

Title	Assessing the utility of geospatial technologies to investigate environmental change within lake systems
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Publication date	2015-10-29
Original Citation	Politi, E., Rowan, J.S. and Cutler, M.E.J. (2016) 'Assessing the utility of geospatial technologies to investigate environmental change within lake systems', Science of The Total Environment, 543, pp. 791-806. http://dx.doi.org/10.1016/j.scitotenv.2015.09.136
Type of publication	Article (peer-reviewed)
Link to publisher's version	10.1016/j.scitotenv.2015.09.136
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Download date	2026-08-18 23:25:25
Item downloaded from	https://hdl.handle.net/10468/3013



Assessing the utility of geospatial technologies to investigate environmental change within lake systems



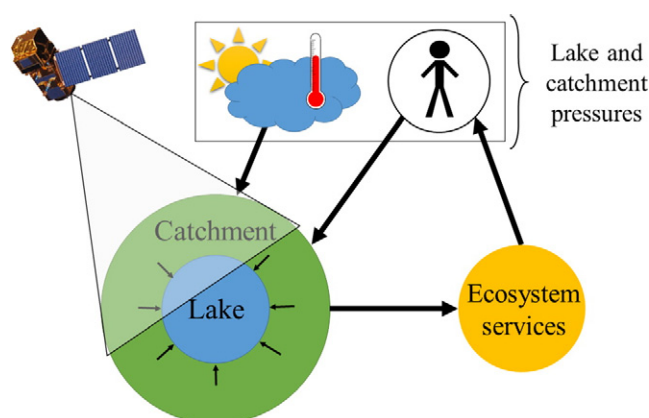
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HIGHLIGHTS

- Lakes and their catchments provide important ecosystem services
- Multi-scale observations required to understand the response of lakes to climate and anthropogenic pressures
- Remote sensing is an important geospatial technology for deriving information about lakes systems
- We review the applicability of remote sensing in linking lake-catchment processes to assess lake response to environmental change

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:

Received 10 March 2015

Received in revised form 21 September 2015

Accepted 25 September 2015

Available online 29 October 2015

Keywords:

Lake change

Ecosystem services

Remote sensing

Geospatial technology

Catchment pressures

ABSTRACT

Over 50% of the world's population live within 3 km of rivers and lakes highlighting the on-going importance of freshwater resources to human health and societal well-being. Whilst covering c. 3.5% of the Earth's non-glaciated land mass, trends in the environmental quality of the world's standing waters (natural lakes and reservoirs) are poorly understood, at least in comparison with rivers, and so evaluation of their current condition and sensitivity to change are global priorities. Here it is argued that a geospatial approach harnessing existing global datasets, along with new generation remote sensing products, offers the basis to characterise trajectories of change in lake properties e.g., water quality, physical structure, hydrological regime and ecological behaviour. This approach furthermore provides the evidence base to understand the relative importance of climatic forcing and/or changing catchment processes, e.g. land cover and soil moisture data, which coupled with climate data provide the basis to model regional water balance and runoff estimates over time. Using examples derived primarily from the Danube Basin but also other parts of the World, we demonstrate the power of the approach and its utility to assess the sensitivity of lake systems to environmental change, and hence better manage these key resources in the future.

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1. Introduction

The world's freshwater ecosystems and the biodiversity they support are vital components of the global biosphere, yet remain fragile and vulnerable to anthropogenic disturbance and climate change (Dokulil, 2013; Schindler and Donahue, 2006; Vörösmarty et al., 2000; Williamson et al., 2009). Whilst recognition grows of their role in the carbon cycle at regional and continental scales (e.g. Knoll et al., 2013; McDonald et al., 2013; Renwick et al., 2008; Yang et al., 2008), understanding their global significance to biogeochemical cycling and ecosystem services has been hampered by uncertainties about absolute numbers and the distributions of different types, as well as limited information on their ecological, chemical and physical condition (Downing et al., 2006; Verpoorter et al., 2012). Verpoorter et al. (2014) enumerated a global inventory of 117 million lakes ($>0.002 \text{ km}^2$), with a combined surface area of about $5 \times 10^6 \text{ km}^2$, equating to 3.7% of the Earth's non-glaciated land mass. In Europe alone there are over 1.5×10^6 lakes with surface areas greater than 0.01 km^2 and at least 500,000 natural lakes larger than 0.1 km^2 (Kristiansen and Hansen, 1994). These systems span a continuum of size, depth, form, altitude, geology, climatic and hydrological regime. Importantly, lakes also sit within a wider landscape, catchment and hydrological network that means one needs to look beyond the lake itself to determine the drivers of lake water behaviour and any changes in that. For example, the Danube Basin is some $801,463 \text{ km}^2$ in size and according to the Global Lakes and Wetlands Database (Lehner and Döll, 2004) includes 592 lakes $>0.1 \text{ km}^2$. The large numbers involved and the relative remoteness of many lake districts, especially within large transnational catchments such as the Danube, presents major challenges in terms of managing the standing water resource and emphasises the need to be able to generalise about behaviour based on limited field observations.

The role that aquatic systems play in underpinning society's activities, health and well-being is increasingly being understood through the concept of ecosystem services, which links nature to an economic value to society (TEEB, 2010). Particularly since the launch of the United Nations Millennium Ecosystem Assessment (MEA) in 2005, there has been an increase in the awareness of the ecosystem services provided by aquatic and terrestrial ecosystems amongst policy makers (de Groot et al., 2010), matched by a significant increase in the number of scientific publications on the topic (de Araujo Barbosa et al., 2015; Large and Gilvear, 2014; Seppelt et al., 2011). Remote sensing has the potential to provide an important source of information for quantifying and mapping dynamic terrestrial and aquatic ecosystem services and hydrological processes, including approaches to hydrologic modelling as reviewed by Xu et al. (2014). In many cases, given the large catchment area of many of the most important river and lake systems in the world (particularly those with large populations dependent upon them and their attendant ecosystem services), the synoptic, wide area coverage and frequent observations provided by satellite-based remote sensing are an important source of standardised information that is not prey to variability in national and regional in situ data collection methodologies and standards. As a result, remote sensing has become an important geospatial technology for deriving information about lakes and their catchments, which alongside advances in in situ sensor systems to capture spatial information in addition to measurements across time (Crawford et al., 2014) and analysis with Geographic Information Systems (GIS), provides an important step forward in our ability to model lake and catchment status and behaviour.

From both passive (e.g. multispectral and hyperspectral) and active (LiDAR and RADAR) remote sensing systems it is possible to retrieve the state of important lake and catchment variables that may vary across space at particular points in time. Recently, either directly or in combination with other data, remote sensing has been successfully used within the Danube Basin to map variations in biomass (Kovács, 2007), carbon stocks in riparian forests (Suchenwirth et al., 2014), habitat

change (Kollár et al., 2011), historical land cover change (Crăciunescu et al., 2010), evapotranspiration (Rodell et al., 2011) and soil moisture (dall'Amico et al., 2012), to name but a few examples. However, it is important to recognise that whilst some catchment properties may be retrieved directly from remotely sensed data (e.g. canopy height with LiDAR or leaf area index from optical data) some catchment properties, such as land use, may only be inferred from remotely sensed data through contextual associations across, whilst others, such as raw material production, will require remotely sensed data to be coupled with other ancillary datasets, for example in situ measurements and modelled data (de Araujo Barbosa et al., 2015).

Following decades of fundamental research and the launch of several new satellite programmes a report by London Economics to the UK Space Agency suggests that we stand at the dawn of a 'New Space Age' (London Economics, 2015, p. 104), one in which there will be substantial growth in applications of remote sensing data. Indeed the future of European (and global) remote sensing for catchment, ecosystem and lake-based studies looks very promising, particularly with respect to data availability and the new generation Copernicus satellites of the European Space Agency (ESA). The Copernicus satellites build on the success and capabilities of other currently operational (e.g. Landsat series) and non-operational (e.g. Envisat MERIS and AATSR) instruments and include the Sentinel-2 Multispectral Imager (MSI) (launched June 2015), Sentinel-3 Ocean and Land Colour Instrument (OLCI) and Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR), the first of which is due for launch late 2015. Sentinel-2 MSI has 13 wavebands in the visible and NIR at 10–60 m spatial resolution and a 5-day revisit time. Sentinel-3 OLCI at a 300 m spatial resolution will employ 21 wavebands in the visible and NIR. Sentinel-3 SLSTR will employ 9 wavebands, with a nominal 500 m spatial resolution in the visible and NIR and 1 km at the TIR. In addition, Sentinel-3 will have a revisit time of 1–2 days. These optical and thermal sensors combine short revisit times, fine spatial resolutions and multiple spectral channels with a free data access policy. Here we signpost some of the new opportunities for catchment and lake studies provided by these new systems by collating experiences of previous research and how these and the plethora of new data sources will contribute to future lake and catchment management.

Several authors have provided comprehensive reviews of the potential and current status of remote sensing to map and quantify a range of ecosystem services (e.g. Andrew et al., 2014; de Araujo Barbosa et al., 2015). This paper builds upon those comprehensive reviews and others by exploring the utility of remote sensing to capture spatial and temporal patterns of change in key catchment processes and the use of these data to inform policy and management decisions. Particular reference is made to examples from the Danube Basin highlighting information derived from remote sensing data relevant for catchment water balance estimation and modelling, as well as land cover change and other critical ecosystem functions. By focussing on the catchment we evaluate how to derive information on drivers of change in lake behaviour rather than explicitly exploring the use of remote sensing to detect change in the lake water quality itself, which is the subject a separate paper in this Special Issue (Tyler et al., in this volume).

2. Lakes, landscape limnology and remote sensing

Soranno et al. (2010) introduced landscape limnology as a new conceptual framework for understanding lake behaviour based on a series of important comparative and regional limnological studies (e.g. Riera et al., 2000; Webster et al., 2000; Soranno et al., 2009). Landscape limnology is the spatially-explicit study of lakes within freshwater, terrestrial and human landscapes to determine the effects of pattern on ecosystem processes over multiple temporal and spatial scales (Fig. 1). It highlights that landscape settings influence lake functions through the hydromorphological setting mediated by the extent of human modification, superimposed upon which is the effect of climate change.

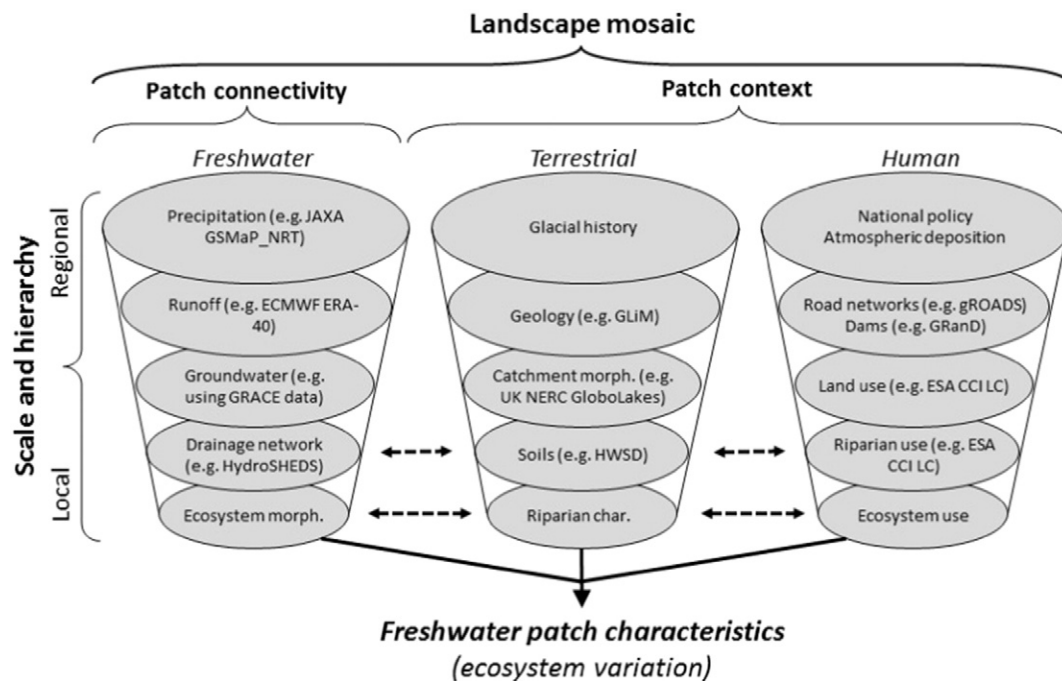


Fig. 1. Landscape limnology framework connecting local and regional lake characteristics with examples of globally available datasets and EO products (after Soranno et al., 2009). JAXA GSMap_NRT (Japan Aerospace Exploration Agency Global Satellite Mapping of Precipitation in Near-Real-Time); ECMWF ERA-40 (European Centre for Medium-Range Weather Forecasts 40-year re-analysis model data); GRACE (NASA/DLR's Gravity Recovery and Climate Experiment); HydroSHEDS (World Wildlife Fund Hydrological data and maps based on Shuttle Elevation Derivatives at multiple Scales); GLIM (Global Lithological Map database); UK NERC GloboLakes (United Kingdom Natural Environment Research Council GloboLakes project); HWSD (Harmonised World Soil Database); gROADS (Global Roads Open Access Data Set); GRand (Global Reservoir and Dam database); ESA CCI LC (European Space Agency Climate Change Initiative Land Cover).

An extension to this framework is shown in Table 1, which uses four hierarchical structuring elements consistent with the water body classification attributes used in the EU Water Framework Directive (EU WFD, 2000). The first element is the ecoregion which sets out the broadest climatic, physiographic and dominant biomes. Landscape setting establishes the specific characteristics in terms of hydro-climatic factors such as continentality, the elevation of the lake and its catchment (e.g. whether montane, piedmont or lowland) and biodiversity characteristics. The lake-catchment relation captures the relative importance of 'catchment' versus 'lake' processes in relation to water, sediment and nutrient budgets, including the critical role of autochthonous versus allochthonous carbon fluxes (cf. Tranvik et al., 2009; Kutser et al., 2015). Finally, lake morphometry (size, shape, orientation, water depth, etc.) governs lake processes and characteristics such as mixing regime, residence time, shore zone energetics and riparian habitats (Hutchinson, 1957).

Untangling the effects of multiple pressures on lake structure and function, and determining the environmental pressures that will have the largest effect on a given lake or lake type, is a challenge that requires multi-scale observations of a suite of functionally relevant and reliable indicators of lake ecosystem condition for a larger number of lakes than has been possible with traditional monitoring. Remote sensing provides a plethora of datasets and products that, in combination with ancillary data (e.g. in situ measurements and observations, modelled data), can be used to improve our understanding of lake system response to climate and non-climate pressures within a catchment. For example, land cover/use (and consequently trends in the riparian development of a lakeshore), soil moisture and elevation are, amongst others, standard remote sensing products, whilst water balance modelling techniques have recently assimilated remotely sensed information on climatic variables (e.g. evapotranspiration, precipitation and land surface temperature), soil moisture and vegetation properties. Taking the catchment of Lake Balaton (the largest freshwater body within the Danube Basin) as an example, we hereby present examples of global datasets that are available from various sources at varying temporal

frequencies, time periods and spatial resolutions (Fig. 2, Table 2), and which are often used as catchment indicators of lake change. The next sections review the applicability of remote sensing in deriving some of these products in the realm of limnological research at catchment-wide scales across the globe, and specifically in the Danube Basin.

3. Catchment water balance

In recent decades the combined effects of economic growth and rapidly increasing global human population has led to increased demand for freshwater, which in turn has resulted in the intensification of water withdrawal from surface freshwater bodies and groundwater pools. Human activities have caused global water scarcity, particularly in arid and semi-arid regions, where overuse of natural water resources has taken place (Wada et al., 2011). At the global scale agriculture is the main water consumer with over 75% of abstractions, far outweighing the amounts used for industrial (20%) or domestic purposes (5%) (FAO, 2014; UNEP, 2008). However, significant regional variations also exist reflecting local climate and physiographic features (Shiklomanov, 2000), imprinting an often complex picture of change when trying to assess the strong impact that global climate change has on freshwater supplies (WWAP, 2012). Determining the extent and severity of impacts of human activities and climate change on water resources across the globe, particularly in ungauged basins, has hitherto been a major issue. This has often been addressed through water balance modelling that can generate spatial and temporal variations of water availability in lake catchments and river basins, and thus contribute towards the management of water resources from local to global scales (Mitsova, 2014).

In principle, water balance models take into account the amount of water input through precipitation and snowmelt, and the amount of water output through evaporation, transpiration, surface (including river) runoff, groundwater discharge and percolation. There exist numerous water balance models, one of the earlier and more simplistic being the Thornthwaite and Mather (TM) model (Thornthwaite and

Table 1

WFD compliant eco-geomorphic framework for contextualising lake behaviour.
Adapted from Rowan (2010).

	Scale	Hydro-climatic	Terrestrial	Biotic	Human
↑ Regional influences	Ecoregion	- Latitude/Longitude - Solar radiation regime - Temperature - Precipitation - Wind regime	- Geological structure and lithology - Physiography - Soils	- Regional biomes - Biomass - Phenology	- Airborne pollution - Climate change
	Landscape setting	- Continentality - Orographic effects - Environ. lapse rates - Runoff quantity and timing - Ice cover	- Elevation - Topographic variation - Drainage network and density - Glacial history	- Habitat diversity - Species dispersal - Flux of humic substances	- Economy - Demographics - Land cover and management - Water resource management
SCALE	Catchment-lake relation	- Hydrological regime - Hydrological pathways - Surface:groundwater contribution	- Hydrogeology - Groundwater and solute flux - Sediment budget - Salinity	- Biological continuity - Nutrient cycling - Acidity	- Impoundments - Water transfers - Drainage - Land management - Riparian land cover
↓ Increasingly site specific	Lake hydromorphology (water body scale)	- Size and shape - Stratification and mixing depth - Water residence time - Resuspension and internal loading	- Shoreline complexity - Littoral:pelagic ratio - Riparian habitat structure	- Appropriate species composition - Integrity of trophic function - Alien species	- Water level manipulation - Cumulative pressures and disturbance
	Meso-habitat patches	- Microclimate - Exposure - Erosion/sedimentation	- Littoral slope - Substrate - Wave energy	- Local carbon flux - Pollution - Habitat patches	Local pressures to shore and lake bed

Mather, 1955, 1957), a revision of an earlier model by Thornthwaite (1948), which requires precipitation, air temperature and latitude to produce estimates of evapotranspiration, soil moisture storage, snow storage, surplus and runoff (McCabe and Markstrom, 2007). Many studies have since developed new or modified existing water balance models for use in different applications and at various spatio-temporal scales and the reader is referred to Xu and Singh (1998, 2004) and Boughton (2005) for comprehensive reviews of various water balance modelling techniques.

A key requirement of large hydrological systems, such as the Danube Basin, is that these water balance techniques and models must be applicable to regional or even continental scales, which is potentially where remote sensing can have a part to play. At a continental scale applicable water balance models include FAO AQUASTAT (2001) that was developed to map agricultural water use in Africa, WaterGAP that simulates global water availability and use in large drainage basins (Döll et al., 2003; Alcamo et al., 2003) and GWAVA that models global water availability with demonstrable applications in Africa, South America and Europe (Meigh et al., 1999). In addition, the European Union Water and Global Change (WATCH) project created a multi-model ensemble bringing together nine large-scale hydrological models to compare their ability to capture mean annual runoff and quantify the uncertainty related to the modelling outputs. It was found that even though the performance of each individual WATCH model differed, their ensemble mean produced reliable estimates of runoff in European catchments (Gudmundsson et al., 2012a, 2012b).

The application of water balance modelling specifically within the Danube Basin in the past has tended to make use of historic weather station measurements and simulation data as input parameters (e.g. Mauser and Bach, 2009; Petrovič et al., 2010; Klein et al., 2011; Kling

et al., 2012) rather than making direct use of remote sensing observations. However, the GLOWA project (Global Change of the water cycle; funded by the German Ministry of Research and Education (BMBF)) is an example of one such initiative that exemplified the potential of remote sensing to address the impact of global change on regional water resources. Within this initiative is included the GLOWA-Danube project (dedicated to the Upper Danube watershed) that aims to investigate the sustainability of future water use using modelling techniques (Ludwig et al., 2003a). Within the GLOWA-Danube framework satellite-retrieved land cover information was used in a physically-based water balance model to provide spatio-temporal estimates of evapotranspiration, soil moisture, snow cover and runoff (Ludwig et al., 2003b). The study combined multi-temporal coarse spatial resolution NOAA AVHRR images and spectral unmixing techniques to produce sub-pixel land cover information at the fine scales required for the detailed description of various hydrological processes, and showed that the approach produced improved model results compared to the use of conventionally used land cover data (e.g. CORINE maps).

3.1. Role of remote sensing in water balance studies

Water balance models require a variety of data ranging from climatic variables to information on soil and vegetation properties. Remote sensing has the potential to produce some of this information at large enough spatial and temporal scales to fulfil the need for continuous water resource monitoring applications at scales varying from local to global (Xu et al., 2014) and it is not uncommon for a combination of remote sensing sensors to be used in hydrological modelling and water balance applications (e.g. Awange et al., 2008; Milzow et al., 2011). Even though remotely sensed observations complement in situ

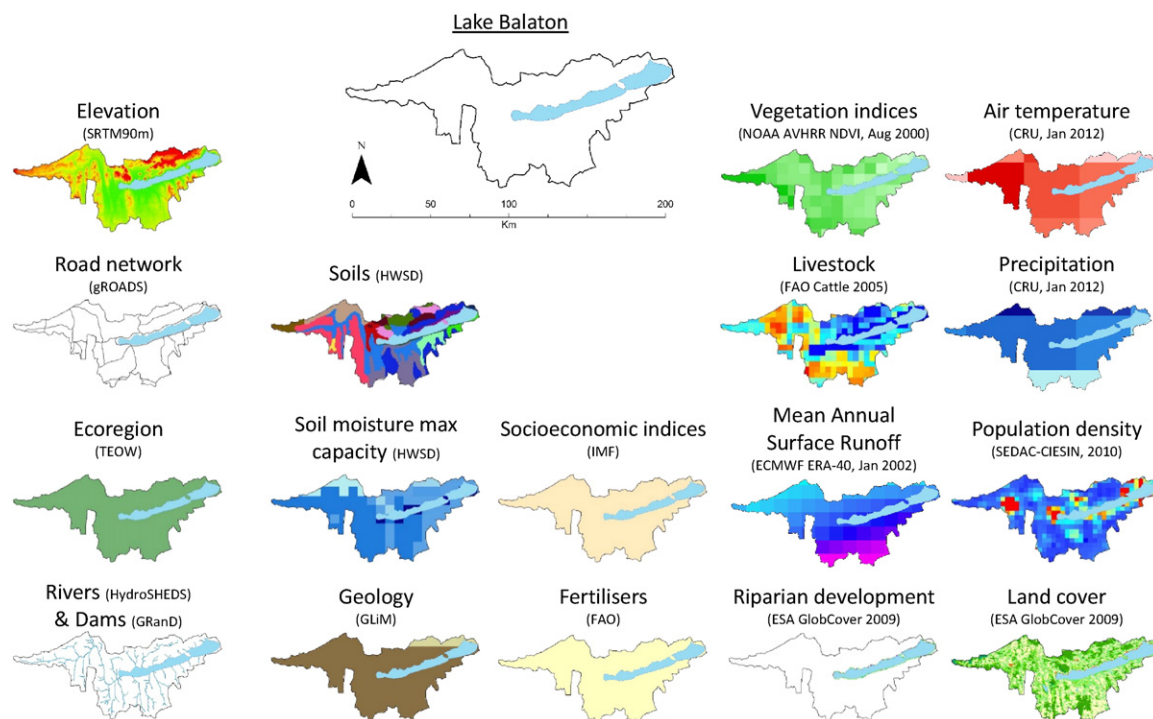


Fig. 2. Examples of climate and non-climate datasets depicting lake pressure attributes in the catchment of Lake Balaton. SRTM90m (Shuttle Radar Topography Mission at 90 m spatial resolution); gROADS (Global Roads Open Access Data Set); TEOW (Terrestrial Ecoregions of the World); GRanD (Global Reservoir and Dam database); HWSD (Harmonised World Soil Database); GLiM (Global Lithological Map database); IMF (International Monetary Fund); FAO (Food and Agriculture Organisation); NOAA (National Oceanic and Atmospheric Administration); AVHRR (Advanced Very High Resolution Radiometer); NDVI (Normalised Difference Vegetation Index); ECMWF ERA-40 (European Centre for Medium-Range Weather Forecasts 40-year re-analysis model data); ESA GlobCover (European Space Agency Global Land Cover product); CRU (Climatic Research Unit); SEDAC (Socioeconomic Data & Applications Center); CIESIN (Center for International Earth Science Information Network).

observations in providing data inputs for water balance modelling techniques, its potential was realised more than four decades ago. For example, evapotranspiration estimations based on remotely sensed canopy temperatures date back to the 1970s (e.g. Stone and Horton, 1974;

Blad and Rosenberg, 1976; Heilman et al., 1976; Jensen and Chery, 1980), as does the estimation of remotely sensed soil water content, also known as soil moisture (Wang and Qu, 2009) and the mapping of snow cover (e.g. Kyle et al., 1978). On the other hand, precipitation

Table 2

Examples of global data sources for deriving catchment attributes (period(s) of projected values are shown in square brackets).

Dataset/database	Product parameter(s)	Time period	Format	Units	Spatial resolution
Harmonised World Soil Database (HWSD)	Soil type	2008	Raster	SMU	1 km
Global Lithological Map Database (GLiM)	Geology	2012	Raster	–	62.5 km
Global Reservoir and Dam Database v.1.1 (GRanD)	Location and age of dams; spatial extent of reservoirs	2011	Vector	–	–
Terrestrial Ecoregions of the World (TEOW)	16 ecoregions	2001	Polygons	–	–
HydroSHEDS (USGS)	River network	2008	Vector	–	1 km
Gridded Population of the World v.3 (GPWv3)	Population density	1990, 1995, 2000, [2005], [2010], [2015]	Raster	Persons per km ²	5 km
Shuttle Radar Topography Mission v.4.1 (SRTM90m)	DEM (elevation)	2008	Raster	m	90 m
Climatic Research Unit Time Series v.3.21 (CRU TS 3.21)	Precipitation	1901–2012; monthly	NetCDF	mm	62.5 km
	Potential evapotranspiration			mm	
	Temperature			10 × °C	
European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-40	Runoff	Sep 1957–Aug. 2002; monthly	NetCDF	m/day	~15 km
Global Roads Open Access Data Set (gROADSv1)	Road network	1980–2010	Vector	–	–
European Space Agency (ESA) Climate Change Initiative (CCI) Land Cover (LC)	Land cover	1998–2002, 2003–2007, 2008–2012	Raster	–	300 m
Gridded Livestock of the World (FAO, Food and Agriculture Organisation)	Cattle, poultry, buffalo, goat, pig, sheep	2000, 2005	Raster	Animals per km ²	5 km
Fertilisers (FAO)	Nitrogen & phosphate	2002–2010; annual	csv	Tonnes per 1000 ha	–
Irrigated land (actual & potential) (FAO)	Agricultural area irrigated; Total area equipped for irrigation	1961–2011; annual	csv	1000 ha	–
Gross Domestic Product (GDP) per capita, International Monetary Fund (IMF)	GDP per capita	1980–[2018]; annual	csv	\$ (USD)	–

can be estimated using remotely sensed data and various global products already exist, but their use in water balance modelling has only recently been realised (e.g. [Pereira-Cardenal et al., 2011](#)). Finally, there are no remote sensing products for air temperature, however [Deus et al. \(2013\)](#) propose the use of remotely sensed land surface temperature (LST) as a substitute for air temperature in water balance modelling, and several methods incorporate LST to estimate evapotranspiration ([Verstraeten et al., 2008](#)). Whilst [Xu et al. \(2014\)](#) and [Karimi and Bastiaanssen \(2015\)](#) provide excellent reviews on the integration of remotely sensed observations to hydrologic modelling in general, here we briefly review the status of remote sensing as a source of functional information to understand the role of the catchment in changing lake behaviours.

3.2. Remote sensing sensors, scales and products

3.2.1. Evapotranspiration (ET)

Remote sensing is a promising tool for the representation of the spatial distribution of evapotranspiration (ET) across large spatial scales, which is required for distributed water balance modelling ([Glenn et al., 2007](#)). Several approaches have been proposed in the literature, commonly using optical and thermal data, and less frequently satellite microwave data. There are two types of methods that are used to estimate ET from remote sensing data; empirical and physical models. Empirical or statistical relationships make use of remotely sensed vegetation indices, such as the normalised difference vegetation index (NDVI) or the soil-adjusted vegetation index (SAVI) ([Glenn et al., 2007](#)), which are based on the fraction of the ground area covered or shaded by vegetation ([Pereira et al., 2015](#)). However, these methods are insensitive to conditions of water or salinity stress, which is not true for physical models ([Pereira et al., 2015](#)). Physical or analytical models solve the surface energy balance (SEB) equation using land surface temperature (LST) estimates based on remote sensing observations. The advantage of SEB models is that they can be used to estimate ET in areas with diverse vegetation types and heterogeneous vegetation cover (e.g. [Minacapilli et al., 2009](#); [Pôças et al., 2013](#)). The reader can refer to, for example, [Glenn et al. \(2007\)](#), [Verstraeten et al. \(2008\)](#), [Kalma et al. \(2008\)](#), [Pereira et al. \(2015\)](#) and [Karimi and Bastiaanssen \(2015\)](#) for detailed reviews of ET estimation methods based on remote sensing data.

The utility of remote sensing in water balance modelling, and particularly in the estimation of ET, depends on the specifications of the sensor and the cloud conditions ([Kalma et al. 2008](#)). Medium spatial resolution sensors, such as the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) on-board the Terra satellite and the Thematic Mapper (TM), Enhanced TM (ETM+) and Operational Land Imager (OLI) on-board the Landsat series have a 16-day revisit capability, which means temporal interpolation techniques are needed to provide the daily inputs often required for hydrological models. However, ASTER has a spatial resolution of 15 m in the visible and NIR wavebands and 90 m in the TIR wavebands, while OLI offers a pixel size of 30 m in the visible and NIR and 100 m in the TIR, which in many cases around the globe and particularly within the Danube Basin, makes them suitable for mapping individual agricultural fields and smaller land parcels ([Pereira et al., 2015](#)). On the other hand, the Terra/Aqua Moderate Resolution Imaging Spectrometer (MODIS) and NOAA Advanced Very High Resolution Radiometer (AVHRR) provide daily observations depending on cloud cover at a spatial resolution of 1 km. Both MODIS and NOAA AVHRR can provide LST estimates with an accuracy of 1.0 °C at 1 km or 5 km spatial resolution ([Glenn et al., 2007](#)) and less than 1.3 °C at 4.4 km ([Pinheiro et al., 2006](#)), respectively. Finally, geostationary satellites at relatively coarse (1–5 km) spatial resolutions in the visible and TIR have very frequent revisit times (15–30 min) and could be used to derive LST, however their constant viewing angle introduces problems at high latitudes which limits their global applicability ([Diak et al., 2004](#)).

Overall, whilst the above illustrate the potential of remote sensing to provide reliable information on ET, its practical application in water balance modelling has often been hindered by concerns over accuracy. As [Karimi and Bastiaanssen \(2015\)](#) note, the reliability of remotely-sensed derived ET is often case and location specific, but the ensemble mean ET products currently under development may be a significant step towards addressing these concerns.

3.2.2. Soil moisture

The most common method for the retrieval of soil moisture is the use of microwave remote sensing sensors, both active and passive, and dates back to the 1970s (e.g. [Eagleman and Ulaby, 1975](#); [Schmugge et al., 1974](#); [Njoku and Kong, 1977](#); [Mo et al., 1982](#)). Remotely sensed soil moisture can only be estimated in the uppermost layer of the soil surface (i.e. top few centimetres), but assimilation of these observations within Soil-Vegetation-Atmosphere Transfer (SVAT) models helps retrieve soil moisture in the root zone ([Wigneron et al., 2003](#)), which is a key variable in hydrological modelling (e.g. [Wilker et al., 2006](#); [Seneviratne et al., 2010](#)).

There are many different surface soil moisture retrieval techniques that have been proposed in the literature, some used to derive global products, and these can be both empirical and physically-based ([de Jeu et al., 2008](#); [Vereecken et al., 2008](#)). While passive microwave sensors (radiometers) detect microwave radiation that is naturally emitted by the Earth's surface, active microwave sensors (RADAR) transmit an electromagnetic pulse and measure the scattered microwave energy back from the Earth surface. The success of microwave sensors in measuring soil moisture lies in the fact that changes in the soil dielectric constant due to changes in water content are detectable, particularly at low-frequency microwave regions (1–10 GHz) (e.g. [Njoku and Kong, 1977](#); [Wagner et al., 2007](#); [de Jeu et al., 2008](#)). A major advantage of microwave remote sensing is that it can be used day and night regardless of cloud cover. A limitation is that dense vegetation cover and soil roughness introduce noise to soil moisture measurements (e.g. [Wagner et al., 2007](#); [de Jeu et al., 2008](#); [Seneviratne et al., 2010](#)), but low-frequency microwave bands have been found to reduce this effect ([Schmugge et al., 2002](#); [Njoku et al., 2003](#)). In addition, a recent study in the Upper Danube basin demonstrated that soil moisture retrieval errors can be spatially diverse due to different factors (e.g. land surface heterogeneity) that introduce noise in the remote sensing observations, and that the retrieval accuracy strongly depends on the scale of observation ([Loew, 2008](#)).

Microwave instruments used in soil moisture retrieval include the non-operational Nimbus 7 Scanning Multichannel Microwave Radiometer (SMMR) (27–148 km spatial resolution), and Aqua Advanced Microwave Scanning Radiometer-EOS (AMSR-E) (38–56 km) for which global soil moisture products exist (e.g. [Njoku et al., 2003](#); [Owe et al., 2008](#)). The F-series Special Sensor Microwave Imager (SSM/I) and Special Sensor Microwave Imager Sounder (SSMIS) lack low-frequency wavebands that are desired for soil moisture retrieval. Nevertheless, soil moisture retrieval methods based on SSM/I data have been proposed in the literature (e.g. [Jackson et al., 2002](#); [Wen et al., 2005](#)). The relatively high-frequency TRMM TMI and WindSat radiometer data have also been used for the retrieval of soil moisture datasets (e.g. [Bindlish et al., 2003](#); [Gao et al., 2006](#); [Parinussa et al., 2012](#)). ESA's Soil Moisture and Oceanic Salinity (SMOS) (30–50 km spatial resolution) was launched in 2009 and employs an L-band, which offers deeper vegetation penetration making it potentially more reliable over densely vegetated regions ([Seneviratne et al., 2010](#)). Within the upper Danube region initial results on the validation of soil moisture products suggested that radio-frequency interference can be a problem ([dall'Amico et al., 2012](#)) but that the spatial pattern of soil moisture variability was similar to in situ measurements, even if SMOS tended to generally underestimate soil moisture ([Schlenz et al., 2012](#)).

Radar scatterometers can also be suitable for the retrieval of soil moisture, depending on the frequency they operate in ([Seneviratne et](#)

al., 2010). These include ESA's ERS-1/2 Advanced Microwave Instrument Scatterometer (AMI-SCAT) (50 km spatial resolution) and the METOP-A/B/C Advanced Scatterometer (ASCAT) (50 km) (Wagner et al., 2003; Bartalis et al., 2007). Finally, NASA's Soil Moisture Active and Passive (SMAP) mission carries on-board active and passive L-band sensors and was launched on the 31st January 2015. The mission is designed to collect global observations of soil moisture at a spatial resolution of 9 km, with a revisit time of 2–3 days.

Soil moisture itself is a Global Climate Observing System (GCOS) Essential Climate Variable (ECV) and ESA's Climate Change Initiative (CCI) programme has funded the creation of a more than 30-year long soil moisture dataset by merging active (ERS AMI-SCAT and METOP ASCAT) and passive (SMMR, SSM/I, TMI, and AMSR-E) soil moisture retrievals (Wagner et al., 2012). This product at 0.25° spatial resolution aims to address the discrepancies that have been observed (e.g. Reichle et al., 2007; Rüdiger et al., 2009) between different products developed for different (or the same) microwave sensors.

Other sensors that have been used in the retrieval of soil moisture include gravity recovery instruments (Seneviratne et al., 2010) and even global positioning system (GPS) receivers (Larson et al., 2008). Seasonal variations in terrestrial water content (TWC), including soil moisture, groundwater, snow and surface water, result in variations of the Earth's gravity field, which can be accurately measured with NASA/DLR's Gravity Recovery and Climate Experiment (GRACE) (e.g. Tapley et al., 2004; Wahr et al., 2004; Andersen et al., 2005; Swenson et al., 2008; Rodell et al., 2009). However, separation of the soil moisture contribution to the total observed terrestrial water content requires knowledge of the other TWC components, making this technique complex and reliant on additional data being available. In addition, any estimates can only be done at much coarser spatial resolutions (at best 400 km) than those offered by microwave remote sensing. GPS satellite receivers use L-band frequencies, similar to the SMOS and SMAP sensors, and have shown the potential to estimate soil moisture at spatial resolutions of circa 300 m, but the effects of ground roughness and of different vegetation and soil types, requires further investigation (Larson et al., 2008). The reader is referred to Schmugge et al. (2002), Wigneron et al. (2003), de Jeu et al. (2008) and Seneviratne et al. (2010) for excellent reviews on the remote sensing of soil moisture.

3.2.3. Precipitation

Precipitation estimates with remote sensing can be generated using both in situ radar systems and space-borne sensors. Michaelides et al. (2009) and Tapiador et al. (2012) provide excellent reviews of remote sensing techniques for precipitation measurements. Typically, single polarisation weather radar systems have been used to derive rainfall rate, but limitations such as calibration issues and contamination by ground returns amongst others make them less than ideal for precipitation mapping. Recent technological advances have led to the development of more suitable polarimetric radar systems (also referred to as dual-polarisation radars) that overcome some of the limitations attached to single polarisation weather radars (Michaelides et al., 2009). For about three decades, rainfall has been retrieved from satellite instruments employing the visible, infrared and microwave regions of the spectrum. However, most of the satellite observations are discarded due to cloud contamination and issues with the variability of emissivity over land-water areas and especially in coastal areas. Another limitation is the coarse spatial resolution of the satellite sensors that ranges from 10 km² over land to 50 km² over the ocean, and the common assumption that rainfall is horizontally and vertically homogeneous.

According to Stephens and Kummerow (2007) the optimal approach to retrieve precipitation from space is by combining data from passive and active sensors. A major step towards this direction was made with the launch in 1997 of the space-borne Tropical Rainfall Measuring Mission (TRMM) that carries on-board two primary rainfall sensors; the 13.8 GHz Precipitation Radar (PR) and the TRMM Microwave Imager (TMI). Numerous algorithms for the retrieval of rainfall from

TRMM data have since been developed (e.g., Iguchi et al., 2000; Haddad et al., 1997), leading to the TRMM PR 2A25 and TRMM TMI 2A12 rainfall products. However, these two products exhibit spatial and seasonal differences that have yet to be explained (Wang et al., 2009) and are geographically limited to latitudes between 35°N–35°S. A third sensor on-board TRMM, the Visible and Infrared Radiometer (VIRS) can only provide indirect estimations of rainfall by means of precipitation indices.

Even though most available precipitation retrieval methods focus on rainfall rather than snowfall, high-frequency passive microwave wavebands (e.g. on AMSU) can provide snow detection and frozen precipitation estimations (Kongoli et al., 2004; Vila et al., 2007; Michaelides et al., 2009). In fact, the Microwave Surface and Precipitation Products System (MSPPS) (now Microwave Integrated Retrieval System (MIRS)) is a suite of operational global products derived from the NOAA Advanced Microwave Sounding Unit (AMSU), including precipitation rate, total precipitable water and snow cover (Ferraro et al., 2005; Vila et al., 2007).

The need for uniformly calibrated precipitation products that are independent of variation caused by different sensors is to be addressed by the international Global Precipitation Measurement (GPM) mission, which employs a constellation of passive microwave sensors. The GPM aims to provide high resolution satellite precipitation products every 2–3 h for use in various applications, such as hydrology and climatic studies. Building on the capabilities of the TRMM PR and TMI, the GPM-Core Observatory, which was launched in February 2014, covers latitudes between 65°N–65°S and contributes to the GPM constellation of sensors that combined cover the entire globe with datasets (Levels 0–3) freely available online. A global dataset for satellite-derived rainfall is the Global Satellite Mapping of Precipitation in Near-Real-Time (GSMaP_NRT) by the Japan Aerospace Exploration Agency (JAXA) Global Rainfall Watch System (Ver. 3.0), which provides global (60°N–60°S) rainfall rate (mm/h) at hourly intervals by combining various remote sensing data, including the GPM-Core Microwave Imager (GMI), TRMM TMI, DMSP (Defence Meteorological Satellite Programme) SSMIS, NOAA AMSU and METOP AMSU.

3.2.4. Snow cover

Both optical and microwave remote sensing are used for snow cover mapping. Even though optical remote sensing is limited to mapping snow extent, much more information can be derived from microwave data; this includes snow water equivalent (SWE; mass of water per unit area), snow depth (SD) (a relevant measurement because of its relationship to SWE), snow extent, and snow state (wet/dry). The use of optical data is based on the fact that snow reflects radiation strongly in the visible and very poorly in the NIR regions of the EM spectrum. Dozier (1989) mapped snow using the ratio of Landsat TM reflectance in the visible and NIR, a technique that had been previously used in the 1970s (e.g. Kyle et al., 1978) and was later adapted to develop the normalised-difference snow index (NDSI) for MODIS (Hall et al., 2002; Hall and Riggs, 2007) and Landsat ETM+ (Salomonson and Appel, 2004). NOAA AVHRR has also been used to map snow cover (e.g. Gesell, 1989; Voigt et al., 1999; Akyürek and Şorman, 2002; Matikainen et al., 2002; Hüsler et al., 2012) despite its coarse spatial resolution (1 km), because it has a long data archive and a very frequent revisit time (twice daily). A limitation of using optical data to map snow cover is that it is often difficult to separate clouds from snow, because snow may show a similar spectral response to clouds in the visible and TIR (Akyürek and Şorman, 2002; Miller et al., 2005). Another challenge is that the reflectance of snow decreases with impurity and age (seasonal and even daily ageing) (König et al., 2001; Dietz et al., 2012) and vegetation (resulting in surface heterogeneity) might also affect the reflected signal (Nolin, 2010).

Snow attenuates microwave radiation, which is positively correlated with the amount of snow in the snowpack (Chang et al., 1987; König et al., 2001; Clifford, 2010). In a similar manner to soils, the dielectric

Table 3
Linkage between selected catchment/landscape features, fluvial processes, ecosystems services and their detection with remote sensing. (builds on Andrew et al., 2014; Large and Gilvear, 2014). *Indicative* means the list is not exhaustive.

Catchment feature, or land cover	Inferred processes and characteristics	Ecosystem functions	Ecosystem services (<i>indicative</i>)	RS products (<i>required</i>)	Remote sensing source (<i>indicative</i>)
Catchment delineation	Catchment area, morphometry and hydrodynamic behaviour	Range of freshwater and terrestrial habitats	Water quantity and quality; seasonality	Topography	DEM derived from varied sources, including LiDAR, RADAR, UAV-based photography and aerial photography
Slope	Low slopes reduce energy gradient for transfer of water, sediment & nutrients, promoting storage and biogeochemical processing; reworking of sediment in active reaches	Hydraulic diversity; channel dynamism; habitat creation; sediment storage; habitat heterogeneity; increased wetted perimeter	Flood mitigation; water quality	Topography	DEM derived from varied sources, including LiDAR, RADAR, UAV-based photography and aerial photography
Catchment water balance and water level fluctuations	Water dynamics, quantity, quality and provenance of water and sediment runoff controlling biogeochemical processes including nutrient flux; snow accumulation; runoff volumes and timings; groundwater recharge and connectivity within alluvial flatlands; seasonal variations in water levels; movement of migratory species; crop phenology	Provisioning; supporting and regulating; cultural climate regulation; removal of pollutants; fish production	Water supply; biodiversity; carbon sequestration; flood mitigation and regulation; migratory species; tourism	Evapotranspiration Precipitation Soil moisture Water, snow/ice extent and duration Water level Groundwater	Thermal RS, VIs, climate data RADAR, PM RADAR (e.g. SMAP) Optical, RADAR, PM RADAR altimetry Gravity surveys, subsidence
Hyporheic zones and groundwater	Links to water flow and water quality in surface waters	Groundwater dependent terrestrial ecosystems including wetlands	Water supply; Flood mitigation and regulation; Biogeochemical filtration; biodiversity	Land cover map Species map, spectral diversity	Multispectral and multitemporal RS, HS. Range or variability of biochemistry, spectral indices or reflectance variation Multispectral RS, HS
Hydromorphological alteration	Elimination of flood inundation; loss of channel dynamism; altered supply of sediment & nutrients	Loss of natural land cover; hydrological alteration; habitat change	None	Land cover Feature extraction (e.g. embankment length, presence of dams etc) Spectral diversity Proxy indicators (e.g. canopy structure, productivity, gap fraction)	Range or variability of biochemistry, spectral indices or reflectance variation Varied e.g. LiDAR, Multispectral, HS, HY, multi-temporal RS
Riparian/river bank woodland	Shading, allochthonous leaf litter and woody debris input	Habitat creation and hydraulic diversity; cooling of water, food source	Biodiversity; fisheries		Range or variability of biochemistry, spectral indices or reflectance variation LiDAR, image texture, Multispectral, HS, HY
Floodplain physical habitat mosaic	Hydromorphological heterogeneity and channel dynamism; varied land use patterns	Range of freshwater-terrestrial habitats; ecotone creation	Biodiversity; fisheries	Spectral diversity, species map, land cover map, LAI, biomass	Range or variability of biochemistry, spectral indices or reflectance variation, LiDAR, image texture, Multispectral, HS, HY

Catchment disturbance	Potential for changing hydrological regime, channel dynamism, nutrient cycling, water quality, biodiversity	Potential loss/degradation of natural land cover; hydrological alteration	Changed natural ecosystem services	Change in biomass/plant traits Plant stress Fire detection Drought monitoring	Multi-temporal RS VIs, HY Thermal anomalies, fire products (e.g. MODIS) Water content, surface temperature & ET
Wetlands	Plant and animal succession processes; enhanced nutrient cycling and storage; semi-aquatic habitats	Carbon sequestration, phosphorous uptake and denitrification; habitat heterogeneity; flow attenuation; refugia	Water supply; water quality; biodiversity	Land cover map Species map; spectral diversity	Multispectral and multitemporal RS, HS. Range or variability of biochemistry, spectral indices or reflectance variation
Floodplain forest	Substrate stabilisation; enhanced hydraulic processes	Flow attenuation, enhanced nutrient cycling and storage; habitat heterogeneity	Carbon sequestration; flood mitigation; biodiversity; water quality	Land cover map; biomass	Multispectral and multitemporal RS, HS
Floodplain lakes	Water storage; nutrient cycling	Refugia; habitat heterogeneity	Water supply; carbon sequestration; water quality; fisheries; biodiversity	Land cover map Water colour (phytoplankton, suspended matter, CDOM) and water clarity, LWST, ice cover	Multispectral and multitemporal RS, HS. Spectral analysis, multispectral RS. Thermal RS
Agriculture	Potential for increased runoff; enhanced sediment input; water quality deterioration	Loss of natural land cover; hydrological alteration	Natural ecosystem services reduced with increased crop production	Land cover map, LAI	Multispectral and multitemporal RS, HS, HY, LiDAR
Woodland plantation	Substrate stabilisation; enhanced hydraulic roughness	Flow attenuation; biomass increase	Timber production; flood mitigation	Land cover map, biomass	Multispectral and multitemporal RS, HS, HY, LiDAR
Urban areas	Potential for increased runoff and water quality deterioration	Loss of natural land cover; hydrological alteration	None	Land cover map	Multispectral and multitemporal RS, HS

LiDAR (Light Detection and Ranging); MS (Multispectral, e.g. Landsat Thematic Mapper); HS (High spatial resolution imagery (e.g. WorldView-3, Google Earth)); HY (hyperspectral imagery/data); PM (passive microwave); VIs (vegetation indices); ET (evapotranspiration); CDOM (coloured dissolved organic matter); LWST (lake water surface temperature).

constants of ice and water are very different, which enables the use of microwave remote sensing to map snow. The depth of snow that can be mapped depends on the microwave wavelength; ranging from a minimum of around 2 cm (Dietz et al., 2012) to a maximum of 100 times the microwave wavelength (Clifford, 2010). In microwave remote sensing of snow, the size and shape of the snow crystals can affect the estimations (Foster et al., 1999), as well as depth, temperature, snow state and density (Schmugge et al., 2002). In addition, the presence of dense vegetation and liquid water in the snowpack can lead to underestimation of SD and SWE (Dietz et al., 2012), when passive microwave sensors are used. Using early morning satellite overpasses (local time) can minimise the impact of wet snow on snow mapping (Schmugge et al., 2002). Alternatively, active microwave remote sensing is more suitable for mapping wet snow (e.g. Baghdadi et al., 1997; König et al., 2001), with the added bonus of finer spatial resolutions than passive microwave satellite sensors.

In the 1980s, the US National Weather Service (NWS) developed operational remote sensing products for snow hydrology, using NOAA AVHRR and GOES to produce periodic river basin snow cover extent maps (Schmugge et al., 2002) and since 2002 the Aqua AMSR-E has been used to produce a global SWE Level 3 product. MODIS data have also been used to derive a suite of snow products at various spatial (500 m–30 km) and temporal (daily-monthly) resolutions. In addition, the snowmelt runoff model (SRM) was adapted to use remotely-sensed snow cover information at basin-scales (Martinez et al., 2008). The reader can refer to, for example, König et al. (2001), Schmugge et al. (2002), Clifford (2010), Nolin (2010) and Dietz et al. (2012) for more detailed reviews on the remote sensing of snow cover.

3.2.5. Land surface temperature (LST)

Atmospherically corrected brightness temperature retrieved using remote sensing thermal sensors are used in land surface temperature retrieval. There are three techniques for the retrieval of LST from remote sensing data; single channel, generalised split window (GSW) and dual angle (or dual algorithm) (DA) approach. The single channel method requires a comprehensive radiative transfer model and atmospheric profiles. The split window approach, combines two thermal wavebands and accounts for atmospheric effects based on the differential absorption in adjacent infrared bands. However, because of the large emissivity differences between thermal wavebands over land due to vegetation, topography and soil, this method can be problematic. Land surface emissivity studies have been conducted to overcome this problem and various techniques have been proposed in the literature for NOAA AVHRR and Terra/Aqua MODIS (e.g. Wan and Dozier, 1996; Becker and Li, 1990; Mao et al., 2005; Pinheiro et al., 2006), (A)ATSR (e.g. Soria and Sobrino, 2007; Galve et al., 2009) and MSG Spinning Enhanced Visible and Infrared Imager (SEVIRI) (e.g. Jiang and Li, 2008; Qian et al., 2013; Freitas et al., 2013). The Terra/Aqua MOD11 LST product uses a split-window approach that utilises thermal bands 31 and 32. The dual angle approach is based on the differential absorption of a single waveband due to different viewing angles. In order to apply this technique two scenes simultaneously acquired by different satellites, e.g. the geostationary MSG and polar-orbiting Television Infrared Observation Satellites (TIROS-series) (Chédin et al., 1982) or a single scene from a satellite with multi-angle acquisition capability, such as the (Advanced) Along-Track Scanning Radiometer ((A)ATSR) on-board Envisat, can be used. The second option is more commonly employed using (A)ATSR data (e.g. Kustas and Norman, 1997; Sobrino et al., 1996, 2004; Soria and Sobrino, 2007) or GOES and Multifunction Transport Satellite (MTSAT) data (Freitas et al., 2013). Finally, a robust empirical technique has been developed specifically for the Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER); the Temperature Emissivity Separation (TES) algorithm (Gillespie et al., 1998) that uses ASTER TIR wavebands to estimate LST. The two main advantages of using Terra ASTER for LST retrievals are its fine spatial resolution (90 m) and more frequent revisit capability (twice daily)

compared to other thermal sensors (e.g. NOAA AVHRR, (A)ATSR, MODIS, etc.).

Even though mostly thermal sensors are used in LST-retrievals, there exist a few studies where passive microwave sensors were employed (Tomlinson et al., 2011), which have the advantage of providing measurements even on cloudy days. Despite the coarse spatial resolution of passive microwave sensors (5–70 km depending on frequency), the AMSR-E (Chen et al., 2011) and more commonly the SSM/I (e.g. McFarland et al., 1990; Basist et al., 1998; Peterson et al., 2000; Williams et al., 2000; Fily et al., 2003) have been used to estimate LST. For examples of in-depth reviews on the remote sensing of land surface temperature, the reader can refer to Prata et al. (1995), Dash et al. (2001), Schmugge et al. (2002), Tomlinson et al. (2011) and Li et al. (2013).

4. Mapping catchment land cover and other drivers of lake behaviour

There are multiple catchment drivers of lake change due to intensification of human activities and climate change. Lakes across the globe can be affected by a combination of different stressors and pressures, based on vicinity to human establishments, type and intensity of human activities within the catchment, type and ratio of natural over altered landscape in the catchment, protection status and geographical location. Human activities such as agriculture, deforestation, urbanisation and industrial activities can be grouped under the umbrella of land cover/land use change (LULC), which may have various direct and indirect effects on lake water quality, for example increased nutrient loading and eutrophication (e.g. Huang et al., 2013; Keatley et al., 2011), pollution (e.g. IJC, 1980), acidification (e.g. Nghiem et al., 2011), anoxic conditions (e.g. Valero-Garcés et al., 2000). The impact of other human activities such as tourism and commercial fishing on lake ecosystem status and ecosystem services is not possible to map and quantify with remote sensing unless their impact is measured indirectly. For example, by mapping forest area reduction due to tourism-related development (Chaplin and Babyn, 2013) or estimating epipelagic fish distribution and abundance in shallow waters (Churnside et al., 2003).

Despite the potential of remote sensing to provide direct estimation of a wide variety of ecosystem functions and services (cf. those described above) both Andrew et al. (2014) and de Araujo Barbosa et al. (2015) note that the majority of published studies that have attempted to map ecosystem functions and services (and by inference related catchment processes) do so using indirect proxies, such as land cover and land use data, derived mainly from remotely sensed sources (Table 3). It is pertinent, therefore, to reflect briefly on how land cover information is derived, and more importantly, the limitations and considerations to its application for monitoring change in ecosystem functions and services of large areas.

Perhaps the most common and one of the most basic forms of land cover analysis using remotely sensed data is land cover classification. This relates spectral and textural information within an image to specific land cover classes (as defined by the user) to produce a land cover map, from which land use may be inferred. There are many methods of image classification, from 'traditional' statistically-based per-pixel methods that assign individual pixels to land cover classes based upon their spectral response, to object-based approaches which segment the landscape into parcels based upon spectral response, shape, texture and other object characteristics. Additionally, a classification may be 'hard' where pixels are assigned to a single class, or 'soft' where pixels are assigned multiple class memberships. The latter is particularly relevant, when information relating to small scale changes in land cover are important and where measuring change requires greater precision. More often it is used when the spatial resolution of the instrument does not match the intrinsic scale of land cover heterogeneity within an area of interest. For example, Probeck et al. (2005) were able to derive subscale land cover information from relatively coarse (1 km)

NOAA AVHRR imagery of the upper Danube by using a fuzzy classification approach, from which results were produced that compared favourably with independent datasets. A similar approach was used by Ludwig et al. (2003b). In both cases the fuzzy classification method used was spectral unmixing but alternatives include the use of artificial neural networks (e.g. Aitkenhead et al., 2008) and other types of machine learning.

The methods used to classify remotely sensed data are a field of research in themselves, and whilst helpful reviews of the current state of land cover extraction from remote sensing are available (e.g. Cihlar, 2000; Aplin, 2004; Li et al., 2014), the myriad of methods and approaches leads to variability in the land cover map outputs derived by individual researchers and groups, limiting their wider applicability. To address this, some studies have employed the use of standardised LULC products (e.g. Table 4). These products tend to be produced from a single satellite sensor, removing variability associated with multiple sensor characteristics. Additionally, products may be single-year or multi-year products, enabling change to be detected using a standardised set of data characteristics and land cover classes. Thus, the use of a LULC product may reduce some of the uncertainty associated with individuals undertaking a classification exercise in isolation. However, the uptake in use of LULC products has been slow, put down partly to a lack of awareness but also a lack of confidence in spatial accuracy (Pfeifer et al., 2012; Congalton et al., 2014). Most operational products are still restricted to coarse spatial resolution data (Table 4), which whilst providing frequent temporal updates may be a deterrent towards their use for some ecosystem studies.

An additional limitation of LULC analysis is determining a biophysical basis for linking particular LULC classes to ecosystem functions and services. For individuals and groups undertaking their own classification there is often a tension when defining appropriate LULC classes to map between those features and classes that can be extracted from remotely sensed data, i.e. those that are spectrally separable, and those features and classes that are directly correlated with ecosystem function and/or catchment processes. The resulting class definitions are, therefore, often a pragmatic solution using features and LULC classes that can be detected remotely and using these as proxy indicators of the environmental variable of interest (e.g. Table 3). These proxies, however, may have limited relevance, being often the result of hypothesised but largely untested relationships (Andrew et al., 2014; Seppelt et al., 2011) leading to unreliable outputs when compared to field observations (e.g. Eigenbrod et al., 2010). This potentially becomes even more problematic when using standardised LULC products, where there are often inconsistencies in class definitions between products (Congalton et al., 2014) and where different products are produced at different spatial resolutions, thus limiting their use as proxy indicators.

Also, by assuming that the same ecosystem value can be applied to the whole of a particular class ignores any scale dependency in ecosystem processes and leads to inaccuracies when compared with independently observed data (Eigenbrod et al., 2010). Thus ecosystem services derived from land cover information will be highly dependent upon the efficacy of linking a land cover class to a particular ecosystem

service/function, the spatial resolution of the data and the accuracy of image classification (de Araujo Barbosa et al., 2015).

The accuracy of image classification is an important, but often ignored factor in determining the reliability of areal change in land cover class(es) derived from a classified map. Change in key indicator classes, such as woodland or urban areas, are important in understanding changes in lake water quality, habitat and other critical ecosystem services. However, as Olofsson et al. (2013) effectively argue, information relating to the accuracy of land cover outputs and products, including commonly used measures such as overall accuracy and the kappa coefficient, fail to provide enough information to effectively judge the effect that classification error has on estimates of areal change. To address this they suggest mapped areas should be adjusted using a stratified estimator approach (Olofsson et al., 2013). At the very least, the uncertainty and error associated with the mapping of ecosystem properties should be addressed and reported, with Rocchini et al. (2013) providing a useful summary of good practise for this very purpose. Even when using globally available LULC products the stated accuracy is not always acceptable for the purpose of mapping change (Congalton et al., 2014). Karimi and Bastiaanssen (2015) noted that the overall accuracies reported for global land cover maps varied between 69 and 87%, suggesting that such products should be used with caution in water accounting applications.

All of the limitations above suggest that whilst LULC information derived from remotely sensed sources has the potential for quantifying and mapping selected catchment and ecosystem functions and services across large areas, the limitations in terms of applicability (biophysical basis of land cover classes), data quality (accuracy) and data properties (spatial and temporal resolution) should be considered carefully when deciding how such data should be used. Fuller et al. (2003) provide a useful commentary on experiences of mapping the UK with remotely sensed data highlighting the limitations of comparing between products, whilst Seppelt et al. (2011) provide a useful review of critical questions that should be raised when reviewing ecosystem service assessments at a regional scale, which are directly relevant to remote sensing-based studies.

5. Remote sensing of lake level and volume

Finally, whilst this review has thus far focussed on catchment functions and characteristics, it is also pertinent to briefly assess the potential of remote sensing to provide information regarding lakes themselves. The remote sensing techniques and sensors used to map lake water quality are reviewed by Tyler et al., in this Special Issue. Remote sensing can also have a role to play in detecting water bodies (e.g. Verpoorter et al., 2014), and estimating lake water level change and volume.

Both water level and volume are important with respect to lake ecology, being determinants of water residence time, flushing rate and mixing. They are also highly influenced by human activities, with the construction of dams and impoundments, and associated freshwater withdrawal for domestic, agricultural and industrial use responsible for significantly altering water level (and, thus, volume) in some lakes

Table 4
Example global land cover datasets suitable for large area land cover analysis.

Product	Sensor	Satellite	Spatial resolution	Temporal resolution
GLC2000 ¹	VGT	SPOT	1 km	Single date: 2000
MCD12Q1 ²	MODIS	Aqua, Terra	500 m	Annual: 2001–2007
ESA CCI-LC ³	MERIS	ENVISAT	300 m	Three epochs: 2008–2012; 2003–2007; 1998–2002
ESA CCI LC Seasonality (Three products: vegetation, snow cover & burned area)	MERIS	ENVISAT	300 m	Annual

¹ European Commission (EC) Global Vegetation Monitoring (GVM) Unit Global Land Cover (GLC) 2000 product.

² NASA Land Processes Distributed Active Archive Center (LP DAAC) Land Cover Type product.

³ European Space Agency (ESA) Climate Change Initiative (CCI) Land Cover (LC) product.

and reservoirs globally (in Lake Chad, for example). However, not all lake water level change is caused by direct human intervention. Climate change and natural climatic fluctuations are also important drivers of water level change/fluctuation in freshwater bodies, particularly in closed lake basins in endorheic regions (Hutchinson, 1957).

5.1. Remote sensing of lake water level

Water level change can be retrieved from remote sensing altimetry data (e.g. Birkett, 1995; Crétaux and Birkett, 2006; Hwang et al., 2011; Mercier et al., 2002; Ponchaut and Cazenave, 1998; Swenson and Wahr, 2009) with very high accuracy (e.g. 3–33 cm; Birkett and Beckley, 2010; 25–53 cm; Frappart et al., 2006). Altimeters can be radar (microwave) or laser (visible and IR), but the second are sensitive to the presence of clouds. They both transmit pulses and receive the reflected signal, so the theoretical basis for measurements is similar (Duan and Bastiaanssen, 2013). Lake surface water level is estimated by calculating the difference between satellite height in respect to a reference surface (e.g. Earth's centre) and the satellite-to-surface range (calculated by the time taken for the pulse to return to the sensor since transmission), correcting at the same time for instrumental, atmospheric and other effects (Duan and Bastiaanssen, 2013). The disadvantage of altimeters is that they can only return measurements from along their track, which does not cover the globe. As a result, only specific water bodies (that fall into the satellite's track) can be detected. Laser altimeters such as the Geoscience Laser Altimeter System (GLAS) on-board ICESat (Ice, Cloud, and land Elevation Satellite) are more suitable for relatively small water bodies due narrower footprint size (~100 m) compared to radar altimeters (several kilometres).

Several radar altimeters were until recently or currently operational, including ERS Radar Altimeter (RA) and Envisat RA-2, the Poseidon sensors on-board TOPEX/Poseidon, Jason-1 and Jason-2 (or Ocean Surface Topography Mission, OSTM), and GeoSat Follow On (GFO) Radar Altimeter. These sensors were used to create three distinguished databases that include lake water level estimates: (1) ESA's River and Lake project, (2) US Department of Agriculture (USDA) Global Reservoir and Lake Monitoring (GRLM) programme, and (3) Laboratoire d'Etudes en Géophysique et Océanographie Spatiales (LEGOS) and Geodesy, Oceanography and Hydrology from Space (GOHS) Hydroweb. A fourth database is based on ICESat laser altimetry; ICESat-GLAS level 2 Global Land Surface Altimetry data (ICESat-GLAS). For an excellent overview of these databases see Duan and Bastiaanssen (2013).

5.2. Remote sensing of lake water quantity (volume)

Lake water quantity (volume) cannot be measured directly from remote sensing. Water level information is combined with bathymetric information of the water body in order to produce estimates of lake volume. Apart from using traditional sonar techniques, bathymetric maps can also be produced using GPS and laser transit survey data (e.g. Wilcox and Los Huertos, 2005), and in fact the notion of a laser bathymeter is not new (Muirhead and Cracknell, 1986). To replace the need for bathymetric predictions, new techniques that make use of visible and IR-based lake surface area estimations have been developed for the retrieval of lake water volume (e.g. Duan and Bastiaanssen, 2013; Lu et al., 2013). Finally, satellite altimetry-derived water levels of lakes can provide estimates of lake water volume change, when combined with satellite or otherwise-derived surface water area (e.g. Becker et al., 2010) or detailed bathymetric maps (Crétaux and Birkett, 2006).

6. Observations and conclusions

We began this review by presenting a suite of datasets (Fig. 2), some derived from remote sensing, that have the potential to capture both status and change in lake catchments. This is presented as a precursor to understanding both the causes and drivers of lake change, and

which can complement direct observations of lake behaviour by satellite remote sensing (Tyler et al., in this issue). Whilst by no means an exhaustive review of the capabilities of remote sensing and geospatial technologies in this field, this paper points towards some of the key catchment variables that can be estimated, both directly and indirectly, as well as the limitations and challenges currently faced.

From the work that is reviewed it is clear that remote sensing is an important tool for mapping ecosystem functions and aiding our understanding of catchment drivers of lake change, with promising results frequently reported. However, it is also clear that many of the results are highly specific to a particular time and/or place, and thus a manifestation of the 'one time one place' approach identified by Woodcock (2002) as a common cause of uncertainty in the application of remotely sensed data for other applications. Time and again various reviews point to continued issues with respect to multiple scales, sensors, reliability and other methodological constraints that limit the operational application of remote sensing for extracting critical ecosystem functions. Many suggest further work is needed to develop techniques that combine multi-source information to provide disaggregated products for catchment monitoring and modelling.

In part a response to these issues, several reviews refer to increasing efforts to integrate information across a variety of sensors and scales, and the development of many standardised remotely sensed products (Andrew et al., 2014; Pfeifer et al., 2012). Issues of spatial and biophysical relevancy persist, but with the advent of higher spatial resolution global datasets becoming available (e.g. Hansen and Loveland, 2012) and the introduction of new complementary in situ sensor systems capable of measurements at high temporal and spatial -frequencies (Crawford et al., 2014) at least some of these concerns will continue to be addressed.

As stated in our introduction, the future of remote sensing for catchment, ecosystem and lake-based studies looks very promising. ESA's Copernicus programme will not only include Sentinel's 2 and 3 (which themselves will include multiple versions, e.g., Sentinel 3A, 3B and 3C, thereby providing a constellation of 'observers') but also includes a C-band SAR sensor on-board Sentinel-1 (launched April 2014) to provide observations of ice, oil spills and land surface monitoring. Additionally, future missions such as ESA's BIOMASS (planned for 2020) will provide enhanced information on above-ground biomass dynamics at 50 m spatial resolution, whilst ESA's FLEX (Fluorescence Explorer), Germany's EnMAP (30 m spatial resolution) and NASA's HYSPIRI (60 m) satellite sensors will allow regional to global assessments of plant biophysical and biochemical status, biogeochemical cycling, erosion monitoring and ecosystem fragmentation and disturbance. Thus the range of spaceborne sensors for deriving quantitative estimates of critical ecosystem and catchment variables appears to be in good shape looking forward.

In addition to new optical and SAR sensors described above and elsewhere in this review, there is clearly much progress in developing geospatial technologies which will have the potential to revolutionise the mapping of ecosystem functions. These include the development of UAV platforms for low cost, high resolution data gathering, as well as new hyperspectral sensor technologies and multispectral LiDAR that have the potential for direct estimation of biophysical variables (Woodhouse et al., 2011) and plant traits, removing the need for reliance on simple proxies. Furthermore, the existence of platforms that facilitate the use of extensive datasets and long remote sensing archives, such as the Google Earth Engine (GEE) for environmental data analysis, can and will provide, in part, the necessary infrastructure that the era of 'Big Data' asks for.

To maximise the exploitation of new technologies for ecosystem service assessment Andrew et al. (2014) note the need for close collaboration between remote sensing scientists, ecologists and social scientists. Clearly, for this application the same is true of remote sensing scientists and limnologists, hydrologists, ecologists and many more to truly understand the drivers of lake change and behaviour across the globe,

with the potential for much of this to be informed by remote sensing observations. Multidisciplinary collaboration is a necessity for the integration and assimilation of geospatial data and new technologies in hydrological modelling and traditional limnological studies, and in order to be able to understand and interpret both the uncertainties of the data used and the research outputs. The inclusion of remote sensing scientists in limnological research is therefore considered prudent and often an essential step towards understanding remote sensing data and the specific uncertainties, interpretation and limitations related to remote sensing products before their use. In this respect, projects such as the UK Natural Environment Research Council-funded GloboLakes project (Global Observatory of Lake Responses to Environmental Change) is one of several initiatives to address issues of lake change in just such a way, and which will lead to paradigm shifting developments in the characterisation of the planet's freshwater resources and responses to environmental change.

Acknowledgements

This work was supported by NERC Consortium Grant NE/J024279/1 – GloboLakes (Global Observatory of Lake Responses to Environmental Change): www.globolakes.ac.uk The Authors also wish to thank the constructive feedback from the anonymous reviewers.

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