Satellite-Derived Light Extinction Coefficient and its Impact on Thermal Structure Simulations in a 1-D Lake Model

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Abstract. One essential optical parameter to specify in lake models is water clarity, which is parameterized based on the light extinction coefficient (K_d). A global constant value of K_d is usually specified in lake models. One-dimensional (1-D) lake models are most often used as lake parameterization schemes in numerical weather prediction and regional climate models. This study aimed to improve the performance of the 1-D Freshwater Lake (FLake) model using satellite-derived K_d for Lake Erie. The CoastColour algorithm is applied to MERIS satellite imagery to estimate K_d and evaluated against K_d derived from Secchi disk depth (SDD) field-based measurements collected during Lake Erie cruises. A good agreement is found between field and satellite-derived K_d (RMSE = 0.63 m^{-1}, MBE = -0.09 m^{-1}, I_a = 0.65) (in situ data was collected in 2004, 2005, 2008, 2011, 2012). The constant (0.2 m^{-1}) and satellite-derived K_d values as well as radiation fluxes and meteorological station observations are then used to run FLake at the location of a buoy where lake surface water temperature (LSWT) was measured in 2008. Results improved compared to using a constant K_d value (0.2 m^{-1}) (lake-specific yearly average K_d value: RMSE=1.54 ºC, MBE= -0.08 ºC; constant K_d value: RMSE=1.76 ºC, MBE= -1.26 ºC). No significant improvement is found in FLake simulated LSWT when K_d variations in time are considered using a monthly average. Therefore, results suggest that a time-independent, lake-specific, and constant satellite-derived K_d value can reproduce LSWT with sufficient accuracy for Lake Erie NDBC station.

A sensitivity analysis is also performed to assess the impact of various K_d values on the simulation of LSWT, mean water column temperature (MWCT), lake bottom water temperature (LBWT), mixed layer depth (MLD), water temperature isotherms as well as ice dates and thickness. Results show that FLake is sensitive to variations in K_d to estimate the thermal structure of Lake Erie. Dark waters result in warmer spring and colder fall temperatures compare to clear waters. Dark waters always produce warmer MWCT, shallower MLD, longer ice cover duration, and thicker ice. The sensitivity of FLake to K_d variations is more pronounced in the simulation of MWCT, LBWT, and MLD. The model is particularly sensitive to K_d values below 0.5 m^{-1}. This is the first study to assess the value of integrating K_d from the satellite-based CoastColour algorithm into the FLake model. Satellite-derived K_d is found to be a useful input parameter for simulations with FLake and possibly other lake models, and with potential for applicability to other lakes where K_d is not commonly measured.

Keywords: Water clarity, extinction coefficient, MERIS, CoastColour, FLake, Lake Erie, lake water temperature

1 Introduction

There has been significant progress made in recent years in the representation of lakes in regional climate models (RCM) and numerical weather prediction (NWP) models. Lakes are known to be an important continental surface component affecting weather and climate, especially in lake-rich regions of the northern hemisphere (Eerola et al., 2010; Martynov et al., 2012; Samuelsson et al., 2010). They can influence the atmospheric boundary layer by modifying the air temperature, wind and precipitation. Therefore, consideration of lakes in NWP/RCM is essential (Kheyrollah Pour et al., 2012, 2014b; Martynov et al., 2010). In order to account for lakes in NWP/RCM, a description of energy exchanges between lakes and the atmosphere is required (Eerola et al., 2010). Lake Surface Water Temperature (LSWT) is one of the key variables when investigating lake-atmosphere energy exchanges (Kheyrollah Pour et al., 2012). There are various approaches to obtaining LSWT and integrating it in NWP models, such as through climatic observations, assimilation and/or lake parameterization schemes (Eerola et al., 2010; Kheyrollah Pour et al., 2014a). Currently, LSWT is broadly modelled in NWP models using one-dimensional (1-D) lake models as lake parameterization schemes (Martynov et al., 2012). For instance, the 1-D Freshwater Lake (FLake) model performs adequately for various lake sizes, shallow to relatively deep (artificially limited to 40-60 m depth (Kourzeneva et al., 2012a)), located in both temperate and warm climate regions (Kourzeneva, 2010; Martynov et al., 2010, 2012; Mironov, 2008; Mironov et al., 2010, 2012; Samuelsson et al., 2010; Kourzeneva et al., 2012a; Kourzeneva et al., 2012b).

One of the optical parameters required as input in the FLake model is water clarity. This variable is considered as an apparent optical property and is parameterized using the light extinction coefficient (K_d) to describe the absorption of shortwave radiation within the water body as a function of depth (Heiskanen et al., 2015). A global constant value of K_d is usually used to run lake models, including FLake. For example, Martynov et al. (2012) coupled FLake in the Canadian Regional Climate Model (CRCM) by specifying a K_d value equal to 0.2 m^{-1} (Martynov, pers. comm., 2015) for all North American Lakes, including Lake Erie for years 2005-2007. Heiskanen et al. (2015) evaluated the sensitivity of two 1-D lake models, LAKE and FLake, to seasonal variations and the general level of K_d for simulating water temperature profiles and turbulent fluxes of heat and momentum in a small boreal Finnish lake. Modelled values were compared to those measured for the lake during the ice-free period of 2013. The study found a critical threshold for K_d (0.5 m^{-1}) in 1-D lake models. Heiskanen et al. (2015) concluded that for too clear waters (K_d < 0.5 m^{-1}), the model is much more sensitive to K_d. The study recommends a global mapping of K_d to run the FLake model for regions with clear waters (K_d < 0.5 m^{-1}) for future use in NWP models. The authors also suggest that this global mapping can be time-independent (i.e. with a constant value per lake) (Heiskanen et al., 2015), and this can be derived from satellite imagery. Potes et al. (2012) used empirically derived water clarity from space-borne Medium Resolution Imaging Spectrometer (MERIS) measurements to test the sensitivity of FLake to this parameter. The sensitivity analysis was conducted using two K_d values, representing the expected extreme water clarity cases for their study (1.0 m^{-1} for clear water and 6.1 m^{-1} for dark~~turbid~~ water). The importance of lake optical properties was evaluated based on the evolution of LSWT and heat fluxes. Their results show that water clarity is an essential parameter affecting the simulated LSWT. The daily mean LSWT range increased from 1.2 ºC in clear water to 2.4 ºC in dark~~turbid~~ water (Potes et al., 2012). Water clarity measurements are included in water quality monitoring programs; however, global measurements of clarity are not yet available. Satellite remote sensing can provide water clarity observations to the modelling communities at higher spatial and temporal resolutions, to fill the gap of field measurements.

In recent years, a number of algorithms have been devised to retrieve different water optical parameters, including water clarity, from satellite observations for coastal (ocean) and lake waters (Attila et al., 2013; Binding et al., 2007, 2015; Olmanson et al., 2013; Potes et al., 2012; Wu et al., 2009; Zhao et al., 2011). Turbid inland and coastal waters are optically more complex compared to open ocean, and large optical gradients exist. There is more than only one component (phytoplankton species, various dissolved and suspended matters with non-covarying concentrations) in coastal waters and lakes that determines the variability of water-leaving reflectance. Considering this complexity, the development of algorithms for coastal waters and lakes is more challenging. MERIS, which operated from March 2002 to April 2012, collected data from the European Space Agency's (ESA) Envisat satellite. The spatial resolution and spectral bands settings were carefully selected in order to meet the primary objectives of the mission; addressing coastal monitoring from space. The best possible signal-to-noise ratio, additional channels to measure optical signatures as well as the relatively high spatial resolution of 300 m are some of the specific instrument characteristics (Ruescas et al., 2014). In 2010, ESA launched the CoastColour project to fully exploit the potential of MERIS instrument for remote sensing of coastal zone waters. CoastColour (CC) is providing a global dataset of MERIS full resolution data of coastal zones that are processed with the best possible regional algorithms to produce water-leaving reflectance and optical properties (Ruescas et al., 2014).

The objectives of this study are to: 1) evaluate satellite-derived K_d values for a large lake in the Great Lakes region; 2) apply the evaluated satellite-derived K_d in FLake model to investigate the improvement of model performance to reproduce LSWTs. Three different values of K_d are used in the simulations: yearly average, monthly average, and a constant value to demonstrate the impact of a time-independent, lake-specific K_d value in simulating LSWT; and 3) understand the sensitivity of the FLake model to K_d values based on simulated LSWT, mean water column temperature (MWCT), lake bottom water temperature (LBWT), mixed layer depth (MLD), and water temperature isotherms during the ice-free season on Lake Erie (from April to November). The impact of K_d variations on ice dates (freeze-up, break-up, and duration) and ice thickness is also evaluated.

2 Data and Methods

2.1 Study Site and Station Observations

Lake Erie (42° 11′N, 81° 15′W; Fig. 1) is a large shallow temperate freshwater lake covering a surface area of 25,700 km^2. The lake is characterized by three basins: shallow western, central, and deep eastern basins with maximum depths of 19 m, 25 m, and 64 m, respectively. Lake Erie is monomictic with occasional dimictic years (Bootsma & Hecky, 2003). It is the shallowest and smallest by volume of the Laurentian Great Lakes (Daher, 1999). These characteristics make Lake Erie unique from the other Great Lakes.

The meteorological forcing variables required for FLake model runs include solar (shortwave) and longwave irradiance, air temperature, air humidity, wind speed, and cloudiness. Mean daily air temperature, wind speed and water temperature measurements were obtained from the National Data Buoy Center (NDBC) of NOAA, station 45005 (2003-2012). The station location is shown in Fig. 1 (41°40' N, 82°23' W, and depth: 12.6 m). Air temperature is measured 4 m above the water surface and anemometer height is 5 m above the water surface to measure the wind speed, whereas the water surface is at 173.9 m above mean sea level. Water temperature is also measured at 0.6 m below the water line. The NDBC station was selected to perform simulations with FLake, since water temperature observations collected at the buoy station can be used to evaluate the model output. The other meteorological forcing variables required for model simulations at the NDBC station were obtained from nearby stations. Air humidity, and cloudiness were available in a daily format from EC-Ontario Climate Center (OCC) for the Windsor station (climate ID: 6139525) (2003-2012). The location of this station is shown in Fig. 1, which is a near-shore station close to the NDBC station. The distance between OCC and NDBC stations is less than 81~~9.5~~ km. Incoming radiation fluxes data was supplied by the National Water Research Institute (NWRI), Environment Canada (EC), from a station located in the western basin of Lake Erie (see Fig. 1). Daily shortwave irradiance measurements were available only for 2004 and 2008. Therefore, a daily time series of solar irradiance for the entire study period (2003-2012) was completed for the NDBC station using solar irradiance model data (see Sect. 2.2). Longwave irradiance was measured only in 2008 at the NWRI-EC station. An empirical equation (see Sect. 2.2) was therefore employed to obtain longwave irradiance for the full period of study (2003-2012).

FLake requires information on water transparency (downward light K_d) as input for model runs. MERIS satellite imagery was used to derive K_d for the NDBC station during the study period. The method is described in details in Sect. 2.3. Available Secchi disk depth (SDD) field measurements were ~~used to estimate lake water clarity. SDD data was~~ collected~~provided~~ by EC research cruises on board the Canadian Coast Guard Ship *Limnos*~~EC~~ and utilized in this study to evaluate the satellite-derived water clarity~~K_d~~. The cruise ~~Research cruises on board the Canadian Coast Guard Ship Limnos~~ visited Lake Erie at a total of 89 distributed stations in five different years (September 2004; May, July, and September 2005; May and June 2008; July and September 2011; and February 2012). The location of stations is shown in Fig. 1.

2.2 Shortwave and Longwave Irradiance

The SUNY model, a satellite solar irradiance model, has been developed to exploit Geostationary Operational Environmental Satellites (GOES) for deriving solar irradiance using cloud, albedo, elevation, temperature, and wind speed observations (Kleissl et al., 2013). The basic principles of solar-irradiance modelling based on inputs from geostationary satellites and atmospheric models are described in Kleissl et al. (2013). Data from these sources are used to generate site and time specific high-resolution maps of solar irradiance with the SUNY model. The daily mean solar irradiance data for the present study was obtained from the second version of the SUNY model (Version 2.4), available in SolarAnywhere® (https://www.solaranywhere.com). The model provides a gridded data set with a spatial resolution of one tenth of a degree (ca. 10 km). The solar irradiance data was extracted from a tile corresponding to the NWRI station (see Fig. 1) for 2004 and 2008, when observations were available for evaluation, and also for FLake model run on Lake Erie for the full study period (2003-2012). ~~As shown in Fig. 2, t~~There is a strong agreement ($R^2 = 0.93$) between model-derived and measured solar irradiance at the NWRI station. The SUNY model slightly underestimates observations by 2.18 Wm^{-2} (N = 362, RMSE = 21.58 Wm^{-2}, MBE = -2.18 Wm^{-2}, I_a = 0.88; see Sect. 2.5 for details).

Longwave irradiance was computed on a daily basis using the equation of Maykut and Church (1973), as implemented in the Canadian Lake Ice Model (CLIMo) (Duguay et al., 2003):

$$E = \sigma T^4 (0.7855 + 0.000312 G^{2.75}) \qquad \text{Eq. (1)}$$

where T is the air temperature at screen height (ºK) and G is the cloudiness in tenth from meteorological stations.

Longwave irradiance calculated from Eq. 1 was evaluated against observations from the NWRI-EC station, only available in 2008~~ (Fig. 3)~~. The two datasets are highly correlated ($R^2 = 0.74$) with the equation underestimating measured irradiance by 0.86 Wm^{-2} (N = 194, RMSE = 17.74 Wm^{-2}, MBE = -0.86 Wm^{-2}, I_a = 0.76). Model-derived incoming shortwave and longwave fluxes were used as input in FLake model simulations for subsequent analyses in NDBC station over the 2003-2012 period.

2.3 Satellite-Derived Extinction Coefficient

MERIS operated on-board the ESA Envisat polar-orbiting satellite until April 2012. The sensor was a push-broom imaging spectrometer which measured solar radiation reflected from the Earth's surface high spectral and radiometric resolutions with a dual spatial resolution (300 m and 1200 m). Measurements were obtained in the visible and near-infrared part of the electromagnetic spectrum (across the 390 nm to 1040 nm range) in 15 spectral bands during daytime, whenever illumination conditions were suitable, and with a full spatial resolution of 300 m at nadir, with a 68.5° field-of-view. MERIS scanned the Earth with a global coverage of every 2-3 days.

In this study, a total of 326 full resolution archived MERIS images encompassing the NDBC station in Lake Erie (see Fig. 1) were acquired from CC (Version 2) products through the Calvalus on-demand processing service for the period of 2003-2012. CC Level2W products are the result of in-water processing algorithms to derive optical parameters from the water leaving reflectance. These parameters include inherent optical properties (IOPs), concentrations of water constituents, and other optical water parameters such as spectral vertical K_d. The IOP parameters are first derived applying two different inversion algorithms: neural network (NN) and Quasi Analytical Algorithm (QAA). The derived IOPs are then converted to estimate constituents' concentrations and apparent optical properties (AOP), including diffuse K_d for different spectral bands applying Hydrolight simulations (Ruescas et al., 2014).

The diffuse K_d product (the average value between visible spectral bands) in CC MERIS L2W data was extracted for the pixel at the geographic location of the NDBC station. The satellite-derived K_d values were also extracted for pixels on the same day and location as the *Limnos* cruise stations to evaluate~~d~~ the CC-derived diffuse K_d values against SDD in situ data collected during *Limnos* cruises. ~~The CC-derived diffuse K_d values were extracted for pixels on the same day and location as the *Limnos* cruise stations. The satellite-derived K_d values were then extracted for the pixel at the geographic location of the NDBC station.~~ A valid pixel expression was defined in all pixel extraction steps that excluded pixels with properties listed in Table 1.

2.4 FLake Model and Configuration

The FLake model is a self-similar parametric representation (assumed shape) of the temperature structure in the four media of the lake including water column, bottom sediments, and in the ice and snow. The water column temperature profile is assumed to have two layers: a mixed layer with constant temperature and a thermocline that extends from the base of mixed layer to the lake depth. The shape of thermocline temperature is parameterized using a fourth-order polynomial function of depth that also depends on a shape coefficient C_T. The value of C_T lies between 0.5 and 0.8 so that the thermocline can neither be very concave nor very convex. FLake has an optional scheme for the representation of bottom sediments layer, which is based on the same parametric concept (De Bruijn et al., 2014; Martynov et al., 2012). The system of prognostic equations for parameters is described in Mironov (2008).

The prognostics ordinary differential equations are solved to estimate the thermocline shape coefficient, the mixed layer depth, bottom, mean and surface water column temperatures, and also parameters related to the bottom sediment layers (Martynov et al., 2012; Mironov, 2008; Mironov et al., 2010). The same parametric concept is applied for the ice and snow layers, using linear shape functions (Martynov et al., 2012). The mixed layer depth is calculated considering the effects of both convective and mechanical mixing, also accounting for volumetric heating which is through the absorption of net shortwave radiation (Thiery et al., 2014). The non-reflected shortwave radiation is absorbed after penetrating the water column in accordance with the Beer-Lambert law (Martynov et al., 2012; Mironov, 2008; Mironov et al., 2010).

Stand-alone FLake simulations were conducted for the NDBC station. The setup condition of NDBC buoy station, such as height of wind measurement (5 m),~~-~~ height of air temperature sensor (4 m)~~, and the depth of water temperature measurement (0.6 m)~~, and the geographic location and depth of this site (41°40' N, 82°23' W, and depth: 12.6 m) were used to configure the model. ~~, as well as t~~The measured meteorological parameters and model-derived irradiance were also used to ~~configure~~force the FLake model. A fetch value of 100 km was used to run all simulations. It was found that there is only little sensitivity to modifications in this parameter for Lake Erie. The same result was found for Lake Kivu in Thiery et al. (2014). The bottom sediments module was switched off in all simulations and the zero bottom heat flux condition is adopted. The initial temperature value for the upper mixed layer and the lake bottom were 4°C. Mixed layer thickness had the initial value of 3 m. The simulations were run in a daily time step (using daily forcing data) for 2003-2012.

The ability of FLake to reproduce the observed temperature variations using different K_d values was tested by comparing the simulated LSWT to the corresponding in situ observations in the NDBC station. Also, the model sensitivity to variations in water clarity was assessed studying the LSWT, MWCT, LBWT, MLD, isotherms, ice phenology, and ice thickness.

2.5 Accuracy Assessment

To assess the model outputs, three statistical indices were calculated: the root mean square error (RMSE), the mean bias error (MBE), and the index-of-agreement (I_a). RMSE is a comprehensive metric that combines the mean and variance of model errors into a single statistic (Moore et al., 2014). The MBE is calculated as the modelled values minus the in situ observations. Therefore, a positive (negative) value of this error shows an overestimation (underestimation) of the parameter of interest. I_a is a descriptive measure of model performance. It is used to compare different models and also modelled against observed parameters. I_a was originally developed by Willmott in the 1980s (Willmott, 1981) and a refined version of it was presented by Willmott et al. (2012). The refined version, which was adopted in this study, is dimensionless and bounded by -1.0 (worst performance) and 1.0 (the best possible performance). These statistical indices are considered as robust measures of model performance (e.g. Hinzman et al., 1998; Kheyrollah Pour et al., 2012; Willmott and Wicks, 1980).

3 Results and Discussion

3.1 Satellite-Derived K_d

3.1.1 Variations of K_d at NDBC Station~~Evaluation of CoastColour K_d~~

Fig. 2 shows the variations of CC-derived K_d for the NDBC station during the full study period (2003-2012). In the shallow section of Lake Erie, re-suspension of bottom sediments is the most important factor that leads to lower water clarity. Therefore, the highest K_d values are related to the turn-over times in spring and fall. The results from applying the CC algorithm on MERIS satellite imagery show that the maximum value of K_d is 3.54 m^{-1}, estimated in April 2003. A minimum value of 0.58 m^{-1} is estimated in June 2007. The average value of K_d during the study period is 0.90 m^{-1} with a standard deviation of 0.38 m^{-1}. Hence, these values, identified as the average, the lower, and the upper limits of clarity at the NDBC station were used to carry out a sensitivity analysis with FLake (see Sect. 3.2.2).

3.1.2 Evaluation of CoastColour K_d

The validation of satellite observations against in situ data is important, because the in situ data are still considered as the most accurate measurement of water clarity. The assessment of the satellite-derived K_d retrieval reliability highly depends on the comparison with independent in situ SDD measurements. The general form of the relationship between K_d and SDD was established by the pioneer study of Poole and Atkins (1929):

$$SDD \times K_d = K \qquad \text{Eq. (2)}$$

where K is a constant value of 1.7 (Poole and Atkins, 1929). Following this important work, there were other studies that derived an empirical relationship between the two parameters. Studies have found a high variability of the constant value (K) depending on the type of the lake considered (Koenings and Edmundson, 1991). Armengol et al. (2003) also show that K_d and SDD are negatively correlated and they developed an empirical relation between these two parameters using Eq. (2).

In this study, applying a cross validation approach, an empirical relation ~~based on Eq. (2)~~ was developed between in situ measured SDD and CC-derived K_d. SDD measurements were conducted 117 times during cruises on Lake Erie from 2004 to 2012. These spatially-distributed measurements have minimum, maximum, mean, and standard deviation values of 0.2, 11, 3.69, and 2.68 m, respectively. CC L2W satellite products were acquired on the same day as the in situ measurements. Applying defined flags produced 49 data pairs (matchup dataset) of CC observations of K_d and SDD in situ data that were collected on the same day and location.

The matchup dataset was divided into training and testing data in 100 iterations. In each iteration, the data used for the equation's training and evaluation were kept independent, where 70% of the sample was used for equation calibration and 30% for evaluation. Ordinary least square regression was used in the calibration step of each iteration to relate the in situ measurements of SDD to the CC-derived K_d. Locally tuned equations were derived from this step and applied on SDD observations to predict K_d in testing matchup data. The statistical parameters of the model performance were derived between the estimated K_d from SDD observations and the paired CC-derived values. These steps were repeated for 100 iterations; and the final statistical indices, slope and power of the locally tuned equation was reported as the average of the ones derived over all iterations.

Results from the above procedure show that K_d can be derived from ~~and~~ SDD, using the equation $K_d = 1.64 \times SDD^{-0.76}$, with a strong determination of coefficient value (~~, are strongly correlated with~~ $R^2 = 0.78$). Arst et al. (2008) obtained a similar regression formula between SDD and K_d for the boreal lakes in Finland and Estonia representing different types of water, expanding from oligotrophic to hypertrophic. ~~The extinction coefficient can be derived from equation $K_d = 1.64 \times SDD^{-0.76}$.~~ ~~T~~Because there is a good agreement between ~~the satellite-derived~~ K_d and the corresponding ones estimated from in situ measured SDD (N = 49, RMSE = 0.63 m^{-1}, MBE = -0.09 m^{-1}, I_a = 0.65; ~~) (~~Fig. 3), the satellite-derived water clarity are deemed to be correct and were used in the modelling for this study.

However, SDD is not always describing K_d values. ~~. Arst et al. (2008) obtained a similar regression formula between SDD and K_d for the boreal lakes in Finland and Estonia representing different types of water, expanding from oligotrophic to hypertrophic.~~ SDD is a suitable characteristic to describe water transparency for small values of K_d. ~~However, f~~For high values of K_d (ranging above 4 m^{-1}), Arst et al. (2008) and Heiskanen et al. (2015) suggest that SDD is unable to describe any changes in K_d. Fig. 3 also shows that SDD cannot describe the scatter of K_d for values above 4 m^{-1}. Therefore, the estimation of K_d from SDD should be used with caution, motivating the investigation on the potential of integrating satellite-based estimations of K_d into lake models.

~~3.1.2 Spatial and Temporal Variations in K_d~~

~~This section describes how the CC satellite observations can detect the spatial and temporal variations of K_d. Spatial variations of K_d derived from the CC algorithm are shown in Fig. 5 for a selected day (3 September 2011). This particular day of 2011 is selected as the lake experienced its largest algal bloom in its recorded history in that year, before the new recent record of 2015 (Michalak et al., 2013; NOAA, 2015). The bloom was expanding from the western basin into the central basin. Algal bloom~~

~~is one of the factors affecting the water clarity of Lake Erie (NOAA, 2015). Other parameters include the concentrations of suspended and dissolved matters in the lake. The western basin is the shallowest region of the lake; and therefore is the most vulnerable to sediment re-suspension that also results in reducing water clarity. The map shows that Lake Erie experienced different levels of clarity in various locations with an average K_d value of 0.90±0.80 m^{-1} over the entire lake on this particular day. The NDBC station is also shown on the satellite-derived map as a reference (with K_d = 0.87 m^{-1} on 3 September 2011).~~

~~Since fully cloud-free MERIS satellite images for consecutive months were only available in 2010, four months (May-August 2010) are selected to illustrate variations in K_d on a monthly-basis for one selected year (Fig. 6). The spatial average of K_d over the full lake for the specific days in May, June, July, and August is 0.82±0.85 m^{-1}, 0.72±1.10 m^{-1}, 0.73±1.20 m^{-1}, 0.78±0.55 m^{-1}, respectively. The western basin is always experiencing the lowest levels of water clarity in comparison to other regions of the lake, with a maximum K_d in May. This can be the result of a spring algal bloom, and also wind-driven re-suspension of sediments. K_d at the NDBC station for these selected days varies between 0.68 m^{-1}, 0.62 m^{-1}, 0.66 m^{-1}, and 0.85 m^{-1} from May to August 2010, respectively.~~

~~Two MERIS images with full coverage of Lake Erie were only available in the month of May for two selected consecutive years (2008 and 2009). Hence, the MERIS images of May 2008 and May 2009 were selected to show variations in K_d between the two years. Although the images are for the same month of the year, K_d still varies across the lake (Fig. 7). In the selected day of May 2008, a spatial average value of 0.77±0.49 m^{-1} is estimated for the entire lake, while on 17 May 2009 the spatial average value is 0.90±0.93 m^{-1}. Comparing the estimated maps for the two years suggests that the spring bloom in 2009 was stronger than the one in 2008 for the western basin. However, algal bloom in all basins of Lake Erie for the complete year of 2008 was recorded as the third largest that the lake experienced before the occurrence of the breaking record blooms in 2011 and 2015 (Michalak et al., 2013; NOAA, 2015). K_d value estimated for the NDBC station is 0.69 and 0.62 m^{-1} in 29 May 2008 and 17 May 2009, respectively.~~

~~Fig. 8 depicts variations of K_d for the NDBC station during the full study period (2003-2012). In the shallow section of Lake Erie, re-suspension of bottom sediments is the most important factor that leads to higher water clarity. Therefore, the highest K_d values are related to the turn-over times in spring and fall. The results from applying the CC algorithm on MERIS satellite imagery show that the maximum value of K_d is 3.54 m^{-1}, estimated in April 2003. A minimum value of 0.58 m^{-1} is estimated in June 2007. The average value of K_d during the study period is 0.90 m^{-1} with a standard deviation of 0.38 m^{-1}. Hence, these values, identified as the average, the lower, and the upper limits of clarity at the NDBC station were used to carry out a sensitivity analysis with FLake (see Sect. 3.2.2).~~

3.2 FLake Model Results

3.2.1 Improvement of LSWT Simulations with Satellite-Derived K_d

Martynov et al. (2012) focused on 2005 to 2007 to run FLake at the NDBC station using a constant value of 0.2 m^{-1} for K_d. They simulated the lake using both realistic and excessive depths of 20 and 60 m, respectively, for a grid tile corresponding to the NDBC station. They showed that applying a more realistic lake depth parameterization improved the performance of the model to reproduce the observed surface temperature. In this section, K_d values were derived from the CC algorithm for different months during the same years (2005-2007) as in Martynov et al. (2012).

Table 2 displays the average K_d values for each month of these years. The monthly averaged values are only focused on the months of the year when both LSWT observations and CC–derived K_d values were available. The average value of K_d in these months in each year is considered as the average value of K_d for that year.

Fig. 4 compares~~shows~~ the results of different LSWT FLake simulations with observations at the NDBC station. LSWT observations have maximum values of 27.53 ºC, 26.48 ºC, and 25.46 ºC in August during 2005, 2006 and 2007. The minimum values of 2.71 ºC, 7.3 ºC, and 3.42 ºC were observed in December 2005, and April in 2006 and 2007. The average LSWT observations in 2005, 2006, and 2007 have values of 18.45 ºC, 17.12 ºC, and 17.75 ºC, respectively. The simulated LSWT values in Fig. 4 are produced by ~~The model was run~~ first applying $K_d = 0.2\ m^{-1}$ from Martynov et al. (2012) using both the real lake depth at the station (12.6 m: CRCM-12.6) and also a tile depth corresponding to the station in their study (20 m: CRCM-20). Then, simulations using the yearly average CC-derived K_d for each year of study are plotted (Avg). The K_d values derived from the monthly average of each year were used to simulate the surface water temperature and produce a merged LSWT product~~. Results of the merged product are also plotted~~ (Merged). Both Avg and Merged simulations used the real lake depth at NDBC station (12.6 m).

Comparing LSWT in situ observations (Obs) with the modelled values in Fig. 4 demonstrate that in Avg and Merged simulations for 2005-2007, surface temperature in spring (April-June) is modelled warmer and colder in summer (July-September) and fall (October-November) than in situ observations (spring: MBE_{Avg} = 1.31 ºC, MBE_{Merged} = 1.25 ºC; summer: MBE_{Avg} = -0.72 ºC; MBE_{Merged} = -0.75 ºC; fall: MBE_{Avg} = -1.82 ºC, MBE_{Merged} = -1.99 ºC; see Fig. 5 for seasonal-based performance of simulations). CRCM-12.6 and CRCM-20 are reproducing a colder LSWT in average with maximum under-prediction in July-August (for 2005-2007: -2.93 ºC $<MBE_{July\text{-}August}<$ -0.99 ºC). Simulation with a larger depth (CRCM-20) tends to more slowly gain (lose) heat in spring (fall), compared to all other simulations.

The performance of each simulation is summarized in Table 3 during the period of data availability. For all years, the average and merged simulations perform better than simulations using K_d ($0.2\ m^{-1}$) as in Martynov et al. (2012), with improvement in RMSE and MBE for both real depth and tile depth. In all three years, LSWT simulated from the K_d value employed in Martynov et al. (2012) results in an underestimation (CRCM-12.6: MBE= -1.52 ºC, -0.98 ºC, -1.08 ºC; CRCM-20: MBE= -1.54 ºC, -1.09 ºC, -1.35 ºC; during years 2005, 2006, and 2007, respectively). In 2005, the average of K_d for the year demonstrates a better performance compared to the merged results; contrary to the results of 2007. However, for the merged results in 2006, the MBE is improved compared to the simulation using the average K_d; whereas its performance decreases in terms of RMSE. The extent of K_d variations in each month might not be captured by the available MERIS images due to cloud coverage in MERIS images or the absence of any satellite overpass. Therefore, a yearly-average K_d can be potentially closer to the actual value of K_d. For this reason, t~~t~~he merged results ~~-~~cannot always perform better than ~~the year average, which~~average simulations ~~can be more representative of K_d variations~~. ~~Considering the months of September-November into the calculations of MBE~~

~~for 2005 can be the reason of underestimating LSWT in this year for both Avg and Merged simulations compared to two other years (2006-2007). Turbid waters in these months simulate colder LSWT.~~

Fig. 5 illustrates the scatterplots of simulated LSWT for all four different runs including three years of data (2005-2007), in comparison with the corresponding in situ observations. All simulated results are in a high agreement with in situ measurements. CRCM simulations (both depths of 12.6 and 20 m) under-predict LSWT with MBE values of -1.26 ºC and -1.37 ºC, respectively. The under-prediction of these model runs is stronger, particularly ~~stronger~~ for LSWT above 12ºC, which can be explained by the K_d value used. This is because, ~~,~~ ~~since~~no matter what depth is used in simulations (either ~~both~~ actual or tile depth),~~depths considered in~~both CRCM runs ~~are as affected~~have larger MBE compared to Avg and Merged simulations. However, the CRCM-20 simulation tends to produce the coldest LSWT (the most under-prediction; MBE = -1.37 ºC). This is due to the lake depth value considered for the model run which corresponds to the tile depth as opposed to the other simulations that were based on using the actual depth at station. ~~This shows clearly that applying a realistic lake depth and K_d value will improve model results and therefore the parameterization schemes.~~

Fig. 5-a and -b show that the resulting LSWT from yearly average (Ave) and monthly average (Merged) K_d are not significantly different, whereas simulations with yearly average K_d reproduces LSWT with improved RMSE and MBE values compared to monthly average (Avg: RMSE=1.54 ºC, MBE=-0.08 ºC; Merged: RMSE=1.57 ºC, MBE=-0.14 ºC). It is possible that the ~~extent of~~actual K_d ~~variations~~ value is best represented by the yearly average value. Therefore, using a constant annual open water season value for K_d could be potentially sufficient to simulate LSWT in 1-D lake models with relatively high accuracy (the range of K_d variations that brings the most sensitivity for the modelling is discussed in Sect. 3.2.2). The time-dependent (monthly average) K_d does not improve simulation results for Lake Erie (K_d ranging from 0.58 to 3.54 m^{-1} with average value of 0.90 m^{-1} during open water seasons of 2003-2012). However, comparing results from Fig. 5-a and –c shows improvement in LSWT simulations when a lake-specific value of K_d is used (Avg: RMSE=1.54 ºC, MBE=-0.08 ºC; CRCM-12.6: RMSE=1.76 ºC, MBE= -1.26 ºC). Under-prediction of LSWT decreases when the yearly-average CC-derived K_d values are used, rather than a generic constant value (0.2 m^{-1}). Heiskanen et al. (2015) suggest that the effect of K_d seasonal variations on LSWT simulations are not significant for lakes with K_d values higher than 0.5 m^{-1} (e.g. Lake Erie). Therefore, in the absence of reliable values of the temporal evolution of K_d, a lake-specific, time-independent, and constant value of K_d can be used in 1-D lake models when the K_d values are higher than 0.5 m^{-1}.

Martynov et al. (2012) conclude that applying a more realistic lake depth parameterization improves the FLake model performance. Using the realistic lake depth (12.6 m) at the NDBC station slightly improves the model performance in reproducing LSWT compared to simulation employing the corresponding tile depth (20 m) (CRCM-12.6: RMSE=1.76 ºC, MBE= -1.26 ºC; CRCM-20: RMSE=1.88 ºC, MBE= -1.37 ºC) (Fig. 5-c and –d).

3.2.2 Sensitivity of FLake to K_d Variations

The sensitivity of FLake to different values of K_d to reproduce LSWT, MWCT, LBWT, MLD, isotherm, ice phenology and thickness is investigated in this section for year 2008. As indicated previously (Sect. 2.1), shortwave irradiance measurements were available in that year and longwave irradiance was also measured from May to October 2008. Therefore, longwave irradiance for the other months of 2008 was modelled as described in Sect. 2.2 to fill the temporal gaps. Fig. 6 presents simulation results for LSWT, MWCT, and LBWT using the real lake depth at NDBC station, and the lowest, average, and highest values of K_d observed in the study period (minimum K_d=0.58 m^{-1}, average K_d =0.90 m^{-1}, maximum K_d =3.54 m^{-1}). The water temperature simulation from CRCM-12.6 (using K_d=0.2 and realistic depth at station) simulation is also plotted.

In the case of extreme clear water (CRCM-12.6), LSWT shows smoother variations during the open water season in 2008 as opposed to the ~~most turbid~~darkest water simulation (maximum or Max) which displays more abrupt LSWT variations (Fig. 6). This is because solar radiation is absorbed more in dark~~turbid~~ waters due to existing particles in water. It penetrates less deeply and warms up only the shallow surface layer (lower LBWT; see Fig. 6-c) causing thinner mixing depth (Fig. 8). The high temperature of this shallow layer causes an increase in latent and sensible heat fluxes. Therefore, ~~is shallow~~ the shallow mixed layer exchanges heat faster with the atmosphere, resulting in sudden surface water temperature variations as opposed to clear waters. The fast heat exchange with atmosphere results in warmer LSWT during spring (start of heating season) and colder LSWT in fall for dark water as opposed to clear one. ~~Also, the maximum turbid water simulation shows warmer LSWT in spring and colder LSWT in fall compared to the results of the more clear water simulation. In spring (the start of heating season), darker surface waters absorb heat faster than clear water because of existing particles in water.~~ On average, the darkest~~most turbid~~ water simulation (Max) resulted in 0.09 ºC higher LSWT compared to the average (Avg) simulation, whereas the clear water (minimum or Min) simulation produced on average 0.02 ºC colder LSWT during 2008. CRCM-12.6 simulation with K_d value of 0.2 resulted in a larger difference compared to Avg simulation, 0.55 ºC colder LSWT. The comparison of the simulated LSWT results show that FLake simulated LSWT is not significantly sensitive to K_d values when this value varies in the range of our Min to Max K_d. However, the sensitivity increases rapidly for K_d values less than our Min (0.58 m^{-1}). This result supports the study of Rinke et al. (2010) that ~~conclude that t~~the thermal structure of lakes is particularly sensitive to changes in K_d when its value is below 0.5 m^{-1}. More recently, Heiskanen et al. (2015) confirmed the critical threshold of K_d (ca. 0.5 m^{-1}). They suggest that the response of 1-D lake models to K_d variations is nonlinear. The models are much more sensitive if the water is estimated to be too clear. Heiskanen et al. (2015) recommend to use a value of K_d that is too high rather than too low in lake simulations, if the clarity of lake is not known exactly.

~~For both clear and dark waters, LSWT is warmer than the MWCT, due to being exposed to more intense solar radiation. Shortwave radiation is attenuated as it reaches a greater depth, particularly in turbid waters. In the extreme clear water simulation, the MWCT is on average 0.99º C colder than LSWT, whereas for the most turbid water the average difference is much higher equal to 4.82º C.~~

The MWCT and LBWT in the darkest~~most turbid~~ condition (Max) are less than for all other clear water simulations. This is because the lower layers in dark waters accumulate less heat during the heating season as opposed to clear waters which results in less heat storage and lower water column temperature in dark~~turbid~~ waters (Heiskanen et al., 2015; Potes et al., 2012). ~~The solar radiation penetrates less deeply and is absorbed by the surface layer, thereby heating it; where the surface layer transfers the energy faster to the atmosphere, resulting in a colder water column in turbid waters.~~ The MWCT decreases by 0.94 ^{0}C (increases by 0.63 ^{0}C) when maximum (minimum) K_d ~~changes from its average to its maximum (minimum)~~ value is used instead of its average value during the study period. The ~~increase in~~ MWCT increases by ~~is even larger when K_d changes from its average to 0.2 m^{-1} (~~2.25 ^{0}C when using K_d value of 0.2 m^{-1} rather than the average value~~)~~. Changes in K_d value from its maximum (minimum) to its average value also causes decrease (increase) of -0.67 ^{0}C (0.67 ^{0}C) in the LBWT. The increase in LWBT is even larger when K_d value of 0.2 m^{-1} is used instead of its average value (6.96 ^{0}C). Therefore, K_d variations have a larger impact on MWCT and LBWT than on LSWT, and the largest difference is when K_d is estimated to be extremely clear.

Fig. 7 displays the simulated isotherms derived from using different K_d values. ~~Comparing isotherms for dark and clear waters also demonstrates the results presented in Fig. 8.~~ It shows that the mixed layer in dark waters is ~~not only shallower as opposed to the clear waters, but~~ warmer in spring and summer and colder in fall. There are a number of factors determining the ~~epilimnion~~mixed layer temperature in lakes, including the radiation fluxes (sensible heat, latent heat, and longwave radiation), and cooling effects from the water below. Persson and Jones (2008) conclude that ~~for colored waters (turbid)~~for dark waters, the combination of these heating and cooling effects leads to a warmer epilimnion initially. The radiation is used to warm up a thinner layer in dark waters leading to higher (lower) temperatures in spring and summer (fall). However, a lower temperature in the ~~epilimnion~~mixed layer is followed due to the gradual lessening of the radiative absorption and increased effect of cooling from the layers below. ~~The reason is that the radiation is used to warm up a thinner layer in dark waters leading to higher (lower) temperatures in spring and summer (fall).~~ Fig. 7 also supports observations by Persson and Jones (2008) and Heiskanen et al. (2015) ~~shows t~~that the depth of the thermocline layer is always deeper in clear waters due to the faster heat distribution between different underneath layers. T~~t~~he deepening of the thermocline layer in clear waters is faster compared to~~monotonic; whereas in~~ dark waters ~~it is slower,~~. The reason is that ~~as~~ the heat transfer in dark waters is slower between water layers.

Fig. 8 is derived from isotherm to only focus on the ~~shows~~ variations of the MLD in 2008, ~~derived from simulations~~ using different values of K_d (~~the~~ Min, Ave, and Max K_d, and CRCM-12.6) in simulations. All simulations show two turnover (complete mixing) events, spring and fall. ~~The highest depth of spring~~Full mixing in spring is at the same time for all simulations; however, fall full mixing occurs at different dates for each simulation. Fall turnover in CRCM-12.6 ~~reaches its maximum MLD (fall turnover)~~is at the end of summer (August 28), while the other three runs show that the fall turnover takes place in late fall, before ice forms. Full mixing in t~~T~~he Min simulation ~~reaches its highest MLD~~ is in early November (November 3), earlier than the Avg and Max simulations (November 21). ~~As a result, the water column in clear water reaches the temperature of maximum density (4^{0}C) much faster than turbid water and therefore the turnover happens earlier.~~

In the darkest water simulation (Max), the MLD is shallower than the other simulations (an average difference of 4.94 m in 2008 between two simulations of Max and CRCM-12.6, with extreme K_d values). ~~In turbid waters, solar radiation does not penetrate as far beyond the water surface as opposed to clear waters; and it will get absorbed by the particles in water. Therefore, c~~Clear waters have a deeper mixed layer when the solar radiation can penetrate further and distribute to a larger volume in the water column. CRCM-12.6 produces a MLD of 3.47 m deeper compared to Avg simulation, whereas the Min (Max) simulations result in MLD of 1.15 m (1.47 m) deeper (shallower) compared to the Avg simulation. Hence, clear water simulates deeper MLD; and the effect of K_d on the MLD is larger when the K_d value is estimated to be too clear. ~~Fig. 13~~

~~displays the simulated isotherms derived from using different K_d values. Comparing isotherms for dark and clear waters confirms the results presented in Fig. 12. It shows that the mixed layer in dark waters is not only shallower as opposed to the clear waters, but warmer in spring and summer and colder in fall. The reason is that the radiation is used to warm up a thinner layer in dark waters leading to higher temperatures. Fig. 13 also shows that the deepening of the thermocline layer in clear waters is monotonic; whereas in dark waters it is slower, as the heat transfer in dark waters is slower between water layers to stabilize the temperatures in different layers.~~

~~Fig. 9 depicts the monthly average of temperature profiles in 2008 for different values of K_d. A warmer epilimnion at the beginning of the heating season occurs in dark waters, whilst temperature in the epilimnion reduces later in fall compared to clear waters. There are a number of factors determining the epilimnion temperature in lakes, including the radiation fluxes (sensible heat, latent heat, and longwave radiation), and cooling effects from the water below. Persson and Jones (2008) conclude that for colored waters (turbid), the combination of these heating and cooling effects leads to a warmer epilimnion initially. However, a lower temperature in the epilimnion is followed due to the gradual lessening of the radiative absorption and increased effect of cooling from the layers below. Fig. 9 supports observations by Persson and Jones (2008) and Heiskanen et al. (2015) that the depth of the thermocline layer is always deeper in clear waters due to the faster heat distribution between different underneath layers, resulting in a colder temperature but thicker and deeper epilimnion. However, the extreme clear water simulation reproduces a warmer hypolimnion as opposed to the other ones, due to the fact that light penetration in clear waters warms up the lower layers (Heiskanen et al., 2015).~~

Fig. 9 shows the impact of K_d variations on lake ice phenology and thickness in winter 2008 (January-March). Freeze-up corresponds to the earliest date that the NDBC station is completely covered by ice, and the earliest date the station is completely free of floating ice is defined as break-up. The Avg simulation reproduces similar ice phenology as the Max simulation, whereas Min and CRCM-12.6 result in the similar break-up/freeze-up dates. The break-up in CRCM-12.6 and Min simulations are on March 23, one day earlier than Max and Avg simulations and freeze-up occurs on January 24, two days after Max and Avg simulations. CRCM-12.6 and Min simulations reproduce 1.28 and 1.27 cm thinner ice than Avg simulation in 2008, respectively. The darkest~~most turbid~~ water (Max) reproduces 0.21 cm thicker ice in 2008 compared to the Avg simulation. The ice sheet forms later in clear waters (CRCM-12.6 and Min) and disappears earlier compared to dark waters (Max and Avg), resulting in a shorter ice cover duration (3 days) and hence thinner ice in clear water simulations.

Lake morphological properties determine ice cover as well as climatic factors. Among morphological aspects, lake depth is the most important factor that can impact the ice cover by influencing the amount of heat storage in the water and hence the time needed for the lake to cool and ultimately freeze (Brown and Duguay, 2010). For a given depth and climatic condition, however, the amount of heat storage is determined by water clarity. Dark waters store more heat in a shallower layer. Therefore, the heat can be transferred faster to the atmosphere through the lake surface, resulting in an earlier freeze-up as mentioned in Heiskanen et al (2015) that freeze-up occurs earlier in ~~more turbid~~darker waters. However, as shown by simulations with 12.6 m, ice phenology in NDBC station is minimally affected by K_d value in FLake. For a larger depth or in a different model, the impact of K_d values in ice onset should be investigated.

3.3 Spatial and Temporal Variations in K_d

As it was described in the previous section, variations in water clarity plays an important role in defining lake heat budget and thermal stratification and thus is a significant parameter for processes in the air-water interface. However, the long term spatial and temporal trends of water clarity cannot be achieved through discontinuous conventional point-wise in situ sampling. These observations can be provided from satellite measurements. This section demonstrates the strength of satellite observations to detect the spatial and temporal variations of K_d in Lake Erie. Spatial variations of K_d derived from the CC algorithm are shown in Fig. 10 for a selected day (3 September 2011). This particular day of 2011 is selected as the lake experienced its largest algal bloom in its recorded history in that year, before the new recent record of 2015 (Michalak et al., 2013; NOAA, 2015). The bloom was expanding from the western basin into the central basin. Algal bloom is one of the factors affecting the water clarity of Lake Erie (NOAA, 2015). Other parameters include the concentrations of suspended and dissolved matters in the lake. The western basin is the shallowest region of the lake; and therefore is the most vulnerable to sediment re-suspension that also results in reducing water clarity. The map shows that Lake Erie experienced different levels of clarity in various locations with an average K_d value of 0.90±0.80 m^{-1} over the entire lake on this particular day. The NDBC station is also shown on the satellite-derived map as a reference (with K_d = 0.87 m^{-1} on 3 September 2011).

Since fully cloud-free MERIS satellite images for consecutive months were only available in 2010, four months (May-August 2010) are selected to illustrate variations in K_d on a monthly-basis for one selected year (Fig. 11). The spatial average of K_d over the full lake for the specific days in May, June, July, and August is 0.82±0.85 m^{-1}, 0.72±1.10 m^{-1}, 0.73±1.20 m^{-1}, 0.78±0.55 m^{-1}, respectively. The western basin is always experiencing the lowest levels of water clarity in comparison to other regions of the lake, with a maximum K_d in May. This can be the result of a spring algal bloom, and also wind-driven re-suspension of sediments. K_d at the NDBC station for these selected days varies between 0.68 m^{-1}, 0.62 m^{-1}, 0.66 m^{-1}, and 0.85 m^{-1} from May to August 2010, respectively.

Two MERIS images with full coverage of Lake Erie were only available in the month of May for two selected consecutive years (2008 and 2009). Hence, the MERIS images of May 2008 and May 2009 were selected to show variations in K_d between the two years. Although the images are for the same month of the year, K_d still varies across the lake (Fig. 12). In the selected day of May 2008, a spatial average value of 0.77±0.49 m^{-1} is estimated for the entire lake, while on 17 May 2009 the spatial average value is 0.90±0.93 m^{-1}. Comparing the estimated maps for the two years suggests that the spring bloom in 2009 was stronger than the one in 2008 for the western basin. However, algal bloom in all basins of Lake Erie for the complete year of 2008 was recorded as the third largest that the lake experienced before the occurrence of the breaking record blooms in 2011 and 2015 (Michalak et al., 2013; NOAA, 2015). K_d value estimated for the NDBC station is 0.69 and 0.62 m^{-1} in 29 May 2008 and 17 May 2009, respectively.

4 Summary and Conclusion

Spatial and temporal variations of K_d in Lake Erie were derived from the globally available satellite-based CC product during open water seasons 2002-2012. The CC product was evaluated against SDD in situ measurements. CC-derived K_d values, modelled incoming radiation flux data, in addition to complementary meteorological observations during the study period, were used to force the 1-D FLake model. The model was run for a selected site (NDBC buoy station) on Lake Erie, a large shallow temperate freshwater lake.

FLake was run with the range of clarity values acquired from satellite observations. Results were compared to a previous study which assumed a constant K_d value due to the lack of data. Results clearly showed that applying satellite-derived K_d values improves FLake model simulations using a derived yearly average value as well as monthly averaged values of K_d. Although K_d varies in time, a time-invariant (constant) annual value is sufficient for obtaining reliable estimates of lake surface water temperature (LSWT) with FLake for Lake Erie NDBC station. It was also shown that the model is very sensitive to variations in K_d when the value is less than 0.5 m^{-1}.This finding is in agreement with the study of Rinke et al. (2010) and the recent study of Heiskanen et al. (2015) who determined that the impact of seasonal variations of K_d on the simulated thermal structure is small, for a lake with K_d values larger than 0.5 m^{-1}. The studies suggest that the response of 1-D lake models to K_d variations is nonlinear. The models are much more sensitive if the water is estimated to be too clear. ~~Heiskanen et al. (2015) recommend to use a value of K_d that is too high rather than too low in lake simulations, if the clarity of lake is not known exactly.~~ Results of our study showed that the sensitivity to K_d variations was more pronounced in simulation results for mean water column temperature (MWCT), lake bottom water temperature (LBWT), and mixed layer depth (MLD) compared to LSWT.

~~-~~Results of this study have~~as~~ important implications for understanding the thermal regime of lakes and show~~s~~ that the transparency of lakes can impact physical processes by influencing changes in seasonal mixing regime. Integrating lake specific K_d values can improve the performance of 1-D lake models. Although~~However,~~ field measurements of K_d are not widely available, ~~. T~~this study demonstrates the strength of ~~that~~ satellite observations and introduces them ~~are~~as a reliable data source to provide lake models with global estimates of K_d with high spatial and temporal resolutions. However, the weakness of this method is that the availability of satellite-derived K_d product can be limited due to cloud coverage or satellite overpass. Also, the in situ measurements are still required for validating satellite observations, because the in situ data collection remains the most accurate solution for water clarity measurement. The accuracy of the satellite-derived K_d product has to be verified for the water body of interest, especially for the ones with complex optical properties. After validation, ~~T~~the on-demand globally available CC product can be simply used for the water body of interest, as a source to fill the gaps in K_d in situ observations, and improve the performance of parameterization schemes and, as a result, further improve the NWP and climate models.~~-~~ Although MERIS is no longer active, the Ocean and Land Colour Instrument (OLCI) to be operated on the ESA Sentinel-3 satellite (launched on February 16, 2016) will provide continuity of MERIS-like data. OLCI has MERIS heritages and improves upon it with an additional six spectral bands. Therefore, investigation of the Sentinel-3 potential to provide lake modelling community with the water clarity information is the next step of the current study. Also, the possible improvement in Flake output, when forcing the model with air humidity data collected directly at the station, can be examined in the future studies.

Author Contribution

The presented research is the direct result of a collaboration with the listed co-authors. All materials in composition of the research article is the sole production of the primary investigator listed as first author. Dr. Claude R. Duguay and Dr. Homa Kheyrollah Pour supported this research through comments and advice related to the FLake model. The manuscripts were edited for content and composition by the co-authors.

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Table 1 Flags of excluded pixels

Level 1	**Level 1P**	**Level 2**
Glint_risk	Land	AOT560_OOR (Aerosol optical thickness at 550 nm out of the training range)
Suspect	Cloud	TOA_OOR (Top of atmosphere reflectance in band 13 out of the training range)
Land_ocean	Cloud_ambigious	TOSA_OOR (Top of standard atmosphere reflectance in band 13 out of the training range)
Bright	Cloud_buffer	Solzen (Large solar zenith angle)
Coastline	Cloud_shadow	NN_WLR_OOR (Water leaving reflectance out of training range)
Invalid	Snow_ice	NN_CONC_OOR (Water constituents out of training range)
	MixedPixel	NN_OOTR (Spectrum out of training range)
		C2R_WHITECAPS (Risk of white caps)

Table 2 CC-derived average values of Kd for each month (2005-2007). The values correspond to the time of year when water LSWT observations, as well as the CC derived Kd values, are available.

Year	**Apr.**	**May**	**June**	**July**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Avg.**
2005	--	0.69	0.62	0.63	0.79	1.07	0.92	0.97	0.81
2006	0.82	0.70	0.62	0.65	0.77	--	--	--	0.71
2007	0.86	0.72	0.64	0.65	0.76	--	--	--	0.73

Table 3 Simulated LSWT compared to in situ observations (2005 – 2007). Period corresponds to the time of year when LSWT and K_d values were available.

Period	**K_d**	**RMSE**	**MBE**	**I_a**
2005 May-Nov	Avg2005	1.69	-0.86	0.87
	Merged	1.76	-0.95	0.86
	CRCM-12.6	1.88	-1.52	0.85
	CRCM-20	2.12	-1.54	0.83
2006 Apr-Aug	Avg2006	1.40	0.59	0.89
	Merged	1.42	0.54	0.89
	CRCM-12.6	1.50	-0.98	0.89
	CRCM-20	1.47	-1.09	0.89
2007 Apr-Aug	Avg2007	1.37	0.62	0.90
	Merged	1.35	0.57	0.91
	CRCM-12.6	1.78	-1.08	0.86
	CRCM-20	1.80	-1.35	0.87

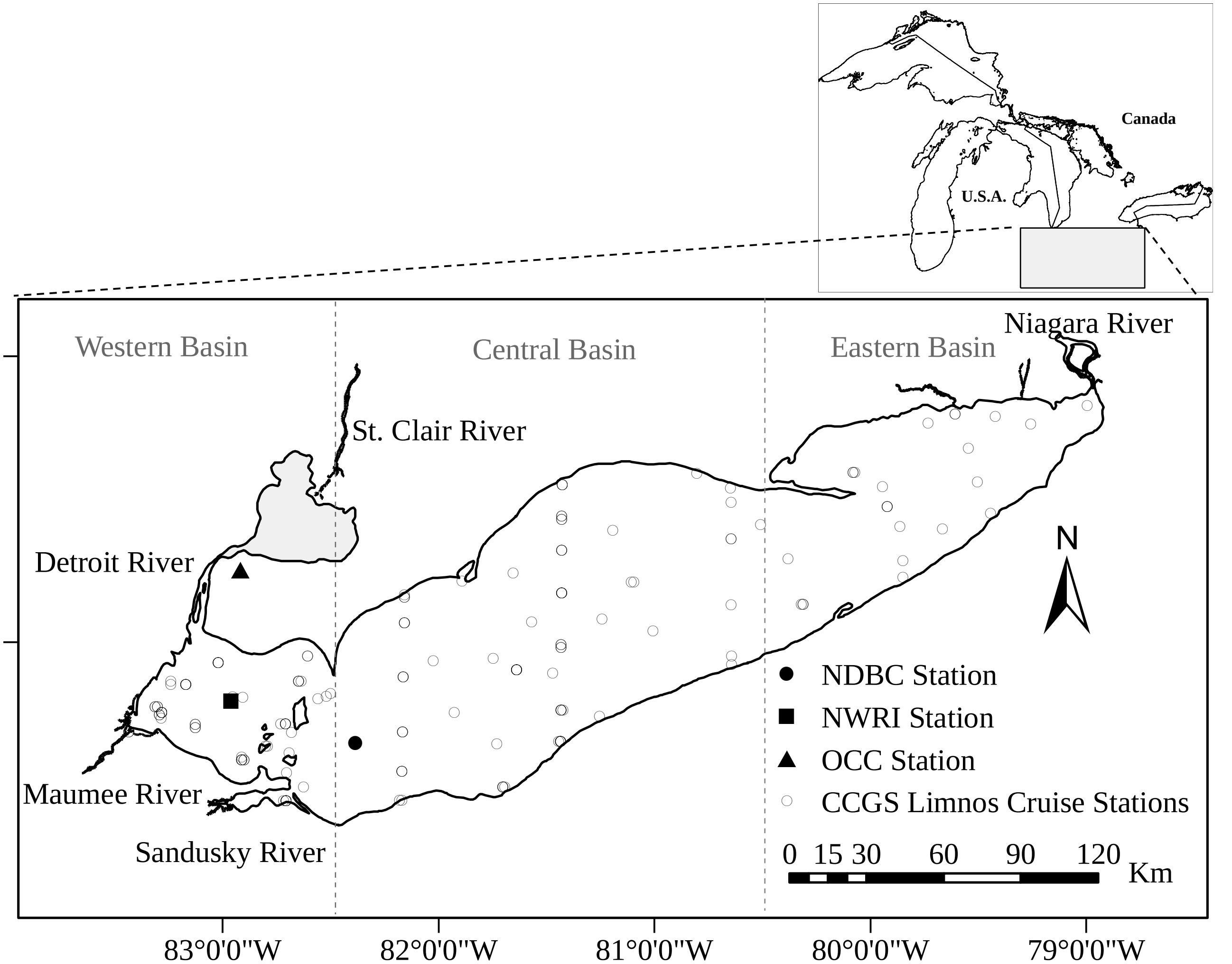


Fig. 1 Maps showing Lake Erie in Laurentian Great Lakes and the location of stations where different parameters were measured.

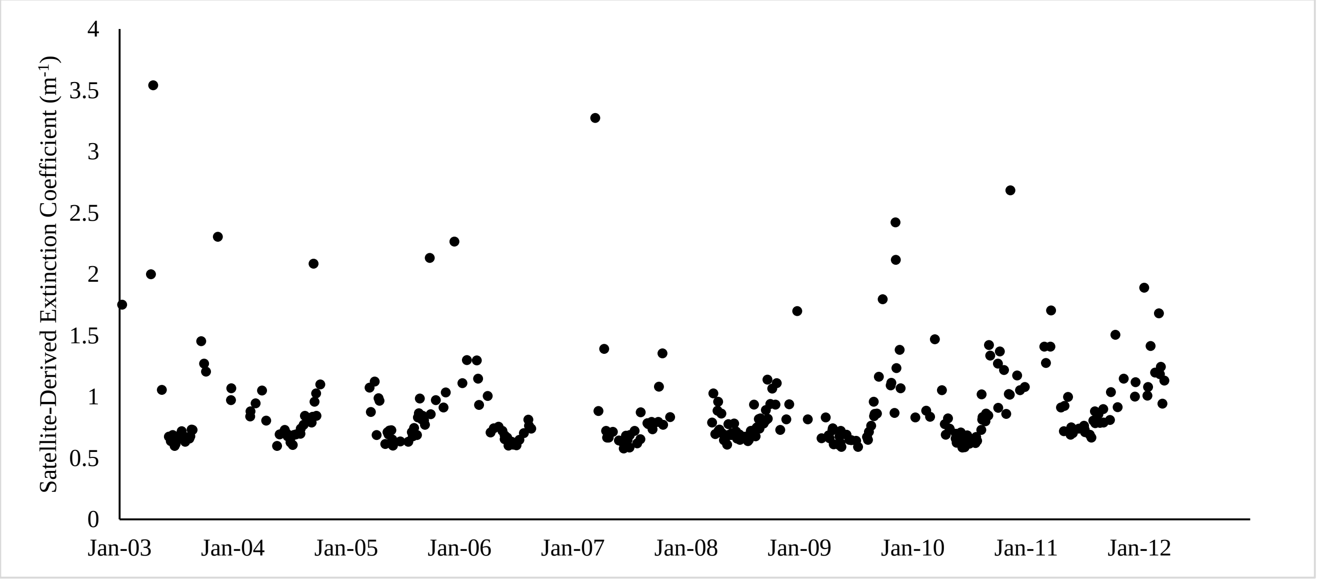


Fig. 2 Variations of CC-derived K_d for the selected location during the study period (2003-2012).

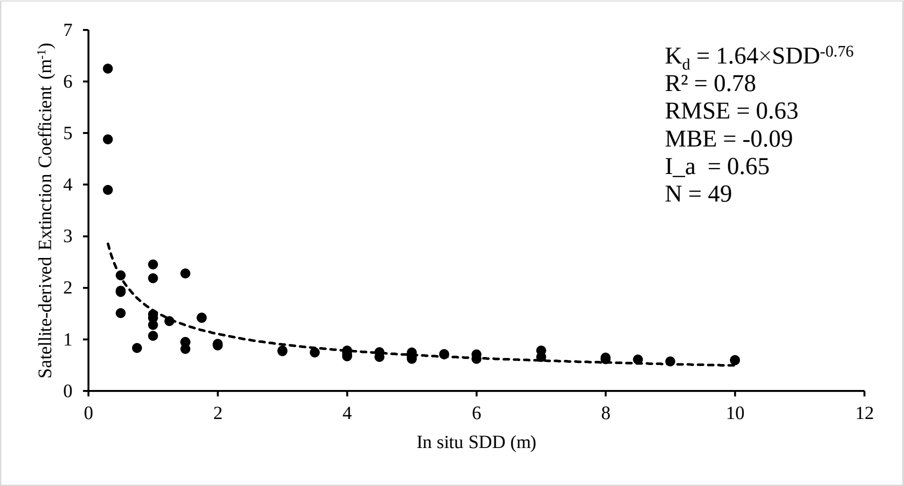
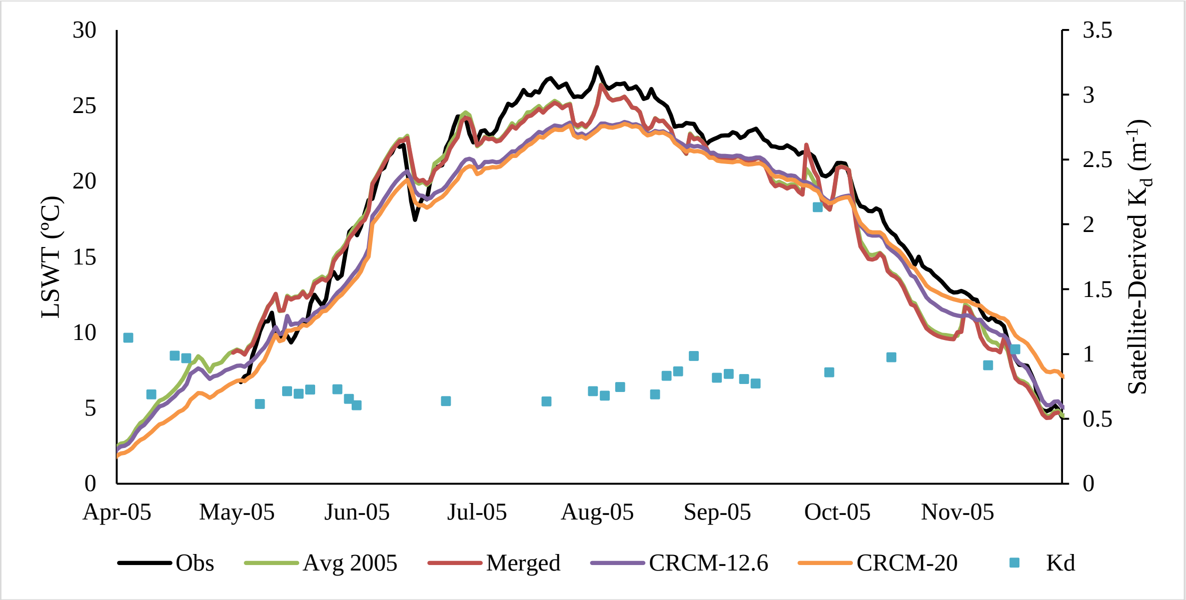
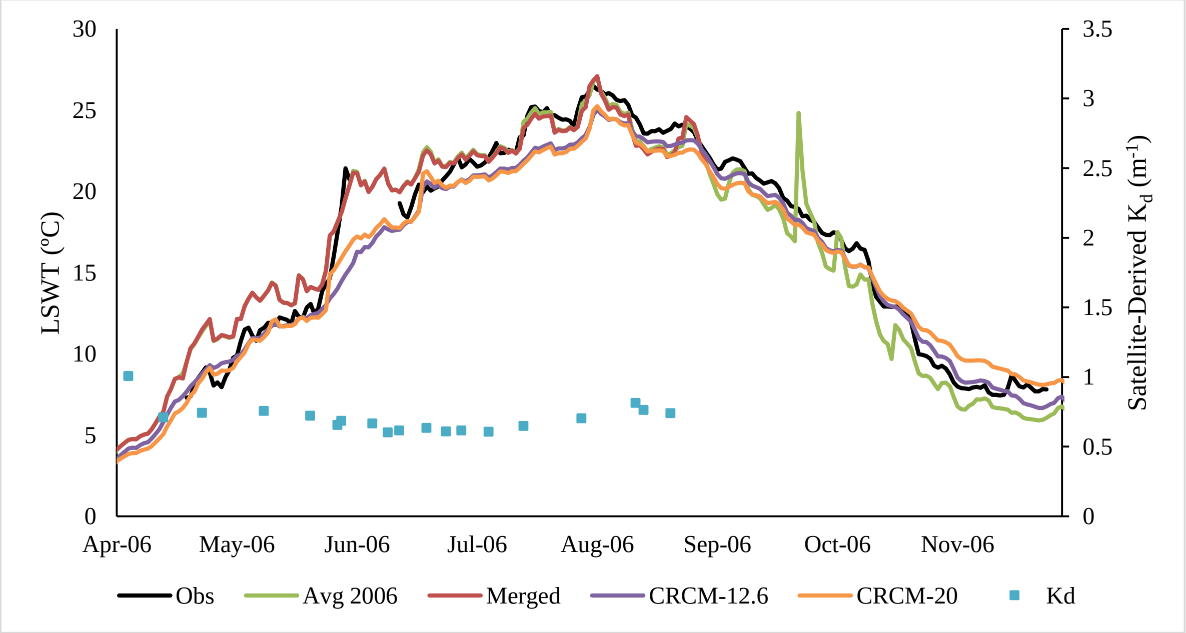


Fig. 3 Relation between satellite-derived K_d and in situ SDD matchups.


LSWT (°C)
Satellite-Derived Kd (m-1)
30
25
20
15
10
5
0
3.5
3
2.5
2
1.5
1
0.5
0
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Obs
Avg 2005
Merged
CRCM-12.6
CRCM-20
Kd


LSWT (°C)
Satellite-Derived Kd (m-1)
30
25
20
15
10
5
0
3.5
3
2.5
2
1.5
1
0.5
0
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Oct-06
Nov-06
Obs
Avg 2006
Merged
CRCM-12.6
CRCM-20
Kd

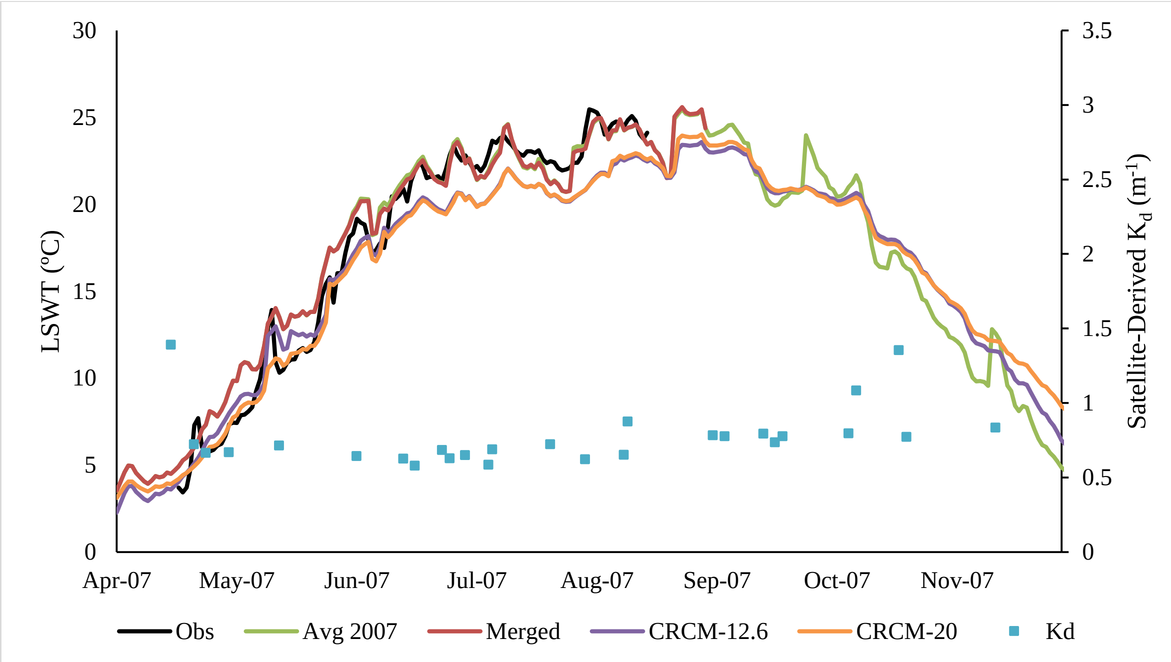


Fig. 4 LSWT simulation results for 2005 - 2007; from: CRCM-12.6, CRCM-20, CC-derived average for K_d during selected month of each year (0.81, 0.71, and 0.73 m^{-1}; respectively), and the merged simulations based on each month average K_d. The corresponding observations for LSWT, and CC-derived K_d values are also plotted. Missing lines mean no data.

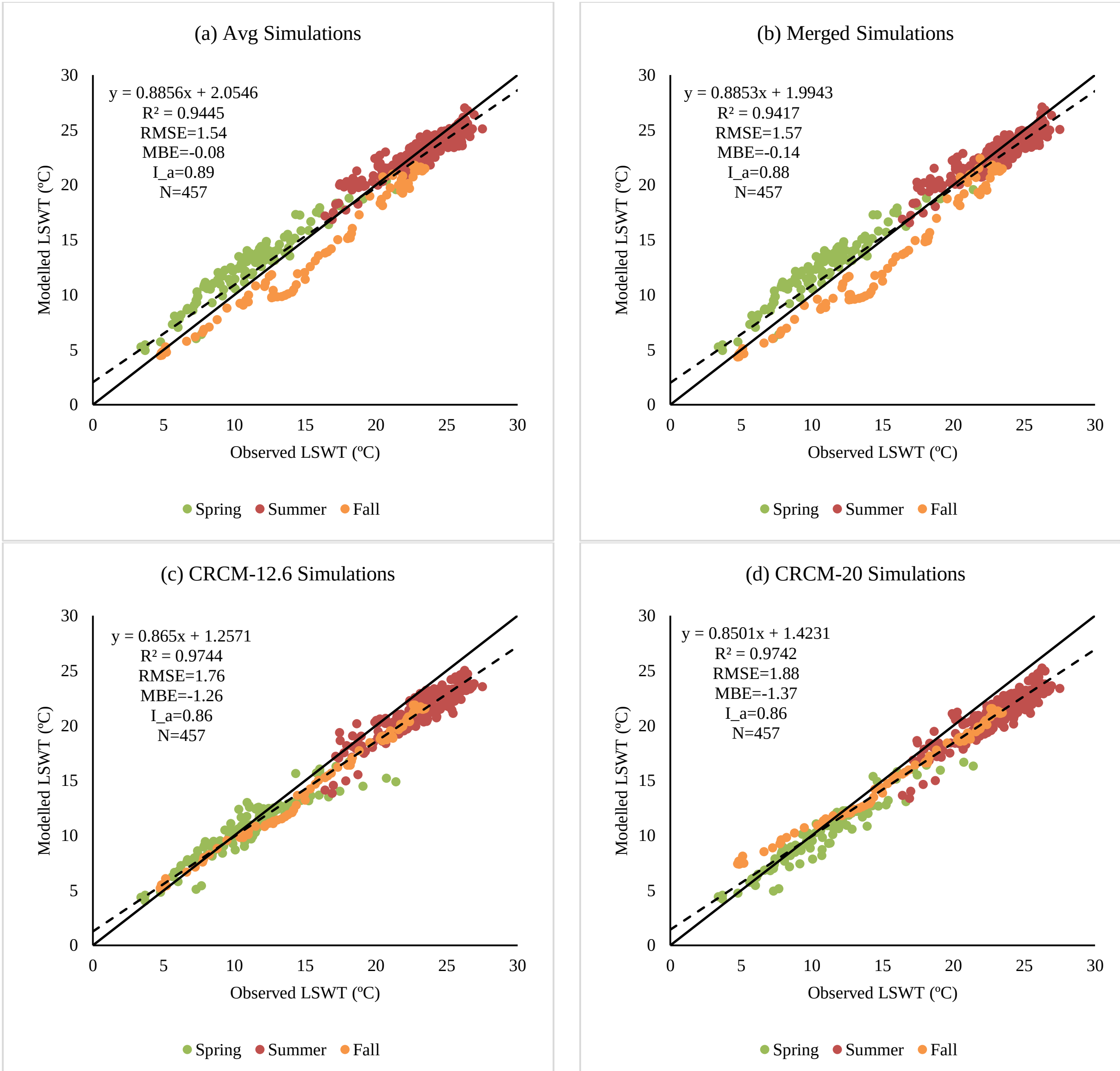


Fig. 5 Modelled (y-axis) versus observed (x-axis) LSWT for yearly average, merged, CRCM-12.6, and CRCM-20 simulations during the ice-free seasons in 2005-2007. A linear fit (dashed line) and its coefficients are shown on the plot. The statistics related to the regression of parameters, and a 1:1 relationship (solid line) are also shown. The average LSWT values of Obs, Avg, Merged CRCM-12.6, and CRCM-20 simulations are 18.64 ºC, 18.56 ºC, 18.50 ºC, 17.38 ºC, 17.27 ºC.

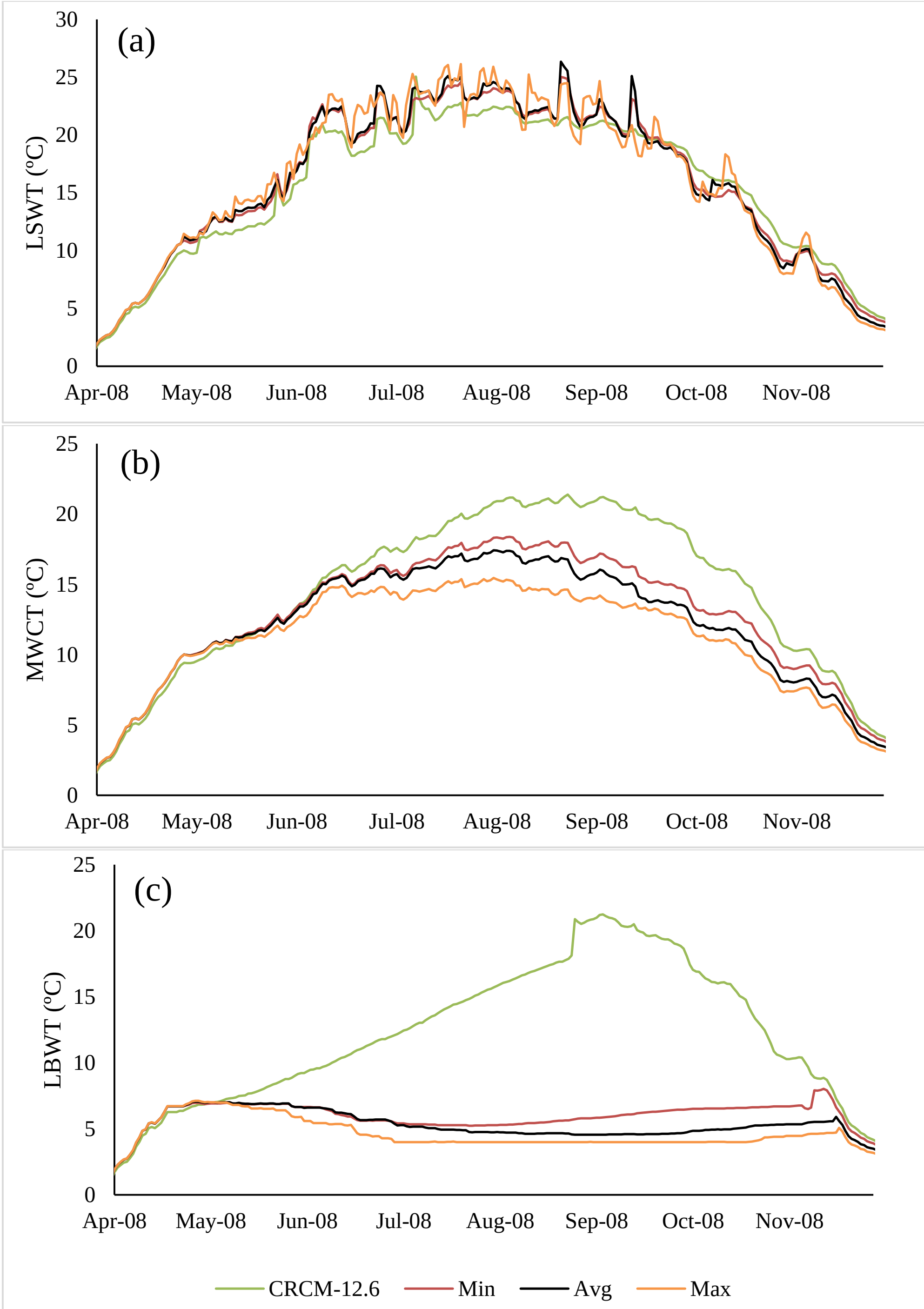


Fig. 6 LSWT (a), MWCT (b), and LBWT (c) simulation results in 2008 for CRCM-12.6 (K_d=0.2 m^{-1}) simulation and the lowest (Min, K_d=0.58 m^{-1}), average (Avg, K_d=0.90 m^{-1}), and the highest (Max, K_d=3.54 m^{-1}) K_d values are shown.

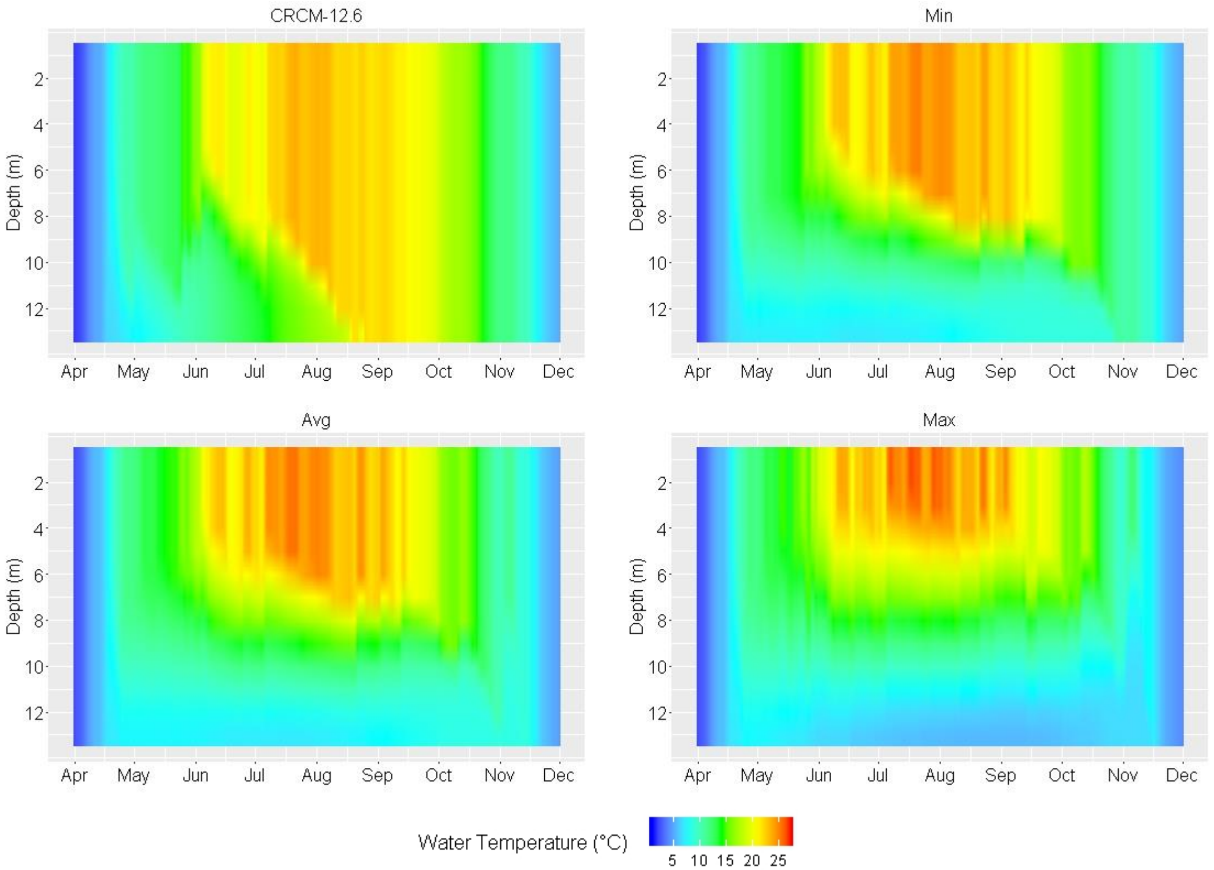


Fig. 7 Isotherms in open water period 2008 for CRCM-12.6 (K_d=0.2 m^{-1}) simulation and the lowest (Min, K_d=0.58 m^{-1}), average (Avg, K_d=0.90 m^{-1}), and the highest (Max, K_d=3.54 m^{-1}) K_d values are shown.~~for CRCM-12.6 simulation and the lowest (Min), average (Avg), and the highest (Max) Kd values are shown.~~

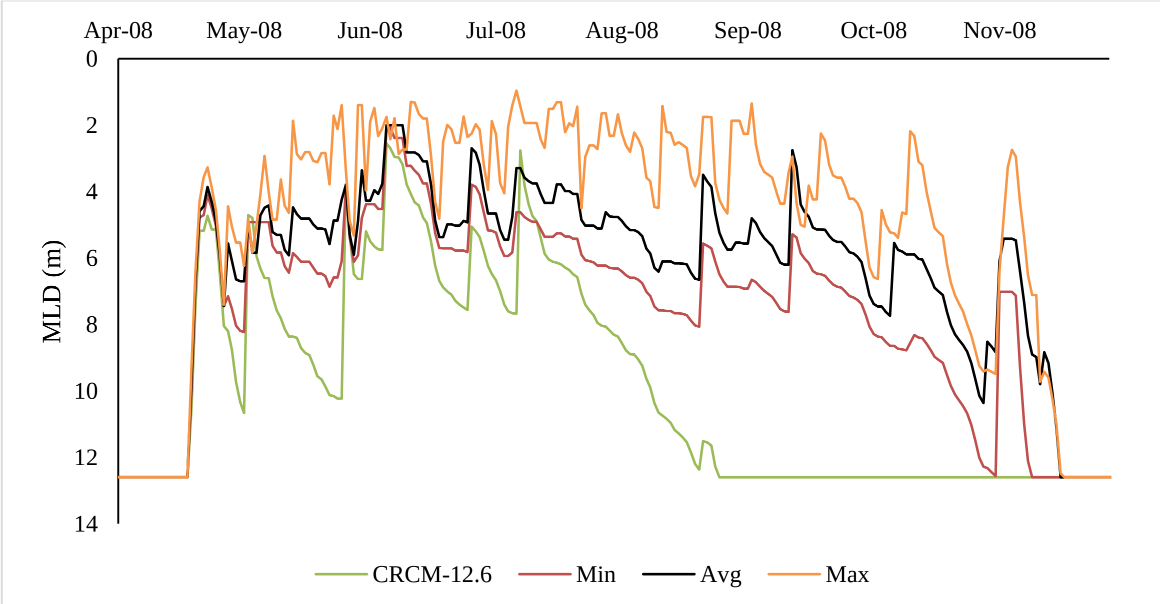


Fig. 8 MLD simulation results in 2008 for CRCM-12.6 (K_d=0.2 m^{-1}) simulation and the lowest (Min, K_d=0.58 m^{-1}), average (Avg, K_d=0.90 m^{-1}), and the highest (Max, K_d=3.54 m^{-1}) K_d values are shown.~~for CRCM-12.6 simulation and the lowest (Min), average (Avg), and the highest (Max) K_d values are shown.~~

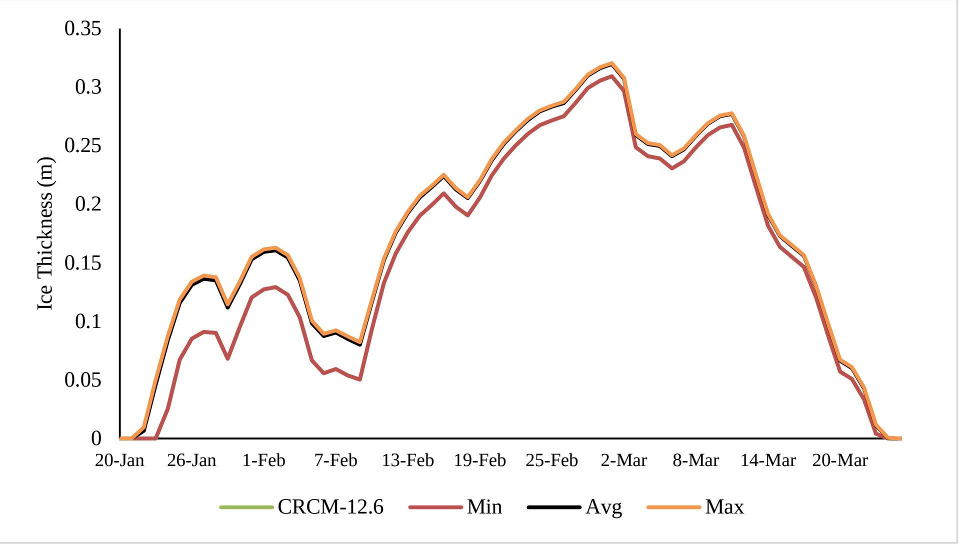


Fig. 9 Ice thickness during 2008 for CRCM-12.6 (K_d=0.2 m^{-1}) simulation and the lowest (Min, K_d=0.58 m^{-1}), average (Avg, K_d=0.90 m^{-1}), and the highest (Max, K_d=3.54 m^{-1}) K_d values are shown.~~for CRCM-12.6 simulation and the lowest (Min), average (Avg), and the highest (Max) K_d values are shown.~~ CRCM-12.6 and Min (Avg and Max) simulations reproduce similar ice thicknesses.

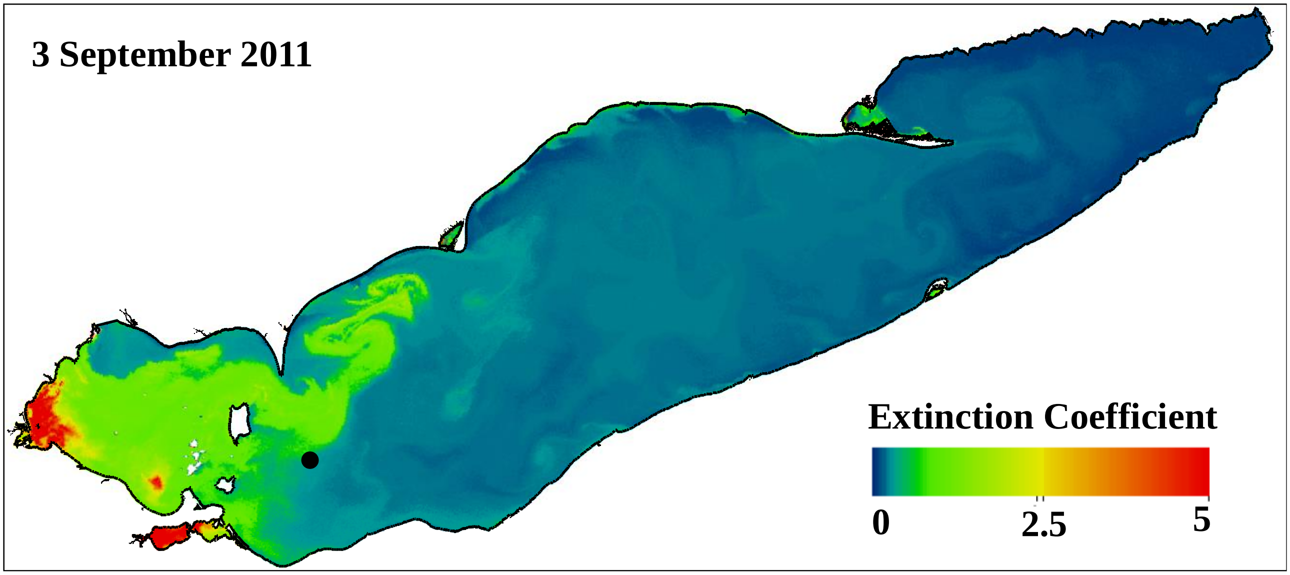


Fig. 10 Spatial variation of satellite-derived K_d in Lake Erie, on 3 September 2011. Location of NDBC station is shown on the map as a solid dot.

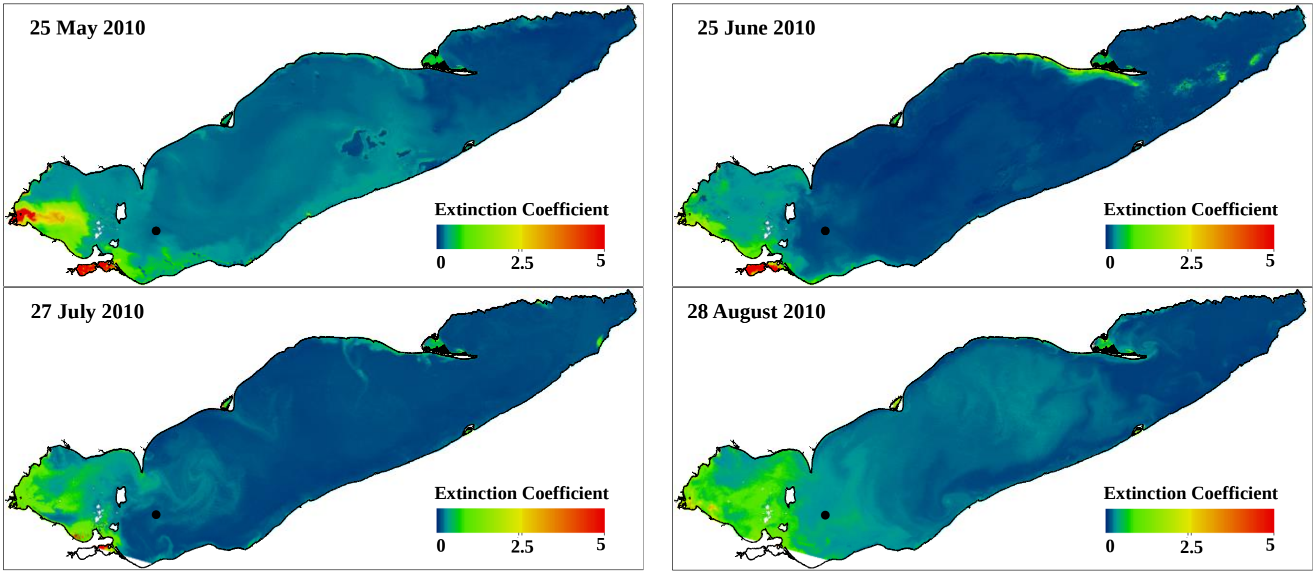


Fig. 11 Temporal and spatial variation of satellite-derived K_d in Lake Erie for different months of a year: May- August 2010. Location of NDBC station is shown on the map as a solid dot.

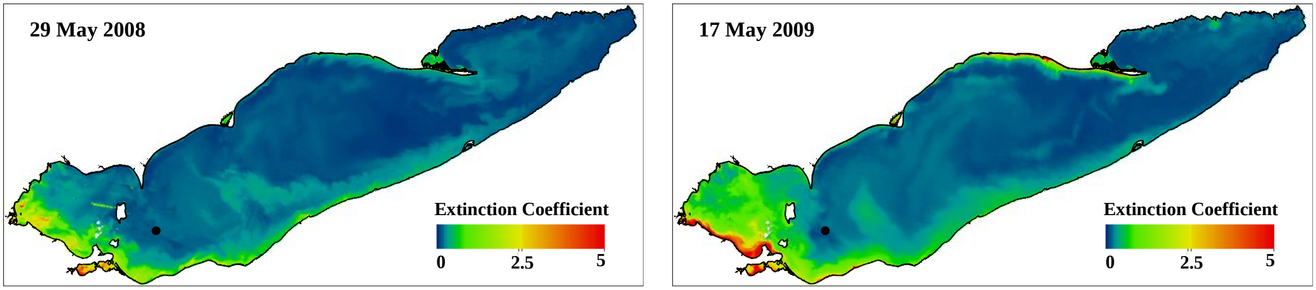


Fig. 12 Temporal and spatial variation of K_d in Lake Erie during May of two consecutive years: 2008 and 2009. Location of NDBC station is shown on the map as a solid dot.

We would like to thank the two reviewers for their constructive comments, which greatly helped us to improve the manuscript. Our replies to the comments are listed below.

Reviewer #2 Comments:

Many major revisions were suggested by the reviewers. Most of these have not been properly addressed in this revised manuscript. For this reason, I have no choice but to recommend not to publish this manuscript.

We are sorry to hear that the reviewer is not satisfy with our answers, despite our efforts to address his/her comments. However, we understand we could do a better job to improve the quality of the paper based on the constructive suggestions provided by the reviewer. This time, we did our best to consider his/her comments more closely and cover his/her questions and concerns in the text. The manuscript is significantly modified and now, we believe the revised version is reflecting his/her thoughts, and we hope this time the reviewer is happy with the new version.

General comments:

This manuscript deals with water optical properties which are acquired by remote sensing, and which are then used as input to 1-D lake modeling. This approach is important and needed addition to current efforts of incorporating lakes and reservoirs to weather prediction models. Water clarity is an important factor in defining lake heat budget and thermal stratification and thus is a significant parameter for processes in the air-water interface. With millions lakes of different sizes around the world, comprehensive direct measurements of water clarity are not possible, highlighting the need for indirect estimates of water optical properties. Satellite measurements show great promise in mapping light extinction coefficient, a parameter to define water clarity, and to my knowledge this study is the first one to incorporate lake modeling to water clarity defined from satellite observations. This is an important study with wide interest in scientist from different fields and therefore I find this study appropriate for HESS. However, there are a few major points which prevents me from recommending this manuscript for publication as it is.

The major topic of this manuscript is that satellite-derived light extinction coefficient, Kd, represents well the in situ measurements of Kd, that it can be used as an input to lake modeling, and that it enhances the performance of FLake as compared to the current approach of using constant Kd of 0.2 m-1. These points should be emphasized. Currently, the manuscript seems unbalanced, with much of the focus given to topics not strictly the main theme of this manuscript. Also some restructuring is needed so that the reader does not get distracted from the main focus. In general, the manuscript would benefit from reducing the amount of figures.

Thanks for your valuable comment. We have done restructuring to emphasize the main theme of the paper, focusing on the mentioned objectives. The first objective of this manuscript (satellite-derived Kd value can represent the in situ measurements of water clarity, and therefore be used as input to lake modeling) is discussed in section 3.1. Section 3.1.1 shows that the variations of water clarity at NDBC station can be derived from satellite observations. Section 3.1.2 shows that these satellite-measured water clarity is representing the in situ measurements of water clarity because there is a high agreement between the field measured values of SDD and satellite observations of Kd. Therefore, the satellite-derived Kd can be used in the lake modeling, as discussed in the next section of manuscript (section 3.2).

The second objective of the paper is to show that using the satellite-derived lake-specific Kd value can improve the performance of lake modeling, compared to the current approaches of using a constant Kd value. This is covered in the next section, section 3.2.1. The range of Kd variations that brings the most sensitivity for the modelling is discussed in section 3.2.2. The next section, section 3.3, shows how remote sensing observations can capture the spatial and temporal variations of Kd, which is not possible through the conventional point-wise field sampling methods. This section highlights the importance and strength of Kd satellite-derived values, which can be utilized in lake modeling to improve their performance.

Some of the figures are removed, as it will be mentioned in the following answers.

Since this is the first approach in combining satellite-derived Kd to lake modeling, it would be of value to describe the strengths and the weaknesses of this approach. How easy and accurate method this is for the modeling community in general; can this be used without in situ measurements of Kd or should there always be e.g. Secchi disk measurements for validation; what are the next steps needed for applying this method in broader context.

Thank you for your comment.

The previous reply: Thank you for the detailed comments. With a few exceptions (e.g. restructuring of the paper which was not a concern for Reviewers #1 and #3), we have considered all suggestions in our revised manuscript.

The strength of integrating satellite-derived Kd values in lake models is mentioned on page 14, lines 9-12 (Integrating lake specific Kd values can improve the performance of 1-D lake models. However, field measurements of Kd are not widely available. This study demonstrates that satellite observations are a reliable data source to provide lake models with global estimates of Kd with high spatial and temporal resolutions).

The weaknesses of this approach could be that the validation of satellite-derived Kd values, and therefore the results of the lake models (which are based on using satellite information), depend on in situ SDD or water clarity. Therefore, in situ data is a requirement for the validation approach. This information was provided on page 7, lines 14-15.

The globally available CC product can be easily used as a source to fill the gaps in Kd in situ observations as well as improving the performance of lake parameterization schemes and, therefore, further improve NWP and regional climate models. This is mentioned on page 14, lines 12-14.

The next steps are mentioned in the manuscript on page 14, lines 14-117: to investigate the potential of Sentinel-3 to provide lake modeling community with the water clarity information. Also, this study demonstrates improvement in a lake surface scheme (Flake) commonly used in NWP and regional climate models.

The new reply: The last paragraph in the conclusion section is modified to represent these points. The strength of integrating satellite-derived Kd values in lake models is mentioned on page 14, lines 8-12 (Results of this study have important implications for understanding the thermal regime of lakes and show that the transparency of lakes can impact physical processes by influencing changes in seasonal mixing regime. Integrating lake specific Kd values can improve the performance of 1-D lake models. Although field measurements of Kd are not widely available, this study demonstrates the strength of satellite observations and introduces them as a reliable data source to provide lake models with global estimates of Kd with high spatial and temporal resolutions.).

The weaknesses of this approach is added on page 14, lines 12-15 (However, the weakness of this method is that the availability of satellite-derived Kd product can be limited due to cloud coverage or satellite overpass. Also, the in situ measurements are still required for validating satellite observations, because the in situ data collection remains the most accurate solution for water clarity measurement.).

Modifications have been made in page 14, lines 15-18 to show how easy and accurate this method can be transferred to other study areas (The accuracy of the satellite-derived Kd product has to be verified for the water body of interest, especially for the ones with complex optical properties. After validation, the on-demand globally available CC product can be simply used for the water body of interest, as a source to fill the gaps in Kd in situ observations, and improve the performance of parameterization schemes and, as a result, further improve the NWP and climate models.).

The next steps are mentioned in the manuscript on page 14, lines 18-23 (Although MERIS is no longer active, the Ocean and Land Colour Instrument (OLCI) to be operated on the ESA Sentinel-3 satellite (launched on February 16, 2016) will provide continuity of MERIS-like data. OLCI has MERIS heritages and improves upon it with an additional six spectral bands. Therefore, investigation of the Sentinel-3 potential to provide lake modelling community with the water clarity information is the next step of the current study. Also, the possible improvement in Flake output, when forcing the model with air humidity data collected directly at the station, can be examined in the future studies).

Specific comments

In regards of restructuring, I will give here an example how the figures (and related discussion) could be rearranged. After the map, I suggest to first show satellite-derived Kd at the site of FLake modeling (current Fig. 8), which is the main input parameter under focus here. For the estimated solar irradiance and incoming long-wave radiation (Figs.2 and 3), the figures add only little to the reported statistics and thus these two figures could be removed. After showing the satellite-derived Kd, it would be logical to show their validation (current Fig. 4). Then the results of models against measurements, i.e. current Figs. 9 and 10. Current Figs. 11, 12, 13 and 14 basically show the same data in different forms. I suggest either to combine Figs. 11 and 12 and show only this, or show only Fig 13. Lastly, current Figs. 5 and 6 could be shown, which would then lead to the discussion of the strengths of satellite-derived Kd and possible future studies (see also the related comment later). **This is only a suggestion for restructuring, it could also be done otherwise.**

The previous reply: Thank you for the suggestion. However, we would like to keep the current structure of the paper. This study is based on using satellite-derived shortwave radiation. Longwave radiation is also estimated. Therefore, these two parameters need to be evaluated for the study area of interest (Figures 2 and 3). We feel that the quality of shortwave and longwave radiation estimates needed to be confirmed first before being used in FLake simulations. Of the other input parameters in the FLake model, the most important one is water clarity which is also derived from satellite observations. Before further discussing the potential of combining satellite observations of water attenuation into the model, first the evaluation was conducted (Figure 4). Following this, Figures 5-7 show the extent of spatial and temporal variations of water clarity (now evaluated) for the entire water body. Figure 8 shows how water clarity has changed at the station of interest (NDBC) during the study period. Based on the variations (min, max, average values of Kd at this station), different simulations were designed to test the sensitivity of FLake to variations of Kd.

Figure 9 shows how observations and different simulations compare over the study period. The figure illustrates if there is any specific time when the difference between simulations and observations is more prominent; whereas Figure 10 is more for statistical evaluation purposes.

Figures 11-14 may somewhat overlap in the presentation of information. However, the figures are used in this study for different purposes. Figure 11 shows LSWT and MWCT, Figure 12 MLD, Figure 13 timing, depth, and temperature of different thermal layers (epilimnion, thermocline) as well as temperature of MLD. Finally, Figure 14, shows the average temperature and depth of each thermal layer. Given the above, we find that the paper follows a logical structure.

The new reply: Thanks for your suggestion regarding restructuring. Figure 2 and 3 in the previous version have been removed and modifications are made in page 5 lines 1 and 12.

The variations of Kd at NDBC station is now moved to the beginning of section 3.1 (new section 3.1.1); and the evaluation and accuracy of the CC-derived Kd is calculated after showing Kd variations in NDBC (new section 3.1.2). Modifications are also made in page 5 lines 31-33 and page 6 line 1.

The spatial and temporal variation of Kd in the full lake is shown in section 3.3 to demonstrate the potential of remote sensing to capture the variation of this water quality parameter, whereas this is not possible using the conventional in situ measurements. These information are added on page 12 lines 27-31.

Figure 14 in the old version of manuscript is removed. We agree that Figures 7-8 (in the new version of manuscript) have overlaps in the presentation of information, but they are shown for different purposes. Figure 7 shows the evolution of different thermal layers during time, as well as their temperature. However, Figure 8 is derived from Figure 7 and temperature is not anymore a factor in Figure 8, and the focus is only on MLD. This way, demonstrating the variations of MLD during time is shown better and more clear compared to Figure 7. We feel that keeping figure 7 and removing Figure 8, to discuss all the points only relying on Figure 7, makes it difficult to convey the information and also to understand the discussion for the reader.

Page 4, line 9. Air humidity, which is used as FLake input, is taken from land 10 km away from the lake site. Air humidity is important for modelled latent heat fluxes. Could the authors briefly state their opinion how well the measured air humidity represent that over lake, and how or if this affects the modeled results.

Thank you for this comment. Yes, we agree that air humidity is important for modeled latent heat flux and would be different over land and over lake. Since warm air holds more moisture than cold air, the percentage of humidity must change with change in air temperature. We expect that the humidity decreases as temperature increases. Large temperature and humidly differences can lead to large sensible and latent heat fluxes. Water is a good absorber of the energy but the land absorbs much faster the energy from the sun. Water heats up much slowly than land and, therefore, the air above land will have higher temperature and therefore less humidity. On the other hand, lack of in situ data over lakes and the distance of the stations from the shoreline (less than 81 km in our case, 10 km was recognized as a mistake in the manuscript, corrected in page 4 line 11 of the new manuscript) is one of the main limitation of lake studies. In this study, all model forcing variables come from the station on land such as air temperature and humidity, therefore in this way the rate of differences between air temperature and humidity was kept constant.

Page 4, lines 19-21. Sentences starting with “Available Secchi disk” and “SDD data was” are repetitive and should be merged to one sentence. Also, it could be mentioned here that the SDD data comes from Limnos cruises.

The previous reply: Thank you for the comment. Page 4, lines 20-21 have now been changed in the new version of the manuscript (“Available Secchi disk depth (SDD) field measurements were used to estimate lake water clarity.”).

The new reply: Thank you for the comment. Page 4, lines 20-22 have now been changed in the new version of the manuscript (“Available Secchi disk depth (SDD) field measurements were collected by EC research cruises on board the Canadian Coast Guard Ship Limnos and utilized in this study to evaluate the satellite-derived water clarity. The cruise visited Lake Erie at a total of 89 distributed stations in five different years”).

Page 6, lines 1-2. Please clarify this sentence. Does this basically mean that only the pixels which were not rejected according to the criteria in Table 1 were used?

Yes, you are correct, this is what we meant.

Page 7, Chapter 3.1.1. A lot of space is dedicated for this, and therefore a justification could be given in the first sentence. E.g. “Validating the satellite-derived Kd with in situ observations is important because. . .” And in the end of the chapter the outcome of the evaluation, e.g. “For these reasons, we deem the satellite-derived Kd correct and thus were confident in using them in the modelling.” Also, in Chapter 3.1.1. or later, the authors could discuss whether this kind of validation is always needed with satellite observations, what are the implications, etc.

The previous reply: The justification of having section 3.1.1 is that the reliability of satellite-derived Kd values, to integrate them in lake models, is highly dependent on their comparison and evaluation against independent in situ SDD measurements. This highlights the importance of this section as mentioned on page 7, lines 14-15.

Also, at the end of this section, the reason and motivation of using satellite-derived water clarity measurements is mentioned on page 8 lines 9-13 (in situ SDD data are not always describing Kd values. Only small values of Kd are described using SDD). On page 7 lines 14-15, it is mentioned that the reliability and validation of satellite-derived Kd values highly depends on comparison with in situ measurements.

The new reply: Thanks for your constructive comment. We applied your suggestion with slight changes to fit in the manuscript. The justification of having section 3.1.2 (in the new version) is added in the new manuscript page 7 line 19-20 (“The validation of satellite observations against in situ data is important, because the in situ data are still considered as the most accurate measurement of water clarity.”)

Also, at the end of this section, the reason and motivation of using satellite-derived water clarity measurements is added on page 8 lines 12-22 (“Results from the above procedure show that Kd can be derived from SDD, using the equation 〖 K〗_d=1.64×〖SDD〗^(-0.76), with a strong determination of coefficient value (R2 = 0.78). Arst et al. (2008) obtained a similar regression formula between SDD and Kd for the boreal lakes in Finland and Estonia representing different types of water, expanding from oligotrophic to hypertrophic. Because there is a good agreement between Kd and the corresponding ones estimated from in situ measured SDD (N = 49, RMSE = 0.63 m-1, MBE = -0.09 m-1, I_a = 0.65; Fig. 3), the satellite-derived water clarity are deemed to be correct and were used in the modelling for this study.

However, SDD is not always describing Kd values. SDD is a suitable characteristic to describe water transparency for small values of Kd. For high values of Kd (ranging above 4 m-1), Arst et al. (2008) and Heiskanen et al. (2015) suggest that SDD is unable to describe any changes in Kd. Fig. 3 also shows that SDD cannot describe the scatter of Kd for values above 4 m-1. Therefore, the estimation of Kd from SDD should be used with caution, motivating the investigation on the potential of integrating satellite-based estimations of Kd into lake models.”)

On page 7 lines 19-21, and page 14 lines 13-15, it is mentioned that in situ data are still considered the most accurate measurement method and therefore the reliability and validation of satellite-derived Kd values highly depends on comparison with in situ measurements.

Page 8, Chapter 3.1.2. This chapter seems interesting but out of place. These results are not further elaborated, and therefore I suggest to move them to the end of the Discussion. This way the authors could show what benefits remote sensing of Kd would bring (spatial and temporal variability, which is not achieved well with manual sampling; perhaps good input for 2D and 3D modeling), which would lead to the discussion of possible next studies. This way also the key input parameter, Kd at the NDBC station, would be shown earlier.

The previous reply: Thank you for the suggestion. This section describes how Kd values vary spatially and temporally over the full lake, and it ends with the variations of Kd at the location of the NDBC station. This section aims to demonstrate how variable Kd can be across the lake and over a period of time, demonstrating the lack of in situ observations to cover these variations temporally and spatially, and highlighting the motivation of using remote sensing observations to overcome these concerns. After highlighting the important role that remote sensing observations can play within lake models, the paper continues by showing the results of integrating satellite-derived water clarity within FLake. Therefore, we would prefer to keep the current structure of the manuscript since, in our minds, it follows a logical sequence.

The new reply: Thank you for the suggestion. The section related to the spatial and temporal variations of satellite-derived Kd is moved to the end of discussion in the new version of manuscript (section 3.3). This section starts with explaining the important role of remote sensing measurements to fill the temporal and spatial gaps in the in situ data collection ("As it was described in the previous section, variations in water clarity plays an important role in defining lake heat budget and thermal stratification and thus is a significant parameter for processes in the air-water interface. However, the long term spatial and temporal trends of water clarity cannot be achieved through discontinuous conventional point-wise in situ sampling. These observations can be provided from satellite measurements. This section demonstrates the strength of satellite observations to detect the spatial and temporal variations of Kd in Lake Erie")

Page 9, Chapter 3.2.1. If the satellite-derived Kd has been validated sufficiently well and it produces better simulations, what would be needed for the simulations to match the measured LSWT more accurately? This could lead to suggestions for future research.

The previous reply: The comment is not clear for us. Section 3.2.1 discusses the improvement in modeling results using the satellite-derived Kd values. The next section (3.2.2) examines the sensitivity of FLake to the variations of Kd, and if it is necessary to consider the temporal variations (monthly basis) of Kd in simulations or simply a constant-lake specific value in the modeling of Lake Erie.

Therefore, if this comment is suggesting to consider the temporal variations of Kd in simulations for further improvement, this has already been considered and tested for the range of Kd values in Lake Erie.

Perhaps having met. station forcing data at the NDBC station directly could slightly improve the LSWT. However, here we would only be speculating. But the land station being 81 km away could be a factor.

The new reply: Thank you for your comment. Section 3.2.1 discusses the improvement in modeling results using the satellite-derived Kd values. The next section (3.2.2) examines the sensitivity of FLake to the variations of Kd, and if it is necessary to consider the temporal variations (monthly basis) of Kd in simulations or simply a constant-lake specific value in the modeling of Lake Erie.

Therefore, if this comment is suggesting to consider the temporal variations of Kd in simulations for further improvement, this has already been considered and tested for the range of Kd values in Lake Erie.

Air humidity data in the current study was provided from a station located 81 km from NDBC station. Therefore, perhaps having met. station forcing data (air humidity in our study) at the NDBC station directly could slightly improve the LSWT. However, here we would only be speculating. But the land station being 81 km away could be a factor. This is added on page 14 line 22-23 to show the potential for future researches.

Page 9, Paragraph starting 'Fig. 9 shows the results. . .'. I suggest to first describe the observed behavior in the temperatures and then discuss how the modelled behaviors compare to these.

The previous reply: The authors did not find it necessary to add the observed temperature behavior to the manuscript. This is because the temperature behaviour in three years, 2005-2007, have a normal fluctuation, increasing from spring to summer and decreasing toward winter. This is a basic knowledge.

The new reply: Thank you for your suggestion. The figure is now Fig. 4 in the revised manuscript. Modifications are made on page 9 line 1-4 ("Fig. 4 compares the results of different LSWT FLake simulations with observations at the NDBC station. LSWT observations have maximum values of 27.53 ºC, 26.48 ºC, and 25.46 ºC in August during 2005, 2006 and 2007. The minimum values of 2.71 ºC, 7.3 ºC, and 3.42 ºC were observed in December 2005, and April in 2006 and 2007. The average LSWT observations in 2005, 2006, and 2007 have values of 18.45 ºC, 17.12 ºC, and 17.75 ºC, respectively. The simulated LSWT values in Fig. 4 are produced by first applying Kd = 0.2 m-1 from Martynov et al. (2012) using both the real lake depth at the station (12.6 m: CRCM-12.6) and also a tile depth corresponding to the station in their study (20 m: CRCM-20). Then, simulations using the yearly average CC-derived Kd for each year of study are plotted (Avg).")

Page 10, lines 17-18. This is quite strong statement and probably not true for all lakes. Lakes are very heterogeneous, be more specific which type of lakes is meant here.

The previous reply: These sentences were meant to explain why results of two simulations of Avg and Merged are comparable, while Avg simulation are producing lower MBE. The statement starts with "it is possible". Therefore, it is only a potential reason for such results in Lake Erie, and not a generalized rule for all lakes. However, modification to the sentence has been applied to clearly make this point (Page 10 line 32 also page 1 lines 19-20).

The new reply: Thanks for your comment. Sorry for the confusion. These sentences were meant to explain why results of two simulations of Avg and Merged are comparable, while Avg simulation are producing lower MBE. The statement starts with "it is possible". Therefore, it is only a potential reason for such results in Lake Erie, and not a generalized rule for all lakes. However, modification to the sentence has been applied to clearly make this point (Page 10 line 3-6 also page 1 lines 19-20). "It is possible that the extent of Kd variations is best represented by the yearly average value. Therefore, using a constant annual open water season value for Kd could be potentially sufficient to simulate LSWT in 1-D lake models with relatively high accuracy (the range of Kd variations that brings the most sensitivity for the modelling is discussed in Sect. 3.2.2)." This statement is more clarified in the next section when the sensitivity of Flake to the variations of Kd is investigated.

Page 10, Chapter 3.2.2. This chapter needs the most restructuring. E.g. the paragraph on page 11, lines 25-28, could be removed. The two first sentences are basic limnological knowledge and the last sentence does not really lead the story further. In this chapter, the theme of light penetration and absorption is discussed in many places, e.g. on page 11, lines 8-9, lines 11-12 and lines 29-34, page 12, lines 11-13 and lines 19-20. Remove excess repetition. The last paragraph on page 12 (starting Fig. 14 depicts. . .) repeats what is said earlier and is not the main focus of this study, therefore I suggest to remove that paragraph. The last paragraph of Chapter 3.2.2. discusses about modeled ice cover. This seems a bit out of scope and there really seems to be no ice measurements against which to validate modeling. For this reason, I suggest to either remove this paragraph or significantly shorten it.

The previous reply: Thank you for the comment. Indeed, in situ measurements of ice are not available at the station. However, we performed a sensitivity analysis of FLake to variations in Kd in reproducing ice phenology and thickness. We feel that this it is useful to see the possible impact of Kd on ice conditions even if no in situ observations are available. This type of sensitivity analysis is commonly performed by the modeling community.

The paragraph starting with "Fig. 14 depicts", discusses how different values of Kd are affecting simulations of different layers of the thermal structure which is one of the objectives of our study. Fig. 14 elaborates more on temperature changes with depth. The timing factor has been removed in this figure compared to Fig. 13, to simplify making this point.

Page 11 lines 25-28 of the old version of manuscript have been removed. To avoid repetition, changes are made on page 11 lines 18-20 of the new manuscript. Also, removed are: page 11 lines 10-12, page 11 lines 31-33, page 12 lines 11-12 and lines 19-20 in the old version of manuscript.

The new reply: Thank you for the detailed comment. Page 11 lines 25-28 of the old version of manuscript have been removed. To avoid repetition, changes are made on page 10 lines 28-30 of the new manuscript. Also, removed are: page 11 lines 10-12, page 11 lines 31-33, page 12 lines 11-12 and lines 19-20 in the old version of manuscript.

The paragraph starting with "Fig. 14 depicts" in the previous version of manuscript is removed and changes are made in page 11 lines 20-30.

Indeed, in situ measurements of ice are not available at the station. However, we performed a sensitivity analysis of FLake to variations in Kd in reproducing ice phenology and thickness. We feel that this is useful to see the possible impact of Kd on ice conditions even if no in situ observations are available. This type of sensitivity analysis is commonly performed by the modeling community.

Page 11, lines 11-12. The authors seem to mix two concepts here. Darker water color is related to dissolved substances, such as colored dissolved organic matter, not to particulate matter.

Thank you for the comment. We agree that the two concepts have been mixed in the manuscript. However, we believe that light attenuation can be described using the terms "dark" and "clear" waters.

Clarity describes concentrations of both dissolved and suspended matters and can be related to attenuation of light. Therefore, the term of "clear water" (as opposed to "dark water") is used in this manuscript to explain waters with low (high) light attenuation coefficients. Light attenuation in clear (dark) waters is low (high) and this could be because of the existence of dissolved (e.g. absorption) or suspended matters (e.g. scattering).

On the other hand, turbidity is an indirect measure of scattering by particles (Bukata et al.,1995). It does not include dissolved matter in its definition. Therefore, the term "turbid water" is related to high concentrations of suspended matters. Turbidity of water could be low but still with high light attenuation due to high dissolved matters concentrations. Therefore, the term "turbid water" has been changed to "dark water" in the manuscript (page 2 lines 31, 33 – page 10 line 28, 29 – page 11 lines 1, 11, 12, 29, page 12 lines 15, 23).

Page 11, lines 13-14. The authors over-simplify the underlying mechanisms for LSWT behavior. The loss of energy to the atmosphere is related to the surface water temperature (and wind), not only in fall but throughout the open-water season. However, the mechanism how mixed layer depth affects the rate of heat loss needs more explaining.

The previous reply: We agree with the comment and have therefore modified page 11 lines 19-28 to reflect this. Considering MLD to explain the reason is basically combining the effect of both temperature and wind. This is because mixing is related to both wind forcing and convection. The mixed layer depth (MLD) affects the speed at which energy is lost to the atmosphere throughout the year.

The new reply: We agree with the comment and have applied modifications. To add explanation about the effect of MLD, page 10 line 31-33 and page 11 line 1-2 are modified. Considering MLD to explain the reason is basically combining the effect of both temperature and wind. This is because mixing is related to both wind forcing and convection. The mixed layer depth (MLD) affects the speed at which energy is lost to the atmosphere throughout the year.

Page 11, lines 18-23. Tie these results from the literature more tightly to the findings in this study, e.g. by writing whether this study supports or opposes previous findings. Also, the sentence on lines 21-23 (starting 'Heiskanen et al. . .') could be removed either from here or from the Summary.

The previous reply: The results of our study is already tied to other studies found in the literature. In page 11 lines 29-31, the result of our study is that the sensitivity of the model increases from Min to CRCM-12.6 simulation (Kd decreasing from 0.58 to 0.2). The statements after these lines (page 11 lines 31-33 and page 12 lines 1-2) are discussing other studies which support the finding of our study. This finding is that FLake is more sensitive to Kd values less than 0.5.

To prevent repetition, the statement starting at "Heiskanen et al. (2015) recommend to use a value of Kd that is too high rather….." has been removed from the summary on page 13 line 31 and page 14 line 1 of the old manuscript.

The new reply: Thanks for your comment. Page 11 line 6 is modified to show that other studies also support the results of our study.

To prevent repetition, the statement starting at “Heiskanen et al. (2015) recommend to use a value of Kd that is too high rather…..” has been removed from the summary on page 13 line 31 and page 14 line 1 of the old manuscript.

Page 12, paragraph starting with ‘Fig. 12 shows’. Here full mixing is described in very atypical way on several occasions, e.g. by ‘highest depth of mixing’ and ‘reaches maximum MLD’. I suggest to describe these occasions either by discussing of overturn, of full mixing or similar.

The previous reply: Lake turnover is the process of lake’s water turning over from top to the bottom, which is full mixing. The maximum/highest possible depth of mixing at NDBC station is 12.4 m, so when MLD reaches this depth turnover happens. This is the reason for describing turnovers using terms such as ‘highest depth of mixing’ and ‘reaches maximum MLD’. However terms of “maximum MLD” and “highest depth of mixing “have been changed to “full mixing “or “”overturn” on page 12, lines 13-17.

The new reply: Thanks for your comment. Terms of “maximum MLD” and “highest depth of mixing “have been changed to “full mixing “or “”overturn” on page 11 line 34, page 12 line 1.

Page 12, lines 8-9. If this is the reason for earlier overturn in simulations with clearer water, how the authors then explain the results shown in Figs. 11 and 13 where it is evident that there is full mixing in the beginning of September in CRCM-12.6 simulation with temperatures of about 20 deg C? Fig. 14 also shows that the clearer the water, the higher the water temperatures in Oct and Nov. Note that in addition to convection, mixing is related to wind forcing and density gradient in the water column.

The previous reply: CRCM-12.6 has the clearest water compared to other simulations, therefore the water column reaches the same temperature in its layers earlier than other simulations, leading to earlier turnover. Figures 11 and 13 and 14 support this statement.

The new reply: Thank you for catching this mistake. The sentence has been removed in the new manuscript since turnover can happen at different temperatures as long as the water column is at the same temperature.

Page 12, lines 16-17. MLD is not influenced by the thermal structure, but it is part of the thermal structure. I would remove this sentence.

Point well taken. The sentence on page 12 lines 16-17 of the previous manuscript has been removed.

Page 12, lines 13-14. Fig. 13 is essentially the same data as in Fig. 12 and therefore one cannot be used to confirm the results of the other.

The previous reply: confirms” has been changed to “also demonstrates” on page 12 line 24.

The new reply: Thank you. This sentence is removed in the new version of manuscript.

Page 12, lines 20-22. Deepening of the thermocline is related e.g. to wind forcing and thus it cannot be suggested that thermocline deepening in clear waters is monotonic. Also, it is not clear what is meant with ‘stabilize the temperatures’. I suggest to remove this sentence.

The previous reply: Figure 13 shows that in the simulation related to the clearest waters (CRCM-12.6), deepening of thermocline is faster, with a constant speed (monotonically increasing), as opposed to the dark waters.

On page 12 line 22 of the previous manuscript, “stabilize” has been removed.

The new reply: These sentences are removed on page 12 lines 21-22 of the previous manuscript. Thanks.

Technical corrections

Page 6, line 23. The same result ’was’ found for. . .

It has been corrected on page 6 line 24. Thanks.

Page 8, line 32. ‘leads to higher water clarity’. The authors must mean lower water clarity.

Thank you for catching this mistake. It has been corrected on page 7 line 15.

Page 9, line 18. The sentence starting ‘The Kd values’ and the sentence after that could be merged and rephrased. E.g. ‘The monthly-averaged Kd were used to simulate the surface water temperature and produce a merged LSWT (Merged).”

Thanks. It has been rephrased on page 9 line 8.

Page 9, line 20. Comparing LSWT in situ observations (Obs) with. . .

It has been added on page 9 line 10. Thank you.

Page 9, line 21. How can the authors compare measured and modelled surface temperatures in April when there seems to be little or no measured LSWT during April, at least according to Fig 9?

The previous reply: Observations for 2006 and 2007 start on 19 and 18 April, respectively, so there is data available for comparison.

The new reply: Unfortunately, there was no in situ measurements available for April 2005. Also, in situ measurements in April 2006 and 2007 starts from 19 and 18 April, respectively. Therefore, these available data were used in calculation of MBE for Spring (April-June) in 2006 and 2007.

Page 10, lines 2-3. Rephrase. Do the authors mean that the annual average of Kd can occasionally be closer to the actual Kd than the monthly-averaged Kd? This same topic is also mentioned in lines 16-17, and at least to me it is unclear how yearly average value (i.e. one single number) can represent the extent of Kd variations (i.e. how big is the range).

Thanks for your comment. Monthly averages are calculated based on satellite-derived Kd values, which might not be available due to cloud coverage in MERIS images. However, there are more MERIS images available in the longer period of one year that can potentially catch the actual variations of Kd value, rather than only a few images (or even none) in a month. Therefore, a yearly-average Kd could potentially be closer to the actual Kd value. The statement has been rephrased on page 9 lines 24-26 and page 10 lines 3-4.

Page 10, line 10. Please clarify what is specifically meant with 'are as affected'.

It means that no matter which depth we used, the actual depth at station or a tile depth, the large under-prediction happened for both simulations of CRCM-12.6 and CRCM-20 (MBE for both is above 1ºC compared to Avg and Merged simulations), especially for temperatures above 12 ºC.

This point is clarified on page 9 line 30-32: "The under-prediction of these model runs is stronger, particularly for LSWT above 12ºC, which can be explained by the Kd value used. This is because no matter what depth is used in simulations (either actual or tile depth), both CRCM runs have larger MBE compared to Avg and Merged simulations."

Page 10, lines 11-12. 'This can be explained by. . .'. Be more specific in telling how lake depth explains this.

Thanks for your comment. CRCM-12.6 and CRCM-20 only differ in the depth used as input in the simulations. Therefore, if CRCM-20 has the most under-prediction compared to all other simulations (including CRCM-12.6), it is related to the input depth. Clarification has been added to the manuscript on page 9 lines 33-34.

Page 10, lines 12-13. This should be self-evident if the model is any good, and therefore I suggest to remove this sentence.

The previous reply: The authors would prefer to keep the statement to emphasize on this and results from other studies which are also mentioned in page 9 lines 18-19.

The new reply: Thanks for your comment. These sentences are removed in the new version of manuscript.

Page 11, line 9. '. . . causing thinner mixing depth (Fig. 12)'

It has been added on page 10 line 30 (Fig. 8 in the new manuscript). Thanks.

Page 11, line 35. Change 'when Kd changes. . .' e.g. to 'when maximum (minimum) Kd is used instead of its average value. . .

Thanks for your comment. It has been rephrased on page 11 lines 14-16.

Page 12, line 1. Similar comment as previous. This is a bit misleading wording since it gives the idea that Kd changes naturally, whereas what is meant that different Kd is used as an input.

Thank you. It has been rephrased accordingly on page 11 line 14-16.

Page 13, line 27. Write open the abbreviation 'LSWT' here. It is not typical abbreviation and not clear for those who only read Summary and conclusions.

Thank you for the comment. It has been added on page 14 line 1 and also for other abbreviation on page 14 lines 6-7.

Page 14, line 3. Change 'has' to 'have'.

Thanks for catching the mistake. It has been corrected on page 14 line 8.

Comments to figures

Fig. 1. It would be of interest to see the main river inlets and outlets. This way it would be easier to assess how much river inflow possibly affects modeling results.

Thank you for the suggestion. Assessing the impact of river inflows and outflows on the simulation results is outside the scope of this paper as these are 1-D simulations. However, inflows/outflows have been added in Fig.1 of the revised manuscript.

Fig. 5. Remove 'Lake Erie boundary' from the legend, it is not needed. Also make the color bar much larger. Same comments for other similar figures.

Thank you. This has been corrected in Figs 10-12 in the revised manuscript.

Fig. 8. It would be of interest to see the SDD at this location (or from the nearest location where those exist) together with these CC-derived Kd. These could be marked to the same graph with secondary y-axis.

Thank you for the suggestion. We agree that adding SDD measurements makes the graph more informative and interesting. However, there are no in situ SDD measurements available for NDBC station. According to Fig. 1, the nearest locations with SDD observations are within about a 20 km distance from NDBC station. On the other hand, water optical properties change in spatial scales much smaller than this distance. Therefore, showing SDD values for those stations are not a good approximation of SDD for the NDBC station, and comparing those to CC-derived Kd is not rationale.

Fig. 10. It would be interesting to see the performance for each year separately. This could shown by plotting each year with different color. Also, it is more standard to show these kind of scatter plots as box plots (both axes of same length).

The previous reply: The performance of each year is shown separately in Table 3. Also, we preferred to add color to Figure 10 to show the seasonal pattern of the three years of LSWT simulations (based on comment from reviewer #3).

The new reply: Thank you for your suggestion. This is a valuable comment that also suggested by another reviewer. Therefore, plots are redrawn using different colors; however, colors are defined based on different seasons rather than different years as our focus here is on the open water season. In addition, the performance of simulations based on each year separately (2005-2007) is already mentioned in Table 3.

The main purpose of these graphs is to show over/underestimation of each type of simulations against observations, for each season. We believe that scatterplot make these points more clear as we are not interested to show the range of the variable and finding the outliers to exclude them from further processing.

Fig. 11. The measured LSWT should be shown. Otherwise, it is impossible to say which simulation performs the best. Use a) and b) for these two graphs. Also in the legend, the Kd values could be shown for each model run.

The previous reply: a) and (b) are now used in the new manuscript for Fig. 11. Details of simulations (Kd value and depth) are given in the manuscript on page 11 lines 15-18. Therefore, to avoid repetition and save space, Kd values are not added to the legends of the figures.

However, because this figure is related to a sensitivity analysis, there is no need to show the observations. Section 3.2.1, which is more related to the accuracy assessment and improvement of simulation results, shows observations.

The new reply: Thank you for your comment. (a), (b), and (c) are now used in the new manuscript for Fig. 6. Details of simulations (Kd value) are added to the caption of Figs 6-9.

This figure is showing a sensitivity analysis, comparing the model response to the Kd change. We are not interested to see which one is closer to the observations. We are interested to see how the model responses to the change of Kd values. For this purpose of sensitivity analysis, we considered the Avg simulation as the base result to compare the results of other simulations and show how different the simulations results are when we change Kd values.

Fig. 15. Model run CRCM-12.6. is not visible. If the resolution can not be increased, describe in the caption where the line is.

Thank you for your comment. Description of the figure is given in the body of manuscript (page 12 lines 11-12). It has now been added as well in the caption of Fig. 9.

Reviewer #3 Comments:

In my opinion, the authors improved the manuscript and responded satisfactorily to most of the questions that I put in my first review. However, I still have disagreements regarding 5 issues. In particular, the question 4 is to me a major issue.

The review is based on the of file hess-2016-82-author_response-version1.pdf

1. page 6, line 21/22

In my first review, I asked: depth of the water temperature measurements: why is it included here? The water temperature is not a forcing parameter...

The authors reply that:

"z_Tw_m" is one of the inputs in FLake model and is the depth of water temperature measurements."

Which is not correct.

I'm not sure about what is z_Tw_m (It is not present in the standard Flake code, see: http://www.flake.igb-berlin.de/docs.shtml), but I have no doubt that Flake don't need any "depth of water temperature measurements" as imput.

Thanks for your comment, we agree with the reviewer. Therefore, modifications have been made in page 6 line 20. This parameter is removed in the revised manuscript.

2. Page 6 line, line 25: I asked "to configure" means force initialize, or both?

The authors reply: The parameters mentioned in the bracket are constant and used to force the FLake model."

I have to insist. The authors made some confusion between configuration parameters and forcing. The height of wind measurement (5 m) and the height of air temperature sensor (4 m) are in fact constant used to configure the model, but the measured meteorological parameters and model-derived irradiance were used to force the FLake model (and not to configure).

We appreciate your comment. The point is now well taken; and changes are made in the manuscript page 6 line 21-22.

3. page 7 line 22 and equation 2

I also insist about equation 2. The authors find the following relation between kd and SDD:

$Kd = 1.64 \times SDD^{-0.76}$

I have nothing against this result, but they should not say that it is of the type of eq 2...

Thanks for your comment. To avoid confusion, the term "based on Eq. (2)" has been removed in the new manuscript, page 7 line 28.

4. Page 10, lines 17-18:

"Dark waters in these months contribute in reproducing colder LSWT for Avg and Merged simulations in 2005."

I cannot understand why water turbidity (or darkness) tends to decrease the lake surface water temperature. As the authors correctly stated along the manuscript, in dark waters the radiation is more absorbed in the surface layer, and so the LSWT tends to be higher by comparison to clear waters. What I proposed in my previous review is that:

The reason lies not in the fact that during those months the water is more turbid, but because the water was more turbid before, during spring and summer, reducing the heating of deep water. This should be discussed further, in particular by analyzing the evolution of deep temperature and column mean temperature (Flake variables).

The authors reply: "According to Table 2, the Kd value for same months of year 2005-2007 are in the same range. But the difference in calculating MBE for 2005 compared to 2006 - 2007 is taking months of Sep-Nov into the calculation of MBE for 2005. Therefore, the underestimation of LSWT in 2005 cannot be related to darker waters before, in spring and summer. It is more related to the months that are taken into the calculation of MBE."

In my opinion the authors don't have reason and must examine and take into account the evolution of lake water bottom temperature (LWBT) and column mean temperature (MWCT). Alternatively they have to provide a physically explanation about how "Dark waters in these months contribute in reproducing colder LSWT(...)".

Thanks for your comment and pointing this out. We examined calculating MBE for 2005-2007, focusing only on the months that are common between three years (May-Aug). The calculated MBE did not resulted in the same conclusion (either overestimation or underestimation) for three years. So our conclusion (Considering the months of September-November into the calculations of MBE for 2005 can be the reason of underestimating LSWT in this year for both Avg and Merged simulations compared to two other years) was not correct. So we removed these sentences in the revised manuscript.

If the in situ data for LBWT and MWCT were available, the performance of simulations for over/underestimation of them could be examined and related to over/underestimation of LSWT in different simulations. However, these in situ data are not available in our study.

Instead, LBWT and MWCT are produced in the Flake simulations. The attached excel file compares LSWT produced from different simulations for each year separately (Page 50-52). In 2005, the underestimation of LSWT increases from Avg to Merged, CRCM12.6, and CRCM20 simulations, respectively. However, the highest LBWT is estimated for CRCM12.6. Therefore, there is no relationship between under/overestimation of LSWT and producing LBWT.

The excel file also compares LSWT produced in each simulation for different years (Page 53-56). In Avg simulation, the LSWT is underestimated in 2005; and overestimation of LSWT in Avg simulation increases from 2006 to 2007, respectively. The graph for LBWT shows that temperature for 2005 was the highest and decreased in 2006 and then 2007, respectively. For CRCM12.6, LSWT is underestimated and the underestimation increases from 2006 to 2007, and 2005, respectively. However, LBWT in CRCM12.6 is highest for 2006, 2005, and 2007, respectively. Therefore, there is not any pattern for relationship between over/underestimation of LSWT in each simulation for different years and the produced LBWT.

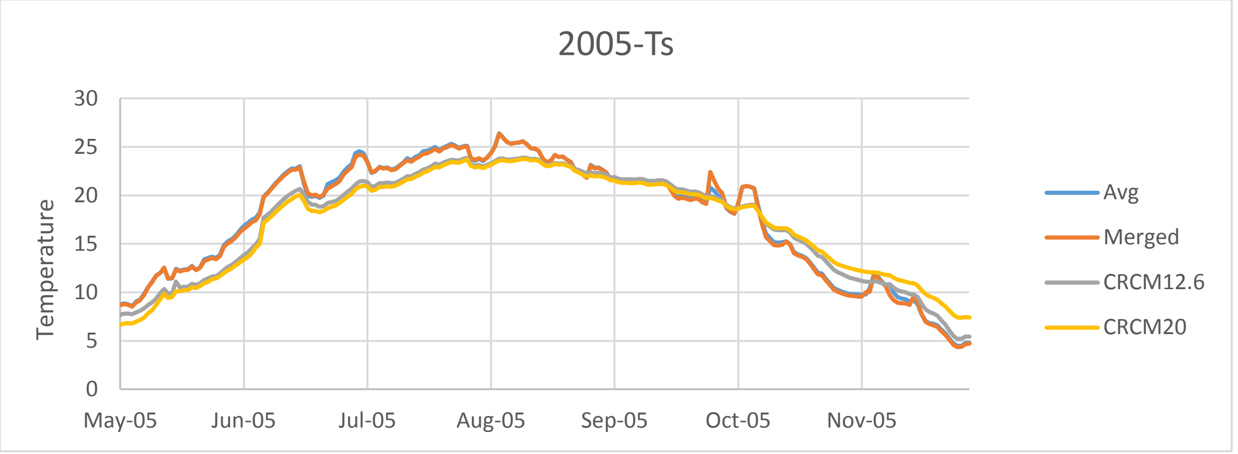
If we only compare simulations for 2006 and 2007, which cover the exact same time of year: in CRCM12.6 and CRCM20 underestimation increases from 2006 to 2007. But, LBWT in CRCM12.6 is higher for 2006 compared to 2007; whereas in CRCM20, LBWT is higher for 2007 compared to 2006.

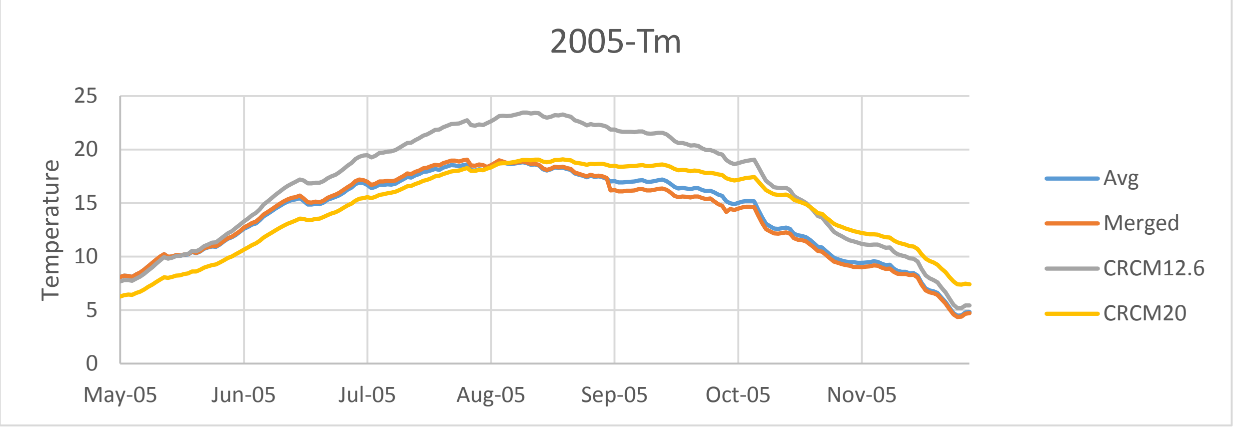
Therefore, we can conclude that LBWT does not have a relationship with under/overestimation of LSWT in different simulations and different years. Similar explanation is correct for MWCT. Therefore, we don’t have any other explanation for underestimation in Avg and Merged simulations for 2005, contrary to overestimation in Avg and Merged simulations for 2006 and 2007. Having more in situ data, especially for LBWT and MWCT, could be helpful to clarify the reason.

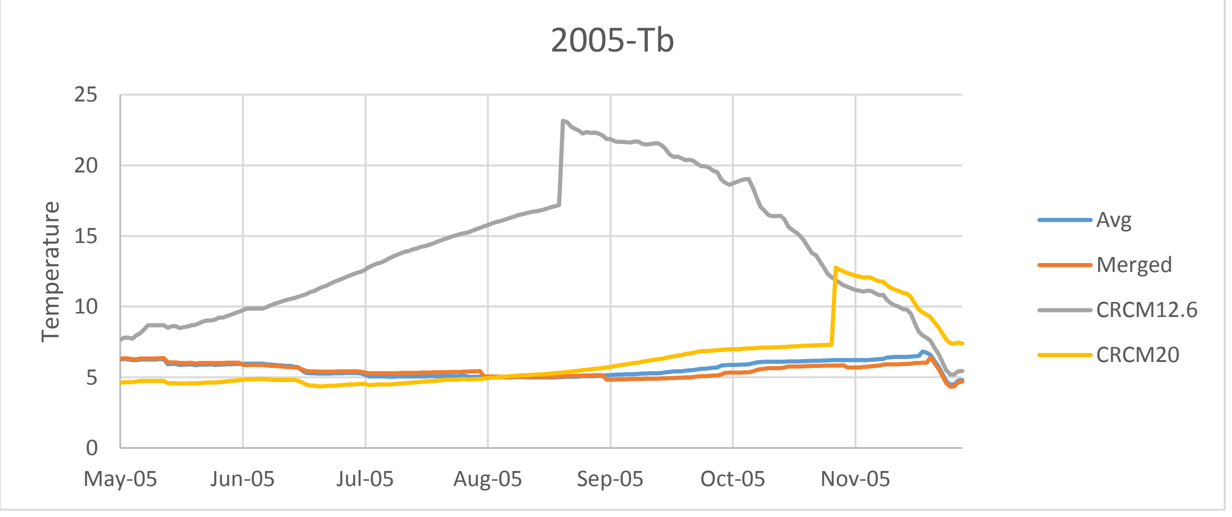
5. Page 13 line 11:

I still consider that the use of the term monotonic is not appropriate

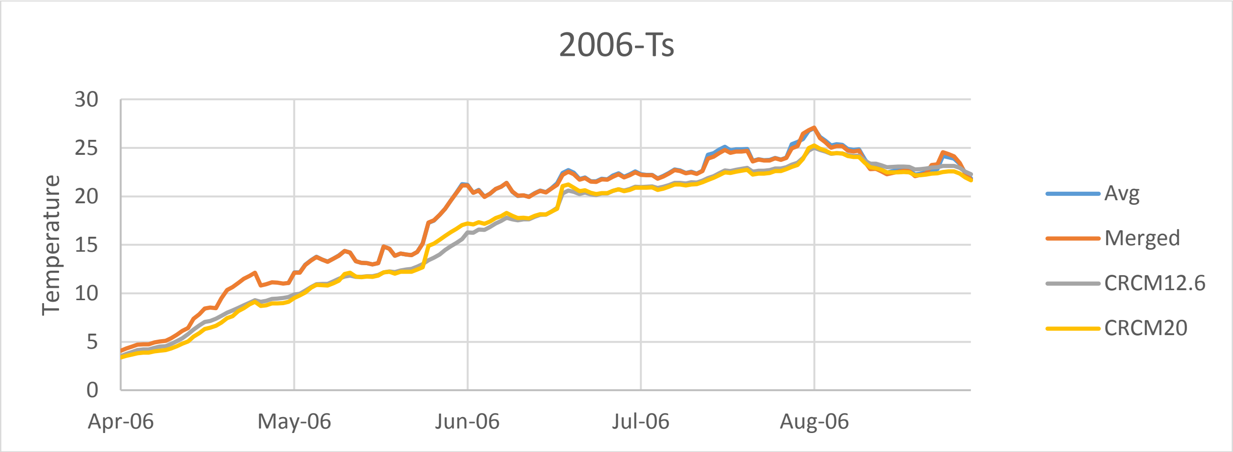
Thanks for your comment. This term has now been removed in the new manuscript.

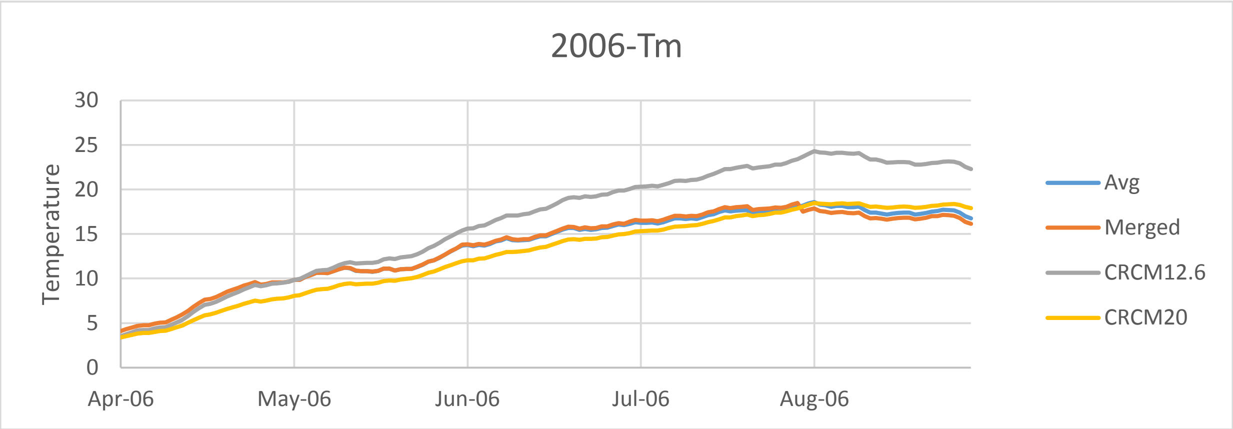

2005-Ts
Temperature
30
25
20
15
10
5
0
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Avg
Merged
CRCM12.6
CRCM20

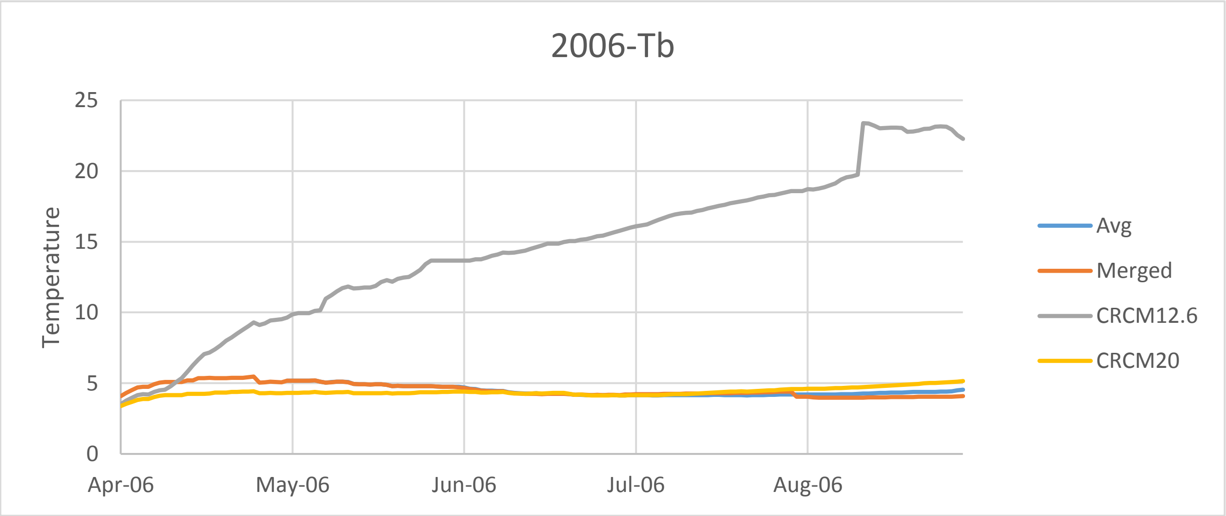

2005-Tm
Temperature
25
20
15
10
5
0
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Avg
Merged
CRCM12.6
CRCM20

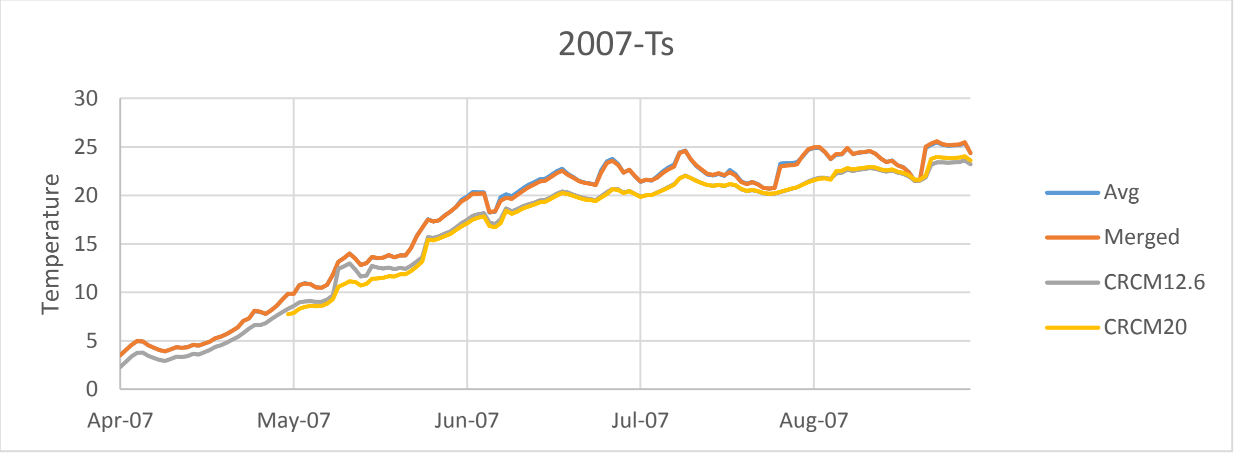

2005-Tb
Temperature
25
20
15
10
5
0
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Avg
Merged
CRCM12.6
CRCM20

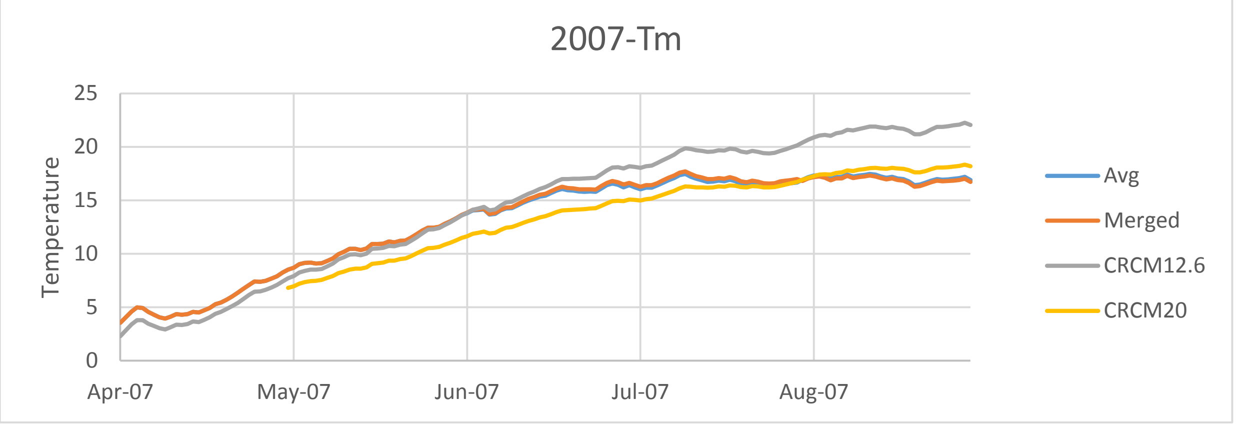
5

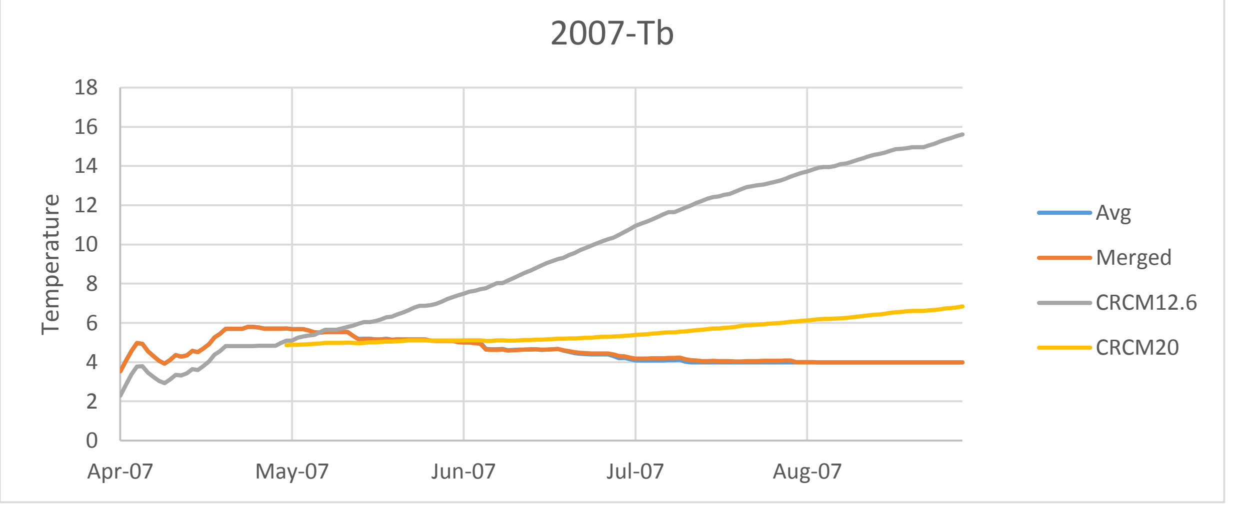

2006-Ts
Temperature
30
25
20
15
10
5
0
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Avg
Merged
CRCM12.6
CRCM20

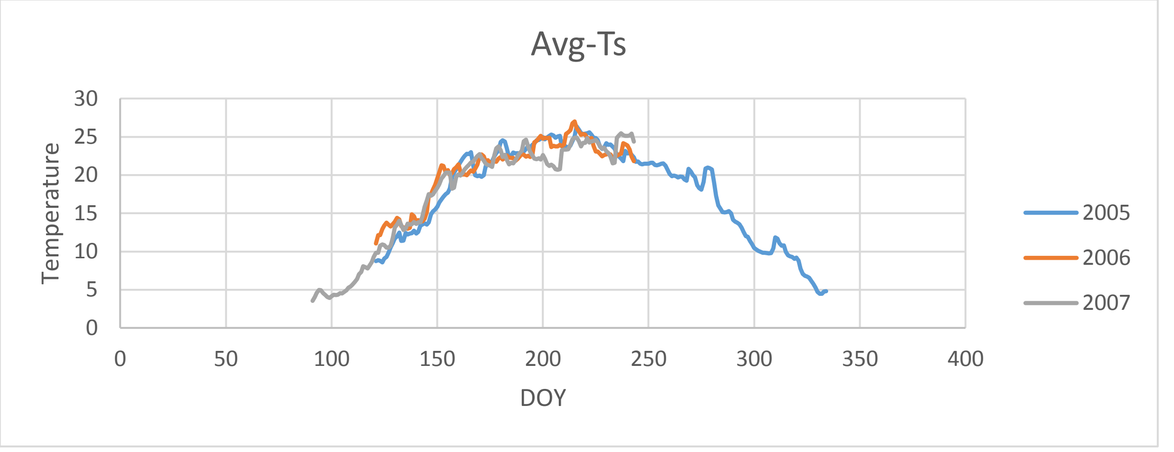

2006-Tm
Temperature
30
25
20
15
10
5
0
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Avg
Merged
CRCM12.6
CRCM20


2006-Tb
Temperature
25
20
15
10
5
0
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Avg
Merged
CRCM12.6
CRCM20

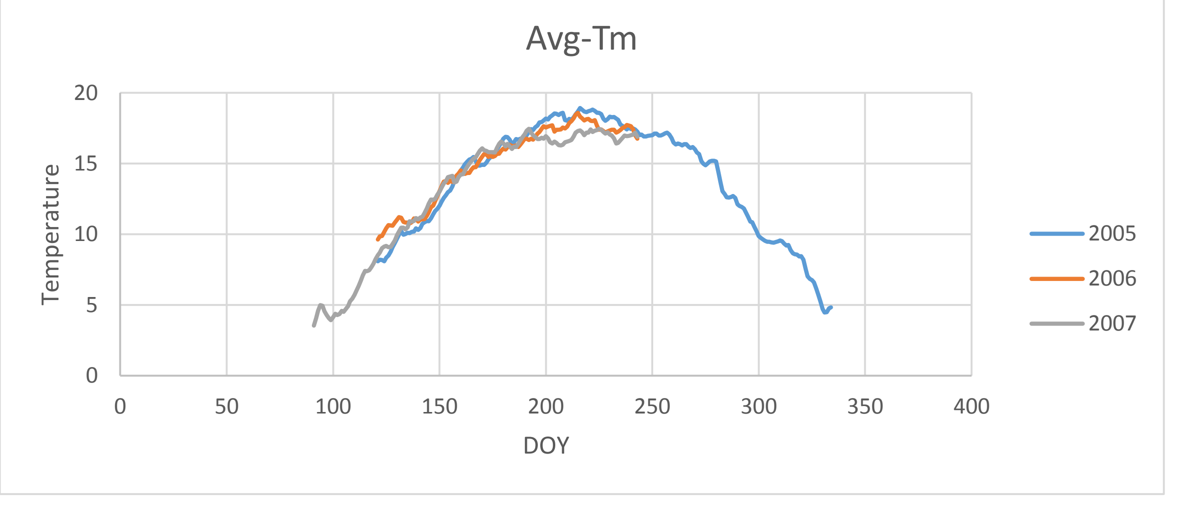

2007-Ts
Temperature
30
25
20
15
10
5
0
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Avg
Merged
CRCM12.6
CRCM20


2007-Tm
Temperature
25
20
15
10
5
0
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Avg
Merged
CRCM12.6
CRCM20

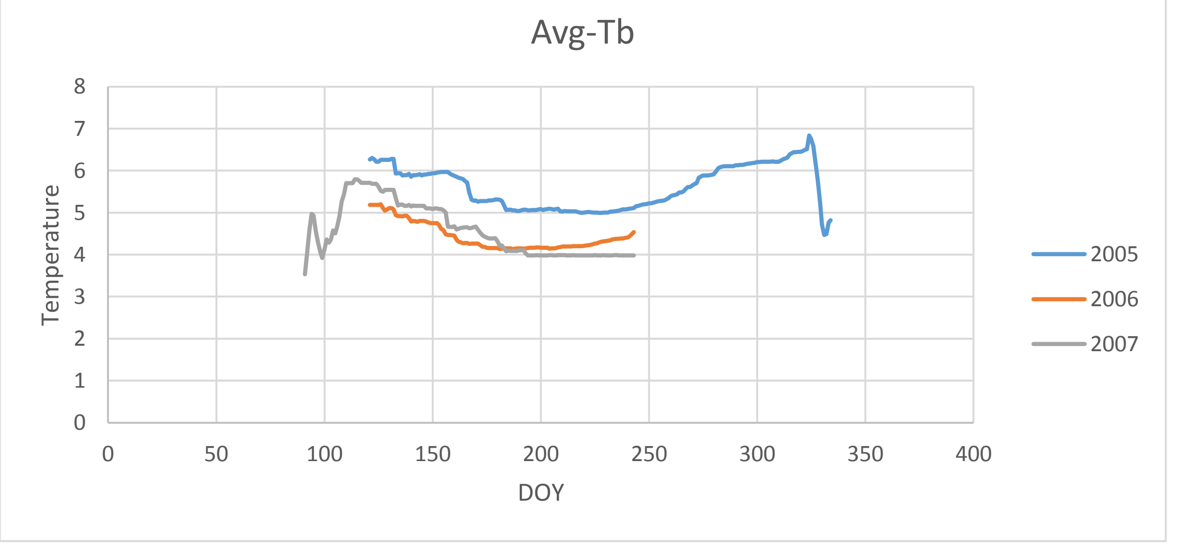

2007-Tb
Temperature
18
16
14
12
10
8
6
4
2
0
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Avg
Merged
CRCM12.6
CRCM20



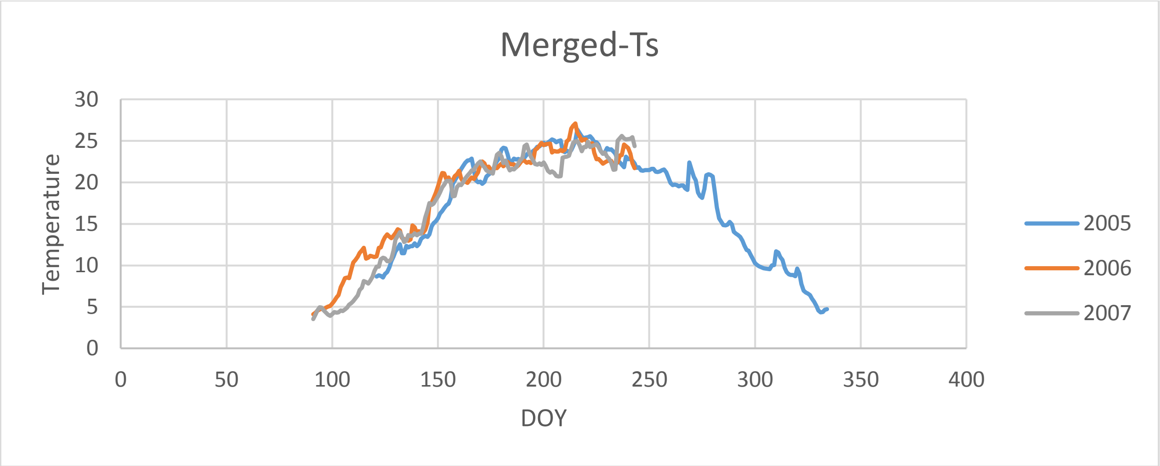
Avg-Ts
Temperature
30
25
20
15
10
5
0
0
50
100
150
200
250
300
350
400
DOY
2005
2006
2007

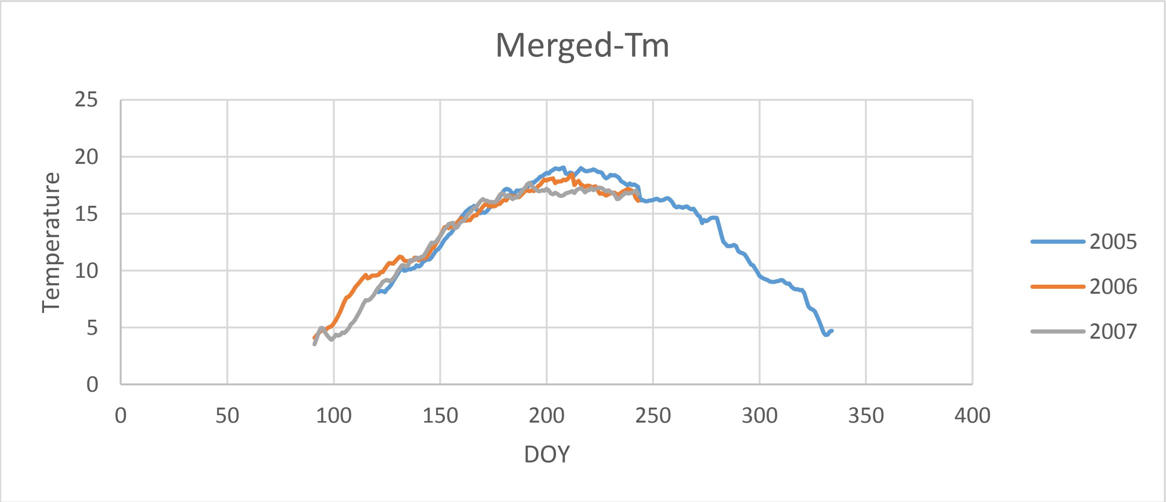


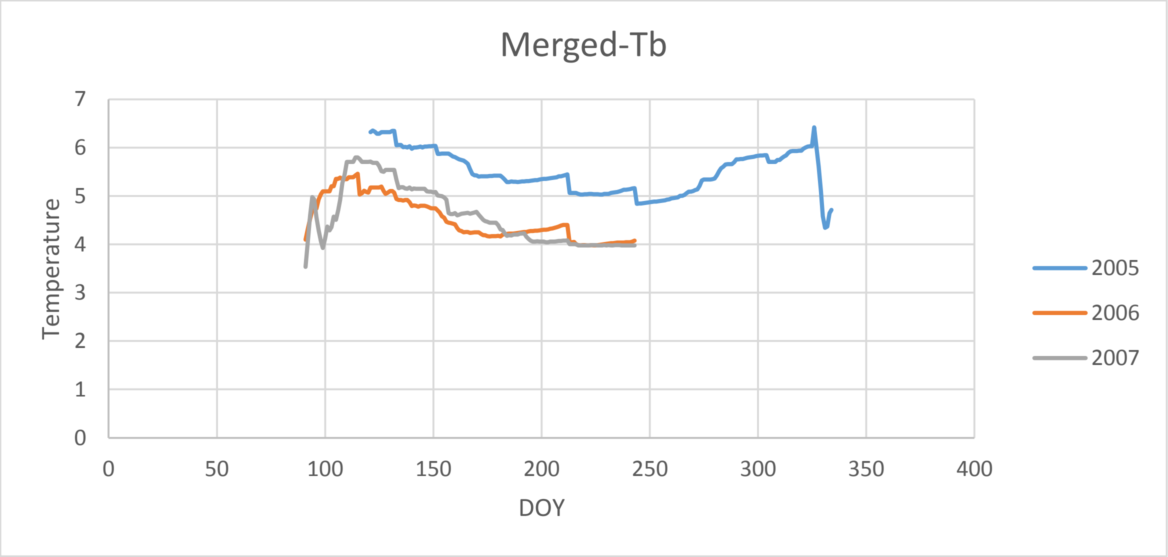
Avg-Tm
Temperature
20
15
10
5
0
0
50
100
150
200
250
300
350
400
DOY
2005
2006
2007

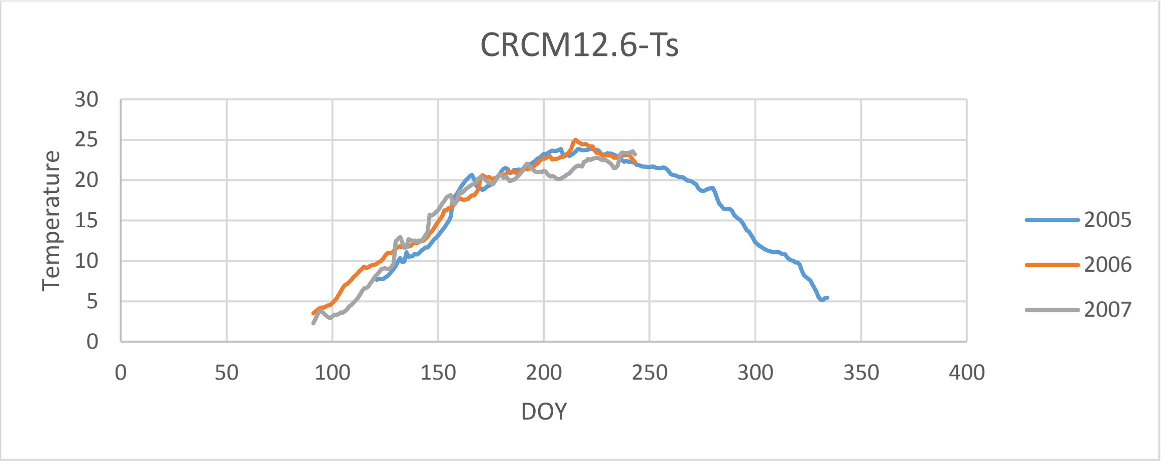


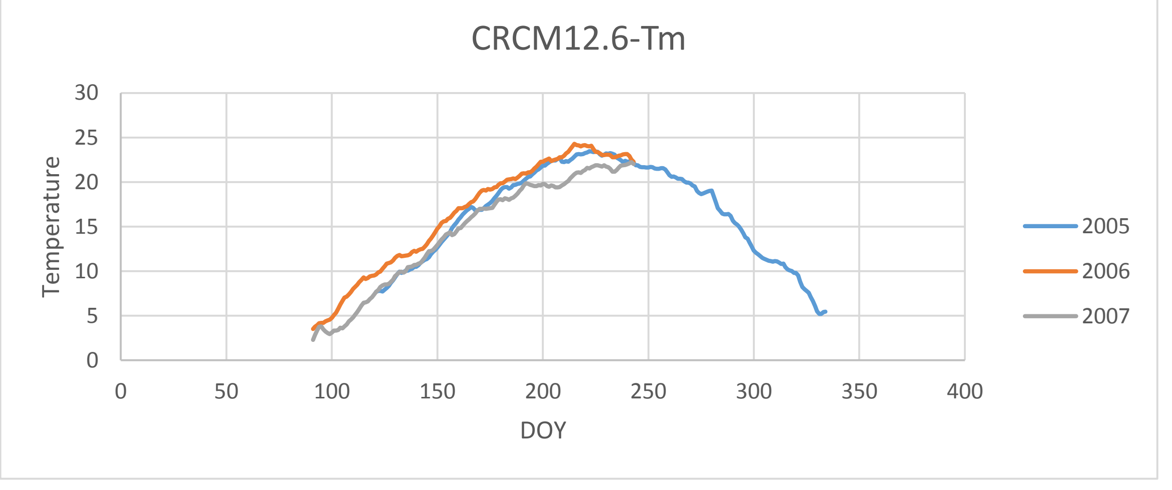
Avg-Tb
Temperature
8
7
6
5
4
3
2
1
0
0
50
100
150
200
250
300
350
400
DOY
2005
2006
2007


Merged-Ts
30
25
20
15
10
5
0
Temperature
0
50
100
150
200
250
300
350
400
DOY
2005
2006
2007


Merged-Tm
25
20
15
10
5
0
Temperature
0
50
100
150
200
250
300
350
400
DOY
2005
2006
2007


Merged-Tb
7
6
5
4
3
2
1
0
Temperature
0
50
100
150
200
250
300
350
400
DOY
2005
2006
2007


CRCM12.6-Ts
Temperature
DOY
2005
2006
2007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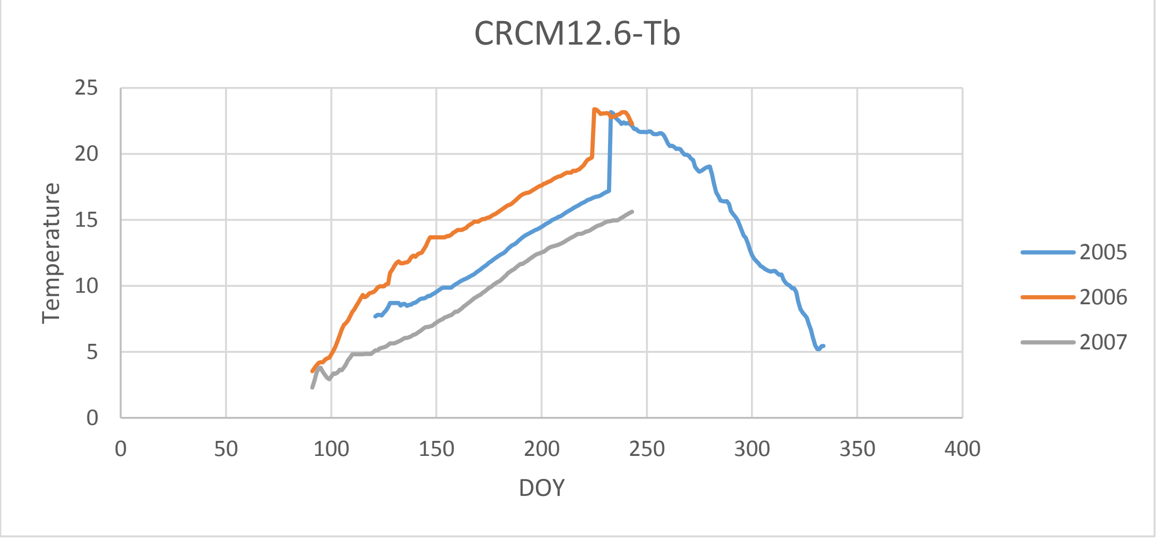
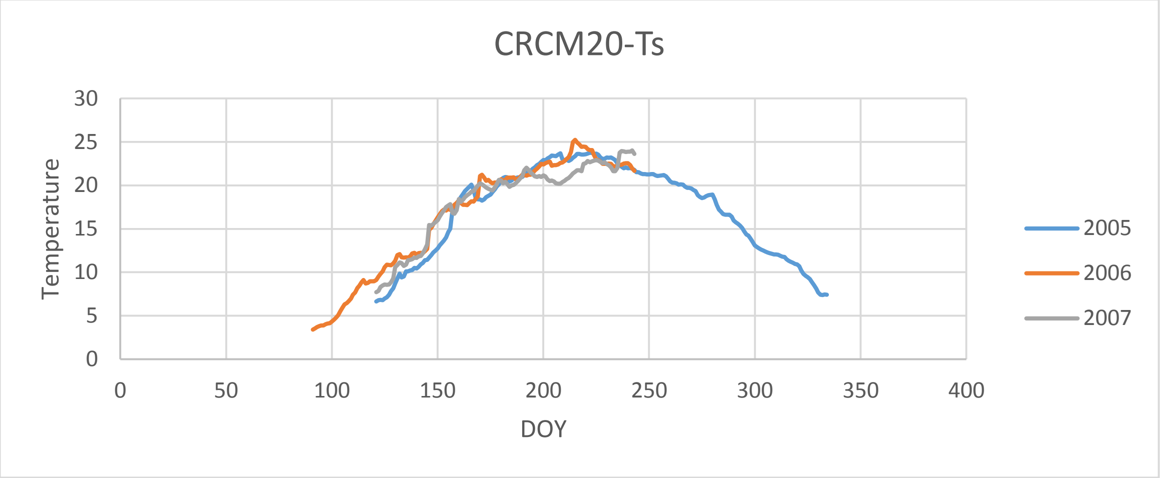
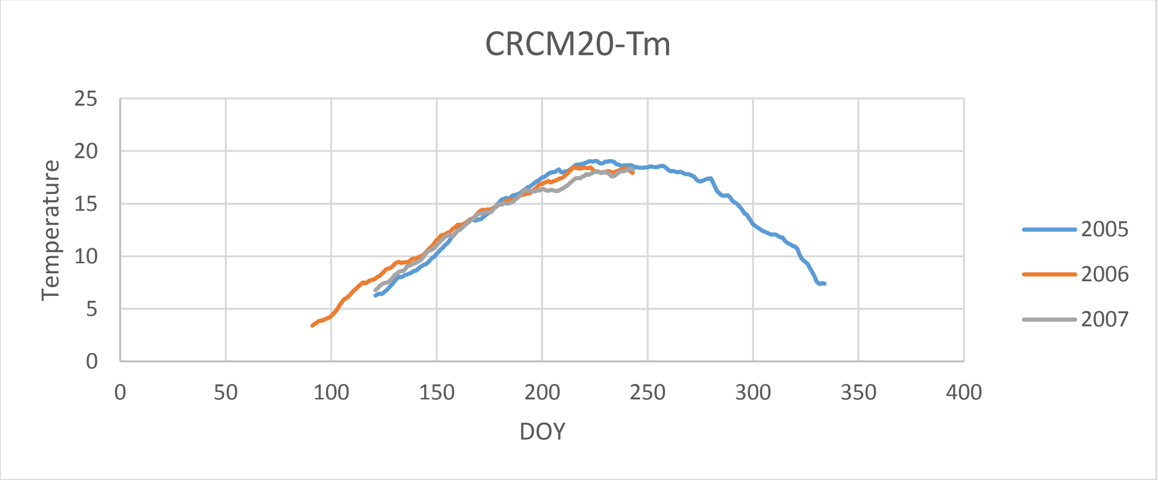
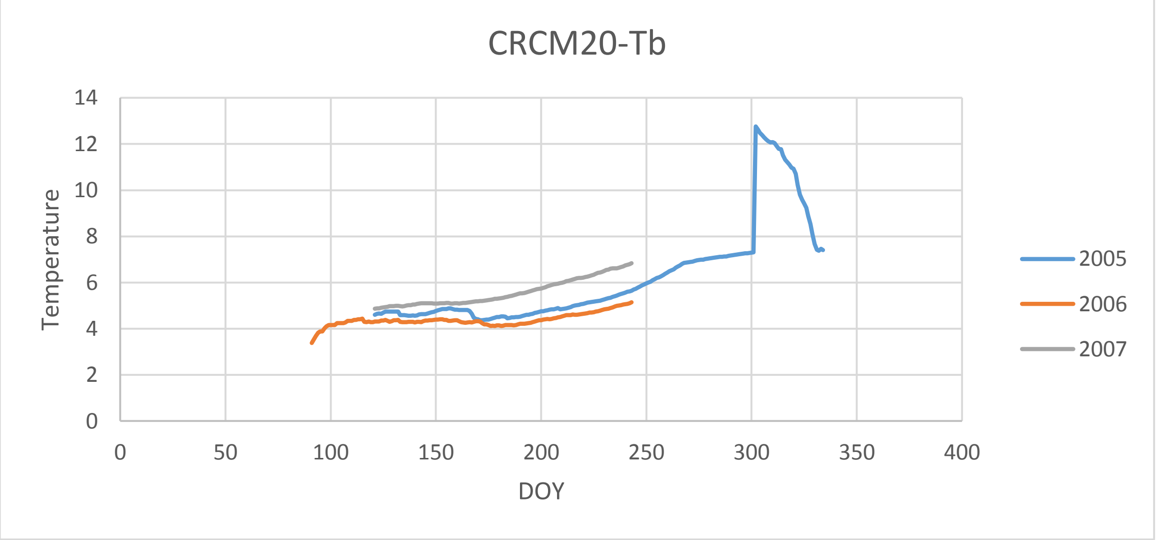
Temperature
DOY
2005
2006
2007


CRCM12.6-Tb
Temperature
DOY
2005
2006
2007


CRCM20-Ts
Temperature
DOY
0
5
10
15
20
25
30
0
50
100
150
200
250
300
350
400
2005
2006
2007


CRCM20-Tm
Temperature
DOY
0
5
10
15
20
25
0
50
100
150
200
250
300
350
400
2005
2006
2007


CRCM20-Tb
Temperature
DOY
0
2
4
6
8
10
12
14
0
50
100
150
200
250
300
350
400
2005
2006
2007