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Coordinating *in situ* lake sampling with satellite acquisition days provides a mechanism for addressing data scarcity: a case study from Lake Yojoa, Honduras

Coordenar a amostragem *in situ* de lagos com dias de aquisição de satélite é um bom mecanismo para lidar com a escassez de dados: um estudo de caso do Lago Yojoa, Honduras

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Abstract: Aim: In this study, we present the results of a project which used Landsat Collection 2 Surface Reflectance data and European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) data to develop a machine learning model to estimate Secchi depth in Lake Yojoa, Honduras. **Methods:** Satellite remote sensing data obtained within a 7-day window of an *in situ* measurement were matched with *in situ* Secchi depth measurements and were partitioned into train-test-validate data sets for model development. **Results:** The machine learning model had good (R^2= 0.57) agreement and reasonable uncertainty (MAE = 0.58 m) between remotely estimated and *in situ* observed Secchi depth. Application of the machine learning model increased the monitoring record of Lake Yojoa from 6 years of measured data to a 23-year record. **Conclusions:** This model demonstrates the utility of coordinating *in situ* sampling schedules of short-term research projects with satellite imagery acquisition schedules in order to increase the temporal coverage of remote sensing derived estimates of water quality in understudied lakes.

Keywords: remote sensing; water clarity; water quality trends.

Resumo: Objetivo: Neste estudo, apresentamos os resultados de um projeto que utilizou dados de refletância de superfície da Landsat Collection 2 e dados de reanálise v5 (ERA5) do Centro Europeu de Previsões Meteorológicas de Médio Prazo (ECMWF) para desenvolver um modelo de aprendizado de máquina para estimar a profundidade do disco de Secchi no Lago Yojoa, Honduras. **Métodos:** Os dados de sensoriamento remoto por satélite, obtidos dentro de uma janela de 7 dias de uma medição *in situ,* foram combinados com medições *in situ* da profundidade de Secchi e particionados em conjuntos de treinamento, teste e validação para o desenvolvimento do modelo. **Resultados:** O modelo de aprendizado de máquina apresentou boa concordância (R^2 = 0,57) e incerteza razoável (MAE = 0,58 m) entre as estimativas remotas da profundidade de Secchi e as observações *in situ*. A aplicação do modelo de aprendizado de máquina ampliou o registro de monitoramento do Lago Yojoa, de 6 anos de dados medidos para um total de 23 anos. **Conclusões:** Este modelo demonstra a utilidade de coordenar cronogramas de amostragem *in situ* de projetos de pesquisa de curto prazo com cronogramas de aquisição de imagens de satélite, aumentando assim a cobertura temporal de estimativas derivadas de sensoriamento remoto da qualidade da água em lagos pouco estudados.

Palavras-chave: sensoriamento remoto; transparência da água; tendências de qualidade da água.

1. Introduction

Remote sensing of water quality has great potential for expanding our understanding of inland waters (Topp et al., 2020). For lake ecosystems, remote sensing provides an opportunity to have spatially rich water quality predictions, avoiding some bias from limited spatial coverage associated with *in situ* data collection (Stanley et al., 2019; Pahlevan et al., 2020). With reliable algorithms that convert surface reflectance to water quality estimates, remote sensing enables regional and global change analyses at an unprecedented spatial scale (Yang et al., 2022; Sillen et al., 2024). Remote sensing can also improve the temporal coverage of lake ecosystem research by adding estimates on additional dates during *in situ* campaigns and by providing estimates of historic conditions predating contemporary monitoring efforts (i.e., hindcasting, Hansen et al., 2020). Remotely sensed estimates of *in situ* parameters also have the potential to fill in large geospatial data gaps necessary for reducing monitoring inequities and addressing challenges in global data disparities.

While there are numerous advantages to optical remote sensing, leveraging historical datasets in locations with frequent cloud cover is challenging since optical sensors do not penetrate cloud cover. Still, in most regions, the rich spatial and temporal coverage provided by remote sensing has the potential to accurately capture the hydrologic and ecological variation observed in the field (Allen et al., 2020). This expansive coverage of remotely sensed water quality allows for explorations of both long-term trends and seasonal changes in lakes (Topp et al., 2021). Identifying such trends is particularly critical because changes in intra-annual variance is an indicator of regime shifts, ecological thresholds and transition points, such as eutrophication (Carpenter & Brock, 2006; Carpenter et al., 2011; Gilarranz et al., 2022).

Remote sensing work across Latin America demonstrates how using satellite imagery can support data collection in data scarce tropical regions (Melack et al., 2009; Flores-Anderson et al., 2020; Lucia Lobo et al., 2021). Here, we present the results from a project where we used remote sensing and climate data to estimate Secchi depth in Lake Yojoa, Honduras for Landsat 7 and 8 imagery. This work exemplifies how coordinating discrete sampling campaigns (Fadum & Hall, 2022; Fadum et al., 2023, 2024) with satellite acquisition schedules provides an opportunity to create data products which extend beyond the duration of shorter studies. Below, we 1) briefly describe our approach to creating Landsat-*in situ* matches and our machine learning model approach, and 2) highlight the model's ability to add to the historical record and capture ecologically relevant changes in Secchi depth. Beyond the collection of remotely sensed data and the development of ecosystem monitoring tools like the described Secchi depth model, the goal of this work is to encourage similar limited-term research projects to consider sampling in accordance with satellite image acquisition schedules. In addition to enabling the creation of ecosystem specific algorithms with improved regional accuracy (as opposed to applying temperate models to tropical ecosystems), this approach will also support the more accurate assessments of uncertainty for algorithms developed at a broader regional or global scale.

2. Material and Methods

Lake Yojoa is a large (~83 km^2 surface area, ~30 m maximum depth) mesotrophic, tropical lake in West-Central Honduras with a contemporary mean annual Secchi depth of 3.1 m and well described intra-annual dynamics (Fadum & Hall, 2022; Fadum et al., 2024). We collected Secchi depth measurements from 18 pelagic locations (twice annual sampling of the 18 locations, identified as A-R in Fadum & Hall (2022) and sampling every 16 days at a subset of five locations, identified as B, E, F, P and R in Fadum et al. (2023) concurrent with the Landsat 7 and 8 imagery acquisition schedules (Figure 1). To identify sampling dates, we used the Landsat Acquisition tool (https://landsat.usgs.gov/landsat_acq).

Landsat Collection 2 Surface Reflectance (Masek et al., 2006; Vermote et al., 2016) values were obtained for the 18 sampling locations in Lake Yojoa following the methods described in Topp et al. (2021). Minor adaptations were made for the transition from Collection 1 (used in Topp et al. (2021)) to Collection 2 to account for differences in scaling factors between collections. Surface reflectance summaries included only 'confident' water pixels as defined by the dynamic surface water extent algorithm (Jones, 2019). Data were filtered for reasonable values for water reflectance (-0.01 < surface reflectance < 0.2) for all bands. Inter-mission handoff coefficients to standardize surface reflectance values due to slight changes in sensors specifications and atmospheric correction methods between missions (Gardner et al., 2021) were calculated based on data acquired from all lakes greater than 25 hectares within Guatemala, Honduras, and El Salvador using Python version 3.8 (Python Software Foundation, https://www.python.org/). Precipitation, air temperature, solar radiation, and wind speed at the approximate geographical center of Lake Yojoa (14.8768°N, 87.9791°W, Figure 1) were obtained from the ERA5 dataset (Muñoz Sabater, 2019) in the Google Earth Engine Code Editor (Gorelick et al., 2017). These data were aggregated for the previous 3, 5, and 7 days of a satellite acquisition date for model development and application (Kloiber et al., 2002). For our model, a previous day and previous 5-day window for pairing meteorological data to satellite imagery yielded the best results. Windows for pairing *in situ* Secchi depth measurements and available satellite imagery were similarly assessed and we determined that a 7-day matchup window was appropriate, except in October and November (when rapid water column turnover is expected). For acquisition days in October and November, only a 1-day window was permitted. While alternative models with slightly different matchup windows yielded moderately higher coefficients of determination, the selected model performed best at higher Secchi depths, a point of focus for the region (Fadum et al., 2023). All Landsat data were acquired using the Google Earth Engine Python Application Programming Interface (Gorelick et al., 2017) in RStudio version 2023.03.0, R version 4.2.3 (R Core Team, 2023), ERA5 data were obtained within the GEE Code Editor, and all data collation and model development were completed in RStudio.

We used the R package xgboost (Chen et al., 2023) to develop the best performing gradient tree boost algorithm for this application. We used a random 60%/20%/20% train-test-validation split for model development, where the train and test sets were provided for model development and the validation was performed with hold-out data to test performance independently of model development (Figure 2). To select the optimal xgboost hyperparameters, we used a grid search method partitioning the top 20 performing models as measured by lowest RMSE. From these models, we selected the booster that had the lowest RMSE and a train-test RMSE that was within 0.15 m to avoid selecting an overfit model. If no models met these conditions the one with the closest train-test RMSE was selected as the optimal xgboost model. We evaluated model performance based on root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), bias, and symmetric mean absolute percentage error (SMAPE).

3. Results

Our results demonstrate that optical remote sensing offers a viable tool for monitoring Secchi depth in Lake Yojoa, Honduras. Our model (RMSE = 0.78 m, MAE = 0.58 m, MAPE = 0.22, Bias = -0.31 m, SMAPE = 0.19) produced comparable estimates of Secchi depth in the validation (hold-out) dataset (R^2 = 0.57, inclusive all locations, Figure 2) and we achieved a comparable RMSE to other studies which used passive remote sensing to estimate Secchi depth (R^2 = 0.89, RMSE = 0.77 m Alikas & Kratzer (2017), and R^2 = 0.97, RMSE = 0.26 m Majozi et al. (2014)) though weaker coefficient of determination.

After creating a location-specific algorithm for estimating Secchi depth from remote sensing *in situ* pairs for Lake Yojoa, we created a timeseries from the full remote sensing record using the same algorithm (Figure 3). While early Landsat data is limited due to a lack of international ground receiving stations (U.S. Geological Survey, 2016; Wulder et al., 2016), application of the model increased the Secchi depth record from limited observations in 2006 and 2018-2022 to a more complete record from 2000-2022. While other studies (e.g. Topp et al., 2021), use the full Landsat

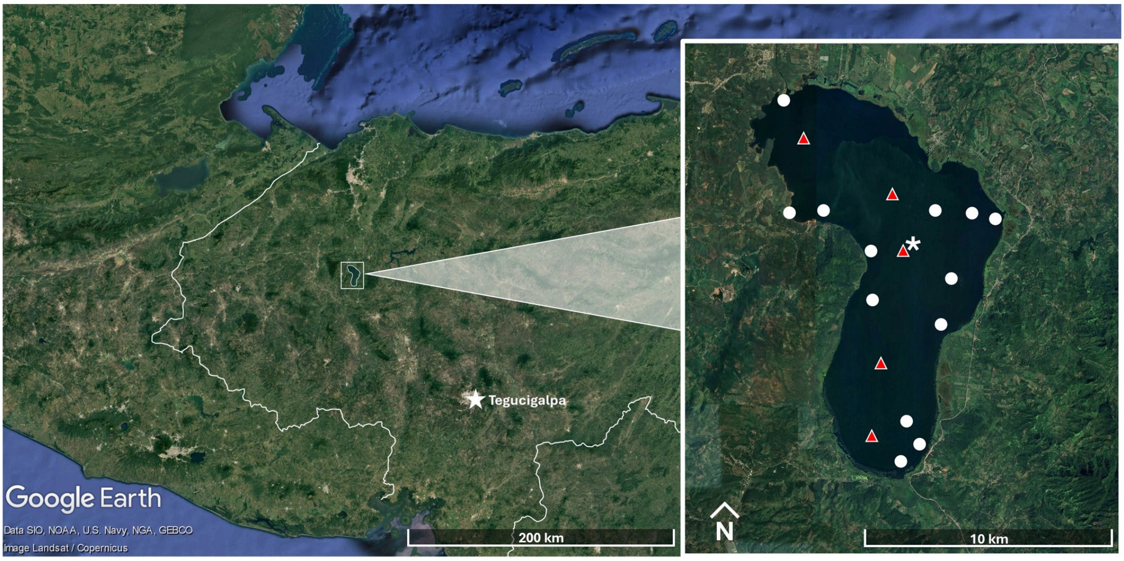

Figure 1. *In situ* sampling points covering bi-annual sampling events (white circles) and bi-monthly sampling points (red triangles). The asterisk (*) identifies the geographic center of Lake Yojoa used to obtain data from ERA5. Exact latitudes and longitudes available in Steele et al. (2023).

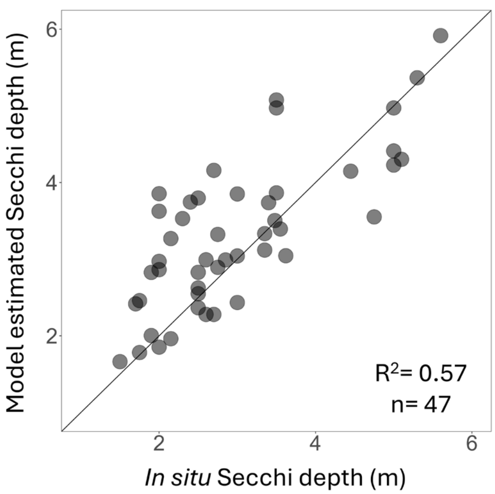

Figure 2. Model performance as observed versus predicted of hold-out data (randomly selected 20% of dataset). Black line is the 1:1 line.

record, including Landsat 5, we explicitly chose not to include predictions from either Landsat 5 or 9, because we had no matchup data to robustly test algorithm performance with these satellites. Early record Secchi depth predictions are limited by cloud-contaminated images despite a 16-day return frequency for Landsat 7. The increased density of modeled Secchi depth beginning in 2013 is due to Landsat 8 deployment which runs co-currently with Landsat 7, separated by 8 days resulting in a virtual 8-day return frequency. *In situ* sampling in 2006 occurred every 3-10 days at the geographic center of Lake Yojoa (Basterrechea, 2008) which differs from the sampling frequency beginning in 2018 which was bi-monthly. Additionally, sampling was disrupted in 2020 due to the COVID-19 pandemic resulting in fewer Secchi depth observations.

Our model captured ecologically meaningful changes in Secchi depth, and subsequently trophic state (Fadum & Hall, 2022), as exhibited by the model's ability to detect the documented increases in water clarity following Hurricanes Eta and Iota (Fadum et al., 2023) (Figure 3). These two large, late season tropical cyclones brought an unprecedented amount of precipitation to the Lake Yojoa watershed in November 2020. The rapid introduction of nutrient depleted water into Lake Yojoa in the subsequent weeks produced a dilution effect which decreased algal productivity and therefore increased Secchi depth above the annual mean. It is possible that the back-to-back timing of Hurricanes Stan and Beta in 2005 were responsible for a similar dilution effect as Hurricanes Eta and Iota (Figure 3). Other tropical cyclone events showed little or no effect on the clarity of Lake Yojoa (e.g., Tropical Depression Barry in 2013) and some tropical cyclone events had too little data before/after to assess whether there was any change (e.g., Tropical Depression 16, Tropical Storm Ida). While we could not identify any other distinct tropical cyclone impacts in Lake Yojoa, the differing impact of back-to-back late season storms compared with more isolated incidents of extreme precipitation highlights the need to further explore characteristics of tropical cyclones which maximally impact ecosystem function in low-latitude lakes.

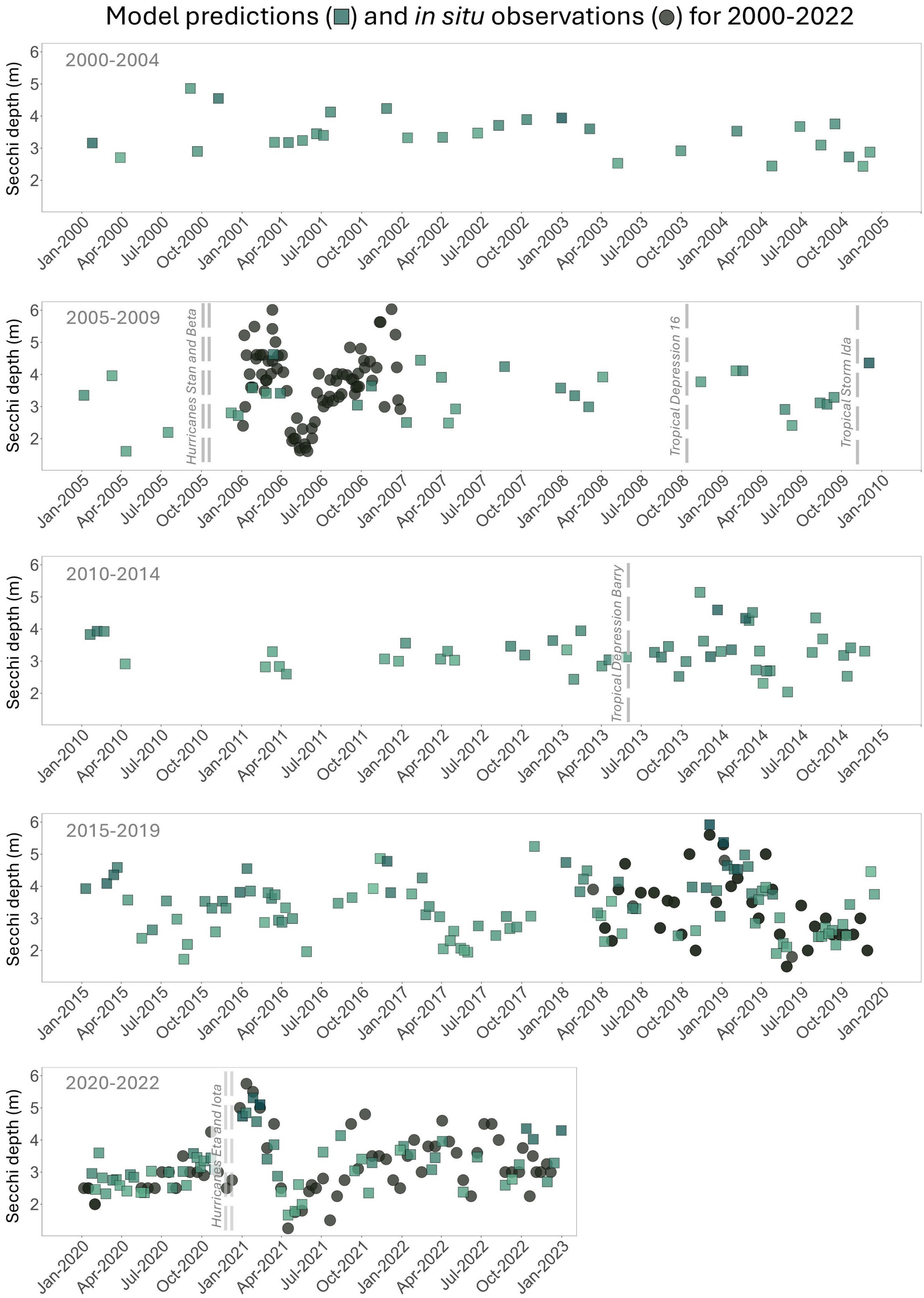

Figure 3. Complete synthetic timeseries of Secchi depth from estimations at center of Lake Yojoa (identified with an asterisk in Figure 1) using remote sensing (squares) and *in situ* observations (black circles). Large rainfall events identified with vertical dashed lines and the name of the tropical cyclone(s).

4. Discussion

The approach we demonstrate here offers a promising tool for understanding inter- and intra-annual variation, and stochastic climatic events such as the impacts of tropical cyclones on understudied tropical freshwater resources. Tropical storms can have devastating impacts on aquatic ecosystems and by extension, water security. Assessing the response of ecosystems to storms of varying intensities is of critical importance to local communities impacted by increasingly frequent and intense hurricane activity in the Atlantic basin (Morris et al., 2002; Bender et al., 2010; Knutson et al., 2010).

In addition to understanding ecosystem disturbance response in Lake Yojoa, aligning routine sampling with satellite image acquisition schedules could increase our understanding of tropical lake ecology more broadly. Future work could build a larger matchup dataset including data not just from Lake Yojoa but from other lakes within the region to create a more generalizable model. The presented work could then be collated with both existing and new studies to create a rich collection of remotely sensed data across Latin American lakes within the region, expanding on efforts such as AlgaeMAP which currently includes reservoirs in and around São Paulo, Brazil (Lucia Lobo et al., 2021). For example, Lakes Zirahuén (Mexico), Atitlán (Guatemala) and Nicaragua have all been the focus of previous remote sensing of trophic state and water quality research (Chang et al., 2017; Flores-Anderson et al., 2020; Pantoja et al., 2021).

While we would expect some lakes to carry unique spectral signatures that may impact the generalizability of a regional or continental model, understanding the broad regional patterns will help identify key aspects of the underlying ecology of individual lakes to better separate the impacts of global and local stressors. For example, Lake Atitlán, which was assessed using the Hyperion satellite (Flores-Anderson et al., 2020), may have similar spectral characteristics as Lake Yojoa during the stratified water column season (summer) because *Lyngbya robusta*, a non-heterocyst forming cyanobacteria, is a dominant lineage in the June epilimnion in Lake Yojoa (Fadum et al., 2024) and dominates summer algal blooms in Lake Atitlán as well (Rejmánková et al., 2011; Komárek et al., 2013). Collating *in situ* and spectral data products for those two lakes over the past 20 years may allow for an estimation of the broad impact of climate that is separate from the regional impact of land use (i.e., distinguishing between local/watershed drivers and global/climatic drivers of ecosystem change). To further generalize a model to estimate Secchi depth throughout other lakes within the region will require collaboration amongst disperse research efforts in tropical lake ecosystems with varying spectral signatures. However, continued remote sensing applications in tropical lakes may provide novel insights into intra-annual ecosystem dynamics and inter-annual trends and help to close the gap in remotely sensed data between Brazilian reservoirs and tropical inland waters at higher latitudes (Watanabe et al., 2015; Watanabe et al., 2018, 2019; Cairo et al., 2020; Pompêo et al., 2021).

We have demonstrated how remotely sensed data can be used to expand the temporal coverage of research efforts in understudied lakes, such as Lake Yojoa. Moreover, this work exemplifies how monitoring schedules that align with satellite acquisition days create an additional opportunity to invest in data availability beyond the duration of a single study through the value of providing data to local communities, stakeholders, and managers. This type of data production, sharing, and accessibility made possible through remote sensing is an important component of environmental justice and may be particularly impactful when paired with interactive platforms and data viewers (Weigand et al., 2019; Sayyed et al., 2024). Possible outcomes of increasing efforts to pair remote sensing data with concurrent monitoring work in low-latitude lakes include increased tropical research, increased access to monitoring technologies, improved understanding of the interactive and distinct impacts of local and global change, reduction of barriers to data-driven management practices, and increased environmental justice through data availability.

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Data availability

All data and code are available at https://zenodo.org/records/8139922.

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