



Spatial evapotranspiration, rainfall and land use data in water accounting – Part 1: Review of the accuracy of the remote sensing data

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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 seasonal 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 % (SD 5 %) and rainfall with an overall absolute accuracy of 82 % (SD 15 %). Land use can be identified with an overall accuracy of 85 % (SD 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 hydrometeorological 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 transboundary 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 preprocessed satellite data. Quality flags are often provided, as well as manuals with explanations on how the satellite data have been preprocessed 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 preprocessed ET data and, in fact, spatial ET modeling is still underdeveloped. 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 data sets of hydrological processes can be used to produce information on water resource conditions in river basins. Tools such as Water Accounting Plus (WA+) (Karimi et al., 2013a, b) 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 are also limitations with what conventional measurement methods can offer especially when spatially distributed data is concerned. For instance, the actual ET of river basins can hardly be measured operationally through ground measurements; therefore, the depletion of water remains difficult to estimate and quantify. Thus, ET is often ignored in water accounting frameworks such as the SEEA-Water system proposed by the United Nations Statistics Division (UN, 2007) and the Australian water accounting system (ABS, 2004).

Remote sensing techniques, however, 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, land use/land cover) is based on the common use in hydrological and water resource 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., 2015) 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. See Appendix D for a glossary of the abbreviations used throughout the paper.

2 Remote sensing data for water accounting (WA+)

2.1 Evapotranspiration

Over the past decades several methods and algorithms to estimate actual 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 Earth's 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 Earth's surface reads

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

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 LE is the equivalent energy amount (W m^{-2}) of the ET flux ($\text{kg m}^{-2} \text{s}^{-1}$ 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 provided in general background material such as Brutsaert (1982), Campbell and Norman (1998) or Allen et al. (1998).

Surface temperature is measured routinely by spaceborne 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–Brazil 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), K. Zhang et al. (2010), 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 subsoil 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 microwave 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 methods 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., 2014; US: Velpuri et al., 2013). New ensemble ET prod-

ucts 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 have been 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 themselves and not a surrogate of rain, such as the cloud type. Microwave radiation with wavelengths in the order of 1 mm–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). Spaceborne radar measurements of rain intensity are possible with the precipitation radar (PR) aboard the NASA Tropical Rainfall Measuring Mission (TRMM) and Global Precipitation Mission (GPM) satellites, which assesses the attenuation of the radar signal caused by the rain. The 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 InfraRed 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), and Huffman et al. (2007). A selection of available rainfall

Table 1. Overview of the 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	<i>N</i>	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–50° S	<i>N</i>	30 min	NOAA/CPC
PERSIANN	Microwave estimates (DMSP F-13, 14, & 15, NOAA-15, 16, 17, and TRMM (TMI))	0.25°	60° N–60° S	<i>N</i>	1 h	UC Irvine
GSMaP	Microwave estimates (DMSP F-13, 14 & 15 (SSM/I), AMSR, AMSR-E, and TRMM (TMI))	0.1°	60° N–60° S	<i>N</i>	1 h	JAXA
NRL-blended	Microwave estimates (DMSP F-13, 14, & 15 (SSM/I), F-16 (SSMIS))	0.25°	60° N–60° S	<i>N</i>	3 h	NRL
TCI (3G68)	Microwave estimates (TRMM (TMI)), and PR	0.5°	37° N–37° S	<i>N</i>	1 h	NASA
TOVS	HIRS, MSU sounding retrievals	1°	Global	<i>N</i>	Daily	NASA
Hydro estimator	GOES IR	4 km	Global	<i>N</i>	15 min	NOAA
TRMM 3B42	Microwave estimates (TRMM, SSM/I, AMSR and AMSU), IR estimates from geostationary satellites	0.25°	50° N–50° S	<i>Y</i>	3 h	NASA
CPC-RFE2.0	Microwave estimates (SSM/I, AMSU-B), IR estimates from METEOSAT	0.1°	20° W–55° E, 40° S–40° N	<i>Y</i>	Daily	FEWS
GPCP 1DD	IR estimates from geostationary satellites, TOVS	1°	50° N–50° S	<i>Y</i>	Daily	NASA/GSFC
CMAP	Microwave estimates (SSM/I), GOES IR	2.5°	Global	<i>Y</i>	5 days	NOAA
TAMSAT	Meteosat thermal-IR	3 km	Africa	<i>Y</i>	10 days	Reading University
TRMM 3B43	Microwave estimates (TRMM, SSM/I, AMSR and AMSU), IR estimates from geostationary satellites	0.25°	40° N–40° S	<i>Y</i>	Monthly	NASA
GPCP_V2	Microwave estimates (SSM/I), IR, TOVS	2.5°	Global	<i>Y</i>	Monthly	NASA/GSFC

products based on remote sensing techniques – sometimes used in combination with other methodologies – is presented in 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+ be-

cause 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 (e.g., 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), Yalaw et al. (2012) and Kiptala et al. (2013). Furthermore, land use classifications for WA+ at river basin scale require a pixel size of 30–100 m 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 10–30 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 phenology. 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 better 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 are 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., 2014). 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 to 1 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 5–10 km (Hartogensis et al., 2010; Meijninger and de Bruin, 2000).

To deal with the problem of measuring ET fluxes in a 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 and 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 data sets. The limitation is however that the duration of these 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 (leaf area index; Y. Zhang et al., 2010),

passive microwave (Bastiaanssen et al., 2012), and the 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 (Jarman 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 which on average is about 5–6 months, 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 (Global Energy and Water Exchanges Project)-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 (root mean square error) 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 Fig. 1.

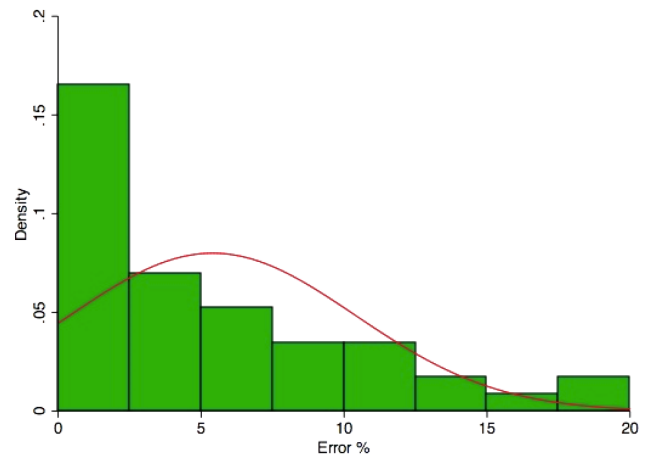


Figure 1. Probability density function of the reported mean absolute percentage error in remotely sensed ET estimates. A season or longer period was considered.

The results demonstrate the absolute error of annual or seasonal ET to vary between 1 and 20 %. The average MAPE is 5.4 %, with a standard deviation of 5.0 %. It is evident from Fig. 1 that the distribution is positively skewed. 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. In many cases, the authors of the papers were both the developers and the testers of the algorithms, and parameter tuning was possible. The left-hand bar in Fig. 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.

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 a MAPE of less than 5 %. These case studies include the 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 in the 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, 5 % difference observed by Bastiaanssen et al. (2002) for the Indus Basin, 1 % difference observed by Evans et al. (2009) for the Murray–Darling Basin, and 0.6, 2.1, 3.9, and 18 % differences for

different algorithms observed by King et al. (2011) for the 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 lysimeters 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. (2008) and Rientjes et al. (2013), this is rarely done because water managers and hydrologists do not accept ET layers as being sufficiently accurate. This new analysis proves that the science of remote sensing in the last 13 years has advanced and that mapping of ET has become more reliable.

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 5 years were 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 (SRFEs) with historical average rainfall data from gauges over the period 1960–1990 in Uganda. The difference between gauged data and SRFEs was found to vary between 2 and 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,

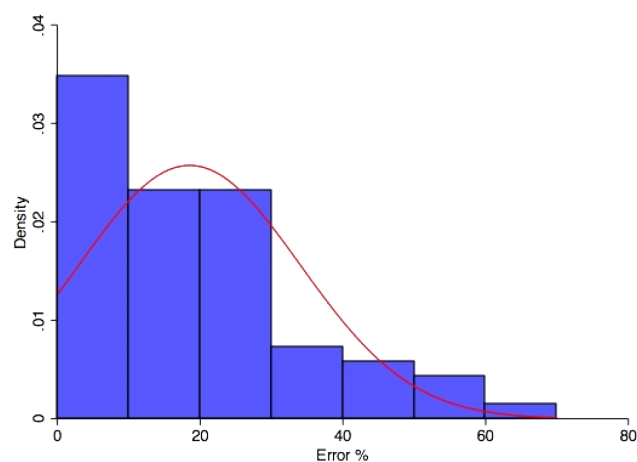


Figure 2. Probability density function of the reported mean absolute percentage error in rainfall estimates from remote sensing. A season or longer period is considered.

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 from TRMM were 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 in the study by Dinku et al. (2011), which compared five SRFEs with rain gauge data in the Blue Nile Basin. Several studies show that local calibration significantly improves the 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 data set is shown in Fig. 2. The mean absolute percentage error varies between 0 and 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 0–10 % deviation. This indicates that for the majority of case studies, the error in calibrated rainfall maps is less than 18.5 %. Large error bands were found

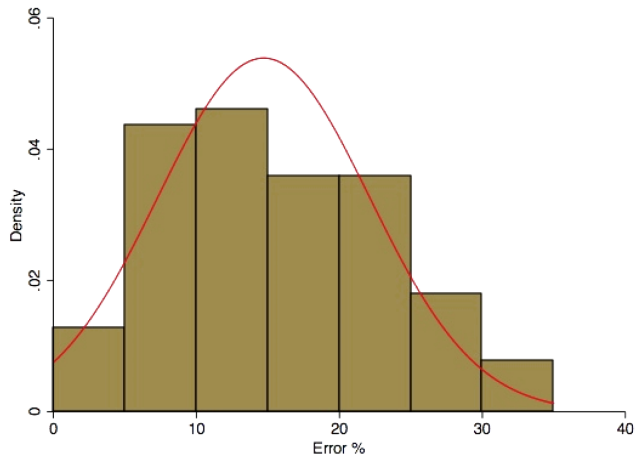


Figure 3. Probability density function of the reported mean absolute percentage error in land use classification using remote sensing.

for all rainfall algorithms, and no 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 conclusions are 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 not satisfactory and requires caution when applied for water accounting and hydrological modeling, despite the fact that most SRFEs have an a priori calibration procedure. More research and development of operational rainfall algorithms using various types of sensors is deemed necessary.

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 data set. The results are presented in Fig. 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

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

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 classifications 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 and 87 % with an average of 76.4 %, which is equivalent to a MAPE of 13–31 % 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 and 98 %. This is in good agreement with the suggested range of 70–90 % 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.

4 Conclusions and way forward

The increasing number 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 the errors and reliability of some of these remotely sensed hydrological variables created by advanced algorithms through an international literature review. Only recent data sets, not older than 13 years, were 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 post-2000 peer-reviewed publications 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 microscale variability and 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, and 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 spatiotemporal resolutions are promising and 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 measurements by different global and regional products for the same pixels,

there is a need for a database 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 the 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 underutilized 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 databases. Such efforts are now underway by various organizations such as the 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 have not yet been made fully 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 in terms of both spatial and temporal resolutions. This is a key factor if satellite-based ET data are to be used extensively in water management and hydrological studies.

Land use mapping was one of the earliest ways in which satellite imagery was used to produce environmental information and it is the most widely studied subject 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 product 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 remote sensing data and methods. Oftentimes the reliability of remote-sensing-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.

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	F. Cassel and M. Robertson (personal communication, 2006)	2
SEBAL	Lysimeter	California, US, 2002	Peaches	7	F. Cassel and M. 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. (2012)	7.9
SEBS	Measurements	Australia, 2009	Irrigated agriculture	16	Ma et al. (2012)	7.5

Table A1. Continued.

Method	Field instrument	Location and year	Land use	No. of images	Source	MAPE (%)
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	B. L. 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, 1989–1991	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 B1. 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)	Ethiopian 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

Table B1. Continued.

Source	Area	Year	RS data source	Deviation
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)	Mekong, SEA	1997–1999	ERA-40	0.4
Voisin et al. (2008)	Mekong, 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 and 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 Mekong	2005	Landsat TM	85
Cheema and Bastiaanssen (2010)	Indus 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
Hubert-Moy et al. (2001)	Baie de Lannion, France	1996–1997	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)	Kocaeli, Turkey	1997	Landsat ETM+	91
Kavzoglu and Colkesen (2009)	Kocaeli, Turkey	1997	Landsat ETM+	90
Kavzoglu and Colkesen (2009)	Kocaeli, Turkey	2002	Aster	88
Kavzoglu and Colkesen (2009)	Kocaeli, Turkey	2002	Aster	93
Kavzoglu and Colkesen (2009)	Kocaeli, Turkey	2002	Aster	91
Kavzoglu and Colkesen (2009)	Kocaeli, Turkey	1997	Landsat ETM+	87
Kaya et al. (2002)	Kenya	2001	RADARSAT-1	85
Keuchel et al. (2003)	Tenerife, Spain	1988	Landsat 5TM	90

Table C1. Continued.

Source	Area	Image year	Image source	Overall accuracy (%)
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 and 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 Koronia, 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

Table C1. Continued.

Source	Area	Image year	Image source	Overall accuracy (%)
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	AVHRR	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)	North 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	Coordination 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 (GSFC)
GSMaP	Global Satellite Mapping of Precipitation
HIRS	High-resolution Infrared Radiation 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	Normalized difference temperature index
NOAA	National Oceanic and Atmospheric Administration
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

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References

- ABS – Australian Bureau of Statistics: Water Account, Australia – 2000–01, Canberra, 2004.
- Abd El-Kawy, O. R., Rød, J. K., Ismail, H. A., and Suliman, A. S.: Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data, *Appl. Geogr.*, 31, 483–494, doi:10.1016/j.apgeog.2010.10.012, 2011.
- Aguirre-Gutiérrez, J., Seijmonsbergen, A. C., and Duivenvoorden, J. F.: Optimizing land cover classification accuracy for change detection, a combined pixel-based and object-based approach in a mountainous area in Mexico, *Appl. Geogr.*, 34, 29–37, doi:10.1016/j.apgeog.2011.10.010, 2012.
- Allen, R. G., Pereira, L., Raes, D., and Smith, M.: Crop evapotranspiration: guidelines for computing crop water requirements, Issues 56–57, Food and Agriculture Organization of the United Nations, Rome, Italy, 1998.
- Allen, R. G., Tasumi, M., Morse, A., and Trezza, R.: A Landsat-based energy balance and evapotranspiration model in Western US water rights regulation and planning, *Irrig. Drain. Syst.*, 19, 251–268, doi:10.1007/s10795-005-5187-z, 2005.
- Allen, R. G., Tasumi, M., Morse, A., Trezza, R., Wright, J. L., Bastiaanssen, W., Kramber, W., Lorite, I., and Robison, C. W.: Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC) – Applications, *J. Irrig. Drain. Eng.*, 133, 395–406, 2007.
- Allen, R. G., Irmak, A., Trezza, R., Hendrickx, J. M. H., Bastiaanssen, W. and Kjaersgaard, J.: Satellite-based ET estimation in agriculture using SEBAL and METRIC, *Hydrol. Process.*, 25, 4011–4027, doi:10.1002/hyp.8408, 2011.
- Almazroui, M.: Calibration of TRMM rainfall climatology over Saudi Arabia during 1998–2009, *Atmos. Res.*, 99, 400–414, 2011.
- Almazroui, M., Islam, M. N., Jones, P. D., Athar, H., and Rahman, M. A.: Recent climate change in the Arabian Peninsula: Seasonal rainfall and temperature climatology of Saudi Arabia for 1979–2009, *Atmos. Res.*, 111, 29–45, doi:10.1016/j.atmosres.2012.02.013, 2012.
- Anderson, M. C., Norman, J. M., Diak, G. R., Kustas, W. P., and Mecikalski, J. R.: A Two-Source Time-Integrated Model for Estimating Surface Fluxes Using Thermal Infrared Remote Sensing, *Remote Sens. Environ.*, 60, 195–216, doi:10.1016/S0034-4257(96)00215-5, 1997.
- Anderson, M. C., Kustas, W. P., Norman, J. M., Hain, C. R., Mecikalski, J. R., Schultz, L., González-Dugo, M. P., Cammalleri, C., d’Urso, G., Pimstein, A., and Gao, F.: Mapping daily evapotranspiration at field to continental scales using geostationary and polar orbiting satellite imagery, *Hydrol. Earth Syst. Sci.*, 15, 223–239, doi:10.5194/hess-15-223-2011, 2011.
- Anderson, M. C., Kustas, W. P., Alfieri, J. G., Gao, F., Hain, C., Prueger, J. H., Evett, S., Colaizzi, P., Howell, T., and Chávez, J. L.: Mapping daily evapotranspiration at Landsat spatial scales during the BEAREX’08 field campaign, *Adv. Water Resour.*, 50, 162–177, doi:10.1016/j.advwatres.2012.06.005, 2012.
- Andre, J. C., Goutorbe, J. P., and Penier, A.: HAPEX-MOBILHY, a hydrologic atmospheric pilot experiment for the study of water budget and evaporation flux at the climatic scales, *B. Am. Meteorol. Soc.*, 67, 138–144, 1986.
- Asadullah, A., McIntyre, N. E. I. L., and Kigobe, M.: Evaluation of five satellite products for estimation of rainfall over Uganda, *Hydrolog. Sci. J.*, 53, 1137–1150, 2008.
- Asadullah, A., McIntyre, N., and Kigobe, M. A. X.: Evaluation of five satellite products for estimation of rainfall over Uganda/Evaluation de cinq produits satellitaires pour l’estimation des précipitations en Ouganda Evaluation of five satellite products for estimation of rainfall over Uganda, *Hydrolog. Sci. J.*, 53, 1137–1150, 2010.
- Austin, P. M.: Relation between measured radar reflectivity and surface rainfall, *Mon. Weather Rev.*, 115, 1053–1070, 1987.
- Awulachew, S. B., Molden, D., Smakhtin, V., and Peden, D.: The Nile River Basin: Water, Agriculture, Governance and Livelihoods, Routledge, Oxon, UK, 2013.
- Bach, M., Breuer, L., Frede, H. G., Huisman, J. A., Otte, A., and Waldhardt, R.: Accuracy and congruency of three different digital land-use maps, *Landsc. Urban Plan.*, 78, 289–299, doi:10.1016/j.landurbplan.2005.09.004, 2006.
- Barrett, E. C.: Precipitation monitoring by satellites. Remote sensing for studies of global environmental changes, ISpra Courses, RS/88/10, Commission of European Communities, Joint Research Center, Ispra Establishment, Ispra, Italy, 1988.
- Barrett, E. C. and Beaumont, M. J.: Satellite rainfall monitoring: An overview, *Remote Sens. Rev.*, 11, 23–48, doi:10.1080/02757259409532257, 1994.
- Bastiaanssen, W. G. M.: Remote sensing in water resources management: the state of the art, International Water Management Institute (IWMI), Colombo, Sri Lanka, 1998.
- Bastiaanssen, W. G. M. and Chandrapala, L.: Water balance variability across Sri Lanka for assessing agricultural and environmental water use, *Agric. Water Manage.*, 58, 171–192, 2003.
- Bastiaanssen, W. G. M., Menenti, M., Feddes, R. A., Holtslag, A. A. M., Pelgrum, H., Wang, J., Ma, Y., Moreno, J. F., Roerink, G. J., and van der Wal, T.: A remote sensing surface energy balance algorithm for land (SEBAL), 1. Formulation, *J. Hydrol.*, 212–213, 198–212, 1998.
- Bastiaanssen, W. G. M., Molden, D. J., and Makin, I. W.: Remote sensing for irrigated agriculture: examples from research and possible applications, *Agric. Water Manage.*, 46, 137–155, doi:10.1016/S0378-3774(00)00080-9, 2000.
- Bastiaanssen, W. G. M., Ahmad, M.-D., and Chemin, Y.: Satellite surveillance of evaporative depletion across the Indus Basin, *Water Resour. Res.*, 38, 9-1–9-9, doi:10.1029/2001WR000386, 2002.
- Bastiaanssen, W. G. M., Miltenburg, I., Evans, R., Molloy, R., Bastiaanssen, F. J. M., and van der Pol, E.: An operational satellite-based irrigation monitoring and scheduling tool for saving water in irrigation, in *Irrigation and Drainage Conference*, Swan Hill, Vic, Australia, 2009.
- Bastiaanssen, W. G. M., Cheema, M. J. M., Immerzeel, W. W., Miltenburg, I., and Pelgrum, H.: The surface energy balance and actual evapotranspiration of the transboundary Indus Basin estimated from satellite measurements and the ETLook model,

- Water Resour. Res., 48, W11512, doi:10.1029/2011WR010482, 2012.
- Batra, N., Islam, S., Venturini, V., Bisht, G., and Jiang, L.: Estimation and comparison of evapotranspiration from MODIS and AVHRR sensors for clear sky days over the Southern Great Plains, *Remote Sens. Environ.*, 103, 1–15, doi:10.1016/j.rse.2006.02.019, 2006.
- Bicheron, P., Defourny, P., Brockmann, C., Schouten, L., Vancutsem, C., Huc, M., Bontemps, S., Leroy, M., Achard, F., Herold, M., Ranera, F., and Arino, O.: GLOBCOVER Products Report Description and Products Description and Validation Report, MEDIAS, France, 2008.
- Bitew, M. M. and Gebremichael, M.: Evaluation of satellite rainfall products through hydrologic simulation in a fully distributed hydrologic model, *Water Resour. Res.*, 47, W06526, doi:10.1029/2010WR009917, 2011.
- Blanco, P. D., Colditz, R. R., López Saldaña, G., Hardtke, L. A., Llamas, R. M., Mari, N. A., Fischer, A., Caride, C., Aceñolaza, P. G., del Valle, H. F., Lillo-Saavedra, M., Coronato, F., Opazo, S. A., Morelli, F., Anaya, J. A., Sione, W. F., Zamboni, P., and Arroyo, V. B.: A land cover map of Latin America and the Caribbean in the framework of the SERENA project, *Remote Sens. Environ.*, 132, 13–31, doi:10.1016/j.rse.2012.12.025, 2013.
- Bolle, H. J., Eckardt, M., Koslowsky, D., Maselli, F., Melia-Miralles, J., Menenti, M., Olesen, F.-S., Petkov, L., Rasool, I., and van deGriend, A.: Mediterranean land-surface processes assessed from space, Series: Regional Climate Studies, XXVIII, Springer, Berlin, 760 pp., 2006.
- Bosch, J. M. and Hewlett, J. D.: A review of catchment experiments to determine the effect of vegetation changes on water yield and evapotranspiration, *J. Hydrol.*, 55, 3–23, doi:10.1016/0022-1694(82)90117-2, 1982.
- Brutsaert, W.: *Evaporation into the Atmosphere, Theory, History and Applications*, D. Reidel Publishing Company, Dordrecht, the Netherlands, 302 pp., 1982.
- Büttner, G., Feranec, J., and Jaffrain, G.: *The thematic accuracy of Corine land cover 2000*, European Environment Agency, Copenhagen, 2006.
- Campbell, G. S. and Norman, J. M.: *An introduction to environmental biophysics*, Springer, New York, 1998.
- Cassidy, L., Southworth, J., Gibbes, C., and Binford, M.: Beyond classifications: Combining continuous and discrete approaches to better understand land-cover change within the lower Mekong River region, *Appl. Geogr.*, 39, 26–45, doi:10.1016/j.apgeog.2012.11.021, 2013.
- Chartres, C. and Varma, S.: *Out of Water: From Abundance to Scarcity and How to Solve the World's Water Problems*, FT Press, New Jersey, 2010.
- Chávez, J. L., Neale, C. M. U., Prueger, J. H., and Kustas, W. P.: Daily evapotranspiration estimates from extrapolating instantaneous airborne remote sensing ET values, *Irrig. Sci.*, 27, 67–81, doi:10.1007/s00271-008-0122-3, 2008.
- Cheema, M. J. M. and Bastiaanssen, W. G. M.: Land use and land cover classification in the irrigated Indus Basin using growth phenology information from satellite data to support water management analysis, *Agric. Water Manage.*, 97, 1541–1552, 2010.
- Cheema, M. J. M. and Bastiaanssen, W. G. M.: Local calibration of remotely sensed rainfall from the TRMM satellite for different periods and spatial scales in the Indus Basin, *Int. J. Remote Sens.*, 33, 2603–2627, 2012.
- Chehbouni, A., Kerr, Y. H., Watts, C., Hartogensis, O., Goodrich, D., Scott, R., Schieldge, J., Lee, K., Shuttleworth, W. J., Dedieu, G., and De Bruin, H. A. R.: Estimation of area-average sensible heat flux using a large-aperture scintillometer during the Semi-Arid Land-Surface-Atmosphere (SALSA) Experiment, *Water Resour. Res.*, 35, 2505–2511, doi:10.1029/1999WR900111, 1999.
- Chen, C., Yu, Z., Li, L., and Yang, C.: Adaptability Evaluation of TRMM Satellite Rainfall and Its Application in the Dongjiang River Basin, *Proced. Environ. Sci.*, 10, 396–402, doi:10.1016/j.proenv.2011.09.065, 2011.
- Choudhury, B. J.: Synergism of optical and microwave observations for land surface studies, in: *Passive microwave remote sensing of land-atmosphere interactions, microwave remote sensing of land-atmosphere interactions*, edited by: Choudhury, B. J., Kerr, Y. H., Njoku, E. G., and Pampaloni, P., VSP BV, Utrecht, the Netherlands, 155–191, 1995.
- Cihlar, J.: Land cover mapping of large areas from satellites?: Status and research priorities, *Int. J. Remote Sens.*, 21, 1093–1114, 2000.
- Cingolani, A.: Mapping vegetation in a heterogeneous mountain rangeland using landsat data: an alternative method to define and classify land-cover units, *Remote Sens. Environ.*, 92, 84–97, doi:10.1016/j.rse.2004.05.008, 2004.
- Clark, M. L., Aide, T. M., Grau, H. R. and Riner, G.: A scalable approach to mapping annual land cover at 250 m using MODIS time series data: A case study in the Dry Chaco ecoregion of South America, *Remote Sens. Environ.*, 114, 2816–2832, doi:10.1016/j.rse.2010.07.001, 2010.
- Cleugh, H. A., Leuning, R., Mu, Q., and Running, S. W.: Regional evaporation estimates from flux tower and MODIS satellite data, *Remote Sens. Environ.*, 106, 285–304, doi:10.1016/j.rse.2006.07.007, 2007.
- Colditz, R. R., López Saldaña, G., Maeda, P., Espinoza, J. A., Tovar, C. M., Hernández, A. V., Benítez, C. Z., Cruz López, I., and Ressler, R.: Generation and analysis of the 2005 land cover map for Mexico using 250m MODIS data, *Remote Sens. Environ.*, 123, 541–552, doi:10.1016/j.rse.2012.04.021, 2012.
- Collischonn, B., Collischonn, W., and Tucci, C. E. M.: Daily hydrological modeling in the Amazon basin using TRMM rainfall estimates, *J. Hydrol.*, 360, 207–216, doi:10.1016/j.jhydrol.2008.07.032, 2008.
- Congalton, R. G.: A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data, *Remote Sens. Environ.*, 46, 35–46, 1991.
- Courault, D., Seguin, B., and Olioso, A.: Review on estimation of evapotranspiration from remote sensing data: From empirical to numerical modeling approaches, *Irrig. Drain. Syst.*, 19, 223–249, doi:10.1007/s10795-005-5186-0, 2005.
- Cracknell, A. P. and Hayes, L.: *Introduction to remote sensing*, Taylor & Francis, London, 1991.
- Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, L., Källberg, P., Köhler, M., Matricardi, M., McNally,

- A. P., Monge-Sanz, B. M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., and Vitart, F.: The ERA-Interim reanalysis: configuration and performance of the data assimilation system, *Q. J. Roy. Meteorol. Soc.*, 137, 553–597, doi:10.1002/qj.828, 2011.
- Dinku, T., Ceccato, P., Grover-Kopec, E., Lemma, M., Connor, S. J., and Ropelewski, C. F.: Validation of satellite rainfall products over East Africa's complex topography, *Int. J. Remote Sens.*, 28, 1503–1526, doi:10.1080/01431160600954688, 2007.
- Dinku, T., Connor, S., and Ceccato, P.: Nile River Basin, in: Nile River Basin, edited by: Melesse, A. M., Springer Netherlands, Dordrecht, 109–127, 2011.
- Duan, Z. and Bastiaanssen, W. G. M.: First results from Version 7 TRMM 3B43 precipitation product in combination with a new downscaling–calibration procedure, *Remote Sens. Environ.*, 131, 1–13, doi:10.1016/j.rse.2012.12.002, 2013.
- Dugdale, G. and Milford, J. R.: Rainfall estimation over the Sahel using Meteosat thermal infrared data, in: ISLSCP Parameterization of Land-Surface Characteristics: use of Satellite Data in Climate Studies, edited by: Rolfe, E. and Battrick, B., ESA, Paris, 315–319, 1986.
- Dunne, S. C., Entekhabi, D., and Njoku, E.: Impact of multiresolution active and passive microwave measurements on soil moisture estimation using the Ensemble Kalman Smoother, *IEEE T. Geosci. Remote*, 45, 1016–1028, 2007.
- Engman, E. T. and Gurney, R. J.: Remote sensing in hydrology, Chapman and Hall Ltd., London, 1991.
- Estes, A. B., Kuemmerle, T., Kushnir, H., Radeloff, V. C., and Shugart, H. H.: Land-cover change and human population trends in the greater Serengeti ecosystem from 1984–2003, *Biol. Conserv.*, 147, 255–263, doi:10.1016/j.biocon.2012.01.010, 2012.
- Euser, T., Luxemburg, W. M. J., Everson, C. S., Mengistu, M. G., Clulow, A. D., and Bastiaanssen, W. G. M.: A new method to measure Bowen ratios using high-resolution vertical dry and wet bulb temperature profiles, *Hydrol. Earth Syst. Sci.*, 18, 2021–2032, doi:10.5194/hess-18-2021-2014, 2014.
- Evans, R., Bastiaanssen, W., Molloy, R., Hulbert, S., and Miltenburg, I.: Improving the picture for irrigation using SEBAL in Australia to measure evapotranspiration (ET), in: Irrigation and Drainage Conference 2009, Swan Hill, Vic, Australia, 2009.
- Feidas, H.: Validation of satellite rainfall products over Greece, *Theor. Appl. Climatol.*, 99, 193–216, doi:10.1007/s00704-009-0135-8, 2009.
- Fernandes, K., Fu, R., and Betts, A. K.: How well does the ERA40 surface water budget compare to observations in the Amazon River basin?, *J. Geophys. Res.*, 113, D11117, doi:10.1029/2007JD009220, 2008.
- Foody, G. M.: Status of land cover classification accuracy assessment, *Remote Sens. Environ.*, 80, 185–201, doi:10.1016/S0034-4257(01)00295-4, 2002.
- Franklin, S. E. and Wulder, M. A.: Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas, *Prog. Phys. Geogr.*, 26, 173–205, doi:10.1191/0309133302pp332ra, 2002.
- Friedl, M. A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., and Huang, X.: MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets, *Remote Sens. Environ.*, 114(1), 168–182, doi:10.1016/j.rse.2009.08.016, 2010.
- Fu, Q., Ruan, R., and Liu, Y.: Accuracy Assessment of Global Satellite Mapping of Precipitation (GSMaP) Product over Poyang Lake Basin, China, *Proced. Environ. Sci.*, 10, 2265–2271, doi:10.1016/j.proenv.2011.09.354, 2011.
- Funk, C. C., Peterson, P. J., Landsfeld, M. F., Pedreros, D. H., Verdin, J. P., Rowland, J. D., Romero, B. E., Husak, G. J., Michaelsen, J. C., and Verdin, A. P.: A Quasi-Global Precipitation Time Series for Drought Monitoring, US Geological Survey Data Series 832, US Geological Survey, p. 4, doi:10.3133/ds832, 2013.
- Gamanya, R., De Maeyer, P., and De Dapper, M.: An automated satellite image classification design using object-oriented segmentation algorithms: A move towards standardization, *Expert Syst. Appl.*, 32, 616–624, doi:10.1016/j.eswa.2006.01.055, 2007.
- García-Mora, T. J., Mas, J.-F., and Hinkley, E. A.: Land cover mapping applications with MODIS: a literature review, *Int. J. Digit. Earth*, 5, 63–87, doi:10.1080/17538947.2011.565080, 2012.
- Getirana, A. C. V., Espinoza, J. C. V., Ronchail, J., and Rotunno Filho, O. C.: Assessment of different precipitation datasets and their impacts on the water balance of the Negro River basin, *J. Hydrol.*, 404, 304–322, doi:10.1016/j.jhydrol.2011.04.037, 2011.
- Glenn, E. P., Huete, A. R., Nagler, P. L., Hirschboeck, K. K., and Brown, P.: Integrating Remote Sensing and Ground Methods to Estimate Evapotranspiration, *CRC, Crit. Rev. Plant Sci.*, 26, 139–168, doi:10.1080/07352680701402503, 2007.
- Glenn, E. P., Doody, T. M., Guerschman, J. P., Huete, A. R., King, E. A., McVicar, T. R., Van Dijk, A. I. J. M., Van Niel, T. G., Yebra, M., and Zhang, Y.: Actual evapotranspiration estimation by ground and remote sensing methods: the Australian experience, *Hydrol. Process.*, 25, 4103–4116, doi:10.1002/hyp.8391, 2011.
- Gong, P., Wang, J., Yu, L., Zhao, Y. C., Zhao, Y. Y., Liang, L., Niu, Z. G., Huang, X. M., Fu, H. H., Liu, S., Li, C. C., Li, X. Y., Fu, W., Liu, C. X., Xu, Y., Wang, X. Y., Cheng, Q., Hu, L. Y., Yao, W. B., Zhang, H., Zhu, P., Zhao, Z. Y., Zhang, H. Y., Zheng, Y. M., Ji, L. Y., Zhang, Y. W., Chen, H., Yan, A., Guo, J. H., Yu, L., Wang, L., Liu, X. J., Shi, T. T., Zhu, M. H., Chen, Y. L., Yang, G. W., Tang, P., Xu, B., Ciri, C., Clinton, N., Zhu, Z. L., Chen, J., and Chen, J.: Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data, *Int. J. Remote Sens.*, 34, 2607–2654, 2013.
- Gonzalez-Dugo, M. P., Neale, C. M. U., Mateos, L., Kustas, W. P., Prueger, J. H., Anderson, M. C., and Li, F.: A comparison of operational remote sensing-based models for estimating crop evapotranspiration, *Agr. Forest Meteorol.*, 149, 1843–1853, doi:10.1016/j.agrformet.2009.06.012, 2009.
- Goutorbe, J. P., Lebel, T., Dolman, A. J., Gash, J. H. C., Kabat, P., Kerr, Y. H., Monteny, B., Prince, S. D., Stricker, J. N. M., Tinga, A., and Wallace, J. S.: An overview of HAPEX-Sahel: a study in climate and desertification, *J. Hydrol.*, 188–189, 4–17, doi:10.1016/S0022-1694(96)03308-2, 1997.
- Gowda, P. H., Colaizzi, P. D., Evett, S. R., Howell, T. A., and Tolck, J. A.: Remote sensing based energy balance algorithms for mapping ET: current status and future challenges, *T. ASABE*, 50, 1639–1644, 2007.
- Groeneveld, D. P., Baugh, W. M., Sanderson, J. S., and Cooper, D. J.: Annual groundwater evapotranspiration mapped

- from single satellite scenes, *J. Hydrol.*, 344, 146–156, doi:10.1016/j.jhydrol.2007.07.002, 2007.
- Guerschman, J. P., Van Dijk, A. I. J. M., Mattersdorf, G., Beringer, J., Hutley, L. B., Leuning, R., Pipunic, R. C., and Sherman, B. S.: Scaling of potential evapotranspiration with MODIS data reproduces flux observations and catchment water balance observations across Australia, *J. Hydrol.*, 369, 107–119, doi:10.1016/j.jhydrol.2009.02.013, 2009.
- Hafeez, M. M., Chemin, Y., Van De Giesen, N., and Bouman, B. A. M.: Estimation of crop water deficit through remote sensing in Central Luzon, Philippines, in: vol. 5, IEEE International Geoscience and Remote Sensing Symposium, 24–28 June, Toronto, Canada, 2778–2780, 2002.
- Hortgen, O. K., Weissenberg, U., Evans, J., van Kesteren, A. J. H., and Beyrich, F.: First Results of two Optical Millimeter-wave Scintillometer Systems during LITFASS2009, 10th EMS Annu. Meet. 10th Eur. Conf. Appl. Meteorol. Abstr., held: 13–17 September 2010, Zürich, Switzerland, <http://meetings.copernicus.org/ems2010/> (last access: 5 October 2013), 2010.
- Hemakumara, H. M. and Chandrapala, L.: Evapotranspiration fluxes over mixed vegetation areas measured from large aperture scintillometer, *Agr. Water Manage.*, 58, 109–122, 2003.
- Houser, P. R., Shuttleworth, W. J., Famiglietti, J. S., and Goodrich, D. C.: Integration of soil moisture remote sensing and hydrologic modeling using data assimilation, *Water Resour. Res.*, 34, 3405–3420, 1998.
- Hubert-Moy, L., Cotonnet, A., Le Du, L., Chardin, A., and Perez, P.: A comparison of parametric classification procedures of remotely sensed data applied on different landscape units, *Remote Sens. Environ.*, 75, 174–187, 2001.
- Huffman, G. J., Bolvin, D. T., Nelkin, E. J., Wolff, D. B., Adler, R. F., Gu, G., Hong, Y., Bowman, K. P., and Stocker, E. F.: The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales, *J. Hydrometeorol.*, 8, 38–55, doi:10.1175/JHM560.1, 2007.
- Hunink, J. E., Immerzeel, W. W., and Droogers, P.: A High-resolution Precipitation 2-step mapping Procedure (HiP2P): Development and application to a tropical mountainous area, *Remote Sens. Environ.*, 140, 179–188, doi:10.1016/j.rse.2013.08.036, 2014.
- Immerzeel, W. W. and Droogers, P.: Calibration of a distributed hydrological model based on satellite evapotranspiration, *J. Hydrol.*, 349, 411–424, doi:10.1016/j.jhydrol.2007.11.017, 2008.
- Irmak, A. (Ed.): *Evapotranspiration Remote Sensing and Modeling*, InTech, Rijeka, Croatia, 2012.
- Irmak, A., Ratcliffe, I., and Hubbard, K.: Estimation of Land Surface Evapotranspiration with a Satellite Remote Sensing Procedure, Great Plains Research 21, University of Nebraska, Lincoln, 73–88, 2011.
- Jackson, T. J., Le Vine, D. M., Griffis, A. J., Goodrich, D. C., Schmugge, T. J., Swift, C. T., and O'Neill, P. E.: Soil moisture and rainfall estimation over a semiarid environment with the ESTAR microwave radiometer, *IEEE T. Geosci. Remote*, 31, 836–841, doi:10.1109/36.239906, 1993.
- Jarmain, C., Klaasse, A., Bastiaanssen, W. G. M., and Roux, A. S.: Remote sensing tools for water use efficiency of grapes in the Winelands region, Western Cape, in: 13th Sanciahs symposium, Cape Town, 2007.
- Jarmain, C., Everson, C., Savage, M., Mengisto, M., Clulow, A., Walker, S., and Gush, M.: Refining tools for evaporation monitoring in support of water resources management, Water Research Commission, Pretoria, South Africa, 2009.
- Jhorar, R. K., Smit, A. A. M. F. R., Bastiaanssen, W. G. M., and Roest, C. W. J.: Calibration of a distributed irrigation water management model using remotely sensed evapotranspiration rates and groundwater heads, *Irrig. Drain.*, 60, 57–69, doi:10.1002/ird.541, 2011.
- Jia, L., Su, B., van den Hurk, B., Menenti, M., Moene, A., and de Bruin, H. A. R.: Estimation of sensible heat flux using the Surface Energy Balance System (SEBS) and ATSR measurements, *Phys. Chem. Earth*, 28, 75–88, 2003.
- Jia, Z., Liu, S., Xu, Z., Chen, Y., and Zhu, M.: Validation of remotely sensed evapotranspiration over the Hai River Basin, China, *J. Geophys. Res.*, 117, D13113, doi:10.1029/2011JD017037, 2012.
- Jiang, L., Islam, S., Guo, W., Singh Jutla, A., Senarath, S. U. S., Ramsay, B. H., and Eltahir, E.: A satellite-based Daily Actual Evapotranspiration estimation algorithm over South Florida, *Global Planet. Change*, 67, 62–77, doi:10.1016/j.gloplacha.2008.12.008, 2009.
- Jiang, S., Ren, L., Hong, Y., Yong, B., Yang, X., Yuan, F., and Ma, M.: Comprehensive evaluation of multi-satellite precipitation products with a dense rain gauge network and optimally merging their simulated hydrological flows using the Bayesian model averaging method, *J. Hydrol.*, 452–453, 213–225, doi:10.1016/j.jhydrol.2012.05.055, 2012.
- Kalma, J. D., McVicar, T. R., and McCabe, M. F.: Estimating land surface evaporation: A review of methods using remotely sensed surface temperature data, *Surv. Geophys.*, 29, 421–469, 2008.
- Kandrika, S. and Roy, P. S.: Land use land cover classification of Orissa using multi-temporal IRS-P6 awifs data: A decision tree approach, *Int. J. Appl. Earth Obs. Geoinf.*, 10, 186–193, doi:10.1016/j.jag.2007.10.003, 2008.
- Karimi, P., Bastiaanssen, W. G. M., and Molden, D.: Water Accounting Plus (WA+) – a water accounting procedure for complex river basins based on satellite measurements, *Hydrol. Earth Syst. Sci.*, 17, 2459–2472, doi:10.5194/hess-17-2459-2013, 2013a.
- Karimi, P., Bastiaanssen, W. G. M., Molden, D., and Cheema, M. J. M.: Basin-wide water accounting based on remote sensing data: an application for the Indus Basin, *Hydrol. Earth Syst. Sci.*, 17, 2473–2486, doi:10.5194/hess-17-2473-2013, 2013b.
- Karimi, P., Bastiaanssen, W. G. M., Sood, A., Hoozeveld, J., Peiser, L., Bastidas-Obando, E., and Dost, R.: Spatial evapotranspiration, rainfall and land use data in water accounting – Part 2: Reliability of water accounting results for policy decisions in the Awash basin, *Hydrol. Earth Syst. Sci.*, 19, 533–550, doi:10.5194/hess-19-533-2015, 2015.
- Kavzoglu, T. and Colkesen, I.: A kernel functions analysis for support vector machines for land cover classification, *Int. J. Appl. Earth Obs. Geoinf.*, 11, 352–359, doi:10.1016/j.jag.2009.06.002, 2009.
- Kaya, S., Pultz, T. J., Mbogo, C. M., Beier, J. C., and Mushinzimana, E.: The Use of Radar Remote Sensing for Identifying Environmental Factors Associated with Malaria Risk in Coastal Kenya, International Geoscience and Remote Sensing Symposium (IGARSS '02), 24–28 June, Toronto, 2002.

- Keuchel, J., Naumann, S., Heiler, M., and Siegmund, A.: Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data, *Remote Sens. Environ.*, 86, 530–541, doi:10.1016/S0034-4257(03)00130-5, 2003.
- Kidd, C.: Satellite rainfall climatology: a review, *Int. J. Climatol.*, 21, 1041–1066, doi:10.1002/joc.635, 2001.
- King, E. A., Van Niel, T. G., Van Dijk, A. I. J. M., Wang, Z., Paget, M. J., Raupach, T., Guerschman, J., Haverd, V., Mcvicar, T. R., Miltenburg, I., Raupach, M. R., and Zhang, Y.: Actual Evapotranspiration Estimates for Australia Inter-comparison and Evaluation, CSIRO: Water for a Healthy Country National Research Flagship Copyright, Canberra, 2011.
- Kiptala, J., Mohamed, Y., Mul, M., Cheema, M. J. M., and van der Zaag, P.: Land use and land cover classification using phenological variability from MODIS vegetation in the Upper Pangani River Basin, Eastern Africa, *Phys. Chem. Earth A/B/C*, 66, 112–122, 2013.
- Kite, G. and Droogers, P.: Comparing evapotranspiration estimates from satellites, hydrological models and field data, *J. Hydrol.*, 229, 1–2, doi:10.1016/S0022-1694(99)00193-6, 2000.
- Kizza, M., Westerberg, I., Rodhe, A., and Ntale, H. K.: Estimating areal rainfall over Lake Victoria and its basin using ground-based and satellite data, *J. Hydrol.*, 464–465, 401–411, doi:10.1016/j.jhydrol.2012.07.024, 2012.
- Klein, I., Gessner, U., and Kuenzer, C.: Regional land cover mapping and change detection in Central Asia using MODIS time-series, *Appl. Geogr.*, 35, 219–234, doi:10.1016/j.apgeog.2012.06.016, 2012.
- Kolios, S. and Stylios, C. D.: Identification of land cover/land use changes in the greater area of the Preveza peninsula in Greece using Landsat satellite data, *Appl. Geogr.*, 40, 150–160, doi:10.1016/j.apgeog.2013.02.005, 2013.
- Kummerow, C., Olson, W. S., and Giglio, L.: A simplified scheme for obtaining precipitation and vertical hydrometeor profiles from passive microwave sensors, *IEEE T. Geosci. Remote*, 34, 1213–1232, doi:10.1109/36.536538, 1996.
- Kustas, W. P. and Norman, J. M.: Use of remote sensing for evapotranspiration monitoring over land surfaces, *Hydrolog. Sci. J.*, 41, 495–516, doi:10.1080/02626669609491522, 1996.
- Kustas, W. P., Anderson, M. C., French, A. N., and Vickers, D.: Using a remote sensing field experiment to investigate flux-footprint relations and flux sampling distributions for tower and aircraft-based observations, *Adv. Water Resour.*, 29, 355–368, doi:10.1016/j.advwatres.2005.05.003, 2006.
- Lal, D., Clark, B., Bettner, T., Thoreson, B., and Snyder, R.: Rice evapotranspiration estimates and crop coefficients in Glenn-Colusa Irrigation District, Sacramento Valley, California, in: US-CID Water Management Conference, Austin, 2012.
- Li, H., Wang, H., Kong, Y., and Li, L.: Estimation of evapotranspiration in Yellow River Delta wetland based on two-source energy balance (TSEB) model, *Remote Sensing Technol. Appl.*, 27, 58–67, 2012.
- Liu, T. and Yang, X.: Mapping vegetation in an urban area with stratified classification and multiple endmember spectral mixture analysis, *Remote Sens. Environ.*, 133, 251–264, doi:10.1016/j.rse.2013.02.020, 2013.
- Liu, X.-H., Skidmore, A. K., and Van Oosten, H.: Integration of classification methods for improvement of land-cover map accuracy, *ISPRS J. Photogramm. Remote Sens.*, 56, 257–268, doi:10.1016/S0924-2716(02)00061-8, 2002.
- Ma, W., Hafeez, M., Rabbani, U., Ishikawa, H., and Ma, Y.: Retrieved actual ET using SEBS model from Landsat-5 TM data for irrigation area of Australia, *Atmos. Environ.*, 59, 408–414, doi:10.1016/j.atmosenv.2012.05.040, 2012.
- Maes, W. H., Heuvelmans, G., and Muys, B.: Assessment of Land Use Impact on Water-Related Ecosystem Services Capturing the Integrated Terrestrial-Aquatic System, *Environ. Sci. Technol.*, 43, 7324–7330, doi:10.1021/es900613w, 2009.
- Mallick, K., Bhattacharya, B. K., Chaurasia, S., Dutta, S., Nigam, R., Mukherjee, J., Banerjee, S., Kar, G., Rao, V. U. M., Gadgil, A. S., and Parihar, J. S.: Evapotranspiration using MODIS data and limited ground observations over selected agroecosystems in India, *Int. J. Remote Sens.*, 28, 2091–2110, 2007.
- Mayaux, P., Eva, H., Gallego, J., Strahler, A. H. A. H., Herold, M., Agrawal, S., Naumov, S., De Miranda, E. E., Di Bella, C. M., Ordoyne, C., Kopin, Y., Roy, P. S. S., Member, S., De Miranda, E. E., and Di Bella, C. M.: Validation of the global land cover 2000 map, *IEEE T. Geosci. Remote*, 44, 1728–1739, doi:10.1109/TGRS.2006.864370, 2006.
- Mcvicar, T. R. and Jupp, D. L. B.: Estimating one-time-of-day meteorological data from standard daily data as inputs to thermal remote sensing based energy balance models, *Agr. Forest Meteorol.*, 96, 219–238, 1999.
- Mcvicar, T. R. and Jupp, D. L. B.: Using covariates to spatially interpolate moisture availability in the Murray – Darling Basin A novel use of remotely sensed data, *Remote Sens. Environ.*, 79, 199–212, 2002.
- Meijninger, W. M. L. and de Bruin, H. A. R.: The sensible heat fluxes over irrigated areas in western Turkey determined with a large aperture scintillometer, *J. Hydrol.*, 229, 42–49, doi:10.1016/S0022-1694(99)00197-3, 2000.
- Milewski, A., Sultan, M., Jayaprakash, S. M., Balekai, R., and Becker, R.: RESDEM, a tool for integrating temporal remote sensing data for use in hydrogeologic investigations, *Comput. Geosci.*, 35, 2001–2010, doi:10.1016/j.cageo.2009.02.010, 2009.
- Miralles, D. G., Holmes, T. R. H., De Jeu, R. A. M., Gash, J. H., Meesters, A. G. C. A., and Dolman, A. J.: Global land-surface evaporation estimated from satellite-based observations, *Hydrol. Earth Syst. Sci.*, 15, 453–469, doi:10.5194/hess-15-453-2011, 2011.
- Moffitt, C. B., Hossain, F., Adler, R. F., Yilmaz, K. K., and Pierce, H. F.: Validation of a TRMM-based global Flood Detection System in Bangladesh, *Int. J. Appl. Earth Obs. Geoinf.*, 13, 165–177, doi:10.1016/j.jag.2010.11.003, 2011.
- Mohamed, Y. A., Bastiaanssen, W. G. M., and Savenije, H. H. G.: Spatial variability of evaporation and moisture storage in the swamps of the upper Nile studied by remote sensing techniques, *J. Hydrol.*, 289, 145–164, doi:10.1016/j.jhydrol.2003.11.038, 2004.
- Molden, D.: Water for food, water for life: A comprehensive assessment of water management in agriculture, Earthscan, London, 2007.
- Molden, D., Dong, B., Loeve, R., Barker, R., and Tuong, T. P.: Agricultural water productivity and savings: policy lessons from two diverse sites in China, *Water Policy*, 9, 29–44, 2007.
- Moon, B., Hong, J., Lee, B., Yun, J. I., Park, E. W., and Kim, J.: CO₂ and energy exchange in a rice paddy for the growing sea-

- son of 2002 in Hari, Korea Byung-Kwan, Korean J. Agric. For. Meteorol., 5, 51–60, 2003.
- Moran, M. S. and Jackson, R. D.: Assessing the spatial distribution of evapotranspiration using remotely sensed inputs, *J. Environ. Qual.*, 20, 725–737, 1991.
- Moran, M. S., Clarke, T. R., Inoue, Y., and Vidal, A.: Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index, *Remote Sens. Environ.*, 49, 246–263, doi:10.1016/0034-4257(94)90020-5, 1994.
- Mu, Q., Heinsch, F. A., Zhao, M., and Running, S. W.: Development of a global evapotranspiration algorithm based on MODIS and global meteorology data, *Remote Sens. Environ.*, 111, 519–536, 2007.
- Mu, Q., Zhao, M., and Running, S. W.: Improvements to a MODIS global terrestrial evapotranspiration algorithm, *Remote Sens. Environ.*, 115, 1781–1800, doi:10.1016/j.rse.2011.02.019, 2011.
- Mucher, C. A., Steinnocher, K. T., Kressler, F. P., and Heunks, C.: Land cover characterization and change detection for environmental monitoring of pan-Europe, *Int. J. Remote Sens.*, 21, 1159–1181, doi:10.1080/014311600210128, 2000.
- Mueller, B., Hirschi, M., Jimenez, C., Ciais, P., Dirmeyer, P. A., Dolman, A. J., Fisher, J. B., Jung, M., Ludwig, F., Maignan, F., Miralles, D. G., McCabe, M. F., Reichstein, M., Sheffield, J., Wang, K., Wood, E. F., Zhang, Y., and Seneviratne, S. I.: Benchmark products for land evapotranspiration: LandFlux-EVAL multi-data set synthesis, *Hydrol. Earth Syst. Sci.*, 17, 3707–3720, doi:10.5194/hess-17-3707-2013, 2013.
- Munthali, K. G. and Murayama, Y.: Land use/cover change detection and analysis for Dzalanyama forest reserve, Lilongwe, Malawi, *Procedia – Social and Behavioral Sciences*, 21, 203–211, doi:10.1016/j.sbspro.2011.07.035, 2011.
- Neale, C. M. U. and Cosh, M. H.: Remote sensing and hydrology, IAHS Red Book Series, Publ. 352, IAHS Wallingford, UK, 482 pp., 2012.
- Nemani, R. R. and Running, S. W.: Estimation of Regional Surface Resistance to Evapotranspiration from NDVI and Thermal-IR AVHRR Data, *J. Appl. Meteorol.*, 28, 276–284, doi:10.1175/1520-0450(1989)028<0276:EORSRT>2.0.CO;2, 1989.
- Norman, J. M., Kustas, W. P., and Humes, K. S.: Source approach for estimating soil and vegetation energy fluxes in observations of directional radiometric surface temperature, *Agr. Forest Meteorol.*, 77, 263–293, doi:10.1016/0168-1923(95)02265-Y, 1995.
- Oldeland, J., Dorigo, W., Lieckfeld, L., Lucieer, A., and Jürgens, N.: Combining vegetation indices, constrained ordination and fuzzy classification for mapping semi-natural vegetation units from hyperspectral imagery, *Remote Sens. Environ.*, 114, 1155–1166, doi:10.1016/j.rse.2010.01.003, 2010.
- Otter, L. B., Guenther, A., and Greenberg, J.: Seasonal and spatial variations in biogenic hydrocarbon emissions from southern African savannas and woodlands, *Atmos. Environ.*, 36, 4265–4275, 2002.
- Otukei, J. R. and Blaschke, T.: Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms, *Int. J. Appl. Earth Obs. Geoinf.*, 12, S27–S31, doi:10.1016/j.jag.2009.11.002, 2010.
- Pan, X., Zhang, S., Zhang, H., Na, X., and Li, X.: A variable precision rough set approach to the remote sensing land use/cover classification, *Comput. Geosci.*, 36, 1466–1473, doi:10.1016/j.cageo.2009.11.010, 2010.
- Peña-Barragán, J. M., Ngugi, M. K., Plant, R. E., and Six, J.: Object-based crop identification using multiple vegetation indices, textural features and crop phenology, *Remote Sens. Environ.*, 115, 1301–1316, doi:10.1016/j.rse.2011.01.009, 2011.
- Pérez-Hoyos, A., García-Haro, F. J., and San-Miguel-Ayanz, J.: A methodology to generate a synergetic land-cover map by fusion of different land-cover products, *Int. J. Appl. Earth Obs. Geoinf.*, 19, 72–87, doi:10.1016/j.jag.2012.04.011, 2012.
- Petropoulos, G. P., Kalaitzidis, C., and Prasad Vadrevu, K.: Support vector machines and object-based classification for obtaining land-use/cover cartography from Hyperion hyperspectral imagery, *Comput. Geosci.*, 41, 99–107, doi:10.1016/j.cageo.2011.08.019, 2012.
- Petty, G. W.: The status of satellite-based rainfall estimation over land, *Remote Sens. Environ.*, 51, 125–137, doi:10.1016/0034-4257(94)00070-4, 1995.
- Petty, G. W. and Krajewski, W. F. W. F.: Satellite estimation of precipitation over land, *Hydrolog. Sci. J.*, 41, 433–452, doi:10.1080/02626669609491519, 1996.
- Pierre, C., Bergametti, G., Marticorena, B., Mougou, E., Lebel, T., and Ali, A.: Pluriannual comparisons of satellite-based rainfall products over the Sahelian belt for seasonal vegetation modeling, *J. Geophys. Res.*, 116, D18201, doi:10.1029/2011JD016115, 2011.
- Qi, Z., Yeh, A. G.-O., Li, X., and Lin, Z.: A novel algorithm for land use and land cover classification using RADARSAT-2 polarimetric SAR data, *Remote Sens. Environ.*, 118, 21–39, doi:10.1016/j.rse.2011.11.001, 2012.
- Rana, G. and Katerji, N.: Measurement and estimation of actual evapotranspiration in the field under Mediterranean climate: a review, *Eur. J. Agron.*, 13, 125–153, doi:10.1016/S1161-0301(00)00070-8, 2000.
- Rango, A., Ritchie, J. C., Kustas, W. P., Schmugge, T. J., Humes, K. S., Hipps, L. E., Prueger, J. H., and Havstad Rango, K. M.: JORNEX: A multidisciplinary remote sensing campaign to quantify plant community/atmospheric interactions in the northern Chihuahuan desert of New Mexico, in: *Hydrology in a Changing Environment*, edited by: Wheeler, H. and Kirby, C., John Wiley, London, UK, 585–590, 1998.
- Ren, G., Zhu, A.-X., Wang, W., Xiao, W., Huang, Y., Li, G., Li, D., and Zhu, J.: A hierarchical approach coupled with coarse DEM information for improving the efficiency and accuracy of forest mapping over very rugged terrains, *Forest Ecol. Manage.*, 258, 26–34, doi:10.1016/j.foreco.2009.03.043, 2009.
- Renó, V. F., Novo, E. M. L. M., Suemitsu, C., Rennó, C. D., and Silva, T. S. F.: Assessment of deforestation in the Lower Amazon floodplain using historical Landsat MSS/TM imagery, *Remote Sens. Environ.*, 115, 3446–3456, doi:10.1016/j.rse.2011.08.008, 2011.
- Rientjes, T. H. M., Muthuwatta, L. P., Bos, M. G., Booij, M. J., and Bhatti, H. A.: Multi-variable calibration of a semi-distributed hydrological model using streamflow data and satellite-based evapotranspiration, *J. Hydrol.*, 505, 276–290, 2013.
- Rodriguez-Galiano, V. and Chica-Olmo, M.: Land cover change analysis of a Mediterranean area in Spain using different sources of data: Multi-seasonal Landsat images, land surface tempera-

- ture, digital terrain models and texture, *Appl. Geogr.*, 35, 208–218, doi:10.1016/j.apgeog.2012.06.014, 2012.
- Roerink, G. J., Su, Z., and Menenti, M.: S-SEBI: A simple remote sensing algorithm to estimate the surface energy balance, *Phys. Chem. Earth B*, 25, 147–157, doi:10.1016/S1464-1909(99)00128-8, 2000.
- Roerink, G. J., Menenti, M., Soepboer, W., and Su, Z.: Assessment of climate impact on vegetation dynamics by using remote sensing, *Phys. Chem. Earth, A/B/C*, 28, 103–109, doi:10.1016/S1474-7065(03)00011-1, 2003.
- Rosema, A.: Comparison of Meteosat-based rainfall and evapotranspiration mapping in the Sahel region, *Int. J. Remote Sens.*, 11, 2299–2309, doi:10.1080/01431169008955176, 1990.
- Rozenstein, O. and Karnieli, A.: Comparison of methods for land-use classification incorporating remote sensing and GIS inputs, *Appl. Geogr.*, 31, 533–544, doi:10.1016/j.apgeog.2010.11.006, 2011.
- Schuurmans, J. M., Troch, P. A., Veldhuizen, A. A., Bastiaanssen, W. G. M., and Bierkens, M. F. P.: Assimilation of remotely sensed latent heat flux in a distributed hydrological model, *Adv. Water Resour.*, 26, 151–159, 2003.
- Scott, C. A., Bastiaanssen, W. G. M., and Ahmad, M.-D.: Mapping Root Zone Soil Moisture Using Remotely Sensed Optical Imagery, *J. Irrig. Drain. Eng.*, 129, 326–335, doi:10.1061/(ASCE)0733-9437(2003)129:5(326), 2003.
- Semire, F. A., Mohd-Mokhtar, R., Ismail, W., Mohamad, N., and Mandeep, J. S. S.: Ground validation of space-borne satellite rainfall products in Malaysia, *Adv. Space Res.*, 50, 1241–1249, doi:10.1016/j.asr.2012.06.031, 2012.
- Setiawan, H., Mathieu, R., and Thompson-Fawcett, M.: Assessing the applicability of the V-I-S model to map urban land use in the developing world: Case study of Yogyakarta, Indonesia, *Comput. Environ. Urban Syst.*, 30, 503–522, doi:10.1016/j.compenvurbsys.2005.04.003, 2006.
- Shao, Y. and Lunetta, R. S.: Comparison of support vector machine, neural network, and CART algorithms for the land-cover classification using limited training data points, *ISPRS J. Photogramm. Remote Sens.*, 70, 78–87, doi:10.1016/j.isprsjprs.2012.04.001, 2012.
- Shimoni, M., Borghys, D., Heremans, R., Perneel, C., and Acheroy, M.: Fusion of PolSAR and PolInSAR data for land cover classification, *Int. J. Appl. Earth Obs. Geoinf.*, 11, 169–180, doi:10.1016/j.jag.2009.01.004, 2009.
- Shrestha, D. P. and Zinck, J. A.: Land use classification in mountainous areas: integration of image processing, digital elevation data and field knowledge (application to Nepal), *Int. J. Appl. Earth Obs. Geoinf.*, 3, 78–85, doi:10.1016/S0303-2434(01)85024-8, 2001.
- Singh, R. K., Irmak, A., Irmak, S., and Martin, D. L.: Application of SEBAL Model for Mapping Evapotranspiration and Estimating Surface Energy Fluxes in South-Central Nebraska, *J. Irrig. Drain. Eng.*, 134, 273–285, doi:10.1061/(ASCE)0733-9437(2008)134:3(273), 2008.
- Singh, R. K., Liu, S., Tieszen, L. L., Suyker, A. E., and Verma, S. B.: Estimating seasonal evapotranspiration from temporal satellite images, *Irrig. Sci.*, 30, 303–313, doi:10.1007/s00271-011-0287-z, 2011.
- Smith, D. M., Kniveton, D. R., and Barrett, E. C.: A Statistical Modeling Approach to Passive Microwave Rainfall Retrieval, *J. Appl. Meteorol.*, 37, 135–154, 1998.
- Smith, E. A., Cooper, H. J., Xiang, X., Mugnai, A., and Tripoli, G. J.: Foundations for Statistical-Physical Precipitation Retrieval from Passive Microwave Satellite Measurements. Part I: Brightness-Temperature Properties of a Time-dependent Cloud-Radiation Model, *J. Appl. Meteorol.*, 31, 506–531, doi:10.1175/1520-0450(1992)031<0506:FFSPPR>2.0.CO;2, 1992.
- Smits, P. C., Dellepiane, S. G., and Schowengerdt, R. a.: Quality assessment of image classification algorithms for land-cover mapping: A review and a proposal for a cost-based approach, *Int. J. Remote Sens.*, 20, 1461–1486, doi:10.1080/014311699212560, 1999.
- Song, M., Civco, D. L., and Hurd, J. D.: A competitive pixel-object approach for land cover classification, *Int. J. Remote Sens.*, 26, 4981–4997, doi:10.1080/01431160500213912, 2005.
- Soppe, R. W., Bastiaanssen, W., Keller, A., Clark, B., Thoreson, B., Eckhardt, J. and Davids, G.: Use of High Resolution Thermal Landsat Data to Estimate Evapotranspiration Within the Imperial Irrigation District in Southern California, *Am. Geophys. Union*, 2006.
- Stavroukoudis, D. G., Theocharis, J. B., and Zalidis, G. C.: A Boosted Genetic Fuzzy Classifier for land cover classification of remote sensing imagery, *ISPRS J. Photogramm. Remote Sens.*, 66, 529–544, doi:10.1016/j.isprsjprs.2011.01.010, 2011.
- Stefanov, W. L., Ramsey, M. S., and Christensen, P. R.: Monitoring urban land cover change?: An expert system approach to land cover classification of semiarid to arid urban centers, *Remote Sens. Environ.*, 77, 173–185, 2001.
- Stephens, G. L. and Kummerow, C. D.: The Remote Sensing of Clouds and Precipitation from Space: A Review, *J. Atmos. Sci.*, 64, 3742–3765, doi:10.1175/2006JAS2375.1, 2007.
- Stisen, S. and Sandholt, I.: Evaluation of remote-sensing-based rainfall products through predictive capability in hydrological runoff modelling, *Hydrol. Process.*, 24, 879–891, doi:10.1002/hyp.7529, 2010.
- Su, F., Hong, Y., and Lettenmaier, D. P.: Evaluation of TRMM Multisatellite Precipitation Analysis (TMPA) and Its Utility in Hydrologic Prediction in the La Plata Basin, *J. Hydrometeorol.*, 9, 622–640, doi:10.1175/2007JHM944.1, 2008.
- Su, Z.: The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes, *Hydrol. Earth Syst. Sci.*, 6, 85–100, doi:10.5194/hess-6-85-2002, 2002.
- Sulla-Menashe, D., Friedl, M. A., Krankina, O. N., Baccini, A., Woodcock, C. E., Sibley, A., Sun, G., Kharuk, V., and Elsakov, V.: Hierarchical mapping of Northern Eurasian land cover using MODIS data, *Remote Sens. Environ.*, 115, 392–403, doi:10.1016/j.rse.2010.09.010, 2011.
- Szuster, B. W., Chen, Q., and Borger, M.: A comparison of classification techniques to support land cover and land use analysis in tropical coastal zones, *Appl. Geogr.*, 31, 525–532, doi:10.1016/j.apgeog.2010.11.007, 2011.
- Taşdemir, K., Milenov, P., and Tapsall, B.: A hybrid method combining SOM-based clustering and object-based analysis for identifying land in good agricultural condition, *Comput. Electron. Agric.*, 83, 92–101, doi:10.1016/j.compag.2012.01.017, 2012.

- Tasumi, M., Trezza, R., Allen, R. G., and Wright, J. L.: U.S. Validation Tests on the SEBAL Model for Evapotranspiration via Satellite, in: Vol. 17, 54th IEC meeting of the international commission on irrigation and drainage (ICID) Workshop remote sensing of ET for large regions, 17 September, Montpellier, France, 1–14, 2003.
- Teixeira, A. H. D. C. and Bastiaanssen, W. G. M.: Five methods to interpret field measurements of energy fluxes over a micro-sprinkler-irrigated mango orchard, *Irrigation Sci.*, 30, 13–28, doi:10.1007/s00271-010-0256-y, 2010.
- Teixeira, A. H. D. C., Bastiaanssen, W. G. M., Moura, M. S. B., Soares, J. M., Ahmad, M. D., and Bos, M. G.: Energy and water balance measurements for water productivity analysis in irrigated mango trees, Northeast Brazil, *Agr. Forest Meteorol.*, 148, 1524–1537, doi:10.1016/j.agrformet.2008.05.004, 2008.
- Teixeira, A. H. D. C., Bastiaanssen, W. G. M., Ahmad, M. D., and Bos, M. G.: Reviewing SEBAL input parameters for assessing evapotranspiration and water productivity for the Low-Middle São Francisco River basin, Brazil, *Agr. Forest Meteorol.*, 149, 462–476, 2009.
- Thenkabail, P. S., Schull, M., and Turrall, H.: Ganges and Indus river basin land use/land cover (LULC) and irrigated area mapping using continuous streams of MODIS data, *Remote Sens. Environ.*, 95, 317–341, doi:10.1016/j.rse.2004.12.018, 2005.
- Thenkabail, P. S., Biradar, C. M., Noojipady, P., Dheeravath, V., Li, Y., Velpuri, M., Gumma, M., Gangalakunta, O. R. P., Turrall, 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, *Int. J. Remote Sens.*, 30, 3679–3733, doi:10.1080/01431160802698919, 2009a.
- Thenkabail, P. S., Turrall, H., Biradar, C., and Lyon, J. G.: Remote sensing of global croplands for food security, CRC Press, Boca Raton, FL, 2009b.
- Thoreson, B., Clark, B., Soppe, R., Keller, A., Bastiaanssen, W. G. M., and Eckhardt, J.: Comparison of evapotranspiration estimates from remote sensing (SEBAL), water balance, and crop coefficient approaches, in: ASCE World Environmental and Water Resources Congress 2009: Great Rivers, 17–21 May, Kansas City, 1–15, doi:10.1061/41036(342)437, 2009.
- Tovar, C., Seijmonsbergen, A. C., and Duivenvoorden, J. F.: Monitoring land use and land cover change in mountain regions: An example in the Jalca grasslands of the Peruvian Andes, *Landsc. Urban Plan.*, 112, 40–49, doi:10.1016/j.landurbplan.2012.12.003, 2013.
- Trambauer, P., Dutra, E., Maskey, S., Werner, M., Pappenberger, F., van Beek, L. P. H., and Uhlenbrook, S.: Comparison of different evaporation estimates over the African continent, *Hydrol. Earth Syst. Sci.*, 18, 193–212, doi:10.5194/hess-18-193-2014, 2014.
- Tseng, M.-H., Chen, S.-J., Hwang, G.-H., and Shen, M.-Y.: A genetic algorithm rule-based approach for land-cover classification, *ISPRS J. Photogramm. Remote Sens.*, 63, 202–212, doi:10.1016/j.isprsjprs.2007.09.001, 2008.
- Twine, T. E., Kustas, W. P., Norman, J. M., Cook, D. R., Houser, P. R., Meyers, T. P., Prueger, J. H., Starks, P. J., and Wesely, M. L.: Correcting eddy-covariance flux underestimates over a grassland, *Agr. Forest Meteorol.*, 103, 279–300, doi:10.1016/S0168-1923(00)00123-4, 2000.
- UN: System of Environmental Economic Accounting for Water, Geneva, 2007.
- Van der Walt, I. J., Struwig, A., and van Rensburg, J. R. J.: Forestry as a streamflow reduction activity in South Africa: Discussion and evaluation of the proposed procedure for the assessment of afforestation permit applications in terms of water sustainability, *GeoJournal*, 61, 173–181, doi:10.1007/s10708-004-2872-7, 2004.
- Velpuri, N. M., Senay, G. B., Bohms, R. K., and Verdin, J. P.: A comprehensive evaluation of two MODIS evapotranspiration products over the conterminous United States: Using point and gridded FLUXNET and water balance ET, *Remote Sens. Environ.*, 139, 35–49, 2013.
- Venturini, V., Islam, S., and Rodriguez, L.: Estimation of evaporative fraction and evapotranspiration from MODIS products using a complementary based model, *Remote Sens. Environ.*, 112, 132–141, doi:10.1016/j.rse.2007.04.014, 2008.
- Verstraeten, W. W., Veroustraete, F., and Feyen, J.: Assessment of Evapotranspiration and Soil Moisture Content Across Different Scales of Observation, *Sensors*, 8, 70–117, doi:10.3390/s8010070, 2008.
- Villarini, G., Krajewski, W. F., and Smith, J. A.: New paradigm for statistical validation of satellite precipitation estimates: Application to a large sample of the TMPA 0.25° 3-hourly estimates over Oklahoma, *J. Geophys. Res.*, 114, D12106, doi:10.1029/2008JD011475, 2009.
- Voisin, N., Wood, A. W., and Lettenmaier, D. P.: Evaluation of Precipitation Products for Global Hydrological Prediction, *J. Hydrometeorol.*, 9, 388–407, doi:10.1175/2007JHM938.1, 2008.
- Vörösmarty, C. J., McIntyre, P. B., Gessner, M. O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S. E., Sullivan, C. A., Liermann, C. R., and Davies, P. M.: Global threats to human water security and river biodiversity, *Nature*, 467, 555–561, doi:10.1038/nature09440, 2010.
- Wagner, W., Verhoest, N. E. C., Ludwig, R., and Tedesco, M.: Editorial “Remote sensing in hydrological sciences”, *Hydrol. Earth Syst. Sci.*, 13, 813–817, doi:10.5194/hess-13-813-2009, 2009.
- Wang, J., Chen, Y., He, T., Lv, C., and Liu, A.: Application of geographic image cognition approach in land type classification using Hyperion image: A case study in China, *Int. J. Appl. Earth Obs. Geoinf.*, 12, S212–S222, doi:10.1016/j.jag.2009.06.003, 2010.
- Wang, J. R., Gogineni, S. P., and Ampe, J.: Active and passive microwave measurements of soil moisture in FIFE, *J. Geophys. Res.*, 97, 18979, doi:10.1029/92JD00848, 1992.
- Wang, K., Wang, P., Li, Z., Cribb, M., and Sparrow, M.: A simple method to estimate actual evapotranspiration from a combination of net radiation, vegetation index, and temperature, *J. Geophys. Res.*, 112, D15107, doi:10.1029/2006JD008351, 2007.
- Wang, Y. and Sun, D.: The ET estimation from ASTER image based on SEBAL and TSEB method, *Proceedings of SPIE 6045, MIPPR 2005: Geospatial Information, Data Mining, and Applications*, 604532, doi:10.1117/12.651845, 2005.
- Waske, B. and Braun, M.: Classifier ensembles for land cover mapping using multitemporal SAR imagery, *ISPRS J. Photogramm. Remote Sens.*, 64, 450–457, doi:10.1016/j.isprsjprs.2009.01.003, 2009.
- Weiers, S., Groom, G., and Wissen, M.: Comparability and subjectivity of land cover maps produced with digital image classification techniques?: some recent experiences from Denmark and

- northern Germany, *Geogr. Tidsskr. Danish J. Geogr.*, 102, 59–77, 2002.
- Whiteside, T. G., Boggs, G. S., and Maier, S. W.: Comparing object-based and pixel-based classifications for mapping savannas, *Int. J. Appl. Earth Obs. Geoinf.*, 13, 884–893, doi:10.1016/j.jag.2011.06.008, 2011.
- Wickham, J. D., Stehman, S. V., Gass, L., Dewitz, J., Fry, J. A., and Wade, T. G.: Accuracy assessment of NLCD 2006 land cover and impervious surface, *Remote Sens. Environ.*, 130, 294–304, doi:10.1016/j.rse.2012.12.001, 2013.
- Wilk, J., Kniveton, D., Andersson, L., Layberry, R., Todd, M. C., Hughes, D., Ringrose, S., and Vanderpost, C.: Estimating rainfall and water balance over the Okavango River Basin for hydrological applications, *J. Hydrol.*, 331, 18–29, doi:10.1016/j.jhydrol.2006.04.049, 2006.
- Winsemius, H. C., Savenije, H. H. G., and Bastiaanssen, W. G. M.: Constraining model parameters on remotely sensed evaporation: justification for distribution in ungauged basins?, *Hydrol. Earth Syst. Sci.*, 12, 1403–1413, doi:10.5194/hess-12-1403-2008, 2008.
- Wu, B., Yan, N., Xiong, J., Bastiaanssen, W. G. M., Zhu, W., and Stein, A.: Validation of ETWatch using field measurements at diverse landscapes: A case study in Hai Basin of China, *J. Hydrol.*, 436–437, 67–80, 2012.
- Wu, C., Cheng, C., Lo, H., and Chen, Y.: Study on estimating the evapotranspiration cover coefficient for stream flow simulation through remote sensing techniques, *Int. J. Appl. Earth Obs. Geoinf.*, 12, 225–232, doi:10.1016/j.jag.2010.03.001, 2010.
- Yalew, S., Teferi, E., and Van Griensven, A.: Land Use Change and Suitability Assessment in the Upper Blue Nile Basin Under Water Resources and Socio-economic Constraints: A Drive Towards a Decision Support System, in: *International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet, Sixth Biennial Meeting*, edited by: Seppelt, R., Voinov, A. A., Lange, S., and Bankamp, D., 1–5 July, Leipzig, Germany, 2124–2131, 2012.
- Yang, Y., Shang, S., and Jiang, L.: Remote sensing temporal and spatial patterns of evapotranspiration and the responses to water management in a large irrigation district of North China, *Agr. Forest Meteorol.*, 164, 112–122, doi:10.1016/j.agrformet.2012.05.011, 2012.
- Zhang, J., Hu, Y., Xiao, X., Chen, P., Han, S., Song, G., and Yu, G.: Satellite-based estimation of evapotranspiration of an old-growth temperate mixed forest, *Agr. Forest Meteorol.*, 149, 976–984, doi:10.1016/j.agrformet.2008.12.002, 2009.
- Zhang, K., Kimball, J. S., Nemani, R. R., and Running, S. W.: A continuous satellite-derived global record of land surface evapotranspiration from 1983 to 2006, *Water Resour. Res.*, 46, W09522, doi:10.1029/2009WR008800, 2010.
- Zhang, X., Sun, R., Zhang, B., and Tong, Q.: Land cover classification of the North China Plain using MODIS_EVI time series, *ISPRS J. Photogramm. Remote Sens.*, 63, 476–484, doi:10.1016/j.isprsjprs.2008.02.005, 2008.
- Zhang, Y., Leuning, R., Hutley, L. B., Beringer, J., McHugh, I., and Walker, J. P.: Using long-term water balances to parameterize surface conductances and calculate evaporation at 0.05° spatial resolution, *Water Resour. Res.*, 46, W05512, doi:10.1029/2009WR008716, 2010.
- Zhu, Z., Woodcock, C. E., Rogan, J., and Kellndorfer, J.: Assessment of spectral, polarimetric, temporal, and spatial dimensions for urban and peri-urban land cover classification using Landsat and SAR data, *Remote Sens. Environ.*, 117, 72–82, doi:10.1016/j.rse.2011.07.020, 2012.