new irrigation map are high and expectable, due to the restriction to the statistics. The highest differences are found in the province of Xinjiang (percentage and absolute) in the North Western part of China. Xinjiang is characterised by a very dry continental climate. Nearly 90% of the area has less than 200 mm of precipitation per year (Hijmans et al., 2005). Therefore, agriculture is almost impossible without irrigation. Similar to the examples in the US and in India, the distribution and the patterns of the irrigated areas fit to the data of Zhu et al. (2014) but are denser. Irrigated areas seem to exceed the official numbers and confirms results of previous studies on water allocation and water consumption in the Tarim basin, where the water consumption exceeds the relevant water quotas (Thevs et al., 2015). The denser distribution of irrigated areas in the Tarim basin shows the overuse of water despite the water quotas of the Chinese government and results in an underestimation of irrigated areas by the official reports.

5 Discussion and Conclusion

This study is about developing a new global irrigation map and its comparison with the most common irrigation maps on the global as well as on the regional scale. The results enable a high spatial resolution global view on the distribution of irrigated areas. The analysis indicates that the high-resolution view allows detecting additional irrigated areas, which were not covered by the existing data sets. This also increases the global estimate of irrigated land by 18% compared to the reported statistics.

Differences between irrigation maps result from the quality and the spatial resolution of the input data and the assumption made. The large differences between our results and the statistics in central Asia (Mongolia, Kazakhstan) may result from classification errors in the underlying input data. Despite the high accuracy of the applied land use data sets, the ESA-CCI-LC and GlobCover land use classification include uncertainties, which lead to errors in mapping irrigated areas. For example grassland, pastures or meadows are sometimes classified as cropland. Especially in dry regions, such as in central Asia, this misinterpretation of cropland leads to a false classification of irrigated area.

The cropland area in the underlying land use data is not given as a proportional area of cropland within a pixel, which may also lead to an overestimation of cropland and thus also of irrigation.

The use of the agricultural suitability may lead to errors because it consists of 16 crops and may neglect e.g. drought resistant varieties or other species that are adapted to regional climatic conditions. Some typically irrigated crops are not considered in the crop suitability data, such as expensive and therefore most likely irrigated vegetables, olive trees, almond trees, as well as irrigated pastures, which potentially leads to an underestimation of irrigated area. On a global scale, these areas are nevertheless assumed to be relatively small.

Errors in classifying irrigated areas could occur through high groundwater levels or the proximity to open water; plants could reach water sources through capillary rise or directly tap the groundwater. This creates alternate water availability for the plants and can mimic irrigation in otherwise unsuitable locations.

Compared with statistics and existing studies, our results show differences in both directions: underestimation and overestimation – depending on the reference data. The example of information on irrigated areas in the USA illustrates that the large discrepancies between the studies can be explained by the input data and the references.

The highest discrepancies to the statistics are generally found in developing countries. Possible reasons are inadequate statistics that may often also be a result of political interests (Thenkabail et al., 2009b). General uncertainties or inadequacies of agricultural statistics are well known in many developing countries and e.g. discussed in Young (1999), and Thenkabail et al. (2009b). The results suggest that not all irrigated areas are correctly reported in the official statistics. This indicates the existence of illegal or unregistered irrigation activities. The results also go along with former analyses that showed large underestimation of irrigated areas in statistical data, especially for India (Thenkabail et al., 2009b) and West Africa (Drechsel et al., 2006). Independent survey techniques are strongly needed to verify the official statistics and reports.

The huge differences in between estimated and reported irrigated area demonstrate the need of further research in the field of irrigation mapping to get a more realistic picture of water withdrawal. The recent progress in the availability of remote sensing instruments through the Copernicus system of the EU (European Commision 2017) that delivers weekly global high resolution (10-20 m) coverage improves the data availability for land use classifications and crop status analysis and is very promising for irrigation mapping.

Irrigation is important to increase agricultural production (Smith, 2012), it reduces vulnerability of crop failures, increases food security and income (Bhattarai et al., 2002). At the same time, more irrigated areas require more water that is mainly taken from surface runoff and groundwater storage. This may increase the pressure in existing water resources and lead to an overuse of regionally available water resources which may threat future agricultural activities (Du et al., 2014). Therefore, an accurate and more detailed inventory of irrigated areas is required to better estimate and manage available water resources to avoid an overuse of water.

Tables and Figures

Name	Description	Period	Resolution	Data Source
Global Map of Irrigation Areas (GMIA) version 5.0	Areas equipped for irrigation in percent of the total pixel area.	2000-2008	5 arc minutes	Siebert et al. (2013)
Agricultural Suitability	Agricultural suitability, rain-fed and irrigated for the period 1980-2010	1981-2010	30 arc seconds	Zabel et al. (2014)
Multiple Cropping	Numbers of crop cycles, rain-fed and irrigated	1981-2010	30 arc seconds	Zabel et al. (2014)
Maximum NDVI	Maximum of global bimonthly NDVI maxima from the ENVISAT MERIS instrument	2004-2006	10 arc seconds	ESA (2007)
7-daily-mean NDVI	7-daily-mean NDVI data SPOT-VGT	1999-2012	30 arc seconds	ESA (2015)
ESA-CCI-LC (v. 1.6.1)	Land classification product	2008-2012	10 arc seconds	ESA (2015)
GlobCover	Land classification product	2009	10 arc seconds	ESA (2010)
WorldClim Precipitation	Yearly reanalysis precipitation data.	1961-1990	30 arc seconds	Hijmans et al. (2005)

Table 1: Applied global data sets.

	ESA-CCI-LC	**GlobCover**	**User's Accuracy**
Cropland rain-fed	88%	82%	
Cropland irrigated	92%	83%	
Mosaic cropland > 50%	59%	97%	

Table 2: Accuracy of the applied land use data sets.

Crop name
Barley (hordeum vulgare)
Cassava (manihot esculenta)
Groundnut (arachis hypogaea)
Maize (zea mays)
Millet (pennisetum americanum)
Oil palm (elaeis guineensis)
Potato (solanum tuberosum)
Rapeseed (brassica napus)

Paddy rice (oryza sativa)
Rye (secale cereale)
Sorghum (sorghum bicolor)
Soy (glycine maximum)
Sugarcane (saccharum officinarum)
Sunflower (helianthus annus)
Summer wheat (triticum aestivum)
Winter wheat (triticum gestivum)

Table 3: List of all considered crops.

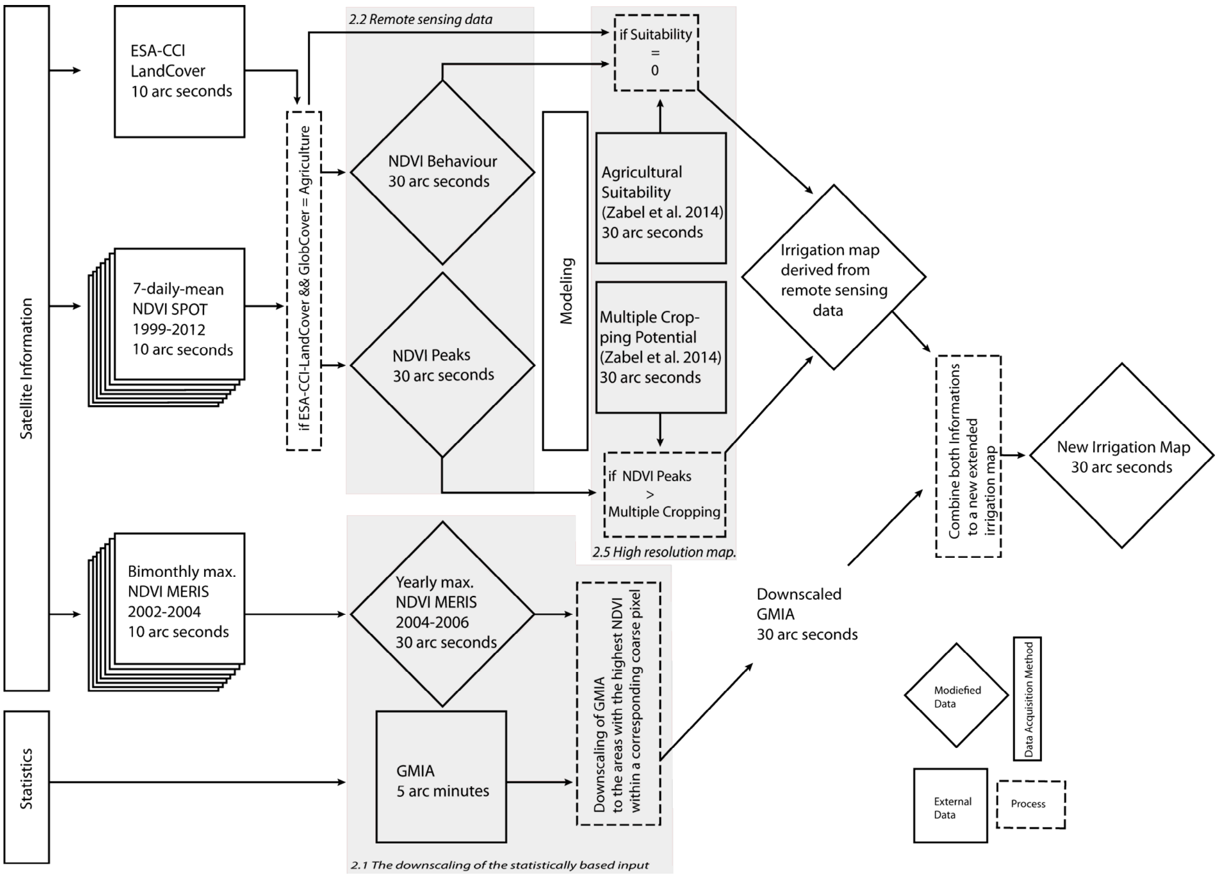

Figure 1: The scheme used for processing and analysing of the different spatial data and the multi decision tree to determine irrigated area. The grey boxes show the described subchapters 2.1, 2.2 and 2.5.

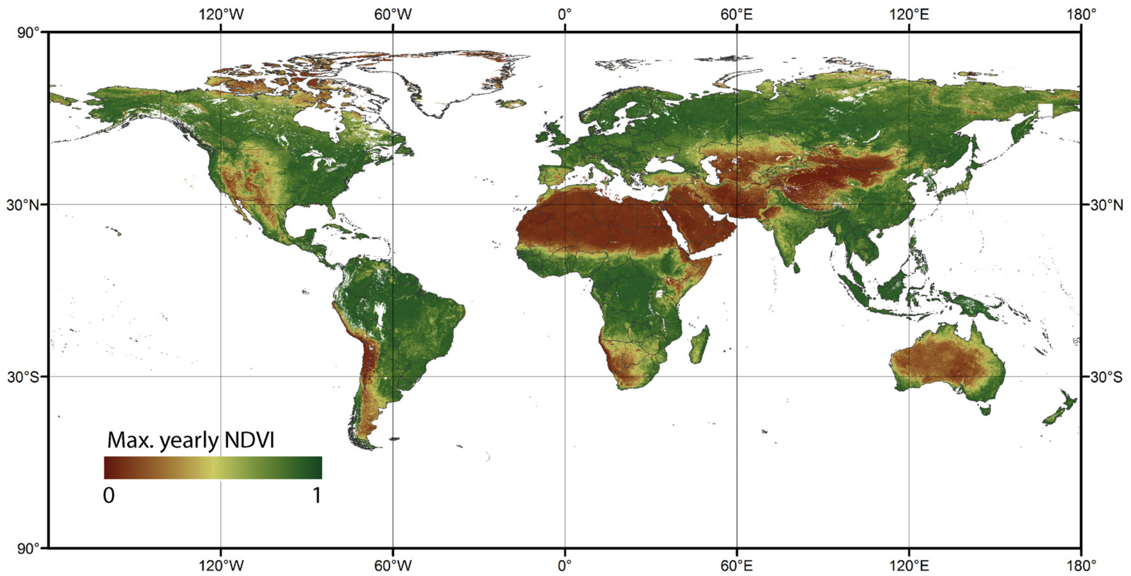

Figure 2: Yearly maximum NDVI derived from maximum bimonthly NDVI data of the EnviSAT MERIS instrument.

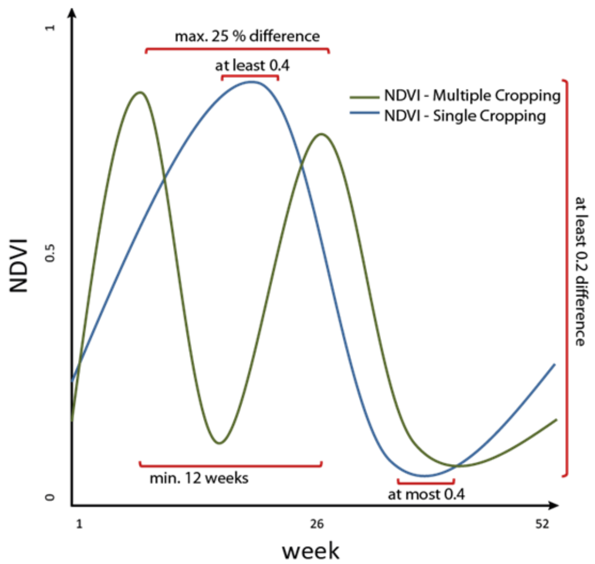

Figure 3: Idealized NDVI course of single- and multi-cropping and the conditions which must be fulfilled.

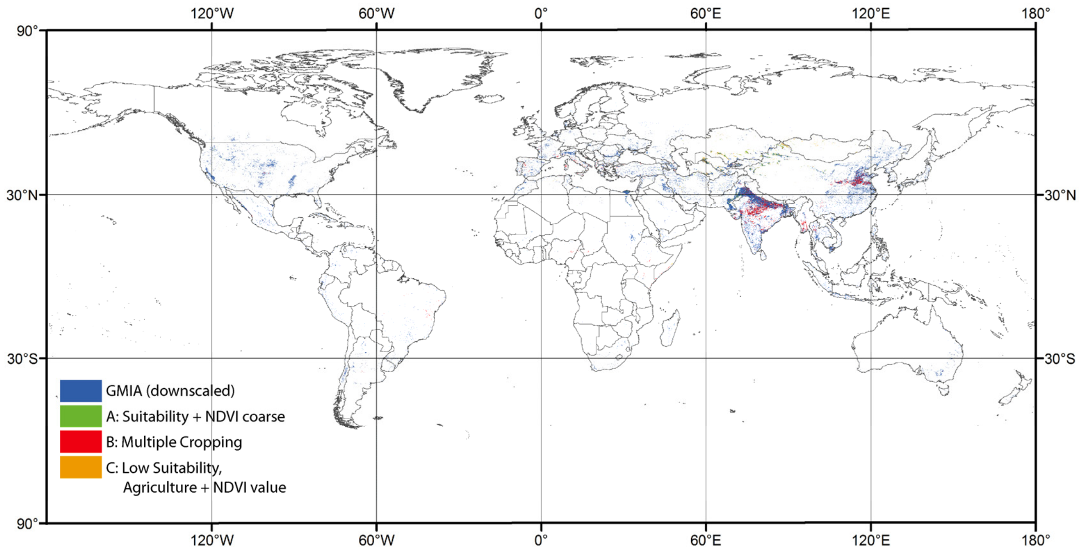

Figure 4: Irrigated areas identified by different approaches.

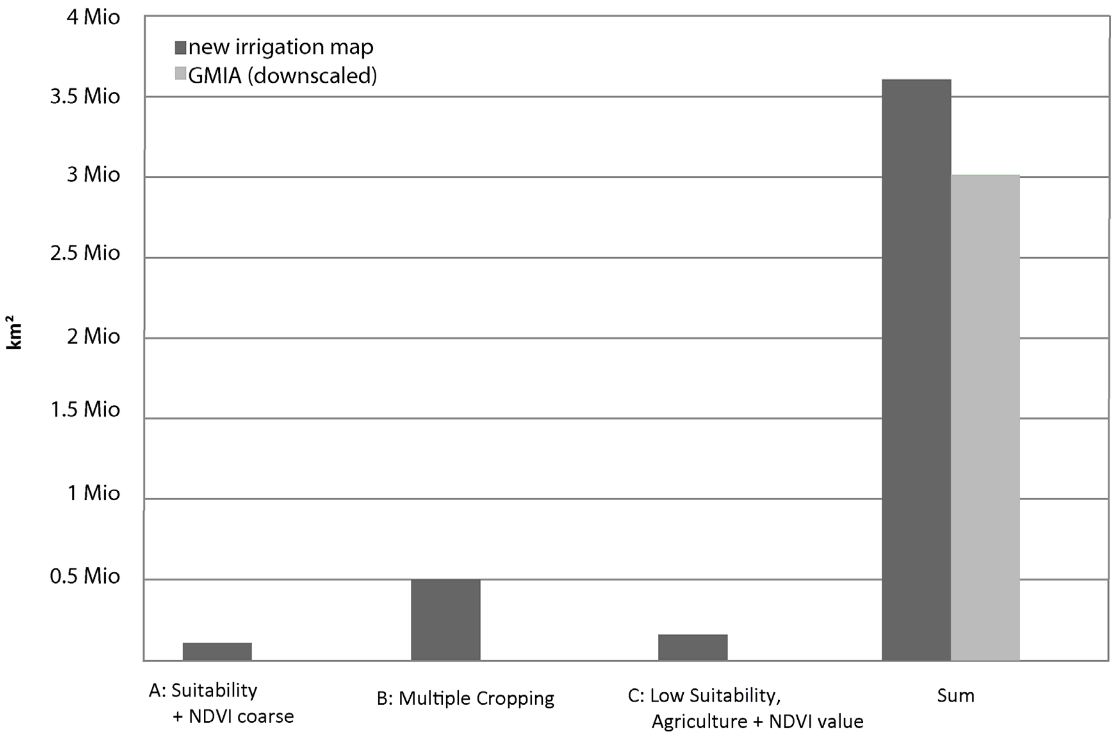

Figure 5: Results of the new irrigation map compared the downscaled GMIA.

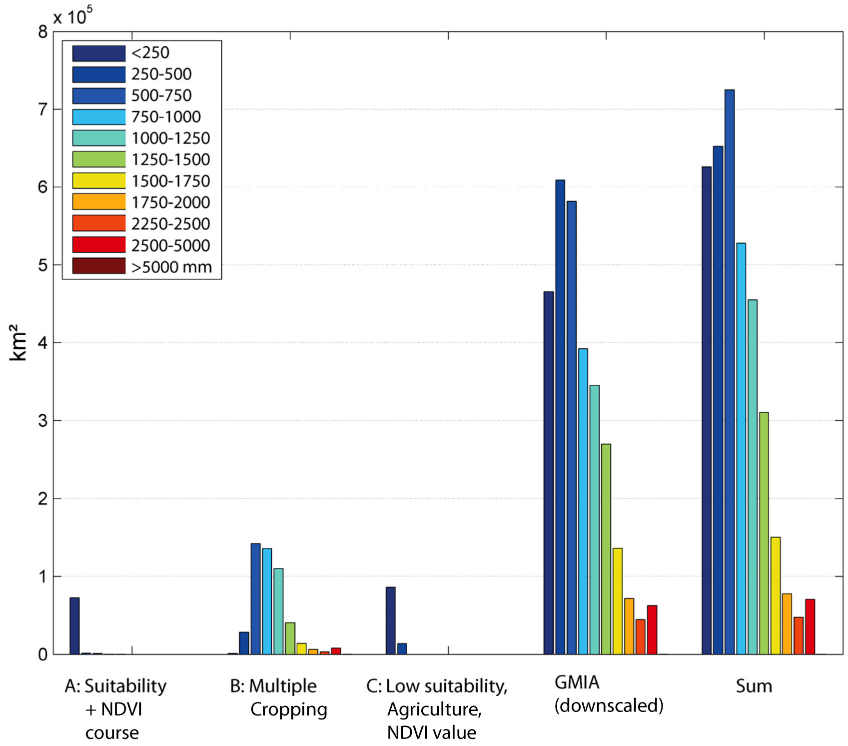

Figure 6: Yearly precipitation within the irrigated areas. Criteria A and C are suitable in dry regions while criterion B identifies in humid regions as well. Further, irrigation decreases with increasing precipitation, but is also used in regions with high yearly precipitation.

Region	New irrigation map [km²]	GMIA downscaled [km²]	FAOSTAT 1999-2012 [km²]
Africa	163,783	136,826	137,817
Eastern Africa	38,232	25,194	24,589
Middle Africa	3,820	1,685	1,692
Northern Africa	89,870	82,853	83,969
Southern Africa	15,844	15,828	15,956
Western Africa	16,018	11,267	11,611
America	520,446	500,106	494,988
Caribbean	13,267	13,248	13,346
Central America	76,072	73,226	70,638
South America	133,743	122,695	135,183
North America	297,365	290,938	275,822
Asia	2,675,125	2,094,375	2,147,293
Central Asia	165,668	102,861	99,412
Eastern Asia	799,187	642,388	664,684
Southern Asia	1,284,744	976,866	1,018,484
South-Eastern Asia	252,997	216,052	213,601
Western Asia	172,528	156,209	151,112
Europe	269,190	238,939	262,372
Eastern Europe	83,967	81,799	109,648
Northern Europe	10,227	10,227	10,015
Southern Europe	130,460	106,134	104,132
Western Europe	44,536	40,780	38,578
Oceania	41,844	41,266	30,673
Australia and New Zealand	41,821	41,242	30,525
Melanesia	24	24	134
Micronesia	0	0	3
Polynesia	0	0	10
World	3,670,390	3,011,512	3,073,142

Table 4: The results of the new irrigation map compared to the downscaled GMIA and FAOSTAT (FAO, 2016b). The countries are grouped according to the UN-Geographical Regions (UNO, 2013).

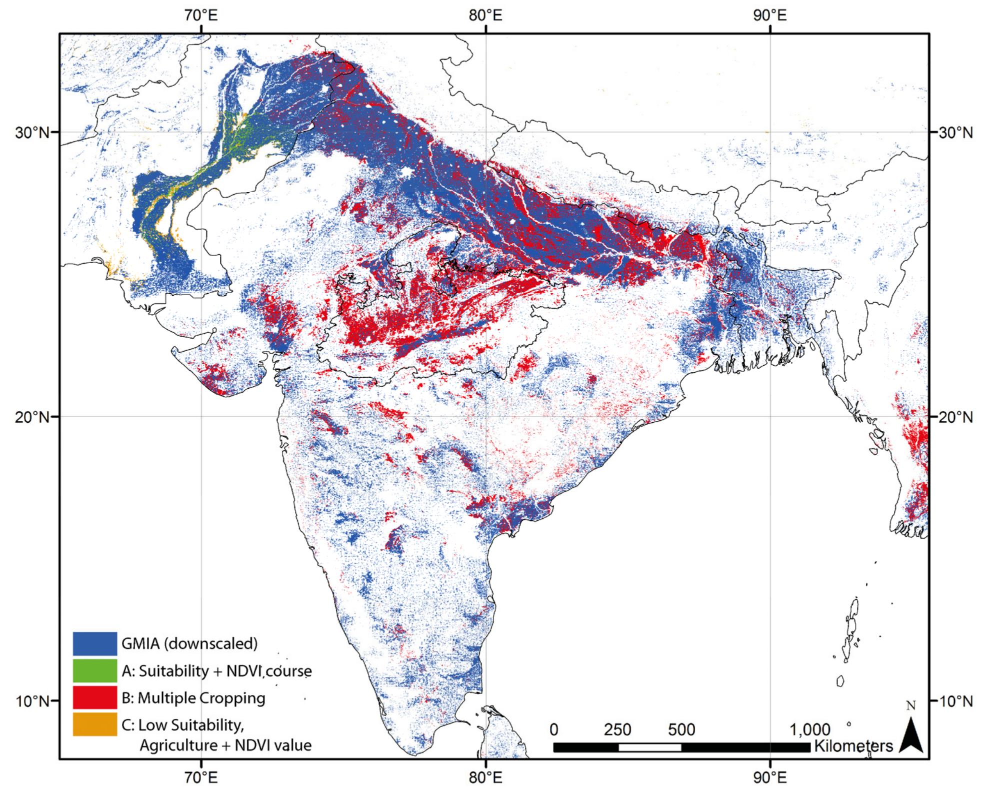

Figure 7: The Indian subcontinent and its identified irrigated areas. The blue areas are the information of the downscaled GMIA. Irrigation is more dense than expected in already irrigated regions and new areas appear in the state Madhya Pradesh.

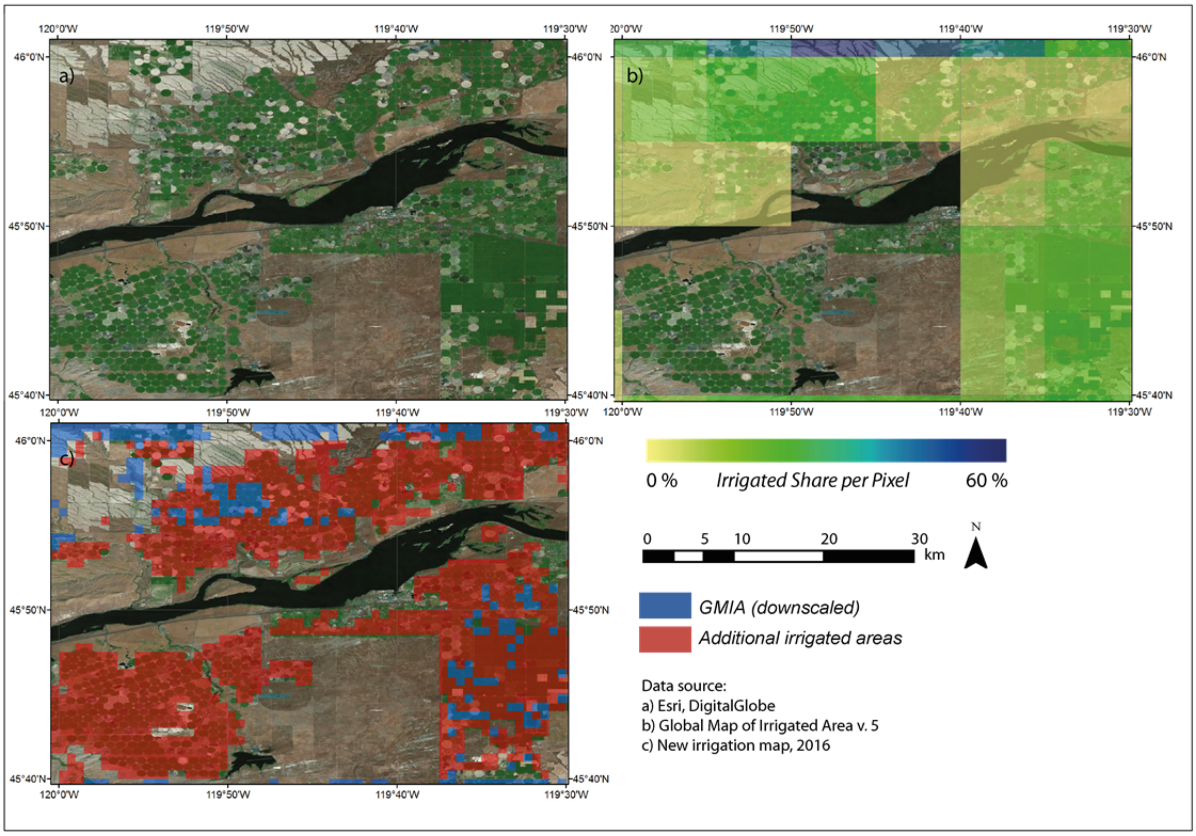

Figure 8: Small scaled analysis of the new irrigation map (lower left) and GMIA (upper right) in the USA.

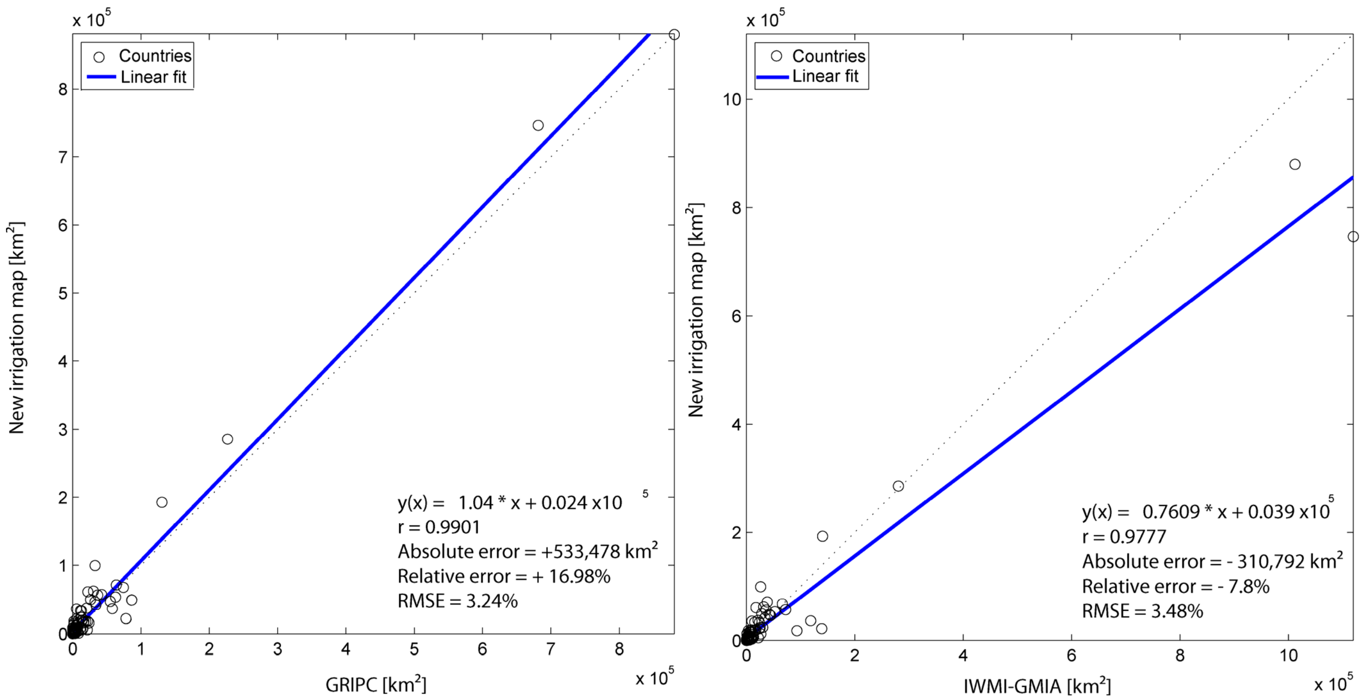

Figure 9: Regression plots of the two compared global data sets. The blue line is the linear fit, the dotted black line the linear equation.

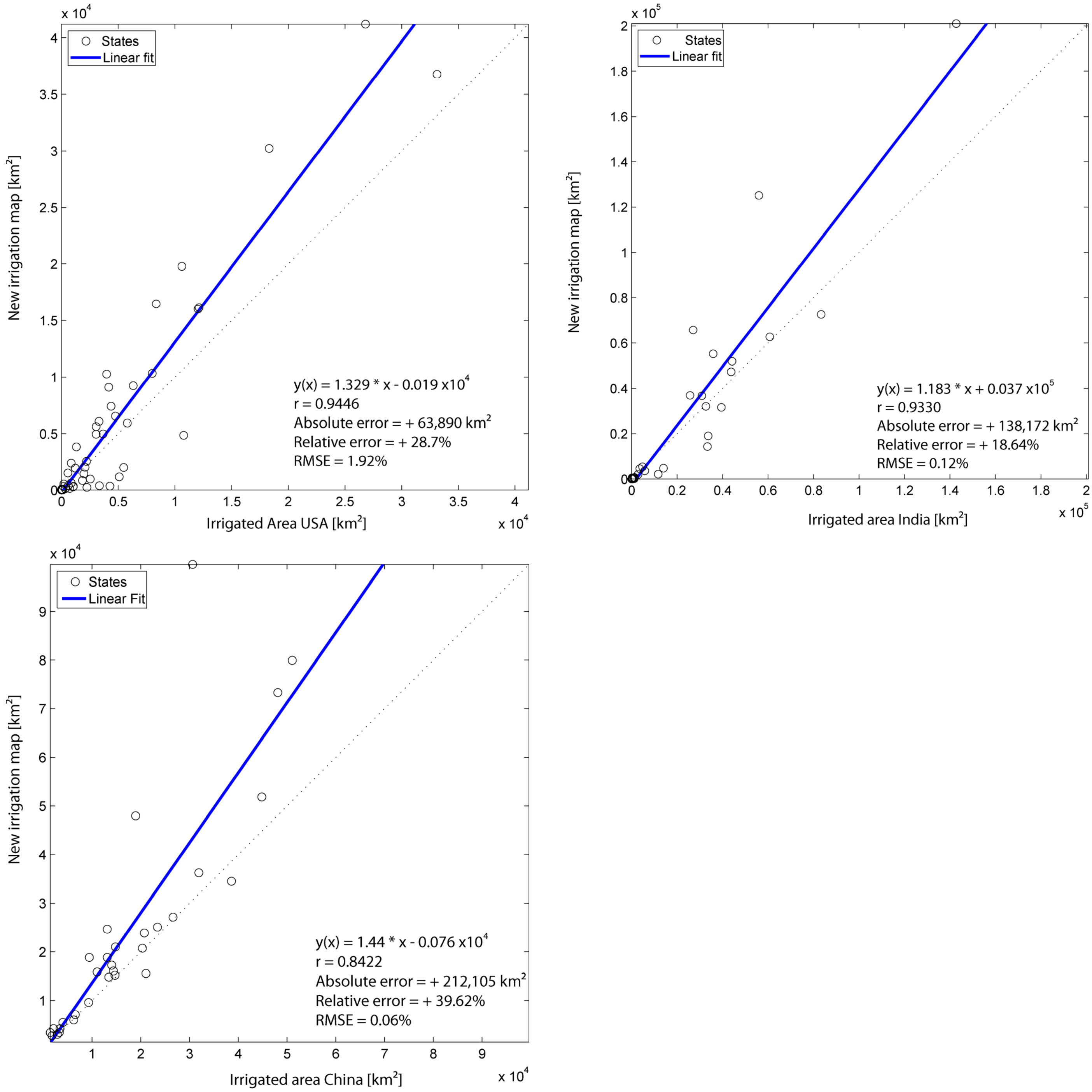

Figure 10: Regression plots of the compared our irrigation map compared to regional data sets of the USA (Ozdogan et al, 2010), India (Ambika et al. 2016) and China (Zhu et al., 2014). The blue line is the linear fit, the dotted black line the linear equation.

References

Abuzar, M., McAllister, A., and Whitfield, D.: Mapping Irrigated Farmlands Using Vegetation and Thermal Thresholds Derived from Landsat and ASTER Data in an Irrigation District of Australia, Photogrammetric Engineering & Remote Sensing, 81, 229-238, 2015.

Alexandratos, N. and Bruinsma, J.: World agriculture towards 2030/2050: the 2012 revision. ESA working paper no. 12-03, Global Perspective Studies Team, FAO Agricultural Development Economics Division, Rome, Italy, 2012.

Ambika, A. K., Wardlow, B., and Mishra, V.: Remotely sensed high resolution irrigated area mapping in India for 2000 to 2015, Sci Data, 3, 160118, 2016.

Bauer, S., Olson, J., Cockrill, A., van Hattem, M., Miller, L., Tauzer, M., and Leppig, G.: Impacts of Surface Water Diversions for Marijuana Cultivation on Aquatic Habitat in Four Northwestern California Watersheds, PLoS ONE, 10, e0120016, 2015.

Bhattarai, M., Sakthivadivel, R., and Hussain, I.: Irrigation impacts on income inequality and poverty alleviation: Policy issues and options for improved management of irrigation systems., Institute, I. W. M. (Ed.), Colombo, 2002.

California Department of Water Resources: Agricultral Land and Water Estimates, http://www.water.ca.gov/landwateruse/anlwuest.cfm, last access: 2017/08/22, 2010

California Environmental Protection Agency: Water Rights Enforcement, http://www.waterboards.ca.gov/waterrights/water_issues/programs/enforcement/complaints/, last access: 2017/08/24, 2017.

Deryng, D., Elliott, J., Folberth, C., Muller, C., Pugh, T. A. M., Boote, K. J., Conway, D., Ruane, A. C., Gerten, D., Jones, J. W., Khabarov, N., Olin, S., Schaphoff, S., Schmid, E., Yang, H., and Rosenzweig, C.: Regional disparities in the beneficial effects of rising CO2 concentrations on crop water productivity, Nature Clim. Change, advance online publication, 2016.

Döll, P. and Schmied, H. M.: How is the impact of climate change on river flow regimes related to the impact on mean annual runoff? A global-scale analysis, Environmental Research Letters, 7, 014037, 2012.

Drechsel, P., Graefe, S., Sonou, M., and Cofie, O. O.: Informal Irrigation In Urban West Africa: An Overview. International Water Management Institute, Colombo, Sri Lanka, 2006.

Du, T., Kang, S., Zhang, X., and Zhang, J.: China's food security is threatened by the unsustainable use of water resources in North and Northwest China, Food and Energy Security, 3, 7-18, 2014.

European Commission: Copernicus - Europe's eyes on Earth, www.copernicus.eu, last access: 2017/08/22, 2017.

European Environment Agency: Coordination of Information on the Environment (CORINE), http://land.copernicus.eu/pan-european/corine-land-cover/clc-2012/view, last access: 2017/08/23, 2014.

European Space Agency (ESA): Bimonthly MERIS FR Composites - NDVI, 2007.

European Space Agency (ESA): ESA CCI Land Cover, http://maps.elie.ucl.ac.be/CCI/viewer/index.php, last access: 2016/11/24, 2015.

European Space Agency (ESA): GlobCover 2009, http://due.esrin.esa.int/page_globcover.php, last access: 2016/11/24, 2010.

Evans, R. G. and Sadler, E. J.: Methods and technologies to improve efficiency of water use, Water Resources Research, 44, 2008.

Food and Agriculture Organization of the United Nations (FAO): AQUASTAT, http://www.fao.org/nr/water/aquastat/data/query/, last access: 2016/06/14, 2016a.

Food and Agriculture Organization of the United Nations (FAO): Did you know...? Facts and figures about, http://www.fao.org/nr/water/aquastat/didyouknow/index3.stm, last access: 2016/11/24, 2014a.

Food and Agriculture Organization of the United Nations (FAO): FAOSTAT, http://faostat3.fao.org/download/Q/QC/E, last access: 2016/06/14, 2016b.

Food and Agriculture Organization of the United Nations (FAO): Total Withdrawal by Sector, http://www.fao.org/nr/water/aquastat/tables/WorldData-Withdrawal_eng.pdf, last access: 2016/11/24, 2014b.

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., Mueller, N. D., O'Connell, C., Ray, D. K., West, P. C., Balzer, C., Bennett, E. M., Carpenter, S. R., Hill, J., Monfreda, C., Polasky, S., Rockstrom, J., Sheehan, J., Siebert, S., Tilman, D., and Zaks, D. P.: Solutions for a cultivated planet, Nature, 478, 337-342, 2011.

Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., Havlik, P., Mosnier, A., Thornton, P., Wood-Sichra, U., Herrero, M., Becker-Reshef, I., Justice, C., Hansen, M., Gong, P., Abdel Aziz, S., Cipriani, A., Cumani, R., Cecchi, G., Conchedda, G., Ferreira, S., Gomez, A., Haffani, M., Kayitakire, F., Malanding, J., Mueller, R., Newby, T., Nonguierma, A., Olusegun, A., Ortner, S., Rajak, D. R., Rocha, J., Schepaschenko, D., Schepaschenko, M., Terekhov, A., Tiangwa, A., Vancutsem, C.,

Vintrou, E., Wenbin, W., van der Velde, M., Dunwoody, A., Kraxner, F., and Obersteiner, M.: Mapping global cropland and field size, Global Change Biology, 21, 1980-1992, 2015.
Godfray, H. C., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., and Toulmin, C.: Food security: the challenge of feeding 9 billion people, Science, 327, 812-818, 2010.
Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A.: Very high resolution interpolated climate surfaces for global land areas, International Journal of Climatology, 25, 1965-1978, 2005.
Jägermeyr, J., Gerten, D., Heinke, J., Schaphoff, S., Kummu, M., and Lucht, W.: Water savings potentials of irrigation systems: global simulation of processes and linkages, Hydrol. Earth Syst. Sci., 19, 3073-3091, 2015.
Jin, N., Tao, B., Ren, W., Feng, M., Sun, R., He, L., Zhuang, W., and Yu, Q.: Mapping Irrigated and Rainfed Wheat Areas Using Multi-Temporal Satellite Data, Remote Sensing, 8, 207, 2016.
Liu, J., Williams, J. R., Zehnder, A. J. B., and Yang, H.: GEPIC – modelling wheat yield and crop water productivity with high resolution on a global scale, Agricultural Systems, 94, 478-493, 2007.
Mankin, J. S., Viviroli, D. J., Singh, D., Hoekstra, A. Y., and Diffenbaugh, N. S.: The potential for snow to supply human water demand in the present and future, Environmental Research Letters, 10, 114016, 2015.
Maupin, M. A., Kenny, J. F., Hutson, S. S., Lovelace, J. K., Barber, N. L., and Linsey, K. S.: Estimate Use of Water in the United States in 2010, United States Geological Survey (USGS), 2014.
Mauser, W., Klepper, G., Zabel, F., Delzeit, R., Hank, T., Putzenlechner, B., and Calzadilla, A.: Global biomass production potentials exceed expected future demand without the need for cropland expansion, Nat Commun, 6, 2015.
Molden, D.: Water for Food Water for Live. A Comprehensive Assessment for Water Management in Agriculture, Earthscan, 2007. 2007.
Neumann, K., Stehfest, E., Verburg, P. H., Siebert, S., Müller, C., and Veldkamp, T.: Exploring global irrigation patterns: A multilevel modelling approach, Agricultural Systems, 104, 703-713, 2011.
Ozdogan, M. and Gutman, G.: A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US, Remote Sensing of Environment, 112, 3520-3537, 2008.
Ozdogan, M., Yang, Y., Allez, G., and Cervantes, C.: Remote Sensing of Irrigated Agriculture: Opportunities and Challenges, Remote Sensing, 2, 2274-2304, 2010.
Prasch, M., Mauser, W., and Weber, M.: Quantifying present and future glacier melt-water contribution to runoff in a central Himalayan river basin, The Cryosphere, 7, 889-904, 2013.
Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Muller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A., Schmid, E., Stehfest, E., Yang, H., and Jones, J. W.: Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison, Proc Natl Acad Sci U S A, 111, 3268-3273, 2014.
Salmon, J. M., Friedl, M. A., Frolking, S., Wisser, D., and Douglas, E. M.: Global rain-fed, irrigated, and paddy croplands: A new high resolution map derived from remote sensing, crop inventories and climate data, International Journal of Applied Earth Observation and Geoinformation, 38, 321-334, 2015.
Shahriar Pervez, M., Budde, M., and Rowland, J.: Mapping irrigated areas in Afghanistan over the past decade using MODIS NDVI, Remote Sensing of Environment, 149, 155-165, 2014.
Siebert, S., Döll, P., Hoogeveen, J., Faures, J. M., Frenken, K., and Feick, S.: Development and validation of the global map of irrigation areas, Hydrology and Earth System Sciences, 9, 535-547, 2005.
Siebert, S., Henrich, V., Frenken, K., and Burke, J.: Update Of The Digital Global Map Of Irrigation Areas to Version 5. Nations, F. a. A. O. o. t. U. and Bonn, U. o. (Eds.), 2013.
Smith, M.: Yield response to water: the original FAO water production function. In: Crop yield response to water, Steduto, P., Hsiao, T. C., Fereres, E., and Raes, D. (Eds.), Food and Agriculture Organization of the United Nations, Rome, 2012.
Strzepek, K. and Boehlert, B.: Competition for water for the food system, Philos Trans R Soc Lond B Biol Sci, 365, 2927-2940, 2010.
Sys, C. O., van Ranst, E., Debaveye, J., and Beernaert, F.: Land Evalutation: Part III Crop Requirements., Agricultural Publications, 1993. 1993.
Thenkabail, P. S., Biradar, C. M., Noojipady, P., Dheeravath, V., Li, Y., Velpuri, M., Gumma, M., Gangalakunta, O. R. P., Turral, H., Cai, X., Vithanage, J., Schull, M. A., and Dutta, R.: Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium, International Journal of Remote Sensing, 30, 3679-3733, 2009a.
Thenkabail, P. S., Dheeravath, V., Biradar, C. M., Gangalakunta, O. R. P., Noojipady, P., Gurappa, C., Velpuri, M., Gumma, M., and Li, Y.: Irrigated Area Maps and Statistics of India Using Remote Sensing and National Statistics, Remote Sensing, 1, 50-67, 2009b.

Thevs, N., Peng, H., Rozi, A., Zerbe, S., and Abdusalih, N.: Water allocation and water consumption of irrigated agriculture and natural vegetation in the Aksu-Tarim river basin, Xinjiang, China, Journal of Arid Environments, 112, 87-97, 2015.
Tilman, D., Balzer, C., Hill, J., and Befort, B. L.: Global food demand and the sustainable intensification of agriculture, Proceedings of the National Academy of Sciences, 108, 20260-20264, 2011.
United Nations Statistics Devisions (UNO): Composition of macro geographical (continental) regions, geographical sub-regions, and selected economic and other groupings, http://unstats.un.org/unsd/methods/m49/m49regin.htm, last access: 2016/11/24, 2013.
United Nations (UNO): Sustainable Development Goals, https://sustainabledevelopment.un.org/sdgs, last access: 2016/11/24, 2016.
U.S. Geological Survey (USGS): Global Land Cover Characteristics Data Base Version 2.0, https://lta.cr.usgs.gov/glcc/globdoc2_0, last access: 2016/11/24, 2000.
Vörösmarty, C. J.: Global water assessment and potential contributions from Earth Systems Science, Aquatic Sciences, 64, 328-351, 2002.
Vorosmarty, C. J. and Sahagian, D.: Anthropogenic disturbance of the terrestrial water cycle, Bioscience, 50, 753-765, 2000.
Wada, Y., Wisser, D., and Bierkens, M. F. P.: Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources, Earth System Dynamics, 5, 15-40, 2014.
Young, A.: Is there Really Spare Land? A Critique of Estimates of Available Cultivable Land in Developing Countries, Environment, Development and Sustainability, 1, 3-18, 1999.
Zabel, F., Putzenlechner, B., and Mauser, W.: Global agricultural land resources--a high resolution suitability evaluation and its perspectives until 2100 under climate change conditions, PLoS One, 9, e107522, 2014.
Zhu, X., Zhu, W., Zhang, J., and Pan, Y.: Mapping Irrigated Areas in China From Remote Sensing and Statistical Data, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7, 4490-4504, 2014.