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# Using multi-source satellite data for lake level modelling in ungauged basins: a case study for Lake Turkana, East Africa

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Received: 17 March 2011 – Accepted: 3 May 2011 – Published: 16 May 2011

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Published by Copernicus Publications on behalf of the European Geosciences Union.

**HESSD**

8, 4851–4890, 2011

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## Abstract

Managing limited surface water resources is a great challenge in areas where ground-based data are either limited or unavailable. Direct or indirect measurements of surface water resources through remote sensing offer several advantages of monitoring in ungauged basins. A physical based hydrologic technique to monitor lake water levels in ungauged basins using multi-source satellite data such as satellite-based rainfall estimates, modelled runoff, evapotranspiration, a digital elevation model, and other data is presented. This approach is applied to model Lake Turkana water levels from 1998 to 2009. Modelling results showed that the model can reasonably capture all the patterns and seasonal variations of the lake water level fluctuations. A composite lake level product of TOPEX/Poseidon, Jason-1, and ENVISAT satellite altimetry data is used for model calibration (1998–2000) and model validation (2001–2009). Validation results showed that model-based lake levels are in good agreement with observed satellite altimetry data. Compared to satellite altimetry data, the Pearson's correlation coefficient was found to be 0.81 during the validation period. The model efficiency estimated using NSCE is found to be 0.93, 0.55 and 0.66 for calibration, validation and combined periods, respectively. Further, the model-based estimates showed a root mean square error of 0.62 m and mean absolute error of 0.46 m with a positive mean bias error of 0.36 m for the validation period (2001–2009). These error estimates were found to be less than 15% of the natural variability of the lake, thus giving high confidence on the modelled lake level estimates. The approach presented in this paper can be used to (a) simulate patterns of lake water level variations in data scarce regions, (b) operationally monitor lake water levels in ungauged basins, (c) derive historical lake level information using satellite rainfall and evapotranspiration data, and (d) augment the information provided by the satellite altimetry systems on changes in lake water levels.

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## 1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) Technical Paper on Climate Change and Water has stressed the fact that increased demand and reduced availability of freshwater under global climate change will significantly affect agriculture and food security in the 21st century (Bates et al., 2008). Due to increases in population, industrialization, and irrigated agriculture, several surface water resources are rapidly depleting. Today, freshwater scarcity affects more than a billion people and the integrity of many of the world's ecosystems (UNEP, 2006). Because of these consequences, it has become increasingly important to accurately identify, quantify, and monitor freshwater resources. Inland lakes provide important sources of freshwater and influence the local hydrological budget. Furthermore, information on the variations in lake levels and areas are often required on a regular basis for climate assessment purposes. The measurements required to answer the questions on the variability of surface water are: (a) surface water area,  $A$ , (b) the elevation of the water surface,  $h$ , (c) temporal change,  $\partial h/\partial t$ , and (d) slope of the water surface,  $\partial h/\partial x$  (Alsdorf et al., 2007). Monitoring changes in lake water levels is essential because they reflect changes in the seasonal distribution of river inflows, precipitation, and evapotranspiration (ET), in some cases integrated over many years (Bates et al., 2008). However, measurements of the variability of water levels over rivers and lakes/reservoirs are one of the critical missing pieces in the terrestrial water budget (NASA Science Plan, 2007). Furthermore, while monitoring of surface water variability is a challenging task in ungauged basins, much of the greatest human impacts are occurring in basins that have none or very limited data (Sivapalan, 2003).

In the past, mostly conventional surveying methods such as direct measurements of lake elevations have been used to monitor variations in lake water levels. Several researchers estimated variations in water levels by estimating water budget of the lake using rain gauge and discharge data (Ayenew, 2002; Tate et al., 2004; Kebede et al., 2006). Moreover, innovative methods of estimating historical lake water variations such

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as the use of tree rings (Stockton and Fritts, 1973), multifold seismic data (Scholz and Rosendahl, 1988), and isotopic techniques (Talbot and Livingstone, 1989) have also been used. Furthermore, public participation and volunteer monitoring mechanisms are being used to collect information on several aspects of lakes including lake water levels (Stokes et al., 2004). Although these methods are robust, they are limited in their widespread applicability by the need for in-situ data collection. Hence, application of these methods is problematic in most remote areas or in ungauged lakes or basins.

More recently, remote sensing data are being used to monitor variations in lake water levels. Optical remote sensing data combined with ground data have been used for lake/reservoir level monitoring (Reis and Yilmaz, 2008). Tan et al. (2004) used radar and Moderate Resolution Imaging Spectroradiometer (MODIS) data combined with hydrological and statistical data to measure lake level changes in China. However, these monitoring methods have not been operationalized because of infrequent availability of the in-situ data or satellite imagery. Radar interferometry and altimetry data are now being used to study water level variations (Birkett, 1994; Birkett and Mason, 1995; Alsdorf et al., 2001). The US Department of Agriculture's Foreign Agricultural Service (USDA-FAS), in cooperation with the National Aeronautics and Space Administration (NASA) and the University of Maryland, are routinely monitoring lake and reservoir height variations for large lakes with an area greater than 100 km<sup>2</sup> around the world using radar altimeter data (Birkett, 1995). Recently, Ice, Cloud, and land Elevation Satellite (ICESat) altimetry data are being used to estimate lake levels (Zhang et al., 2010). These altimetry systems are providing wealth of data on lake level variations especially in ungauged lakes and reservoirs globally. Though there has been an increase in the use of satellite altimeter data for lake level studies recently, most of these systems focus only on those lakes that opportunistically lie below the orbital tracks of the satellites, a limitation that misses millions of the world's lakes and associated storage changes (Judge and Bolten, 2010). Hence, supplemental approaches are necessary to enhance the global information on surface water variability.

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The objective of this paper is to present an approach that could supplement operational monitoring at short to medium time scales for field engineers, disaster managers, and lake/reservoir operators in ungauged basins or in areas where ground observations of lake levels are either limited or not available. This paper presents a multi-sensor approach to monitor lake water levels by integrating digital elevation data, satellite-based rainfall estimates, modelled ET, runoff data, and other satellite products to produce information on variations in lake water levels without relying on in-situ data sources. Furthermore, the model presented here can also be used to derive historical lake water level variations when rainfall and climate data are available.

## 2 Data used

The data used in this study are summarized in Table 1. The National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) produces satellite-based rainfall estimates (RFE) for the Famine Early Warning System (FEWS) project of the US Agency for International Development (USAID). The data are produced daily with a spatial resolution of  $0.1 \times 0.1^\circ$  since June 1995 and are available to the public in near-real time. The spatial extent of the product covers the entire African continent and a few surrounding regions. RFE data from June 1995 to 31 December 2000, were produced using the RFE 1.0 algorithm (Herman et al., 1997), and since 1 January 2001, RFE data are being produced using the version 2.0 algorithm (Xie and Arkin, 1996). RFE data from January 1998–December 2009 are used in this study.

The reference evapotranspiration (ET<sub>o</sub>) data used in this study is produced at the USGS Earth Resources Observation and Science Center from 6-hourly Global Data Assimilation System (GDAS) climate parameters using the standardized Penman-Monteith equation, then downscaled to  $0.1^\circ$  for this study (Senay et al., 2008). Historical average dekadal (10-day) Normalized Difference Vegetation Index (NDVI) datasets (1982–2006) described by Tucker et al. (2005) from the Advanced Very High Resolution Radiometer (AVHRR) are used to characterize the Land Surface Phenology

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(LSP) and to estimate actual evapotranspiration (ET<sub>a</sub>) on a pixel-by-pixel basis at 0.1° resolution. The canopy interception parameter is estimated using the global percent tree cover product produced from MODIS Vegetation Continuous Field (Hansen et al., 2003). Area weighted average interception losses are estimated for each modelling pixel based on the percentage of bare, herbaceous, and tree cover for each pixel. The interception coefficient for each modelling unit varies from a minimum of zero in bare cover types to a high of 35% in areas with a dense forest cover. The Digital Soil Map of the World (FAO, 1995) is used to estimate water holding capacity (WHC) for the dominant soil type for each grid cell. Shuttle Radar Topography Mission (SRTM) 90-m digital elevation model (DEM) data are obtained from the Consultative Group on International Agricultural Research (CGIAR) Consortium for Spatial Information (CSI) website. These void-filled DEM data are used to derive hydrological derivatives such as (a) streams and river networks and (b) sub-basins and basins. The DEM is also used to estimate lake surface area at various depths.

### 3 Methods

#### 3.1 Lake level modelling (LLM) approach

A multi-sensor physical based hydrologic model hereafter called Lake Level Model (LLM) is developed to estimate lake water levels. The LLM approach (Fig. 1) used in this study can be illustrated in four steps:

*Step 1:* First, weather data (RFE and GDAS ET<sub>o</sub>) are used to estimate runoff (m) on a pixel-by-pixel basis using the phenology based ET model (VegET) (Senay, 2008; Senay et al., 2009). The VegET model is based on standard water balance principles comparable to those outlined in Allen et al. (1998) and Senay and Verdin (2003). The modelling approaches in VegET model can be explained by Eqs. (1) and (2):

$$ET_a = K_{cp} \times K_s \times ET_o \quad (1)$$

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$$SW_i = SW_{i-1} + RFE_i - ETa_i - (IL_i \times RFE_i) \quad (2)$$

where ETa is the actual ET;  $K_{cp}$  is the LSP-based cropq coefficient;  $K_s$  is the soil water stress coefficient; ETo is the global GDAS reference ET; RFE is the satellite-based rainfall estimate; and SW represents soil water content.  $IL_i$  represents interception losses; subscript  $i$  represents the current modelling time-step, and subscript  $i - 1$  represents the previous time-step. The VegET model estimates runoff for each time-step based on the principle of soil saturation excess, where soil water content in excess of the water holding capacity (WHC) of the soil is considered runoff. Variables ETa, ETo, RFE, IL, and SW all are in units of (m unit time-step<sup>-1</sup>). Further description of the VegET modelling approach is found in Senay (2008) and Senay et al. (2009).

*Step 2:* The average basin runoff volume,  $\overline{R}_V$  (m<sup>3</sup> unit time-step<sup>-1</sup>) is then estimated by multiplying the average basin runoff,  $\overline{Q}_{\text{Basin runoff}}$  (m unit time-step<sup>-1</sup>) with the total basin area,  $A_{\text{basin}}$  (m<sup>2</sup>). This is based on the assumption that runoff generated in the farthest point would reach the lake within the modelling time step.

$$\overline{R}_V = (\overline{Q}_{\text{Basin runoff}} \times A_{\text{basin}}) \quad (3)$$

*Step 3:* The change in lake level (m) for each time-step  $i$  is determined using average basin runoff volume ( $\overline{R}_V$ ) and lake surface area ( $L_{\text{Area}}$ ) as

$$Q_{\text{runoff}} = \overline{R}_V \div L_{\text{Area}} \quad (4)$$

*Step 4:* Finally, lake depth,  $D_i$  (m) for each time-step is estimated using the water balance principle, which can be described with the following equation

$$D_i = D_{i-1} + Q_{\text{rain}} + Q_{\text{runoff}} + Q_{\text{gw}} - Q_{\text{evap}} - Q_{\text{outflow}} - Q_{\text{seep}} \quad (5)$$

where  $D_i$  and  $D_{i-1}$  are lake depths for current and previous time-steps and  $Q$  represents the fluxes of the variables for the current time-step; rain is direct rainfall over the lake; runoff is inflows into the lake; gw is ground water inflow into the lake; evap is over-the-lake ETo; outflow is outflow from the lake; and seep is seepage losses from the lake.

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### 3.2 Application of the LLM approach for Lake Turkana Basin

The study is conducted over Lake Turkana, one of the lakes in the Great Rift Valley of East Africa (Fig. 2). The lake is about 250 km in length and 15–30 km in width, with a surface area of nearly 6750 km<sup>2</sup>. The lake catchment is 203 080 km<sup>2</sup> and extends over Ethiopia in the north, Kenya in the south, and Sudan and Uganda in the west. The lake has a maximum depth of nearly 110 m and an average depth of 30 m. Three rivers, the Omo, Turkwel, and Keiro, constitute the lake inflows. The Omo River is perennial and meanders nearly 1000 km before emptying into the northern tip of the lake. It accounts for more than 80 % of the lake inflows (Ricketts and Johnson, 1996). In contrast, the Turkwel and Keiro Rivers are intermittent and contribute little to the total volume of the lake (Carr, 1998). Lake Turkana Basin has four distinct seasons with two distinct dry periods (December–February and July–August) and two rainy seasons (March–June and September–November). Lake Turkana is considered an endorheic lake with no surface outlet and insignificant seepage (Rickett and Johnson, 1996). The outflow is dominated only by evaporation. Reasons for choosing Lake Turkana for this study are: (a) it is an ungauged lake, and (b) it is a closed-basin lake. The latter case makes the lake more sensitive to changes in regional water balance and therefore, a better indicator of changes in regional climate.

Runoff estimates for the Lake Turkana Basin are estimated using the VegET model (Eqs. 1 and 2) on daily time steps. Furthermore, using Eqs. (3) and (4), monthly total basin runoff volume is estimated. Lake Turkana's groundwater inflows and outflows were minimal or found to be negligible (Yuretich and Cerling, 1983; Cerling, 1986). Hence Eq. (5) is simplified as

$$D_j = D_{j-1} + Q_{\text{rain}} + Q_{\text{runoff}} - Q_{\text{evap}} - Q_{\text{seep}} \quad (6)$$

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The lake water balance model was run at a monthly time scale, and monthly lake water levels are estimated using Eq. (6). Finally, the lake level model is formulated to handle Eq. (1) through Eq. (6). The model was run from January 1998 to December 2009. Since GDAS ETo data is available from 2001, long-term monthly mean ETo values were used from 1998–2000. The model is calibrated using the first three years of data (1998 to 2000) and tested using the rest of the data (2001 to 2009). Initial Lake Turkana water level information for January 1998 was obtained from the French Space Agency website. For each water level, the Lake Turkana surface area is determined using depth surface area relationship developed from seamless elevation data obtained by combining SRTM elevation and bathymetry data for the lake (Velpuri and Senay, 2009). Bathymetry information for Lake Turkana was obtained from Kallqvist et al. (1988).

### 3.3 Uncertainties in LLM approach

In physically based modelling, it is important to distinguish between the predictive performance of a model and its ability to explain environmental phenomena (Beven, 2001). Uncertainty in hydrologic model includes (a) uncertainties in the structure of the model (b) uncertainties in the model parameters/input data and (c) uncertainties in the solution of the model (Addiscott et al., 1995). We believe that in physically based hydrologic models using satellite data such as LLM approach, major uncertainties in the model outputs can be attributed to the model parameters or input data. Satellites provide spatially explicit data acquired using consistent methodologies and have high precision; however they often contain a bias compared to ground truth measurements. In order to understand the uncertainty in the LLM model, the impact of the bias in the input data is to be understood. But, it is neither possible nor desirable to evaluate and eliminate all of the uncertainties associated with data and models because resources are always limited and must be used effectively (Van Rompaey and Govers, 2002). Hence those parameters that are likely to contribute most to the uncertainties associated with the model results were evaluated. In the case of LLM model, parameters such as WHC, interception losses, climatological NDVI and DEM are static across years and hence

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would result in only minimal random errors. Errors in other parameters such as rainfall, runoff and ET on the lake surface are critical and thus affect model results. Validation of RFE rainfall over the Ethiopian highlands using gauge data suggested that RFE can be reliably used for early warning systems to empower the decision making process (Dinku et al., 2008; Beyene and Meissner, 2010). RFE is believed to have some under-estimation in rainfall estimates during peak rainy seasons and overestimation in other seasons (Laws et al., 2004) with an average bias of  $-0.15 \text{ mm d}^{-1}$  (NOAA/CPC, 2002). Few validation studies indicate estimates of errors for different locations in Africa and over different time periods (Laws et al., 2004; Dinku et al., 2008). However, these error estimates cannot be extrapolated for Turkana Basin considering its complexity. Further studies in this direction are required to determine the true errors in RFE data over the period of 1998–2009 for the Turkana Basin. Although, the relationship between rainfall and runoff is not linear from individual storms, we assume an average rainfall-runoff coefficient to evaluate the propagation of average bias in RFE into modelled runoff. Other important input in the LLM approach is the ET data. Currently there is no published evidence of validation of GDAS reference ET in Africa. However, modelled ET data was validated in the United States using California Irrigation Management Information System (CIMIS) reference ET data and was found to show a mean underestimation up to 5% over 16 sites (Senay et al., 2008). Hence, the relationships between the change in the lake levels in relation to basin rainfall, runoff and ET were derived and the impact of these errors on the modelled lake water levels was understood.

### 3.4 Model calibration

Rykiel (1996) defines calibration as “the estimation and adjustment of model parameters and constants to improve the agreement between model output and a data set.” Model calibration is an essential step in making a model as consistent as possible. Since all hydrological models and their parameters are approximations to the reality, there is a general need for model calibration or checking the model results with the observed data (Maidment, 1992). This becomes a necessity in most ungauged basins as

some parameters required for modelling are not available. Hence, approximate values of such parameters are estimated during the model calibration process. In this study calibration is performed to fix (a) magnitude and (b) lag time of modeled lake levels when compared to satellite altimetry data. Data from the years 1998 to 2000 were used for calibration.

### 3.4.1 Calibration of lake level magnitude

The Lake Turkana water levels are primarily driven by runoff, ET, and to lesser extent by seepage losses. Any errors in the estimation of inflows and outflows would lead to errors in modelling. In this study, magnitude differences in lake levels were minimized by estimating values for two unknown parameters: (a) fraction of ETo (ETf) to estimate over-the-lake ET and (b) seepage loss from the lake ( $Q_{\text{seep}}$ ). GDAS ETo is the sum of evaporation from the soil surface and transpiration from a standardized reference clipped grass surface (Allen et al., 1998). However, evaporation from open water bodies like lakes and rivers is lower than the pan evaporation and reference ETo (Allen and Tasumi, 2005), and it can be represented by ETf. Allen and Tasumi (2005) evaluated evaporation over American Falls reservoir in Idaho, USA, and found that the ETf ranged from 0.2 to 0.7 depending on the season. However, since Lake Turkana is located in an arid environment, we assumed that the fraction would be higher than the fraction observed in temperate lakes or reservoirs and would be uniform throughout the seasons. Also, since sufficient information on Lake Turkana ETf and  $Q_{\text{seep}}$  are not available in literature, an ETf and  $Q_{\text{seep}}$  were assumed to be equal to one and zero, respectively in the initial model run. Not accounting for ETf and  $Q_{\text{seep}}$  in lakes and reservoirs could lead to errors in magnitude while performing water balance of the lake. Hence, during the calibration of magnitude, values for ETf were varied from 0.5 to 1.0 (with an increment of 0.05), and values for  $Q_{\text{seep}}$   $\text{day}^{-1}$  were varied from 0 to 5  $\text{mm day}^{-1}$  (with an increment of 1 mm) for each iteration. Lake levels modelled using different combinations of varying ETf and  $Q_{\text{seep}}$  were compared with satellite altimetry data, and the parameters that provided minimum value of mean absolute error were selected.

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### 3.4.2 Estimation of lag time

Any observed lags in hydrological model predictions are due to the time delay in runoff before it reaches the sink. Most hydrological models with cell-to-cell routing algorithms account for this time delay. Any lags seen in the lake levels modelled using the LLM approach could be attributed to a lack of a routing algorithm. Calibration of the model was performed to compensate for the lag time in the modelled lake levels. First, flow length was estimated using SRTM elevation data. Since flow velocity data from the Omo River was not available, average flow velocities recorded in different locations along the Omo River were obtained from literature. EEPKO (2009) recorded flow velocities in the upper Omo Sub-Basins and the mean flow velocities ranged from 0.1 to 1.2 m s<sup>-1</sup>. As the flow length and range of flow velocities are known, lag time for each value of flow velocity from 0.1 m s<sup>-1</sup> to 1.2 m s<sup>-1</sup> (with an increment of 0.1 m s<sup>-1</sup>) was estimated as follows:

$$\text{Lag Time} = \text{Flow length} \div \text{Flow velocity} \quad (7)$$

Lag times for each flow velocity are introduced into the model, and the lag time that produces minimum MAE when compared to altimetry data is chosen. Lag time are also estimated using several first order approaches for consideration and comparison. It is to be noted that most of the simplified methods shown in Table 2 are empirical and/or developed for small watersheds.

### 3.5 Validation of modelled lake water levels using satellite altimetry data

Ideally, in-situ observations of lake levels are required for validating modelled estimates. But for Lake Turkana, such in-situ observations of lake water levels are not available. This is particularly true in most ungauged basins. Therefore, modelled Lake Turkana water levels are validated using satellite altimetry data estimated from TOPEX/Poseidon (T/P), Jason-1, and ENVISAT. T/P is a joint space mission conducted by the United States and France primarily designed to measure sea-surface heights

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since 1992 (Fu et al., 1994). Jason-1 is the T/P follow-on mission and has been measuring ocean surface topography since December 2001. Both T/P and Jason-1 data have also been widely used to study inland lake level variations (Birkett, 1995). Moreover, lake levels derived from satellite altimetry data are highly reliable with errors in the order of a few centimeters (Morris and Gill, 1994; Birkett, 1995; Alsdrof et al., 2001). Hence, satellite altimetry data are considered as proxy to in-situ lake level measurements and used for model validation.

### 3.6 Model accuracy

Model results were compared with the altimetry data to evaluate the model performance. Pearson's correlation coefficient ( $r$ ) is estimated to observe the degree of relationship between the modeled lake levels and satellite altimetry data for calibrated, un-calibrated and combined data. Improvements in  $r$  for each dataset are tested for significance using Fisher's z-test. Further, to derive statistical "goodness of fit" of the simulated lake water levels, several statistical estimates are computed. First, root mean square error (RMSE) was computed using the following equation:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{N}} \quad (8)$$

where  $P$  is the modelled lake water level,  $O$  is the altimetry lake water level,  $N$  is the total number of observations, and  $i$  represents time step.

Willmott and Matsuura (2005) reported that mean absolute error (MAE) is more appropriate over RMSE in assessing average model performance because MAE is not influenced by large errors. MAE was computed using the following equation:

$$\text{MAE} = \frac{\sum_{i=1}^n |P_i - O_i|}{N} \quad (9)$$

Also, a widely used measure in hydrology, the Nash-Sutcliffe Coefficient of Efficiency (NSCE), was used to compute the model efficiency. The advantage of NSCE is that it

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accounts for the model errors in estimating the mean of the observed datasets. The NSCE is an indicator of the model's ability to predict about the 1 : 1 line (Nash and Sutcliffe, 1970). A value of 1 represents a perfect match and value of 0 or less is no more accurate than predicting the mean value. NSCE was computed using the following equation:

$$NSCE = 1 - \frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (10)$$

where  $\bar{O}$  is the mean value of the observed variable. Finally, mean bias error (MBE) between the modelled lake water levels and satellite measurements is computed using the following equation:

$$MBE = \frac{1}{N} \sum_{i=1}^N P_i - O_i \quad (11)$$

To understand the significance of each estimate of error statistic, percent error with respect to the long-term natural variability of Lake Turkana water levels was computed. Modelled lake level data from January 2001 to December 2009 were used for the accuracy assessment.

## 4 Results

### 4.1 Modelled lake levels

Modelled Lake Turkana water levels from January 1998 to December 2009 are shown in Fig. 3. Visual analyses of patterns observed in modelled lake levels show that seasonal variations and patterns in lake water levels are captured reasonably well. Since the end of 1998, lake water levels gradually declined until mid-2006. However, after mid-2006, the model showed a steep increase in the lake water levels up to mid-2007

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and then gradually decreased by the end of 2009. In this section, the patterns observed in the modelled lake levels are compared with rainfall and climatic patterns observed in the region. For comparison purpose, the lake water level variations for 1998–2007 are divided into five time periods. The trends observed in each time period are compared with general rainfall trends and are supported by citations from literature.

*Period 1 (1998):* The model results show an increase in the lake water level up to 2 m until end of 1998. The 1997–1998 El Niño caused heavy rains over East Africa (Galvin et al., 2001; Behera, et al., 2005). Anyamba et al. (2001) reported that during this period, East Africa had above normal NDVI due to excess rainfall, and Southern Africa had below normal NDVI due to a rainfall deficit. This trend is captured by the model (Fig. 3). This increase in the trend up to 2 m of lake water level shown by the model is corroborated by Birkett et al. (1999), who reported a nearly 2 m increase in Lake Turkana water levels during this time period.

*Period 2 (1999–2002):* After the heavy El Niño rains in 1998, there was a prolonged dry period for four consecutive years until 2003. WFP (2000) reported that drought in 1999 was estimated as the worst on record for East Africa. Furthermore, Anyamba et al. (2002) reported that most of the Horn of Africa had NDVI deficits on the order of 30 % to 80 % below normal. The model results show that the lake water levels decreased gradually until 2003. As a result of dry weather and possibly very high ET losses, the lake water levels dropped 2 to 3 meters during this period.

*Period 3 (2003–2006):* As the Turkana Basin experienced below normal rainfall during this period, modelled lake water levels show that water levels declined steeply and reached a minimum lake level observed during the 1998–2009 time period.

*Period 4 (2006–2007):* The model results for this period show a steep increase in the lake water levels. This increase is caused by high runoff generated by heavy rains that occurred in 2006 and 2007. The model estimated that the lake water levels increases up to 4 m because of the heavy rainfall and subsequent floods in Ethiopia in 2006 and early 2007. The Disaster Preparedness and Prevention Agency (DPPA) of Ethiopia confirmed that the floods in the Southern Omo River Valley killed 364 people

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and displaced approximately 1000 people (IFRC, 2006). Moreover, Moges et al. (2010) reported that the 2006 floods in Ethiopia were exceptionally severe by intensity, water volume, geographical coverage, and magnitude of damage.

*Period 5 (2008–2009):* During this period, modelled lake levels show a gradual decrease, with lake levels dropping up to 2 m because of normal to below normal rainfall in 2008 and 2009.

## 4.2 Uncertainties in LLM approach

The relationships between rainfall, runoff and ET on changes in Lake Turkana water level are shown in Fig. 4. The monthly data is classified into wet and dry months with respect to the lake, where wet and dry months correspond to the months when lake level increase and decrease, respectively. It is to be noted in Fig. 4a that relationship between rainfall and lake level changes is not always linear as rainfall has to meet the soil moisture and other storage demands in the basin, before generating runoff. On the other hand, once the runoff is generated and reaches the lake, it shows a linear relationship with the lake level changes (Fig. 4b). However, basin runoff/inflows have to be more than evaporative demand of the lake to cause a net increase in lake levels. Figure 4c shows that ET over wet months does not show any relation. However, it shows a strong relation over the dry months, when the effect of ET on the lake level changes is substantial.

Using relationships derived in Fig. 4 the impact of the errors on the lake water levels are estimated. We assume that the errors in RFE 1.0 are minimal. It is found that the bias in RFE data ( $-0.15 \text{ mm d}^{-1}$ ) would translate up to  $1 \text{ cm month}^{-1}$  of error in the modelled lake levels during peak rainy seasons (March to June and September to November). The runoff coefficient of 0.21 is obtained from monthly analysis between rainfall and modelled runoff data. Using this coefficient, the error in monthly runoff data is estimated to be up to  $0.3 \text{ mm month}^{-1}$  which would further introduce up to  $2.5 \text{ cm month}^{-1}$  of error in the modelled lake level data over peak rainy seasons. Together, rainfall and runoff would result up to an error of  $3.5 \text{ cm month}^{-1}$ . The magnitude

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of error during other months would be less as the number of days of rainfall would be low. Assuming consistent errors globally, errors in the ET data (up to 5% underestimation) are introduced in the model and its impact on the modelled lake levels is estimated using the relationship obtained in Fig. 4c. Our results indicate that errors in ET data would translate up to 4 to 5 cm month<sup>-1</sup> of error in lake levels and would perhaps cancel out the RFE and runoff errors to some extent. More evaluation is needed to understand the impact of these errors on lake level dynamics.

### 4.3 Model calibration

#### 4.3.1 Calibration of magnitude

The MAE for different combinations of varying ETf and  $Q_{\text{seep}}$  ranged from 0.32 to 2.39 m. An ETf value of 0.75 and  $Q_{\text{seep}}$  value of 2 mm d<sup>-1</sup> provided least MAE (0.32 m) when compared to the satellite altimetry data. Hence these parameter estimates are considered for further modelling. The errors in the model and input datasets used in the LLM model are corrected during this process.

#### 4.3.2 Calibration of lag time

The flow length of 790 km is estimated using SRTM based on the longest path runoff would travel before entering Lake Turkana. Using flow length estimate, lag times of up to 3 months were obtained for different sets of flow velocity values. Since the model is run at monthly time steps, all the lag times that were less than a month are ignored and only lag of a month and greater are introduced into the model. MAE for modelled lake levels with lag periods of 1, 2, and 3 months are 0.29, 0.30, and 0.37 m, respectively. Since, a lag of one month provided least MAE, it is considered for further modeling.

Table 2 shows the lag time estimated using several simple approaches. However, lags estimated for Omo River using different approaches were found to range from 3 to 43 days. One of the reasons for this inconsistency is because the simplified equations

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used in this analysis were developed for small agricultural watersheds and/or totally empirical. Since there was no consistency in the lag estimates derived using different approaches, lag time estimated using the calibration process was chosen for further model testing and validation. However, it is interesting to note that methods such as

- 5 Simplified Manning's Equation, Upland Velocity Method, Kinematic Wave Method and Manning's Kinematic Equations gave closer estimates of lag time of 1 month obtained from the calibration process.

#### 4.4 Model validation using satellite altimetry data

Modelled lake levels are validated using lake level estimated from satellite altimetry data. Figure 5a shows the comparison of un-calibrated modelled lake levels with altimetry-based lake levels. It is evident from Fig. 5a that the patterns and seasonal variations in water level fluctuations are captured reasonably by the model. However, the un-calibrated model shows a difference in magnitude and lag shift when compared to the altimetry data with MAE of 0.88 m. After considering ET<sub>f</sub> of 0.75 and  $Q_{seep}$  of

15  $2 \text{ mm d}^{-1}$ , the magnitude difference in modelled vs. altimetry was reduced with MAE of 0.48 m over the validation period (Fig. 5b). Further, after calibration of lag, the modelled lake levels match reasonably well with the satellite altimetry data with a MAE of 0.46 m over the validation period (Fig. 5c). Mean basin total monthly rainfall, modelled ET, runoff, are illustrated in Fig. 6a–6c. Modelled monthly lake water levels from

20 January 1998 to December 2009 are illustrated against altimetry data in Fig. 6d. Possible reasons for the errors observed between the model and altimetry-based lake level estimates are listed here.

In the LLM approach, the model-based lake water levels are primarily driven by runoff and ET. The increase in the lake water levels is driven by the runoff derived from the rainfall estimates. The differences seen while the lake water levels are increasing could be attributed to inaccuracies in the satellite rainfall estimates or the modelling errors. On the other hand, the decline in the lake water levels is mostly dependent on the

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over-the-lake ET and seepage losses. The slope of the declining trend as seen in modelled lake levels matches reasonably well with the altimetry data, which means that the error contributed from ET, could be minimal.

The wetland complex located in the Omo River Delta could act as temporary reservoir and possibly reduce the flow rate which could result in the errors in the modelled estimates. Another reason for the difference could be caused by small percentage of subsurface groundwater drainage occurring in the basin. Information on the subsurface drainage occurring in the upper Turkana Basin is not available. Other sources of discrepancy in modelled lake levels could be also due to (a) changes in lake surface pressure (b) wind-driven events or tides (c) fluctuations in the volume of the column due to an alternating temperature or composition, which could also influence lake water levels (Mercier et al., 2002). Further, much of the differences in lake levels are observed during the peak rainy season. This is because, during heavy rains, water floods over the low lying areas along the river reaches and causes high ET losses over the flood plains. Subsequently, vegetation cover increases after the floods recede and in turn causes a reduction in the volume of runoff reaching the lake due to higher ET, interception losses, and reduced stream flow over the flood plains. The greatest discrepancy between the modelled and the satellite-based estimates is seen in 2007. This might be due to heavy rains that occurred in the later part of 2006 and early 2007 (IFRC, 2006; Moges et al., 2010). Modelled runoff in 2006 is found to be very high when compared to other years. A similar trend was observed for 2007 runoff (Fig. 6a,c), which could have triggered the lake levels to rise higher than the satellite altimeter estimates. Furthermore, such incidents of unusually high rainfall could also result in errors in the modelled runoff would have a direct influence on the modelled lake levels.

Minor discrepancies seen after 2003 can be also explained by the Gilgel gibe hydro-electric dam-I on the lower Omo River commissioned in 2004. The impact of the dam on the lake water levels is not clearly understood. However, it can be assumed that with the production of electricity, much of the runoff is released back to the river with a delay. Further, ET losses from the reservoir would also decrease the total volume

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of water that would end up in the lake and could subsequently lead to the delay in the lake level hydrograph. The effect of the Gibe-I dam on the lake levels is not modelled as information on the operational strategies for the dam is unavailable.

In spite of these differences, the LLM approach offers a simple solution to managers and decision makers especially in ungauged basins. The multi-sensor based physical hydrologic model presented here could support operational monitoring needs for which the trends and patterns of lake level variations are more important. However, in applications where precise day-to-day lake levels are required, an inclusion of a routing algorithm is recommended. The power of this method lies in its ability to simulate the lake water level variations fairly well using satellite-based estimates when only limited ancillary data or ground-based observations are available.

Annual trends in lake water level variations are derived for both satellite and modelled lake water levels (Fig. 7). The results indicate that even the un-calibrated model could capture the long-term trends reasonably well. Further, calibrated modelled lake levels capture the observed trends very well. Hence, the approach presented here can be used to model the long-term historic trends of several ungauged lakes and reservoirs with reasonable accuracy even when limited ground truth data are available. This method will be particularly useful for decision making where anomalies and patterns are important.

#### 4.5 Model accuracy

Accuracy assessment is performed by comparing modelled lake water levels with the estimates from satellite altimetry data (Table 3). The un-calibrated modelled lake water levels and the satellite measurements yielded a reasonable degree of correlation with Pearson's correlation coefficient ( $r$ ) values of 0.73, 0.60 and 0.71 for calibration, validation and combined periods. On the other hand, calibrated lake levels showed high degree of correlation with correlation coefficient ( $r$ ) values of 0.87, 0.81 and 0.88 for calibration, validation and combined time periods, respectively. These improvements in  $r$  values after calibration were found to be significant with  $z$  values of 1.64, 3.14 and

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4.1, respectively at 95% confidence. Error statistics in Table 3 were estimated using calibrated lake levels (magnitude + lag) for calibration, validation and combined time periods. The model efficiency estimated using NSCE is found to be 0.93, 0.55 and 0.66 for calibration, validation and combined periods, respectively. For the validation period, the RMSE and MAE were found to be 0.62 m and 0.46 m, respectively and the model showed a positive MAE mean bias error of 0.36 m. The MAE, RMSE and bias are found to be 10%, 13% and 8% of the long-term natural variability observed for Lake Turkana (4.8 m), respectively. As a result, the LLM approach can be used to model lake levels with confidence. Figure 8 illustrates scatter plot between the modelled and the satellite altimetry measurements. The modelled versus satellite altimetry data lie reasonably close to 1 : 1 line except for the year 2007.

## 5 Discussion

The objective of this paper is to present an approach that would supplement current satellite altimetry based systems to monitor variations in lake water levels and support operational monitoring in ungauged basins. The approach presented here can derive lake water levels using readily available satellite-derived data such as rainfall, modelled runoff, and ET data even when limited ground truth observations are available. Although the accuracy of un-calibrated modelled estimates is low, this method can be conveniently used to study the long-term patterns in lake level variations when ground truth data are not available. Model accuracy was significantly improved when calibrated with limited ground truth data. Further, this approach can be easily applied to other lakes that are not being continuously monitored. The specific advantages and limitations of this approach are discussed here.

The advantages of using the LLM approach are its ability to (a) reasonably simulate variations in lake water levels; (b) capture seasonal variations in lake water levels; (c) monitor lakes/reservoirs in areas where in-situ lake level data are not available; and (d) to model lake water levels using cost-free satellite data. The LLM approach

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can be used to monitor lakes where satellite altimetry observations are not available. The satellite altimetry estimates of lake levels are only available on those lakes that opportunistically lie beneath the orbital tracks of the satellites. Thus, LLM approach can be used to supplement data provided by the satellite altimetry systems by modelling water levels in lakes and reservoirs that are not being currently monitored.

Detection of changes in flow regimes is important for operational monitoring applications such as the enforcement of international water sharing agreements. When used in conjunction with reliable satellite estimates or the ground truth observations of lake water levels, the LLM framework can be used to identify such changes. Ideally, in the water balance approach, water levels in closed lakes are primarily driven by rainfall and ET; therefore, the lake levels derived using the LLM approach would infer “what ought to be” scenarios or natural lake levels which are not impacted by any of the basin level disturbances. This is especially true in case of LLM approach as the model assumes no changes in land cover/land use (LCLU) other than rainfall and ET. In the real world, the actual water levels in the lakes are not only driven by rainfall and ET but also affected by human actions such as sudden LCLU change, irrigation water use, or newly imposed regulations or construction of dams upstream. Such sudden changes in upstream water use patterns are not accounted in water balance models, which would result in deviations in the model predictions from observations. Since the T/P and Jason-1 satellite altimetry data or the ground truth data measure the actual water levels in the lakes, they represent “what it is” scenarios (total impact of climate and human actions). Assuming constant modelling errors in the modelled lake level estimates when compared to satellite observations, any abrupt variations in the lake levels could indicate changes in lake inflows due to human actions. Hence, the LLM approach could also be used to study the impact of human actions on the lake water levels.

This hypothesis would help to study the potential impact of such basin developmental activities or resultant land use/land cover changes on the downstream water resources. The inclusion of phenology based on real-time NDVI instead of climatological

NDVI would account for such land cover changes; therefore, the model would allow researchers to study or simulate the impact of various land use/land cover changes such as irrigation, deforestation, forest fires, or slash and burn agriculture on basin hydrology. Operation managers could use such information as a trigger to initiate more intensive in-situ investigations.

Moreover, since this approach is based on climatological variables (rainfall, runoff, and ET), it is possible to assess the impacts of climate on lake water levels when data over longer time periods (>30 yr) are available. With current concerns about climate change, the ability to simulate lake level variations under different climate and LCLU scenarios makes the model an important tool in understanding local climate impacts and planning adaptation measures. This is a distinct advantage over satellite altimetry methods which cannot be used in a predictive mode to study the impact of changes in the watershed. However, further investigation is required in this direction.

The limitations or uncertainties in LLM approach are (a) lake depths cannot be simulated precisely because of inaccuracies in the input data and hydrological model (b) this approach cannot close the water balance particularly in lakes where outflows are significant and un-quantified or where inflows are heavily regulated and unknown (c) for complex basins, information on more parameters would be required to close the water balance which could be a challenging task especially in ungauged basin (d) lack of ground truth data or gauge observation for model calibration and validation is a problem when precise lake level estimates are required.

Future NASA missions such as Global Precipitation Measurement (GPM) and the Visible Infrared Imager Radiometer Suite sensor on board the National Polar Orbiting Operational Environmental Satellite System (NPOESS) will enable reliable estimation of climate variables and improve the accuracy of rainfall and ET products, making LLM approach more useful.

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## 6 Conclusions

The lake level modelling approach presented here uses satellite-derived rainfall and modelled runoff and ET data. This modelling approach is particularly important to monitor lake water levels in ungauged basins where available data are either limited or unavailable. The LLM approach can be used to delineate historical lake water levels when satellite-based rainfall estimates are available. The model presented here is used to derive Lake Turkana water level variations over 12 yr (1998–2009). The major findings of this research are:

1. Using rainfall, modelled ETa, runoff, and other satellite data, the LLM approach can be used to monitor lake water level variations.
2. The model results showed that the LLM approach could reasonably capture the patterns and seasonal variations of the lake water level fluctuations including the effect of El Niño in 1998 and the effect of drought in 2000.
3. Lake Turkana water levels derived from the T/P, Jason-1, and ENVISAT satellite altimetry data is used for model calibration and validation.
4. Model validation results showed that calibrated lake levels showed a significant improvement in correlation when compared to un-calibrated lake levels.
5. When compared to the satellite estimates, the modelled lake water levels showed a Pearson's correlation coefficient value of 0.81 during the validation period (2001–2009).
6. During the validation period, the RMSE, MAE and bias were found to be 0.62, 0.46 and 0.36 m, respectively. These estimates were found to be less than 15% of the natural variability observed in the lake, thus giving high confidence on the modelled lake level estimates.

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*Acknowledgements.* This work was made possible by the funding of Applied Science Program of NASA Earth-Sun System Division contract # NNA06CH751 in collaboration with USGS EROS center.

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**Table 1.** Satellite data and products used in the lake level modelling (LLM) approach.

No	Data	Satellite sensor/ source	Frequency	Resolution/ scale	Reference
1	Rainfall estimate for Africa	SSM/I, AMSU	Daily	$0.1^\circ \times 0.1^\circ$	Herman et al. (1997); Xie and Arkin (1996)
2	Global GDAS reference ET	Model assimilated satellite data	Daily	$0.1^\circ \times 0.1^\circ$	Senay et al. (2008)
3	Climatological NDVI	NOAA AVHRR	Dekadal	8 km	Tucker et al. (2006)
4	Digital soil map of the world	National statistics	Single date	1 : 5 000 000	FAO (1995)
5	Global percent tree cover map	MODIS VCF	Single date	500 m	Hansen et al. (2003)
6	Digital elevation model	SRTM	Single date	90 m	Farr et al. (2000)
7	Lake Turkana water levels	TOPEX/Poseidon, Jason-1, ENVISAT	Daily	> 200 m	Birkett (1995)

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**Table 2.** Lag time for Omo River estimated using simple approaches.

Sl. no	Method used	$T_c$ for Omo River (days)	Equations	Reference <sup>b</sup>
1	Simplified Manning's equation	43	$T_c = L / (KS^{0.5})$	NRCS (1986)
2	Upland velocity method	43	$T_c = (L/V)^a$	McCuen (1998)
3	Kinematic wave method	24	$T_c = (0.0938 L^{0.6} n^{0.6}) / (i^{0.4} S^{0.3})$	Woolhiser and Liggett (1967)
4	Manning's kinematic equation	48	$T_c = 0.42 / P_2^{0.5} (nL / S^{0.5})^{0.8}$	Welle and Woodward (1986)
5	SCS lag formula	14	$T_c = 0.00526 L^{0.8} ((1000/CN) - 9)^{0.7} S^{-0.5}$	McCuen (1998)
6	Kirpich's method	3	$T_c = 0.0078 L^{0.77} S^{-0.385}$	Kirpich (1940)
7	Simplified kinematic wave method	3	$T_c = 1.2(nL / S^{0.5})^{0.6}$	Yen and Chow (1983)

**Notes:**

$T_c$  is the estimated lag time for the Omo River in days.

$L$  is the flow length estimated using SRTM elevation data ( $L = 791410$  m or  $2596480$  ft).

$S$  is the overall slope of the Omo River estimated using SRTM elevation data ( $S = 0.003$  m m<sup>-1</sup> or  $0.01$  ft ft<sup>-1</sup> or  $0.3\%$ ).

$n$  is the Manning roughness coefficient for natural streams – major rivers ( $n = 0.035$ ).

$K$  is the roughness parameter or the intercept coefficient ( $K = 7.0$ ).

$i$  is the intensity of rainfall computed using RFE rainfall data ( $i = 0.08$  mm hr<sup>-1</sup> or  $0.003$  ft hr<sup>-1</sup>).

CN is the curve number (CN number for Omo-River Basin =  $74.8$ ).

$P_2$  is 2 yr 24 h rainfall estimated using RFE rainfall data ( $P_2 = 3.25$  mm hr<sup>-1</sup> or  $0.13$  in hr<sup>-1</sup>).

<sup>a</sup>  $V$  estimated as  $0.21$  m s<sup>-1</sup> or  $0.7$  ft s<sup>-1</sup> from nomograph as a function of slope,  $S$ .

<sup>b</sup> References for the methods used in this study to estimate the lag independently for the Omo River.

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**Table 3.** Results of calibration and accuracy assessment of modeled lake water levels using satellite altimetry data.

Dataset	Calibration period (1998–2000)	Validation period (2001–2009)	Combined period (1998–2009)
Pearson's correlation coefficient ( $r$ ):			
Un-calibrated	0.73 <sup>a</sup>	0.60 <sup>a</sup>	0.71 <sup>a</sup>
Calibrated (magnitude)	0.79 <sup>a</sup>	0.74 <sup>a</sup>	0.83 <sup>a</sup>
Calibrated (magnitude + lag)	0.87 <sup>a</sup>	0.81 <sup>a</sup>	0.88 <sup>a</sup>
Error statistic <sup>b</sup> (units):			
RMSE (m)	0.32 (7 %)	0.62 (13 %)	0.57 (12 %)
MAE (m)	0.29 (6 %)	0.46 (10 %)	0.42 (9 %)
Bias (m)	0.14 (3 %)	0.36 (8 %)	0.31 (6 %)
NCSE (no units)	0.93	0.55	0.66

<sup>a</sup>  $p$ -value  $\leq 0.001$ .

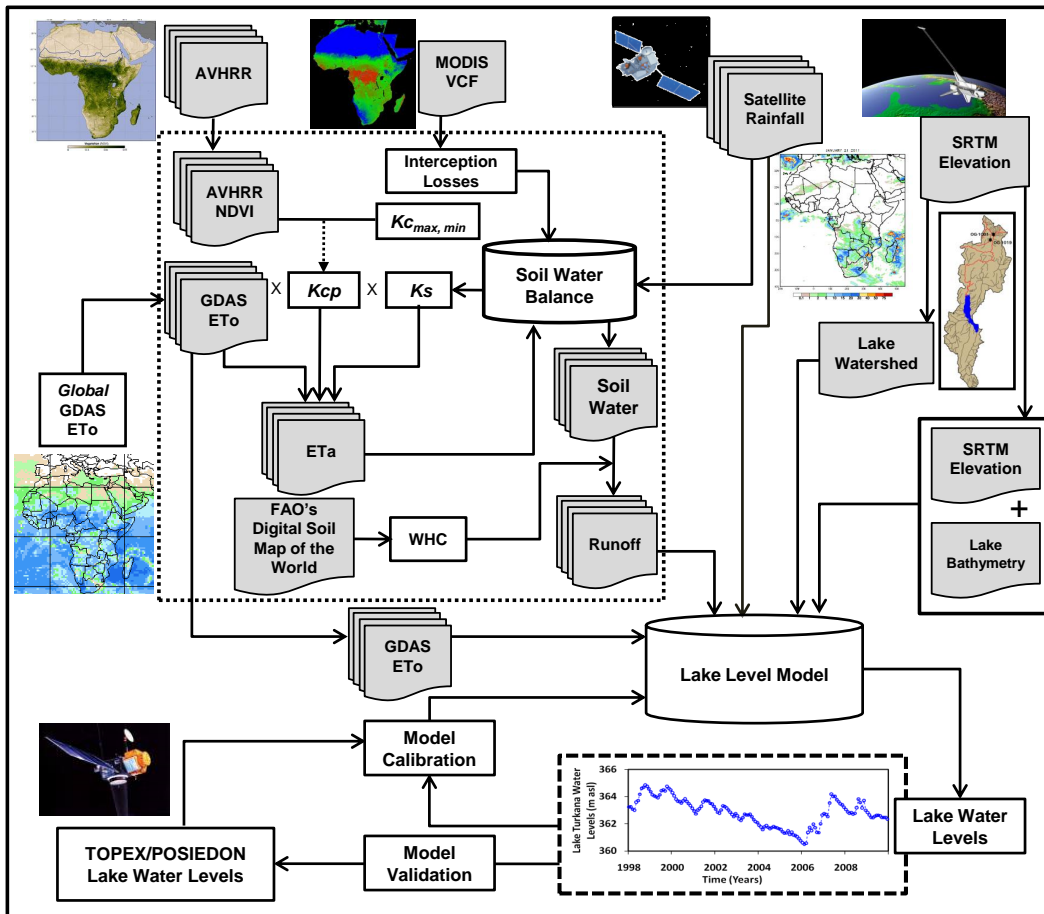
<sup>b</sup> Error statistic estimates are made using calibrated data (magnitude + lag).

Note: Value next to estimate of each error statistic denote percent error with respect to the natural lake level variability of 4.8 m.



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**Fig. 1.** Flowchart showing lake level modelling (LLM) approach using multi-source satellite data.

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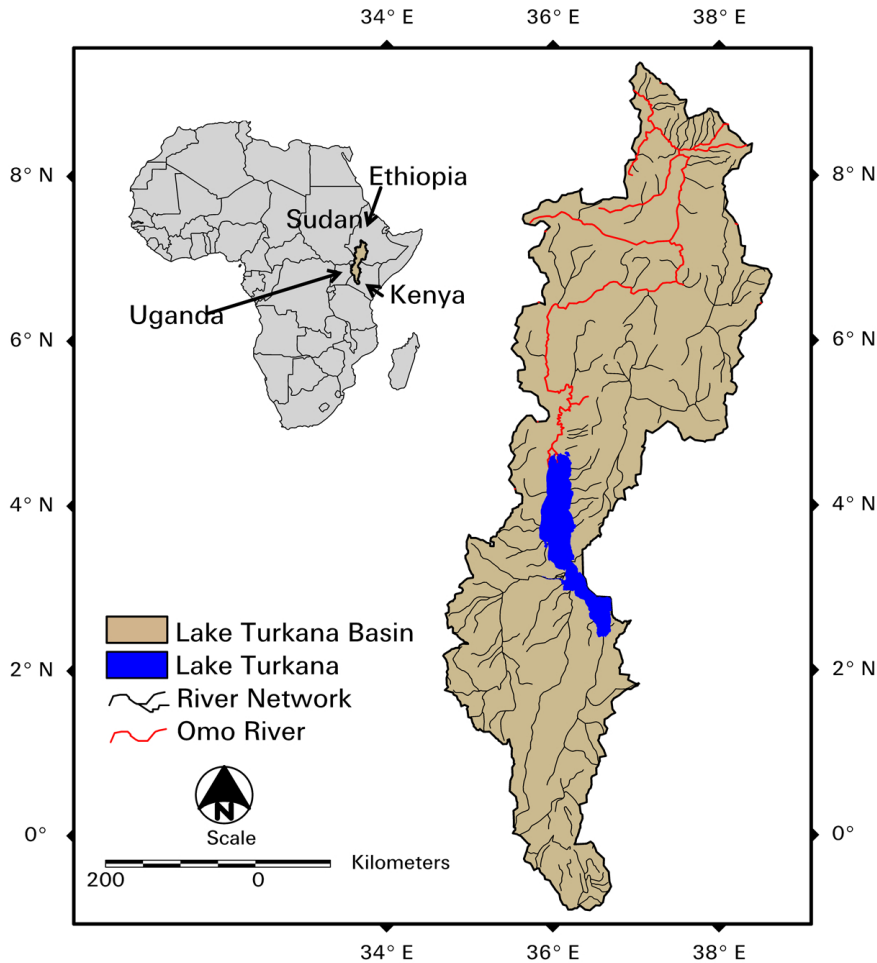
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**Fig. 2.** Map of the study area showing spatial extent of the Lake Turkana Basin in East Africa.

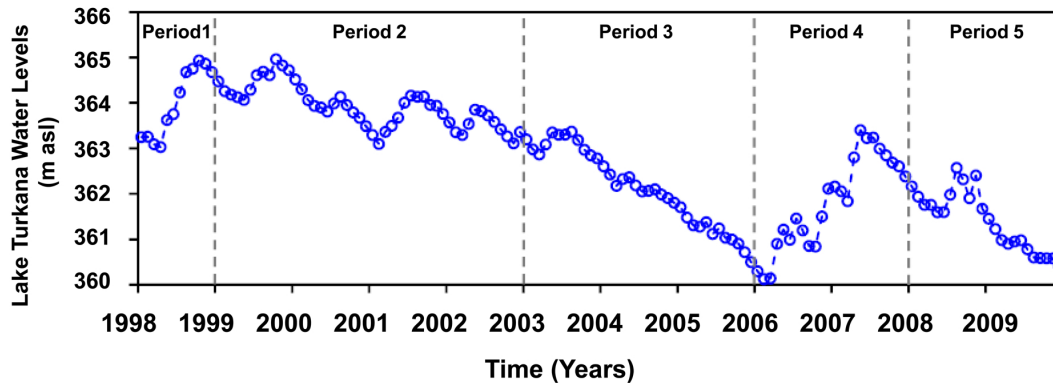
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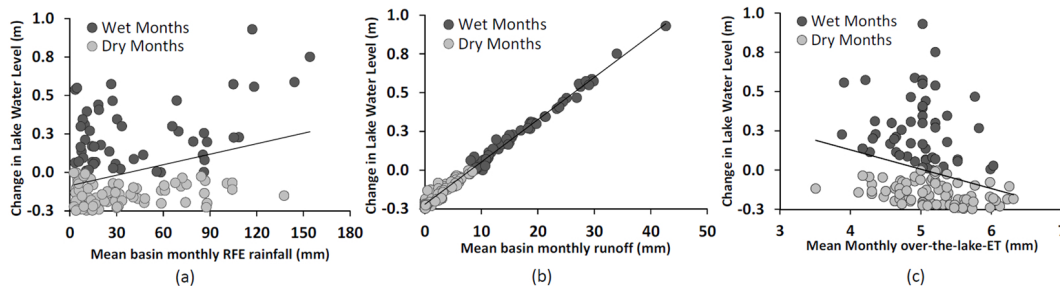


**Fig. 3.** Lake Turkana water levels modelled using the lake level modelling approach and multi-source satellite data. Estimated errors with respect to the modelled runoff and ET data are too small to be visible with respect to the data points.

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**Fig. 4.** Relationship between key model parameters and change in Lake Turkana water levels: **(a)** relationship between mean basin monthly RFE rainfall and change in lake water levels ( $Y = 0.0023X - 0.0863$ ); **(b)** relationship between mean monthly runoff and change in lake water levels; ( $Y = 0.0273X - 0.2205$ ) and **(c)** effect of ET on change in lake water ( $Y = -0.1236X + 0.6231$ ). All the trend lines and equations are derived using combined data (Wet + dry months). Monthly data from 1998–2009 is used in this analysis.

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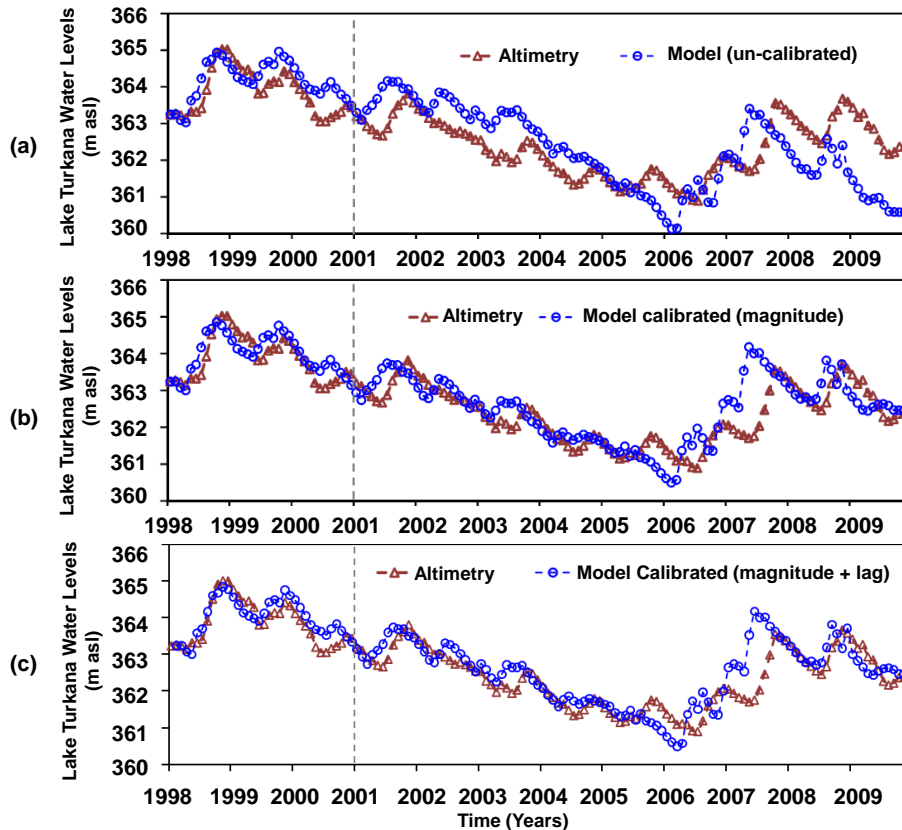
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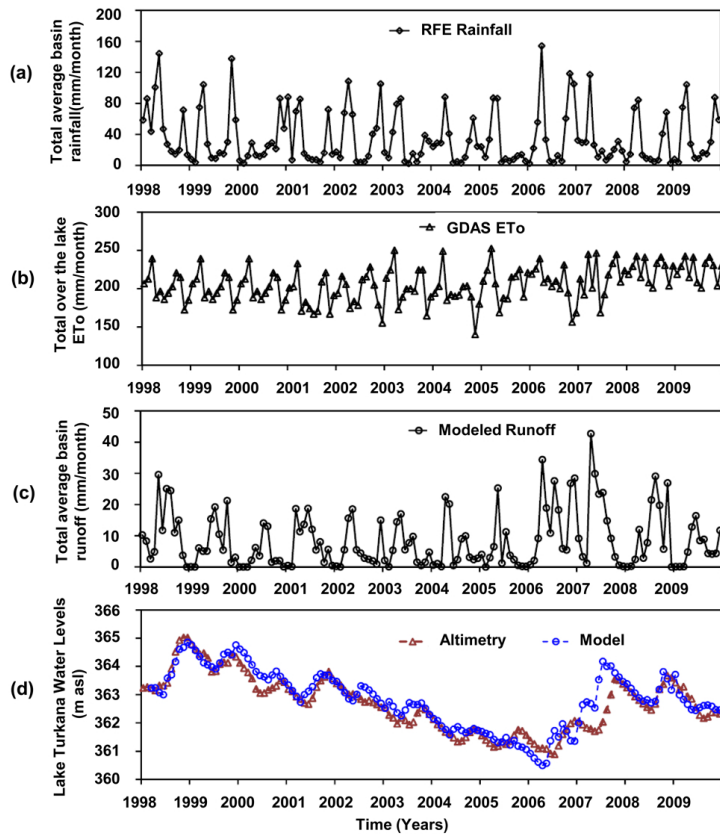
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**Fig. 5.** Comparison of Lake Turkana water levels modelled using the LLM approach and satellite altimetry data: **(a)** un-calibrated lake levels ( $ET_f = 1.0$  and  $Q_{seep} = 0$ ), **(b)** calibrated lake levels for magnitude ( $ET_f = 0.75$  and  $Q_{seep} = 2 \text{ mm d}^{-1}$ ) **(c)** calibrated lake levels for magnitude plus lag ( $ET_f = 0.75$ ;  $Q_{seep} = 2 \text{ mm d}^{-1}$  and lag = 1 month). The calibration is performed on data from 1998 to 2000 and the model is validated using data from 2001 to 2009.

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**Fig. 6.** (a) Total average basin rainfall ( $\text{mm month}^{-1}$ ) modeled using satellite rainfall estimates. (b) Total over-the-lake ETo ( $\text{mm month}^{-1}$ ) estimated from GDAS ETo. (c) Total average basin runoff ( $\text{mm month}^{-1}$ ) modeled for the Turkana Basin. (d) Lake Turkana water levels for 1998–2009. Modelled daily lake levels (in blue) and lake levels estimates from TOPEX/Poseidon (T/P), Jason-1, and ENVISAT satellite altimetry data (in brown).

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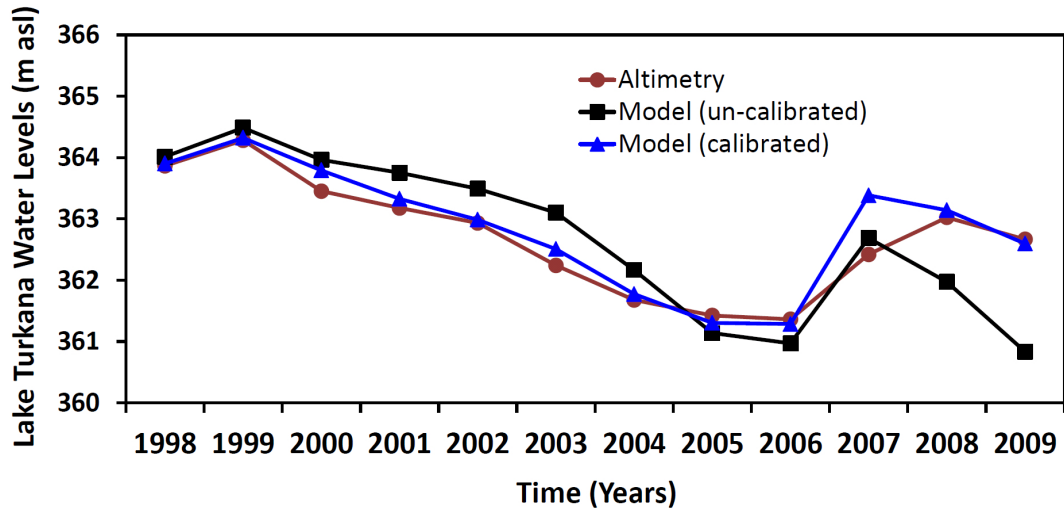
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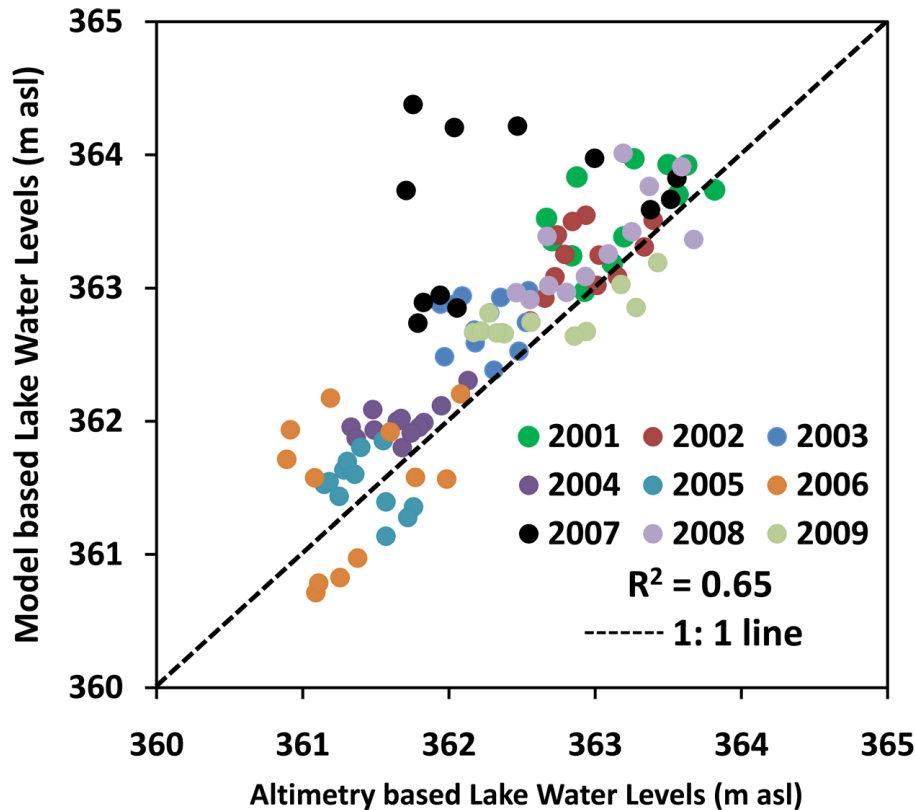
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**Fig. 7.** Mean annual lake water levels derived from modelled lake levels and satellite altimeter data.

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**Fig. 8.** Scatter plot of modelled lake water levels and satellite altimetry data showing a Pearson's correlation of 0.81 ( $R^2 = 0.65$ ). Each point represents mean monthly modelled lake water levels (calibrated for magnitude + lag) over the validation period (January 2001 through December 2009).

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