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From skin to bulk: An adjustment technique for assimilation of satellite-derived temperature observations in numerical models of small inland water bodies

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ABSTRACT

Data Assimilation (DA) has been proposed for multiple water resources studies that require rapid employment of incoming observations to update and improve accuracy of operational prediction models. The usefulness of DA approaches in assimilating water temperature observations from different types of monitoring technologies (e.g., remote sensing and in-situ sensors) into numerical models of in-land water bodies (e.g., lakes and reservoirs) has, however, received limited attention. In contrast to in-situ temperature sensors, remote sensing technologies (e.g., satellites) provide the benefit of collecting measurements with better X-Y spatial coverage. However, assimilating water temperature measurements from satellites can introduce biases in the updated numerical model of water bodies because the physical region represented by these measurements do not directly correspond with the numerical model's representation of the water column. This study proposes a novel approach to address this representation challenge by coupling a skin temperature adjustment technique based on available air and in-situ water temperature observations, with an ensemble Kalman filter based data assimilation technique. Additionally, the proposed approach used in this study for four-dimensional analysis of a reservoir provides reasonably accurate surface layer and water column temperature forecasts, in spite of the use of a fairly small ensemble. Application of the methodology on a test site - Eagle Creek Reservoir - in Central Indiana demonstrated that assimilation of remotely sensed skin temperature data using the proposed approach improved the overall root mean square difference between modeled surface layer temperatures and the adjusted remotely sensed skin temperature observations from 5.6°C to 0.51°C (i.e., 91% improvement). In addition, the overall error in the water column temperature predictions when compared with in-situ observations also decreased from 1.95°C (before assimilation) to 1.42°C (after assimilation), thereby, giving a 27% improvement in errors. In contrast, doing data assimilation without the proposed temperature adjustment would have increased this error to 1.98°C (i.e., 1.5% deterioration).

1. Introduction

Management of water quality in in-land water bodies, such as lakes and reservoirs, is critical for minimizing human and ecological risks from contaminants. In the 1999 Drinking Water Infrastructure Needs Survey conducted by the Environmental Protection Agency (EPA), it was reported that an investment of $150 billion in drinking water systems over a 20-year period will be needed to ensure clean and safe drinking water (United States 2009). Water column temperature is among the primary factors that affect water quality because of its significant impact on mixing processes and rate kinetics of multiple contaminants (Babbar-Sebens et al., 2013). Vertical stratification caused by temperature affects vertical exchanges of mass, energy and momentum within the water column (Piccolroaz et al., 2013). Hence, numerical water quality models that predict spatio-temporal changes in water column temperature have become critical tools for water managers operating lakes and reservoirs for human use and consumption (Jin and Ji, 2004; Tetra Tech, 2009; United States Environmental Protection Agency (USEPA) 2002). However, the prediction efficiency of such models is dependent on multiple parameters and state variables that must be calibrated using all available data. While calibration techniques help improve the consistency between the model predictions and

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historic observations (Duan et al., 1992, 1993, 2003; Gupta et al., 1998; Sorooshian et al., 1993), they are not enough to ensure that a well-calibrated model will continue to predict accurately under operational and evolving conditions in water bodies.

For time dependent water quality numerical models, sequential data assimilation techniques can be used towards continued updating of an operational model's state variables, as and when new observations of the changing system become available (Evensen, 2007). A data assimilation process also has the potential to reduce uncertainty in prediction by integrating real-time observations from a variety of monitoring technologies (Moradkhani, 2008). However, using diverse data sources for updating water quality models requires an understanding of both strengths and limitations of individual data sources that may impact the assimilation process (Babbar-Sebens et al., 2013; Moradkhani, 2008). For example, Satellites provide spatially-dense observations of skin temperature in water bodies. But they cannot be used to obtain sub-surface parameters, and have limited temporal resolution. On the other hand, in-situ sensors can provide multiple temporal observations at multiple sub-surface depths to complement remote sensing data, even though in-situ sensors may not have a good X-Y coverage. With respect to remote sensing data, several studies in different fields have incorporated them in data assimilation. These include studies investigating the assimilation of temperature (Ezer and Mellor, 1997; Keppenne and Rienecker, 2003; Troccoli and Haines, 1999), aquatic contaminants (Dorigo et al., 2007; Madsen et al., 2006; Mao et al., 2009; Seo et al., 2003; Voutilainen et al., 2007), soil moisture (Galantowicz et al., 1999; Houser et al., 1998; Ines et al., 2013; Ottlé and Vidal-Madjar, 1994; Pauwels et al., 2001), subsurface soil moisture (Olioso et al., 1999), and snow cover (Andreadis and Lettenmaier, 2006; Dong et al., 2005; Hall et al., 2002; Slater and Clark, 2006). However, there are limited papers that report whether assimilation of remotely-sensed water surface temperature observations would produce updated models that are also accurate with respect to in-situ water column measurements. Babbar-Sebens et al. (2013) recently used a variational data assimilation approach that used remotely sensed water temperature to correct the initial condition of the hydrodynamic model. Their results demonstrated that assimilation of remotely sensed data derived from Landsat-5 Thematic Mapper (TM) satellite reduced the overall error from 20.9% to 15.9%, when the model forecasts were compared to tests datasets derived from the same satellite. However, when they compared the water column temperature of model layers in the original and updated model with the in-situ measurements at different depths, it was found that the model error had actually increased by 50%, specifically from 1.8 °C (before assimilation) to 2.7 °C (after assimilation) (Babbar-Sebens et al., 2013). While Babbar-Sebens et al. (2013) did not provide any solution to resolving this discrepancy between performance of updated models estimated by different data sources, their study highlighted the need for an adjustment method that would enable a direct comparison between skin temperature measurements obtained from satellites and the bulk temperatures of water column layers simulated by the numerical water quality model. The relationship between skin temperature and bulk temperature has been investigated by some previous studies (Donlon et al., 2002; Hook et al., 2003; Hulley et al., 2011; Jessup and Branch, 2008; Piccolroaz et al., 2013). Hook et al. (2003) used four monitoring stations permanently deployed on Lake Tahoe, California–Nevada to compare the surface skin temperature and bulk temperature. They found that during the diurnal cycle, there is a noticeable difference between the bulk and skin temperatures which is related to strong solar radiation and low wind speeds at the site in the morning (Hook et al., 2003). Donlon et al. (2002) using the remotely sensed sea surface temperature (SST) and high quality in-situ data obtained from radiometer systems considered the relationship between the SST_{skin}, the subsurface SST at depth (SST_{depth}), and the surface wind speed. They found that for wind speed lower than 6 m/s, there is a complicated relationship between SST_{skin} and SST_{depth} during the day because of the stratification of upper layers of ocean, while at night the skin layer is usually cooler. Also for wind speed higher than 6 m/s, there is a cool bias of -0.17 ± 0.07 K rms for both day and night conditions (Donlon et al., 2002).

In this study, we have proposed a novel strategy for adjusting remotely sensed skin temperature collected in an operational setting. The adjustment enables incoming satellite-derived data to be converted into a representative bulk temperature of surface layer, before it can be used for assimilation in numerical hydrodynamic and water quality models. Additionally, coupling of the adjustment and assimilation techniques takes advantage of easily available daily air temperature, and the intermittently available in-situ observations that may or may not be collected on days and times when the remote sensing observations are obtained. The scientific merit of this work is that it provides an efficient adjustment and bias correction technique for extrapolating remotely sensed skin temperature observations to temperatures representing surface layers of numerical models that simulate in-land water bodies. Another scientific and practical merit is that the overall approach is able to produce an updated model with reasonably accurate forecasts in spite of the use of a small ensemble size during data assimilation. This is especially important for the purpose of high computational efficiency, when data assimilation is performed under operational settings.

The main research objective of this study is to investigate whether assimilation of remotely sensed temperature observations using the proposed data fusion approach can also improve model accuracy with respect to in-situ temperature observations. The proposed data fusion approach was tested using a hydrodynamic-temperature model of Eagle Creek Reservoir (ECR) in central Indiana, and involved the steps below:

(1) Adjust the remotely sensed water skin temperature observations by using daily air temperatures and intermittently available in-situ water column temperatures, and, thereby, resolve the problem of bias arising due to sampling depths of remote sensing observations and in-situ measurements.
(2) Assimilate the water temperature using adjusted remotely sensed water skin temperature from multi-spectral Landsat-5 TM band into the hydrodynamic-temperature model, and update the model's initial conditions using an ensemble Kalman filter data assimilation framework.
(3) Compare the predictions from the model updated using the proposed methodology with incoming new in-situ observations to validate whether the updated model also produces more accurate sub-surface water column forecasts.

The remainder of the paper is organized in the following sections: Section 2 (Methodology) describes the study area and data collection, simulation model, sources of observations, relationship between remote sensing and in-situ observations and data assimilation algorithm, Section 3 describes the results of various experiments conducted in this study, and finally Section 4 provides concluding remarks.

2. Methodology

2.1. Study area and data collection

Eagle Creek Reservoir (ECR), located northwest of Indianapolis, Indiana, was used as the test site in this study (Fig. 1). It lies within the Eagle Creek watershed and has a catchment area of about 419 km^2. The Eagle Creek Reservoir was originally constructed in