Spatial Evapotranspiration, Rainfall and Land Use Data in Water Accounting. Part 1: Review of the accuracy of the remote sensing data

P. Karimi[1] and W.G.M. Bastiaanssen[1,2,3]

[1]UNESCO-IHE Institute for Water Education, Delft, The Netherlands
[2]International Water Management Institute, Battaramulla, Sri Lanka
[3]Faculty of Civil Engineering and Geosciences, Water Management Department, Delft University of Technology, Delft, The Netherlands

Correspondence to: P. Karimi (P.karimi@Unesco-ihe.org,)

Abstract

The scarcity of water encourages scientists to develop new analytical tools to enhance water resource management. Water accounting and distributed hydrological models are examples of such tools. Water accounting needs accurate input data for adequate descriptions of water distribution and water depletion in river basins. Ground-based observatories are decreasing, and not generally accessible. Remote sensing data is a suitable alternative to measure the required input variables. This paper reviews the reliability of remote sensing algorithms to accurately determine the spatial distribution of actual evapotranspiration, rainfall and land use. For our validation we used only those papers that covered study periods of one season to annual cycles because the accumulated water balance is the primary concern. Review papers covering shorter periods only (days, weeks) were not included in our review. Our review shows that by using remote sensing, the absolute values of evapotranspiration can be estimated with an overall accuracy of 95% (STD 5%) and rainfall with an overall absolute accuracy of 82% (STD 15%). Land use can be identified with an overall accuracy of 85% (STD 7%). Hence, more scientific work is needed to improve the spatial mapping of rainfall and land use using multiple space-borne sensors. While not always perfect at all spatial and temporal scales, seasonally accumulated actual evapotranspiration maps can be used with confidence in water accounting and hydrological modeling.

1. Introduction

The demand for fresh water is increasing worldwide due to economic and population growth (Molden et al., 2007; Vörösmarty et al., 2010). Proper planning of such scarce water resources in terms of storage, allocation, return flow and environmental services is vital for optimizing the resource (Chartres and Varma, 2010). There is, however, a lack of fundamental data on vertical and lateral water flows, water stocks, water demand, and water depletion. At the same time, there is a decline in the network density of operational hydro-meteorological field stations. The absence of adequate field data sets is an important obstacle for sound, evidence-based water resource management decisions. The consequence of data scarcity is more severe in trans-boundary river basins where, apart from collection, the accessibility of data is hindered by political issues (Awulachew et al., 2013).

Remotely sensed hydrological data are an attractive alternative to conventional ground data collection methods (Bastiaanssen et al., 2000; Engman and Gurney, 1991; Wagner et al., 2009, Neale and Cosh, 2012). Satellites measure the spatial distribution of hydrological variables indirectly with a high temporal frequency across vast river basins. There are many public data archives where every user can download pre-processed satellite data. Quality flags are often provided, as well as manuals with explanations on how the satellite data have been pre-processed and can be reproduced. These recurrent data sets are highly transparent, politically neutral and consistent across entire river basins, even for large basins such as the Nile and the Ganges. While certain satellite data sets have been processed to a first level of reflectance, emittance and backscatter coefficients, others will even provide second level products that can be directly explored for water resource planning purposes (e.g. land cover, soil moisture, and rainfall). Evapotranspiration (ET) is one of the parameters that often requires additional processing of the spectral data; only a very few public domain data archives provide pre-processed ET data, and in fact, spatial ET modeling is still under developed. Examples of several remotely sensed ET algorithms that could be applied to interpret raw satellite data into spatial layers of ET are well summarized in a recent book edited by Irmak (2012).

Time series of various hydrological variables such as precipitation, evapotranspiration, snow cover, soil moisture, water levels, and aquifer storage can be downloaded from public domain satellite-based data archives. With the right analytical tools and skills, these abundant datasets of hydrological processes can be used to produce information on water resource condition in river basins. Tools such as *Water Accounting Plus* (WA+) (Bastiaanssen, 2009; Karimi et al., 2013a, 2013b) are expressly designed to exploit remote sensing estimates of hydrological variables. Water accounting is the process of communicating water related information about a geographical domain, such as a river basin or a country, to users such as policy makers, water authorities, basin managers, and public users. Water accounting information can be key to river basin management policy, especially when administrations are reluctant to share their – sometimes imperfect - in situ data with neighboring states and countries. WA+ can facilitate conflict management in internationally shared river basins. In addition to that, hydrological variables derived from remote sensing can also be used for spatially distributed hydrological modeling. Studies by Houser et al. (1998), Schuurmans et al. (2003), and Immerzeel and Droogers (2008) have for instance demonstrated that such inputs have improved hydrological model performance for river basins in Australia, The Netherlands and India respectively.

A major point of criticism that is commonly laid down on remote sensing data has been the lack of accuracy. With the improvement of technology the accuracy has however improved significantly over the last 30 years; yet it is necessary to remain critical. It is important to note that the conventional methods of measuring hydrological processes (e.g. rainfall and discharge) are not flawless either, and thus the accuracy of both types of measurements needs to be verified. There is also limitations with what conventional measurements methods can offer especially when spatially distributed data is concerned. For instance the actual evapotranspiration (ET) of river basins can hardly be measured operationally through ground measurements, and therefore the depletion of water remains difficult to estimate and quantify. Thus it is often ignored in water accounting frameworks such as the SEEAW system proposed by the United Nations Statistics Division (UN, 2007) and the Australian water accounting system (ABS, 2004). Remote sensing techniques on the other hand can provide spatially distributed daily estimates of actual ET and this opens new pathways in the accounting of water depletion (Karimi et al., 2013a).

This paper investigates the errors and reliability of remotely sensed ET, rainfall, and land use based on a comprehensive literature review. The choice of the variables that have been investigated in this paper (ET, Rainfall, LULC) is based on the common use in hydrological and water resources management studies. Only recent publications on accumulated ET and rainfall for a minimum time period of one growing cycle have been consulted, which implies that some of the well-known reference papers are excluded because they relate to shorter flux observation periods. Elder remote sensing algorithms were also excluded. . The companion paper (Karimi et al., 2013c) investigates impacts of the errors associated with the satellite measurement for ET, rainfall and land use on the accuracy of WA+ outputs, using a case study from the Awash basin in Ethiopia.

2. Remote Sensing Data for Water Accounting (WA+)

2.1 Evapotranspiration

Over the past decades several methods and algorithms to estimate actual evapotranspiration (ET) through satellite measurements have been developed. Most of these estimates are based on the surface energy balance equation. The surface energy balance describes the partitioning of natural radiation absorbed at the earth surface into physical land surface processes. Evapotranspiration is one of these key processes of the energy balance, because latent heat (energy) is required for evaporation to take place. The energy balance at the earth surface reads as:

$$LE = R_n - G - H \qquad (W\ m^{-2}) \qquad (1)$$

Where R_n is the net radiation, G is the soil heat flux, H is the sensible heat flux, and LE is the latent heat flux. The sensible heat flux H is a function of the temperature difference between the canopy surface and the lower part of the atmosphere, and the soil heat flux G is a similar function related to the temperature difference between the land surface and the top soil. A rise of surface temperature will thus usually increase H and G fluxes. Evaporative cooling will reduce H and G, and result in a lower surface temperature. The latent heat flux LE is the equivalent energy amount (W m^{-2}) of the ET flux (kg m^{-2} s^{-1} or mm d^{-1}). The net radiation absorbed at the land surface is computed from shortwave and long wave radiation exchanges. Solar radiation is shortwave and is the most important supplier of energy. More information on the energy balance is provide in general background material such as Brutsaert (1982), Campbell and Norman (1998) or Allen et al. (1998).

Surface temperature is measured routinely by space borne radiometers such as the Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectrometer (MODIS), Visible Infrared Imager Radiometer Suite (VIIRS), Landsat, Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER), China Brasil Earth Resources Satellite (CBERS), and the Chinese HJ and Feng Yung satellites. Remotely sensed surface temperature is the major input variable in ET algorithms. Examples of thermal infrared ET algorithms are provided by EARS (Rosema, 1990), SEBAL (Bastiaanssen et al., 1998), TSEB (Norman et al., 1995), SEBS (Su, 2002; Jia et al., 2003), METRIC (Allen et al., 2007), ALEXI (Anderson et al., 1997), and ETWatch (Wu et al., 2012). The differences among these algorithms are often related to the parameterization of H, general model assumptions, and the amount of input data required to operate these models.

Other groups of ET algorithms are based on the vegetation index and its derivatives such as published by Nemani and Running (1989), Guerschman et al. (2009), Zhang et al. (2010a), Mu et al. (2011), and Miralles et al. (2011). ETLook (Bastiaanssen et al., 2012) is a new ET model that directly computes the surface energy balance using surface soil moisture estimations for the top soil (to feed soil evaporation) and sub-soil moisture for the root zone (to feed vegetation transpiration). Soil moisture data can be inferred from thermal measurements (e.g. Scott et al., 2003) or from microwaves measurements (e.g. Dunne et al., 2007). Microwave measurements provide a solution for all weather conditions and can be applied at any spatial scale for which moisture data is available.

A different school of remote sensing based ET algorithms is built around the derivation of a relative value of ET using trapezoid/triangle methods. Trapezoid/triangle diagrams are constructed from a population of pixel values of surface temperature and vegetation index and used to infer the relative value of ET (e.g. Choudhury, 1995; Moran et al., 1994; Roerink et al., 2000; Wang et al., 2007). In these diagrams, the range of surface temperature values at a given class of vegetation index is the basis for determining relative ET, assuming that the lowest temperature in a certain range of vegetation index represents potential ET. The highest temperature coincides with zero evaporation. The main assumption in triangle/trapezoidal method is that the variation in vegetation index relation to surface temperature is driven primarily by the variation in soil water content rather than differences in atmospheric conditions.

Merging different global ET products such as MOD16 (Mu et al., 2011) and ERA-Interim (Dee et al., 2011) at global and regional scales into one ET product is another approach that has been used by a group of scientists. This approach mainly uses statistical methods to combine ET products that are based on different methods, algorithms, and origins (e.g. Global: Mueller et al., 2013; Africa: Trambauer et al., 2013; US: Velpuri et al., 2013). New ensemble ET products on the basis of several open access and global scale operational ET products from earth observations are under development, but are not published yet.

Review papers on advanced algorithms for estimating spatial layers of ET in general are published by Moran and Jackson (1991), Kustas and Norman (1996), Bastiaanssen (1998), Courault et al. (2005), Glenn et al. (2007), Gowda et al. (2007), Kalma et al. (2008), Verstraeten et al. (2008), and Allen et al. (2011). While these review papers provide a good understanding of the evolution of ET algorithm development, they rarely report the accuracies attainable, especially at a seasonal or longer time frame.

2.2 Rainfall

There are different algorithms to infer rainfall from satellite data. The four essentially different technologies are (i) indexing the number and duration of clouds (Barrett, 1988), (ii) accumulated cold cloud temperatures (Dugdale and Milford, 1986), (iii) microwave emissivity (Kummerow et al., 1996), and (iv) radar reflectivity (Austin, 1987). Techniques using microwave wavelength information are promising alternatives for measuring rainfall because of the potential for sensing the raindrops itself and not a surrogate of rain, such as the cloud type. Microwave radiation with wavelengths in the order of 1 mm to 5 cm has a strong interaction with raindrops, since the drop size of rain is comparable to this wavelength. This feature makes them suitable to detect rainfall intensity. Active microwave (radar) measurements of rainfall are based on the Rayleigh scattering caused by the interaction of rain and the radar signal (Cracknell and Hayes, 1991). Space borne radar measurements of rain intensity are possible with the Precipitation Radar aboard the NASA Tropical Rainfall Measuring Mission (TRMM) and Global Precipitation Mission satellites, which assesses the attenuation of the radar signal caused by the rain. The precipitation radar (PR) has a pixel size of 5 km and can oversee a swath of 220 km. Unfortunately, it is usually necessary to evaluate the rainfall radar reflectivity factor empirically on a region-by-region basis over lengthy periods of time. In other words, rain radar systems – both ground-based and satellite-based – need calibration for proper rainfall estimates. We will conclude later that most papers investigated in our review process do apply a certain level of field calibration. Several operational rainfall products based on satellite measurements have been created or improved more recently. Among the new ensemble rainfall products is the Climate Hazards Group IR Precipitation Station (CHIRPS) that provides promising results (Funk et al., 2013).

Review papers on the determination of rainfall from satellite measurements have been prepared, by for instance Barrett (1988), Barrett and Beaumont (1994), Petty (1995), Petty and Krajewski (1996), Kummerow et al. (1996), Smith et al. (1998), Kidd (2001), Stephens and Kummerow (2007), Huffman et al. (2007) and . A selection of available rainfall products based on remote sensing techniques – sometimes used in combination with other methodologies - is presented in Table 1.

Table 1.

2.3 Land use

Whereas land cover describes the physical properties of vegetation (e.g. grass, savannah, forest), land use denotes the usage of that land cover (e.g. pasture, crop farming, soccer field). Maps of land use are fundamental to WA+ because it determines the services and processes in a spatial context. Different types of land use provide benefits and services such as food production (agricultural land), economic production (industrial areas), power generation (reservoirs), environmental ecosystems (wetlands), livelihoods etc., and they have an associated water consumptive use. Land use classification based on the use of water, differs from classical land use – land cover maps that focus mainly on the description of woody vegetation such as forests and shrubs for ecological and woodland management purposes. WA+ needs land use maps focused on crop types (rainfed potatoes, irrigated maize) and the source of water consumed (e.g. surface water and groundwater). Some of the first maps dedicated for agricultural water management were prepared by Thenkabail et al. (2005), Cheema and Bastiaanssen (2010), Yalew et al. (2012) and Kiptala et al. (2013). Furthermore, land use classifications for WA+ at river basin scale require a pixel size of 30 to 100 meter that can be delivered by Landsat-8 and Proba-V satellite data respectively. It is expected that the arrival of Sentinel-2 data during the course of 2014 with pixel sizes ranging between 10 to 30 m and a short revisit time of 5 days will greatly enhance development of new land use classifications that are tailored for water use and water accounting.

Land use changes affect the water balance of river basins and thus also the amount of water flowing to downstream areas. Bosch and Hewlett (1982) and Van der Walt et al. (2004) discuss for instance how replacing natural vegetation by exotic forest plantations reduced the stream flow in South Africa. Maes et al. (2009) evaluated the effect of land use changes on ecosystem services and water quantity on basins in Belgium and Australia. The role of land use is thus a crucial component of sound water accounting and water resource management (Molden, 2007).

Land use is usually identified on the basis of spectral reflectance and its change with vegetation phonology. The reflectance in the near and middle infrared part of the electromagnetic spectrum especially, is often related to certain land use classes. The relationship between reflectance and land use is however not unique, and field inspections are usually needed for interpretation. Soil type, soil moisture and surface roughness all have an influence on reflectance. The health of the vegetation and factors such as the angle and size of leaves also affect the photosynthetic activity of the plants. There is another land use mapping technology that is entirely based on the difference in time profiles of spectral vegetation indices. Fourier analysis of vegetation index can be used to quantify land use classes and crop types (e.g. Roerink et al., 2003), especially when time profiles can be linked to existing cropping calendars.

All the land use classification papers we reviewed report on a confusion matrix that describes the overall classification accuracy by showing how often certain land use classes are confused in the remote sensing analysis with other land use classes. Congalton (1991) and Foody (2002) give a full explanation on errors in land use data.

Review papers on the use of remote sensing for land use land cover classification are provided in Bastiaanssen (1998), Smits et al. (1999), Mucher et al. (2000), Cihlar (2000), Franklin and Wulder (2002), Thenkabail et al. (2009b), and García-Mora et al. (2012).

3. Results

3.1 Accuracy of spatial evapotranspiration data

The lack of validation of spatial layers of ET is one of the drawbacks in defining the reliability of remotely sensed ET products. There are no reliable and low cost ground-based ET flux measurement techniques, although new inventions are always underway (Euser et al., 2013). It is simply too costly to install instruments that have the capacity to measure ET operationally at various locations dispersed across a river basin. The main methods to measure ET at the field scale include lysimeters, Bowen ratio, eddy covariance systems, surface renewal systems, scintillometers and classical soil water balancing. Lysimeters can be very accurate for in-situ measurements of ET at small scale if they are properly maintained. Bowen ratio and Eddy covariance flux towers and surface renewal systems are fairly accurate methods for estimating ET at scales of up to1 km (Rana and Katerji, 2000), although not free of errors (e.g. Teixeira and Bastiaanssen, 2010; Twine et al., 2000). Scintillometers have the capability to measure fluxes across path lengths of 5 to 10 km (Hartogensis et al., 2010; Meijninger and de Bruin, 2000).

To deal with the problem of measuring ET fluxes in composite terrain, large-scale field experiments in the African continent (e.g. Sahel: Goutorbe et al., 1997; Southern Africa: Otter et al., 2002), the European continent (e.g. France: Andre et al., 1986; Spain: Bolle et al., 2006), the American continent (e.g. Kansas: Smith et al., 1992; Arizona & Oklahoma: Jackson et al., 1993) and the Asian continent (e.g. China: Wang et al., 1992: Korea: Moon et al., 2003) were set up to measure fluxes simultaneously within a certain geographic region at a number of sites with different land use classes. Several remotely sensed ET algorithms were developed and validated using these datasets. The limitation is however that the duration of these special field campaigns was for budgetary reasons restricted to several weeks only.

Validation studies with different ET algorithms using the same spatial ground truth data sets are very interesting. The International Water Management Institute (IWMI) undertook for instance a validation study to determine the accuracy of various ET methods for irrigated cotton and grapes in Turkey (Kite and Droogers, 2000). Although here, the period was not sufficiently long to encompass one growing season. The Commonwealth Science and Industrial Research Organisation (CSIRO) in Australia studied the predictions of eight different ET products, at a minimum monthly frequency and at a spatial resolution of at least 5 km, using flux tower observations and watershed data across the entire continent as part of the Water Information Research and Development Alliance (WIRADA) project (Glenn et al., 2011). The studied ET products were based on different methods including large scale water balance modeling, thermal imagery (Mcvicar and Jupp, 1999, 2002), spectral imagery (Guerschman et al., 2009), inferred LAI (Zhang et al., 2010b), passive microwave (Bastiaanssen et al., 2012), and global MODIS reflectance based algorithm (Mu et al., 2007). The results showed that at annual scale remote sensing based ET estimates, barring the global MODIS product that was at the time an unrefined method that needed improvements (Mu et al., 2011), had an acceptable mean absolute percentage error (MAPE) ranging from 0.6% to 18% with an average MAPE of 6% (King et al., 2011). Along similar lines, the Council for Scientific and Industrial Research (CSIR) in South Africa conducted a remote sensing study on a smaller scale to investigate the performance of three ET algorithms (Jarmain et al., 2009).

To assess the overall error in accumulated ET products, a comprehensive literature review was conducted and reported errors by various authors were synthesized. All the papers included in the review were published within the past 13 years (hence from the year 2000 onwards) and they cover a range of in-situ measurements and remote sensing ET algorithms. The reviewed papers cover a range of remote sensing methods for ET measurements including SEBAL, METRIC, SEBS, TSEB, ALEXI, ET Watch, and SatDAET. In essence, the spatial ET layers reported in these papers were not a priori calibrated and the authors reported on the validation aspect. Since the primary purpose of this study was to quantify errors in accumulated ET, only papers that report errors on ET estimates over a minimum period of one growing cycle, hereafter called seasonal ET, were consulted. Papers dealing with ET over shorter periods were thus excluded in our review (e.g. Anderson et al., 2011; Chávez et al., 2008; Gonzalez-Dugo et al., 2009; Mu et al., 2011). This, also, implies that GEWEX related field experiments could not be used because intensive campaigns with multiple flux covered periods of weeks only. The manifold flux campaigns organized by the US Department of Agriculture (Kustas et al., 2006; JORNEX: Rango et al., 1998; SALSA: Chehbouni et al., 1999) also did not meet our criterion. To be able to compare error levels from different studies only papers that report errors in terms of mean error were included in the review. Thus, some of the valuable papers on this topic that use RMSE to describe errors without including mean error could not be included in the review (e.g. Batra et al., 2006; Cleugh et al., 2007; Guerschman et al., 2009; Venturini et al., 2008). The data sources consulted are summarized in Appendix A. It reflects the accumulated ET conditions encountered in 11 countries. Thirty one publications met the criteria specified and were analyzed. One publication often contains more data points due to multiple models, multiple years, and multiple areas. Hence, the total number of points was n=46. Considering this number, the probability density function is unlikely to change if other papers – or more papers – were to be considered in the review.

The probability distribution of mean absolute percentage error in remote sensing ET estimates is presented in Figure 1. The results demonstrate the absolute error of annual or seasonal ET, ET during growing season which on average is about 5-6 months, to vary between 1 to 20%. The average MAPE is 5.4%, with a standard deviation of 5.0%. It is evident from Figure 1 that the distribution is positively skew. These results are closely in line with findings by King et al. (2011) in Australia, both in terms of average and the range of error in ET estimates.

Many of the publications reported an error of less than 5%, a remarkable good and unexpected result. Many authors of the papers are both the developer and the tester of the algorithms, and parameter tuning was possible. The left hand bar of in Figure 1 is – we believe – a biased view of the reality. For this reason, the data points were fitted by means of a skewed normal distribution so that less weight is given to the class with exceptionally low errors.

Figure 1.

Figure 1: Probability density function of the reported absolute deviations between ET estimates from remote sensing, and field measurement of ET. A season or longer period was considered.

There are seven papers that report a mean absolute percentage error of 1 % for the ET of cropland. Without exception, all these papers are based on the Surface Energy Balance Algorithm for Land (SEBAL) and its related algorithm Mapping ET at High Resolution with Internalized Calibration (METRIC). Apparently these algorithms work well for crops, which was recognized earlier by Bastiaanssen et al. (2009) and (Allen et al., 2011). Another interesting observation is that at river basin scale – i.e. the scale where water accounting is done - all papers report MAPE of less than 5%. These case studies include: 3% difference between the measured ET and remotely sensed ET of selected river basins in Sri Lanka (Bastiaanssen and Chandrapala, 2003), 1.7% difference observed by Singh et al. (2011) for the Midwest USA using the METRIC algorithm, 1.8% and 3% differences observed by Wu et al. (2012) using ET Watch in the Hai Basin of the North China plain, and 5% difference observed by Bastiaanssen et al. (2002) for the Indus Basin, 1% difference observed by Evans et al. (2009) for Murray darling, and 0.6%, 2.1%, 3.9%, and 18% difference for different algorithm observed by King et al. (2011) for Australian continent.

At the other end of the spectrum, the largest ET deviations were found by Jiang et al. (2009) for alkali scrubs in south Florida. They used the SatDAET algorithm which is an ET estimation method that uses the contextual relationship between remotely sensed surface temperature and vegetation index to calculate evaporative fraction (EF). They compared the estimated ET using SatDAET for both clear and cloudy days with ET from lysimeter and observed a 19% difference for 1999.

There is no single preferred ET model. The selection of the algorithm depends on the application, the required spatial resolution, the period for which the ET fluxes should be estimated for, the size of the study area, the land use classes present etc. A useful distinction is to discern global scale models (few) and local scale models (many). Also the level of validation and application of these models widely differ. Whereas certain models are tested with a single experimental flux site, other models have been applied in more than 30 countries.

Considering this positive evaluation, spatial layers of ET should be encouraged for applications in water accounting and hydrological modeling. Except for Jhorar et al. (2011), Winsemius et al. (2009) and Muthuwatte et al. (2013), this is rarely done because water managers and hydrologists do not accept ET layers as being sufficiently accurate. This new analysis proofs that the scientific research from the last 13 years has advanced and that mapping of ET became more confident.

3.2 Accuracy of spatial rainfall data

A comprehensive literature review - similar to ET – was conducted for remote sensing rainfall products. Twenty four peer reviewed papers that describe the accuracy of annual and seasonal rainfall from satellites, published over the last five years have been reviewed (see Appendix B). Sixty eight data points were reconstructed from these publications. The selected papers used various remote sensing rainfall products including TRMM, PERSIANN, RFE, ERA40, CMORPH, and CMAP. A common problem is the scale mismatch between rain gauges and the area integrated rainfall of one single microwave-based pixel of the satellite image.

Several of these papers compared different rainfall algorithms. Some also used the same field data to verify several rainfall algorithms. For example, Asadullah et al. (2008) compared five satellite-based rainfall estimates (SRFE) with historical average rainfall data from gauges over the period 1960-1990 in Uganada. The difference between gauged data and SRFEs was found to vary between 2% to 19%. Products such as CMORPH, TRMM 3B42, TAMSAT, and RFE underestimated rainfall by 2%, 8%, 12%, and 19% respectively, while PERSIANN overestimated by 8%. Stisen and Sanholt (2010) compared three global SRFE products, i.e. CMORPH, TRMM 3B42 and PERSIANN, and two SRFEs made for Africa, i.e. CPC-FEWS v2 and a locally calibrated product based on TAMSAT data, with the average gauge rainfall in Senegal River basin. They concluded that rainfall estimation methods that are designed for Africa significantly outperform global products. This superior performance is attributed both to the inclusion of local rain gauge data and to the fact that they are made specifically for the atmospheric conditions encountered on the African continent. Of the global products, SRFEs TRMM was found more accurate, presumably because monthly calibration of the 3B43 product is a default process of the algorithm. The global SRFEs showed an improved performance after bias correction and recalibration. The positive effects of the inclusion of rain gauge data in SRFEs is also reported by Dinku et al. (2011) in their study which compared five SRFEs with rain gauge data in the Blue Nile basin. Several studies show that local calibration significantly improves accuracy of satellite based rainfall estimates: Almazroui et al. (2012) in Saudi Arabia, Cheema and Bastiaanssen (2012) in the Indus basin, Duan and Bastiaanssen (2013) in the Lake Tana and Caspian Sea regions, and Hunink et al. (2014) in the high elevation Tungurahua province in the Andes mountain range of Ecuador.

The error probability distribution function curve reconstructed from the a priori calibrated rainfall dataset is shown in Figure 2. The mean absolute percentage error varies between 0 to 65%, and the average MAPE for calibrated satellite rainfall estimates is 18.5%. The standard deviation is 15.4%, with a positive skewness of 0.9. As with the density function for ET, the curve fitting of the distribution was forced with a skewed normal distribution to ensure that less weight is assigned to the class of 0 to 10% deviation. This indicates that for the majority of case studies, the error in calibrated rainfall maps is 18.5%. Large errors bands were found for all rainfall algorithms, and it is not obvious that one particular algorithm performs better in terms of variance. The unresolved problem of the pixel - gauge scale mismatch is one major source of this problem. The average MAPE is 14, 17, 21, 23, 28, and 29% for TRMM, ERA40, GPCP 1DD, CMORPH, RFE, and PERSIANN respectively. These average values represent the average MAPE of each SRFE regardless of the product version.

The interim conclusion is therefore that (i) the processes to derive rainfall from satellite data are more complex than the derivation of ET and (ii) that the performance of existing rainfall products is less satisfactory and requires caution when applied for water accounting and hydrological modeling, despite the fact that most SRFE's have an a priori calibration procedure. More research and development of operational rainfall algorithms using various types of sensors is deemed necessary.

Figure 2.

Figure 2: Probability density function of the reported absolute deviations between rainfall estimates from remote sensing, and field measurement of rainfall. A season or longer period is considered.

3.3 Accuracy of land use land cover maps

The publications listed in Appendix C were reviewed for land use estimations. Sixty five papers were reviewed. Seventy eight data points were reconstructed from these papers. Rather diverging land use classes and data from 35 different countries were included in this comparative dataset. The results are presented in Figure 3. The shape of the probability density function of error differs from the ones obtained for ET and rainfall: it is tending towards a standardized normal distribution, which implies that the number of very good results and very poor results are similar. Table 2 provides a summary of the statistical results. The mean absolute percentage error defined as 1 minus overall accuracy, for land use classification is 14.6%, with a standard deviation of 7.4% and a skewness of 0.35.

The overall performance is rather good, and this can be partially explained by the fact that high resolution satellites were often used for the land use and land cover classification. The spectral measurements of Landsat and Aster satellites were especially often applied, because they have bands suitable for the detection of a range of land use classes in the near and middle infrared part of the spectrum. To investigate the impact of the spatial resolution of the used imagery on the accuracy of the land use product, we divided the data points into two groups based on the reported resolution. The MAPE for land use classification that are based on high resolution images, 30 m and less, is 12.9%, whereas for those that use moderate and low resolution images, more than 200 m, the MAPE is 19.8%. The number of land use classes shows no significant impact on the overall accuracy of the map. The results reveal that the global scale land cover maps have lower overall accuracy due to their large pixel size. The overall accuracies of global maps varies between 69 to 87% with an average of 76.4%, which is equivalent to a deviation of 13 to 31% and average of 23.4%. This observation shows that global land cover maps should be used with caution in water accounting applications.

The overall accuracy in the reviewed papers varies between 68% to 98%. This is in good agreement with the suggested range of 70% to 90% by Bach et al. (2006) in their review paper. The review also revealed that Landsat products, with 42 case studies out of the total 78, are the most commonly used imagery for land use land cover classification purposes. The free access Landsat-8 data may thus set the directions for near future development of land use classifications, especially when being complemented with Sentinel data. The Finer Resolution Observation and Monitoring Global Land Cover (Gong et al., 2013) is an example of that.

Many land use studies are based on ground truth data sets that are used for controlling or supervising the classification process. The data in Appendix C thus have an element of a priori calibration which increases the overall accuracy. Without ground-truthing the overall calibration can be expected to be lower. Also, it must be noted that only the overall accuracy of the confusion matrix is used. While the overall accuracy might be acceptable, it is likely that the error in certain individual land use classes is significantly different.

Figure 3.

Figure 3: Probability density function of the reported absolute deviations between land use estimates from remote sensing, and field inventories of land use.

Table 2.

4. Conclusions and way forward

Increasing numbers of satellite-based measurements of land and water use data are provided by generally accessible data archives, although evapotranspiration data sets are under development. Satellites provide spatial information with a high temporal frequency over wide areas, which make remotely sensed maps of land use and hydrological variables an attractive alternative to conventionally collected data sets. However, the uncertainty about the possible errors in remote sensing estimates has been an ongoing concern among the users of these products. The goal of this study was to investigate an international literature review on the errors and reliability of some of these remotely sensed hydrological variables created by advanced algorithms. . Only recent data sets not older than 13 years have been reviewed.

The main interest of this review was to understand the measure of error in remote sensing data for water accounting. The review focused on ET, precipitation, and land use classifications. A comprehensive literature review was conducted and for each variable several numbers of peer-reviewed publications post 2000 were consulted for reported differences between satellite-based estimates from conventional ground measurements. It is important to note that conventional ground measurements come with their own errors and uncertainty that should ideally be taken in consideration when used for verifying the accuracy of satellite-based estimates. This holds true for ET where the number of operational flux towers is limited, but also for rainfall that has distinct micro-scale variability, that cannot be measured by a single gauge. However, in most documented studies these ground measurements are treated as “the best available estimates“ in the absence of reliable information on their accuracy. As such they are widely used to validate satellite based data. The probability distribution functions of the mean absolute percentage errors for all three variables were created, and these functions have more value than a single research paper, with a single algorithm applied to a particular location.

The results show that the average MAPE for satellite-based estimates of annual or seasonal ET, rainfall, and land use classification are 5.4%, 18.5 %, 14.6% respectively. The largest error is thus associated with rainfall. Bias correction and local calibration of global and regional rainfall products seem to improve the quality of the data layers. However, more research is needed to improve remotely sensed rainfall estimation algorithms (e.g. CHIRPS), with a focus on downscaling procedures as the standard pixel size is often too large. Radar based regional precipitation estimates that offer higher spatio-temporal resolutions are a promising option that need to be utilized further. Also the attenuation of microwave signals between cellular communication networks can be used for assessing areal averaged rainfall. In addition, given the differences among reported precipitation by different global and regional products for the same pixels, there is a need for a data base that offers an ensemble based on a rigorous and statistically sound method.

In contrast to rainfall, the error in satellite-based ET is relatively small, especially at the aggregation level of a river basin. ET is a vital component of hydrological cycle and reliable estimates of local ET are essential for modeling river basin hydrology accurately. Remotely sensed ET can be used both as input to distributed hydrological models, and as a means to calibrate the simulations, although locally large errors can occur. Nonetheless, despite its existing potential and accuracy, satellite-based ET is under-utilized in hydrological studies. Contributing factors are presumably the difficulty to access and acquire reliable ET data through the public domain, and the difficulty to compare it with reliable field data. Thus, future focus should be on development of open access ET data bases. Such efforts are now underway by some organizations such as US Geological Survey, US Department of Agriculture, the Commonwealth Science and Industrial Research Organization of Australia and the Chinese Academy of Sciences. However, these products are not yet made all available to the public, albeit first estimates of an ensemble ET product are under development. There is also a need for higher resolution ET data both spatial and temporal. This is key factor if satellite based ET data are to be used extensively in water management and hydrological studies.

Land use mapping is one of the earliest ways in which satellite imagery was used to produce environmental information and it is the most widely studied subject in employing remote sensing. The quality of the classifications has improved over time by the availability of high resolution images and local research projects. The low resolution and operational land classification mapping produce is, however, still the standard method. Global high resolution Land Use and Land Cover databases are conceived as the next generation of information systems for WA+ and other applications, and the product created by Tsinghua University is a first example. The land use classifications come with an overall MAPE of 14.6%, and accuracy of 85%. This level of accuracy, although acceptable, calls for improvements given the wide use of these maps. Another important issue is the need for a new type of land use mapping dedicated to agricultural and river basin water management issues. This is of essential value when land use maps are used in hydrological and water management related studies such as water accounting.

As revealed by the results of this review study, there is a great deal of heterogeneity regarding the accuracy and reliability of remotely sensing data and methods**.** Oftentimes reliability of RS-based products is rather case and location specific. Future research could, therefore, aim at cross-comparing remote sensing data and methods on ET, rainfall and land use for different regions. Ensemble mean ET products are currently under development.

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Table 1: Overview of main existing regional and global scale satellite-based data sources of rainfall. The column “gauge” indicates whether a calibration against ground data is included

Product	Main principle data	Resolution	Spatial coverage	Gauge	Minimum time steps interval	Producer
MPE	Meteosat 7, 8, 9 10	3 km	Indian ocean	N	15 min	EUMETSAT
CMORPH	Microwave estimates (DMSP F- 13, 14 & 15 (SSM/I), NOAA-15, 16, 17 & 18 (AMSU-B), AMSR-E, and TRMM (TMI)), IR motion vectors	8 km	50˚N-S	N	30 min	NOAA/CPC
PERSIANN	Microwave estimates (DMSP F-13, 14, & 15, NOAA-15, 16, 17, and TRMM (TMI))	0.25˚	60˚N-S	N	1-hour	UC Irvine
GSMap	Microwave estimates (DMSP F-13, 14 & 15 (SSM/I), AMSR, AMSR-E, and TRMM (TMI))	0.1˚	60˚N-S	N	1-hour	JAXA
NRL-Blended	Microwave estimates (DMSP F-13, 14, & 15 (SSM/I), F-16 (SSMIS))	0.25˚	60˚N-S	N	3-hour	NRL
TCI(3G68)	Microwave estimates (TRMM (TMI)), and PR	0.5˚	37˚N-S	N	1-hour	NASA
TOVS	HIRS, MSU sounding retrievals	1˚	Global	N	daily	NASA
Hydro Estimator	GOES IR	4 km	Global	N	15 min	NOAA
TRMM 3B42	Microwave estimates (TRMM, SSM/I, AMSR and AMSU), IR estimates from geostationary satellites	0.25˚	50˚N-S	Y	3-hour	NASA
CPC-RFE2.0	Microwave estimates (SSM/I, AMSU-B), IR estimates from METEOSAT	0.1˚	20˚W-55˚E, 40˚S-40˚N	Y	daily	FEWS
GPCP 1DD	IR estimates from geostationary satellites, TOVS	1˚	50˚N-S	Y	daily	NASA/GSFC
CMAP	Microwave estimates (SSM/I), GOES IR	2.5˚	Global	Y	5 days	NOAA
TAMSAT	Meteosat thermal-IR	3 km	Africa	Y	10 days	Reading University
TRMM 3B43	Microwave estimates (TRMM, SSM/I, AMSR and AMSU), IR estimates from geostationary satellites	0.25˚	40˚N-S	Y	monthly	NASA
GPCP_V2	Microwave estimates (SSM/I), IR, TOVS	2.5˚	Global	Y	monthly	NASA/GSFC

Table 2: Mean deviation of the input variables and the distribution of the error

Remote sensing parameter	Calibration	Mean absolute percentage error (%)	Standard deviation error (%)	Skewness (-)	No. of data points
ET	No	5.4	4.9	1.18	41
Rainfall	Yes	18.5	15.4	0.90	69
Land use	Yes	14.6	7.4	0.37	78

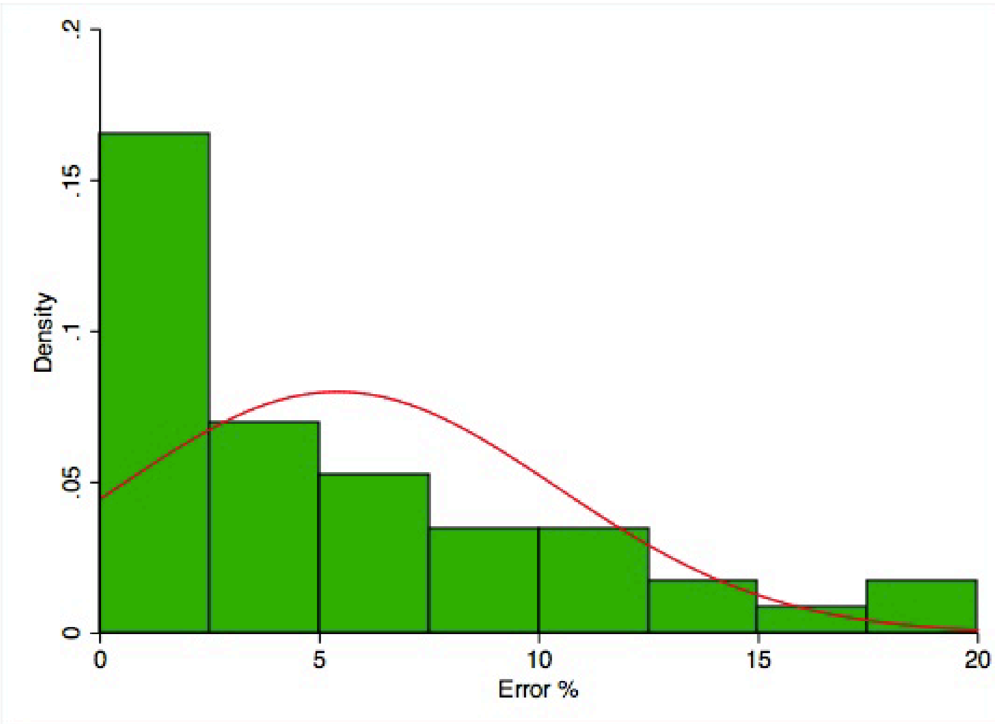

Figure 1: Probability density function of the reported absolute deviations between ET estimates from remote sensing, and field measurement of ET. A season or longer period was considered.

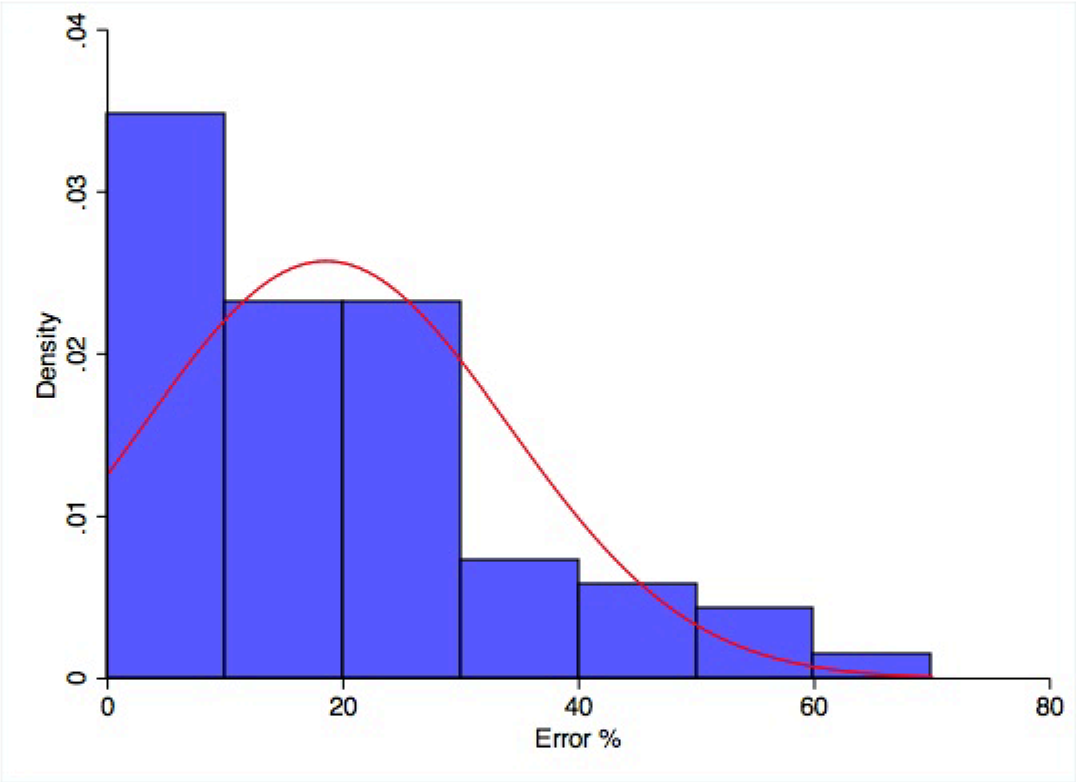

Figure 2: Probability density function of the reported absolute deviations between rainfall estimates from remote sensing, and field measurement of rainfall.

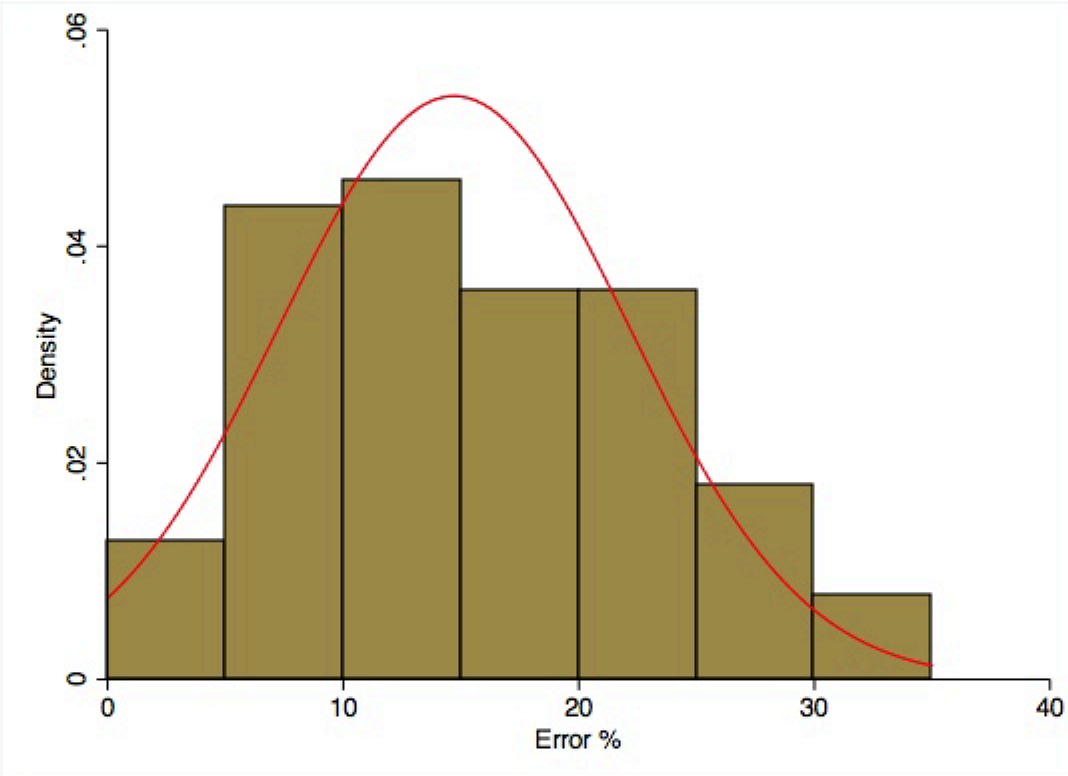

Figure 3: Probability density function of the reported absolute deviations between land use estimates from remote sensing, and field inventories of land use.

Appendix A: Literature review on evapotranspiration

Table A1: Selected ET validation papers that describe experimental data sets covering a season or longer

Method	Field instrument	Location and year	Land use	No. of images	Source	MAPE (%)
METRIC	Lysimeter	Idhao, US, 1985	Native sedge forage	4	Allen et al. (2005)	4
METRIC	Lysimeter	Idaho, US, 1989	Sugar beet	12	Allen et al. (2007)	1
ALEXI	Eddy covariance	New Mexico, US. 2008	Agricultural areas	6	Anderson et al. (2012)	6.7
SEBAL	Water balance	Sri Lanka	River basin	-	Bastiaanssen and Chandrapala (2003)	1
SEBAL	Water balance	Indus, Pakistan	River basin	20	Bastiaanssen et al. (2002)	5
SEBAL	Lysimeter	California, US, 2002	Alfalfa	7	Cassel and Robertson (personal communication, 2006)	2
SEBAL	Lysimeter	California, US, 2002	Peaches	7	Cassel and Robertson (personal communication, 2006))	7
SEBAL	Water balance	Murray Darling Basin, Australia	river basin	-	Evans et al. (2009)	1
NDVI based model	Eddy covariance	New Mexico, US	Cottonwood, saltcedar	10	Groeneveld et al. (2007)	2.2
NDVI based model	Bowen ratio	Colorado, US, 2006	Greasewood, salt rabbitbrush	5	Groeneveld et al. (2007)	12.2

NDVI based model	Eddy covariance	California, US, 2000-2002	Salt grass, alkali sacaton	9	Groeneveld et al. (2007)	12.5
SEBAL	Water balance	Central Luzon, 2001	Rice	3	Hafeez et al. (2002)	10.5
SEBAL	Scintillometer	Horana, 1999	Palm trees and rice	5	Hemakumara and Chandrapala (2003)	0.9
METRIC	Bowen ratio	Nebraska,US, 2005	Corn	4	Irmak et al. (2011)	4.3
METRIC	Bowen ratio	Nebraska, US, 2006	Corn	4	Irmak et al. (2011)	4.2
SEBAL	Water balance	Western Cape, South Africa 2004-2006	Grapes	12	Jarmain et al. (2007)	12
ETWatch	Water balance	Hai basin, China – 2002 - 2009	Basin	135	Jia et al. (2012)	8.3
SatDAET	Lysimeter	Florida, US, 1998	alkali scrub	8	Jiang et al. (2009)	14
SatDAET	Lysimeter	Florida, US, 1999	alkali scrub	3	Jiang et al. (2009)	19
CMRS1	Water balance	Australia	river basin	NA	King et al (2011)	2.1
CMRS2	Water balance	Australia	river basin	NA	King et al (2011)	0.6
NDTI	Water balance	Australia	river basin	NA	King et al (2011)	18
ETLooK	Water balance	Australia	river basin	NA	King et al (2011)	3.9
SEBAL	Scintillometer	Gediz basin, Turkey, 1998	Grapes, cotton	4	Kite and Droogers (2000)	16
SEBAL	Surface renewal	Sacramento Valley, US, 2001	Rice	8	Lal et al. (2012)	1

TSEB	Measurements	Yellow river, China, 2004	Wetlands	-	Li et al. (2011)	7.9
SEBS	Measurements	Australia, 2009	Irrigated agriculture	16	Ma et al. (2012)	7.5
METRIC/SEBAL	Water balance	India, 2003	Irrigated agriculture	40	Mallick et al. (2007)	11.6
SEBAL	Water balance	Sudd, Sudan, 2000	Wetland	-	Mohamed et al. (2004)	1.8
SEBAL	Water balance	Sobat, Sudan, 2000	Wetland	-	Mohamed et al. (2004)	5.7
SEBAL	Water balance	California, US, 2002	Almonds	7	Sanden (personal communication, 2005)	1
SEBAL	Bowen ratio	Nebraska, US	Corn	7	Singh et al. (2008)	5
METRIC	Eddy covariance	Nebraska, US	River basin	8	Singh et al. (2011)	1.7
SEBAL	Water balance	California, US	Irrigated agriculture	5	Soppe et al. (2006)	1
SEBAL	Lysimeter	Idaho, US, 1989-91	Irrigated agriculture	11	Tasumi et al. (2003)	4.3
SEBAL	Eddy covariance	Petrolina, 2001-2007	Mango, grapes	9	Teixeira et al. (2008)	1
SEBAL	Eddy covariance	Brazil	Natural vegetation and irrigated crops	18	Teixeira et al. (2009)	1
SEBAL	Water balance	Imperial Valley, 1997-1998	Several	12	Thoreson et al, (2009)	1

SEBAL	Eddy covariance	Middle Rio Grande, US, 2002-2003	Pecan, alfalfa	7	Wang and Sun (2005)	3
ETWatch	Lysimeter	Hai basin, China, 2002 - 2005	wheat-maize rotation	-	Wu et al. (2012)	9
ETWatch	Eddy covariance	Hai basin, China, 2002 - 2005	River basin	20	Wu et al. (2012)	3
ETWatch	Water balance	Hai basin, China, 2002 - 2005	River basin	-	Wu et al. (2012)	1.8
SEBAL	Water balance	North district, China	Regional scale	26	Yang et al. (2012)	5.6
WUE* based model	Eddy covariance	Jilin province, China 2003	Mixed forest	45	Zhang et al. (2009)	4
WUE based model	Eddy covariance	Jilin province, China 2004	Mixed forest	45	Zhang et al. (2009)	2
WUE based model	Eddy covariance	Jilin province, China 2005	Mixed forest	45	Zhang et al. (2009)	0.4

* Water Use Efficiency

Appendix B: Literature review on rainfall

Table B2: Selected validation papers that describe experimental data sets covering a season or longer.

Source	Area	Year	RS Data source	Deviation
Almazroui et al. (2011)	Saudi Arabia	1998-2008	TRMM	0
Almazroui et al. (2012)	Saudi Arabia	1998-2008	TRMM	12.05
Asadullah et al. (2010)	Uganda	2003-2007	CMORPH	2
Asadullah et al. (2010)	Uganda	2003-2007	PERSIANN	8
Asadullah et al. (2010)	Uganda	2003-2007	RFE 2.0	19
Asadullah et al. (2010)	Uganda	2003-2007	TRMM 3B42	8
Asadullah et al. (2010)	Uganda	2003-2007	TAMSAT	12
Bitew and Gebremichael (2011)	Gilgel, Ethiopia	2006-2007	CMORPH	29
Bitew and Gebremichael (2011)	Gilgel, Ethiopia	2006-2007	TRMM 3B42RT	29
Bitew and Gebremichael (2011)	Gilgel, Ethiopia	2006-2007	PERSIANN	58
Bitew and Gebremichael (2011)	Gilgel, Ethiopia	2006-2007	TRMM 3B42	64
Cheema and Bastiaanssen (2012)	Indus	2007	TRMM 3B43 V6	6.1
Cheema and Bastiaanssen (2012)	Indus	2007	TRMM 3B43 V6	10.9
Chen et al. (2011)	Dongjing basin, China	2002-2010	TRMM 3B42RT	22.1
Collischonn et al. (2008)	Tapajo ´s basin, Brazil	1997-2006	TRMM 3B42	12
Dinku et al. (2007)	Ethipian Highlands	1998-2004	TRMM 3B43	8
Dinku et al. (2011)	Blue Nile, Ethiopia	1981-2004	CMAP	3
Dinku et al. (2011)	Blue Nile, Ethiopia	1981-2004	GPCP	5
Dinku et al. (2011)	Blue Nile, Ethiopia	2003-2004	CMORPH	1
Dinku et al. (2011)	Blue Nile, Ethiopia	2003-2004	TRMM 3B42	5
Dinku et al. (2011)	Blue Nile, Ethiopia	2003-2004	RFE	48
Duan and Bastiaanssen (2013)	Lake Tana	1999, 2000, 2004	TRMM 3B43 V7	1
Duan and Bastiaanssen (2013)	Caspian sea, Iran	2000-2003	TRMM 3B43 V7	20
Feidas (2009)	Greece	1998-2006	TRMM 3B42	4.2
Feidas (2009)	Greece	1998-2007	TRMM 3B43	7.6
Feidas (2009)	Greece	1998-2008	GPCP-1DD	28.7
Fernandes et al. (2008)	Amazon basin, South America	1980-2002	ERA-40	10
Fernandes et al. (2008)	Amazon basin, South America	1980-2002	GPCP	7

Fu et al. (2011)	Poyang basin, China	2003-2006	GSMaP	54
Getirana et al. (2011)	Negro basin, South America	1998-2002	TMPA	18
Getirana et al. (2011)	Negro basin, South America	1998-2002	NCEP-2	13
Getirana et al. (2011)	Negro basin, South America	1998-2002	ERA-40	18
Jiang et al. (2012)	Mishui Basin, China	2003-2008	CMORPH	41
Jiang et al. (2012)	Mishui Basin, China	2003-2008	3B42RT	43
Jiang et al. (2012)	Mishui Basin, China	2003-2008	3B42V6	4.54
Kizza et al. (2012)	Lake Victoria	2001-2004	TRMM 3B43	5
Kizza et al. (2012)	Lake Victoria	2001-2004	PERSIANN	1
Milewski et al. (2009)	Egypt		TRMM	15
Moffitt et al. (2011)	Bangladesh	2000-2005	TRMM 3B42V6	11.6
Pierre et al. (2011)	Sahelian belt	2004-2007	RFE 2.0	23
Pierre et al. (2011)	Sahelian belt	2004-2007	TRMM 3B42	6
Pierre et al., (2011)	Sahelian belt	2004-2007	CMORPH	34
Semire et al. (2012)	Malaysia	2001-2010	TRMM 3B43 V6	15
Stisen and Sandholt (2010)	Senegal river basin	2003-2005	CMORPH	34
Stisen and Sanholt (2010)	Senegal river basin	2003-2005	PERSIANN	47
Stisen and Sanholt (2010)	Senegal river basin	2003-2005	TRMM	23
Stisen and Sanholt (2010)	Senegal river basin	2003-2005	CCD	6
Stisen and Sanholt (2010)	Senegal river basin	2003-2005	CPC-FEWs	21
Su et al. (2008)	La Plata Basin	1998-2006	TRMM	6
Villarini et al. (2009)	Oklahoma, USA	1998-2003	TRMM	10
Voisin et al. (2008)	Amazon	1997-1999	ERA-40	26.5
Voisin et al. (2008)	Amazon	1997-1999	GPCP 1DD	24.7
Voisin et al. (2008)	Mississippi, USA	1997-1999	ERA-40	32.3
Voisin et al. (2008)	Mississippi, USA	1997-1999	GPCP 1DD	25.3
Voisin et al. (2008)	Mackenzie, Canada	1997-1999	ERA-40	1.1
Voisin et al. (2008)	Mackenzie, Canada	1997-1999	GPCP 1DD	28.8
Voisin et al. (2008)	Congo, Africa	1997-1999	ERA-40	13.4
Voisin et al. (2008)	Congo, Africa	1997-1999	GPCP 1DD	31
Voisin et al. (2008)	Danube, Europe	1997-1999	ERA-40	29.1
Voisin et al. (2008)	Danube, Europe	1997-1999	GPCP 1DD	17.1

Voisin et al. (2008)	Meckong, SEA	1997-1999	ERA-40	0.4
Voisin et al. (2008)	Meckong, SEA	1997-1999	GPCP 1DD	4.1
Voisin et al. (2008)	Senegal	1997-1999	ERA-40	51.6
Voisin et al. (2008)	Senegal	1997-1999	GPCP 1DD	23.3
Voisin et al. (2008)	Yellow river, China	1997-1999	ERA-40	1.3
Voisin et al. (2008)	Yellow river, China	1997-1999	GPCP 1DD	30.4
Voisin et al. (2008)	Yenisei, Russia	1997-1999	ERA-40	0.7
Voisin et al. (2008)	Yenisei, Russia	1997-1999	GPCP 1DD	26.2
Wilk et al. (2006)	Okavango basin	1991-1996	TRMM	20

Appendix C: Literature review on land use & land cover

Table C1: Selected validation papers that report on confusion matrices

Source	Area	Image Year	Image source	Overall accuracy (%)
Abd El-Kawy et al. (2011)	Nile Delta, Egypt	2005	Landsat ETM+	96
Aguirre-Gutiérrez et al. (2012)	Sierra Madre, Mexico	2006	Landsat ETM+	87
Bach et al. (2006)	Erda, Germany	1989-1992	CORINE (Landsat TM)	75
Bach et al. (2006)	Erda, Germany	1994	Landsat-5 TM	79
Bach et al. (2006)	Stein., Germany	1989-1992	CORINE (Landsat TM)	69
Bach et al. (2006)	Stein., Germany	1994	Landsat-5 TM	74
Bicheron et al. (2008)	Global	2004-2006	MERIS/Envisat	73
Blanco et al. (2013))	Latin America	2008	Modis-Terra	84
Büttner et al. (2006)	Global	1999-2000	Landsat ETM+/SPOT	87
Cassidy et al. (2013)	Lower Meckong	2005	Landsat TM	85
Cheema and Bastiaanssen (2010)	Inuds basin	2007	SPOT/vegetation	77
Cingolani (2004)	Cordoba, Argentina	1997	Landsat 5 TM	86
Clark et al. (2010)	Dry Chaco, South America	2000-2008	MODIS	80
Colditz et al., (2012)	Mexico	2005	MODIS	83
Cotonnec and Du (2001)	Baie de lannion, France	1996-97	Landsat 5TM	89
Estes et al. (2012)	Serengeti National Park	2002-2003	Landsat ETM+	83
Friedl et al. (2010)	Global	2000-2001	Modis 5	75
Gamanya et al. (2007)	Central Zimbabwe	2001	ASTER	92
Gamanya et al. 2007)	Central Zimbabwe	2001	Landsat TM	89
Kandrika and Roy (2008)	Orissa, India	2004-2005	AWiFS IRS-P6	87
Kavzoglu and Colkesen (2009)	Kocaeil, Turkey	1997	Landsat ETM+	91
Kavzoglu and Colkesen (2009)	Kocaeil, Turkey	1997	Landsat ETM+	90
Kavzoglu and Colkesen (2009)	Kocaeil, Turkey	2002	Aster	88
Kavzoglu and Colkesen (2009)	Kocaeil, Turkey	2002	Aster	93
Kavzoglu and Colkesen (2009)	Kocaeil, Turkey	2002	Aster	91
Kavzoglu and Colkesen, 2009)	Kocaeil, Turkey	1997	Landsat ETM+	87
Kaya et al. (2002)	Kenya	2001	RADARSAT-1	85
Keuchel et al. (2003)	Tenerife, Spain	1988	Landsat 5TM	90
Keuchel et al. (2003)	Tenerife, Spain	1988	Landsat 5TM	88
Keuchel et al. (2003)	Tenerife, Spain	1988	Landsat 5TM	93
Klein et al., (2012)	Central Asia	2009	MODIS	91
Kolios and Stylios (2013)	Greece	2009	Landsat 7 ETM+	97

Liu and Yang (2013)	Jilin, China	2009	Landsat TM	95
Liu et al. (2002)	Rondonia, Brazil	1995/1997	Landsat TM/Spot	80
Mayaux et al. (2006)	Global	1999-2000	SPOT-Vegetation	68
Munthali and Murayama (2011)	Dzalanyama, Malawi	2008	ALOS	79
Munthali and Murayama (2011)	Dzalanyama, Malawi	2000	Landsat ETM+	78
Oldeland et al. (2010)	Rehoboth, Namibia	2005	HyMap	98
Otukei and Blaschke (2010)	Pallisa, Uganda	2001	Landsat 7 ETM+	94
Pan et al. (2010)	Honghe Reserve, China	2006	Landsat-5 TM	88
Peña-Barragán et al. (2011)	Yolo County, California	2006	ASTER	79
Pérez-Hoyos et al. (2012)	Regional/Europe	-	Merged-global maps	87
Petropoulos et al. (2012)	Greece	2009	Hyperion	89
Qi et al. (2012)	Panyu, China	2009	RADARSAT-2 PolSAR	87
Ren et al. (2009)	NW-Yunnan, China	2000	Landsat ETM+	97
Reno et al. (2011)	Amazon, Brazil	2008	Landsat 5	83
Renó et al., 2011)	Amazon, Brazil	1970	Landsat 2	86
Rodriguez-Galiano and Chica-Olmo (2012)	Granada, Spain	2004	Landsat 5TM	86
Rozenstein and Karnieli (2011)	Israel	2009	Landsat 5 TM	81
Setiawan et al. (2006)	Yogyakarta, Indonesia	1994	Landsat TM	80
Shao and Lunetta (2012)	North Carolina & Virginia, USA	2000-2009	MODIS	91
Shimoni et al. (2009)	Glinska Poljana, Croatia	2001	E-SAR	84
Shrestha and Zinck (2001)	Likhu basin, Nepal	1988	Landsat TM	94
Song et al. (2005)	Connecticut, USA	2001	Landsat ETM	85
Stavrakoudis et al. (2011)	Lake Kronia, Greece	2005	IKONOS	93
Stefanov et al, (2001)	Arizona, USA	1998	Landsat TM	85
Sulla-Menashe et al. (2011)	Regional/Northern Eurasia	2001-2005	MODIS	73
Szuster et al. (2011)	Thai island, Thailand	2004	ASTER	95
Szuster et al. (2011)	Thai island, Thailand	2004	ASTER	94
Szuster et al. (2011)	Thai island, Thailand	2004	ASTER	94
Taşdemir et al. (2012)	Bulgaria	2009	Rapideye	94
Thenkabail et al. (2009a)	Global	1997-1999	AVHHR	79
Tovar et al. (2013)	Cajamarca, Peru	2007	Landsat 5 TM	80
Tseng et al. (2008)	Connecticut, USA	1987	Landsat TM	98
Wang et al. (2010)	Hengshan, China	2003	Hyprion	80
Waske and Braun (2009)	Jena, Germany	2005	ENVISAT/ ERS-2	83
Weiers et al (2002)	Schleswig-Holstein, Germany	1992-1997	Landsat TM	85
Weiers et al. (2002)	Denmark	1992-1997	Landsat TM	70

Whiteside et al. (2011)	Florence creek, Australia	2000	ASTER	79
Wickham et al. (2013)	USA	2001	Landsat TM	79
Wickham et al. (2013)	USA	2006	Landsat TM	78
Wickham et al. (2013)	USA	2001	Landsat TM	85
Wickham et al. (2013)	USA	2006	Landsat TM	84
Wu et al. (2010)	Dan-Shuei, China	1995	Landsat 5 TM	88
Zhang et al. (2008)	Northern China plain, China	2003	MODIS_EVI	75
Zhu et al. (2012)	Massachusetts, USA	2007	ALOS	72
Zhu et al. (2012)	Massachusetts, USA	2000-2007	Landsat/ALOS	94
Zhu et al. (2012)	Massachusetts, USA	2000-2002	Landsat	93

Appendix D. Glossary

Table D1. Glossary

Term	Description
1DD	One Degree Daily
3B42RT	3B42 real time
ALEXI	Atmosphere-Land Exchange Inverse
ALOS	Advanced Land Observing Satellite
AMSR-E	Advanced Microwave Sounding Radiometer-Earth
AMSU	Advanced Microwave Sounding Unit
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CBERS	China Brazil Earth Resources Satellite
CMAP	CPC Merged Analysis of Precipitation
CMORPH	CPC Morphing technique
CMRSET	CSIRO MODIS Reflectance-based Scaling ET
CORINE	CO-ordination of INformation on the Environment
CPC	Climate Prediction Center
CSIRO	Commonwealth Science and Industrial Research Organisation
DMSP	Defense Meteorological Satellite Program
EARS	Environmental Analysis and Remote Sensing
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
FEWS	Famine Early Warning Systems (FEWS)
GOES	Geostationary Operational Environmental Satellites
GPCC	Global Precipitation Climatology Centre
GPCP	Global Precipitation Climatology Project
GPI	GOES precipitation index
GSFC	Goddard Space Flight Center's (GSFC)
GSMaP	Global Satellite Mapping of Precipitation
HIRS	High-Resolution Infrared Sounder
IR	Infrared
IWMI	International Water Management Institute
METRIC	Mapping EvapoTranspiration at high Resolution with Internalized Calibration
MODIS	Moderate Resolution Imaging Spectrometer
MPE	Multi-Sensor Precipitation Estimate
NASA	National Aeronautics and Space Administration
NDTI	Normalised Difference Temperature Index
NOAA	National Oceanic and Atmospheric Administratio
PERSIANN	Precipitation Estimation From Remotely Sensed Information using Artificial Neural Networks

PR	Precipitation radar
RFE	Rainfall Estimation Algorithm
SatDAET	Satellite daily ET
SEBAL	Surface Energy Balance Algorithm for Land
SEBS	Surface Energy Balance System
SEEAW	System of Environmental-Economic Accounts for Water
SPOT	Satellite Pour l'Observation de la Terre
SSM/I	Special Sensor Microwave/Imager
TAMSAT	Tropical Applications of Meteorology using Satellite data
TCI	TRMM Combined Instrument
TMI	TRMM Microwave Imager
TOVS	TIROS Operational Vertical Sounder
TRMM	Tropical rainfall measuring mission
TSEB	Two source energy balance
VIIRS	Visible Infrared Imager Radiometer Suite
WIRADA	Water Information Research and Development Alliance