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# Seasonal variation in landcover estimates reveals sensitivities and opportunities for environmental models

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**Abstract.** Most readily available landuse/landcover (LULC) data are developed using growing season remote sensing images often at annual time steps. We used the Dynamic World near real-time global LULC dataset to compare how geospatial environmental models of water quality and hydrology respond to growing vs. non-growing season LULC for temperate watersheds of the eastern United States. Non-growing season LULC had more built area and less tree cover than growing season data due to seasonal impacts on classifications rather than actual LULC changes (e.g., quick construction or succession). In mixed-LULC watersheds, seasonal LULC classification inconsistencies could lead to differences in model outputs depending on the LULC season used, such as an increase in watershed nitrogen yields simulated by the Soil and Water Assessment Tool. Within reason, using separate calibration for each season may compensate for these inconsistencies, but lead to different model parameter optimizations. Our findings provide guidelines on the use of near real-time and high temporal resolution LULC in geospatial models.

## 1 Introduction

Environmental models incorporating landuse/landcover (LULC) data are common in many fields including hydrology, biogeochemistry, ecology, and climate science, often with decision-making implications (Hu et al., 2021; Baumgartner and Robinson, 2017; Naha et al., 2021; Li et al., 2021). Studies relating hydrology and water quality to LULC often use an LULC dataset developed primarily from growing season data, such as the United States National Landcover Database (NLCD; Jin et al., 2019) or Cropland Data Layer (CDL; Boryan et al., 2011), and/or use an LULC dataset available at an annual time step (Sulla-Menashe and Friedl, 2018; Buchhorn et al., 2020; Gray et al., 2022). Characteristics of LULC (e.g., canopy density and precipitation interception) vary seasonally, particularly in temperate regions where vegetation leaf cover is reduced during the non-growing season compared to the growing season (van Beusekom et al., 2014). This has prompted popular hydrological models such as the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) to include

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seasonal cycles for factors like leaf area and crops (Nkwasa et al., 2020; Frans et al., 2013). However, there can also be temporal inconsistencies in LULC classifications due to variation in spectral signals that are often not accounted for, such as built LULC being classified as other types within the course of a year, or other classes being classified as trees too quickly for natural succession (Cai et al., 2014; Gómez et al., 2016).

Present day high temporal resolution LULC datasets, such as the global Dynamic World (Brown et al., 2022), can facilitate the study of non-growing season and near real-time impacts of LULC classifications on environmental models, including those of hydrology and water quality. Dynamic World, which has a 10 m spatial resolution at 5-day intervals from Sentinel-2 satellites (2A and 2B), has comparable classification accuracy to other LULC datasets including the NLCD, European Space Agency World Cover, and ESRI Land Cover data (Venter et al., 2022; Brown et al., 2022), and its 5-day temporal resolution is much more frequent than the annual-or-longer frequency of other common LULC datasets. For environmental research to take advantage of these high temporal resolution data, we need to understand the impacts of potential seasonal variation in LULC estimates on geospatial models, which use LULC data to support water resources management across the globe (Fu et al., 2019; Guo et al., 2020; Murphy, 2020).

Worldwide, investigations of LULC impacts to hydrology and water quality often employ regression-based models (Fu et al., 2019; Dow and Zampella, 2000), SWAT models simulating LULC change (Ni et al., 2021; Tong et al., 2009), and/or SWAT model configurations compared objectively to evaluate model performance (Fuka et al., 2012; Li et al., 2019). We used the Dynamic World LULC dataset to demonstrate how estimates of LULC can change between the growing and non-growing seasons. We then used a long-term United States National Park Service (NPS) water quality dataset for temperate watersheds in the eastern United States, along with the above hydrologic and water quality models, to assess the use of seasonal LULC data as an input for three modeling cases ranging from low to high complexity. We asked "How different are model outputs (effect sizes) when using growing vs. non-growing season LULC inputs?" and "Are there differences in calibrated model performance if growing vs. non-growing season LULC input is used?"

## 2 Materials and Methods

### 2.1 Study area and data

Our study area was 37 current (plus 18 historic) wadeable stream water quality sites monitored by the National Park Service National Capital Region Network (NCRN), with sites in Maryland, Virginia, West Virginia, and Washington DC, USA (Case #1; Figure 1). All sites are in the Chesapeake Bay watershed and were chosen to help inform natural resources management (Norris et al., 2011). This includes the 167 $km^2$ Rock Creek Watershed of Rock Creek National Park (Case #2) and the 150 $km^2$ Difficult Run Watershed of George Washington Memorial Parkway (Case #3), selected from the above watersheds for having continuous calibration and evaluation data.

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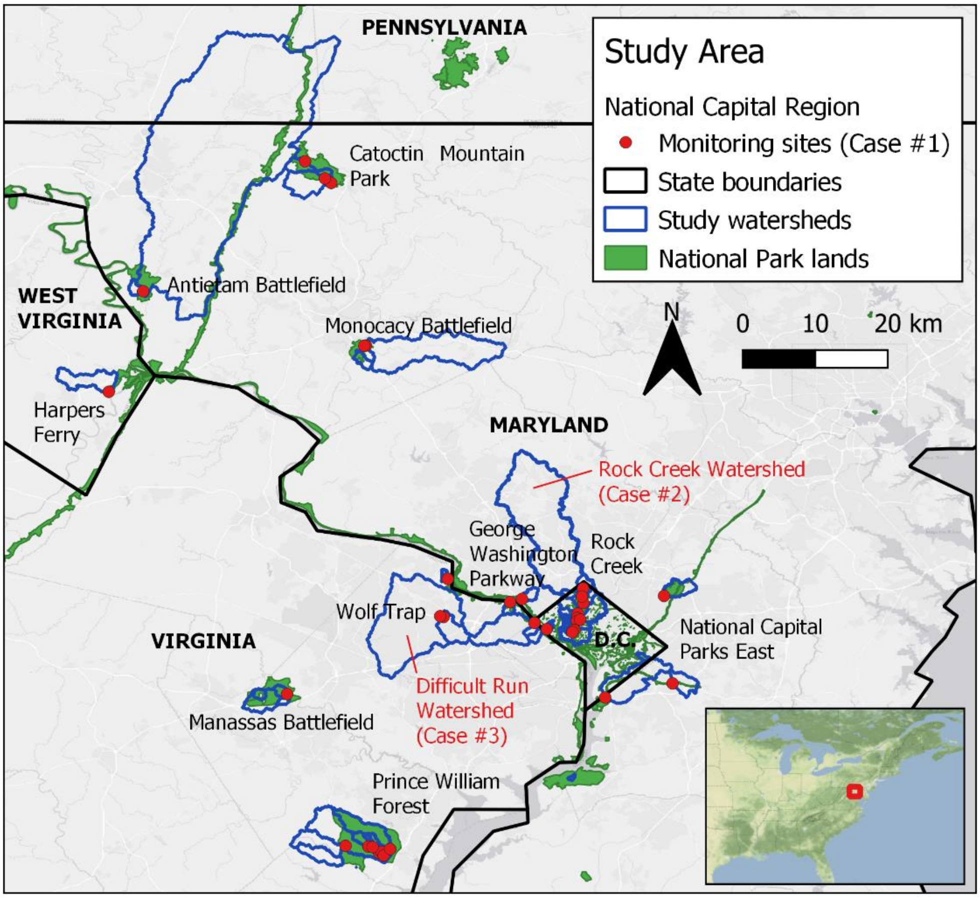


**Figure 1:** Study area map showing active monitoring sites and all (active + historic) watersheds.

Specific conductance (SC) can be used as an indicator of the overall amount of anthropogenic impacts to stream water quality in a watershed (Dow and Zampella, 2000). SC data from 2005-2018 for our study sites (Norris et al., 2011) were downloaded from the Water Quality Portal (https://www.waterqualitydata.us/; accessed 9 October, 2022). Discrete samples were taken every one to three months for each site following data quality controls and protocol (Norris et al., 2011), with an average of 179±89 measurements per site. Median values over the entire time period were used to compare water quality tendencies between monitoring sites (Dow and Zampella, 2000). Model calibration data are described in Sect. 2.5.

## 2.2 Seasonal landcover comparisons

We used Google Earth Engine (Gorelick et al., 2017) to generate a different Dynamic World LULC dataset for growing season (spring equinox to autumn equinox, 2016) and non-growing season (autumn equinox, 2015 to spring equinox, 2016) for the monitored watersheds by taking dominant LULC for each pixel over these time periods, following the suggested approach (Brown et al., 2022). Thus, there was one composite image for each season (growing and non-growing) that

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represented the most common LULC class for each pixel over the time period of individual images, as developing a SWAT model requires the input of one LULC layer. Dynamic World's built class aggregates both hard structures (e.g., buildings and parking lots) and the surrounding vegetation, as is done in other common SWAT LULC inputs such as NLCD developed classes (Brown et al., 2022; Jin et al., 2019). We chose the years 2015-2016 because that was the earliest available Dynamic World data and nearest to the center of our 2005-2018 time period for water quality data, but repeated the process for every year of available Dynamic World data (2016-2021) for the Rock Creek and Difficult Run Watersheds to verify there was a seasonal cycle throughout years (see below). The timing of the data also aligned with the instance of NLCD data from 2016 for comparisons.

### 2.3 Experimental design

Different watersheds were tested in each case to demonstrate that the seasonal LULC estimate differences were not limited to a single watershed (Figure 2). For our water quality regressions (Case #1), we developed linear least-squares regression models of median stream SC values over the entire 2005-2018 period for 37 currently monitored NCRN sites explained by seasonal Dynamic World 2016 built LULC. The purpose for the water quality regressions case was to evaluate how well Dynamic World data could identify an LULC forcing affecting water quality at the watershed scale, following the common regression approach used in water quality investigations worldwide (Fu et al., 2019). Performance measures including Akaike's Information Criterion (AIC; Akaike, 1974) were used to compare models from different seasons. For the LULC change simulation (Case #2), we developed and calibrated SWAT hydrologic and nitrogen (nitrate-N + nitrite-N) yield models for the Rock Creek Watershed, then used them to simulate an LULC change between growing and non-growing seasons. The purpose for the LULC change simulation case was to evaluate how a model calibrated to one LULC season could respond to LULC data from another season, such as when simulating impacts of a watershed LULC change, particularly with regards to sensitivity to potential illogical LULC transitions in the high temporal frequency data. For the independently calibrated models (Case #3), we developed and calibrated SWAT hydrologic models with growing and non-growing season Dynamic World 2016 inputs independently of one another for the Difficult Run Watershed. The purpose for the independently calibrated models case was to assess the performance of seasonally tuned models rather than the single model of the land cover change case, to provide fairer comparison of calibrated model performances since each model was optimized to its unique LULC situation. For each case we repeated the analysis with LULC from the commonly-used NLCD 2016 for comparison.

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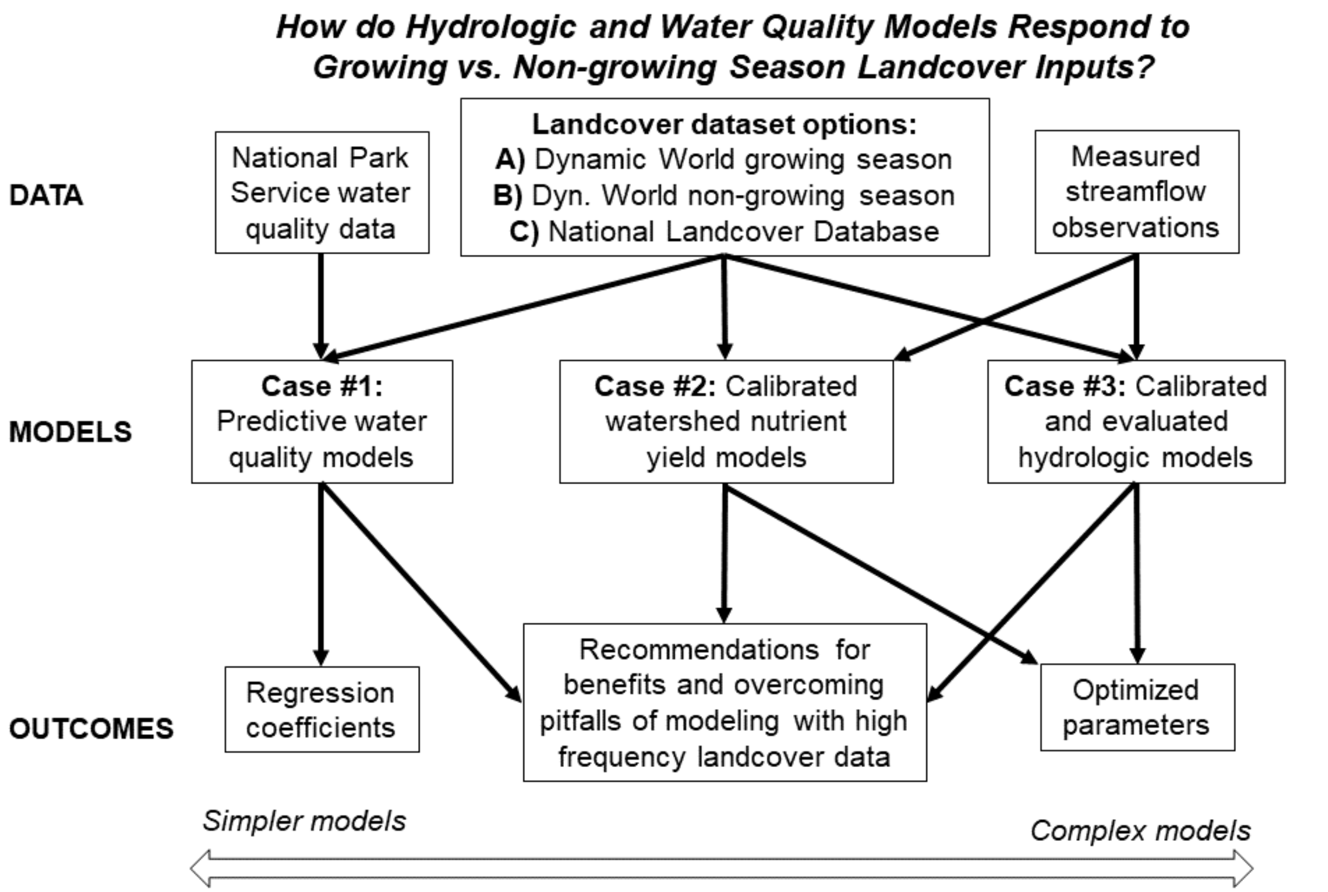


**Figure 2:** Conceptual diagram of the study.

### 2.4 Soil and Water Assessment Tool

The SWAT models (rev. 681) used in this study simulated streamflow using a water balance approach (Arnold et al., 1998), surface runoff using the runoff curve number (NRCS, 1986), groundwater flow using a water balance for shallow aquifer storage (Arnold et al., 1998), snowmelt based on snowpack temperature (Fontaine et al., 2002), and evapotranspiration using the Penman-Monteith method (Monteith, 1965; Ritchie, 1972). Nitrogen yields were simulated based on estimates of runoff, crop use, lateral flow, percolation, and concentrations in soil and water (Arnold et al., 1998). SWAT divides a watershed into spatial subbasins, which may be further divided into unique combinations of soils, landuse, and slopes called Hydrologic Response Units (HRUs). Subbasins were delineated using the program QSWAT. In the development of the SWAT models, one spatial data layer for each of elevation, soils, and LULC (Table S1) was input to generate tables that represent base watershed conditions (Abbaspour et al., 2019; Leeper et al., 2015; Lehner et al., 2006; Lindsay, 2022; Sugarbaker et al., 2014; USGS, 2022; USDA, 2022; Ries et al., 2017). We created a new SWAT LULC look-up table for QSWAT to read Dynamic World data (Table S2). The Rock Creek models for LULC change simulation (Case #2) had 13 subbasins, each assigned the

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dominant HRU, as has been done to more efficiently use computational resources (Myers et al., 2021b; Arabi et al., 2008). Gridded 4 km GridMET historic weather inputs were used as the Rock Creek watershed extends over 30 km from north to south (Abatzoglou, 2013). The Difficult Run SWAT models (Case #3) had 7 subbasins. Our Difficult Run Watershed SWAT models were constructed so that the maximum number of HRUs was incorporated, as has been done to compare independently calibrated model performance (Fuka et al., 2012), with weather data from National Oceanic and Atmospheric Administration (NOAA) station USW00093738 (Table S1). We chose the SWAT model for this study because it can be used to support water resource decision making in mixed-LULC watersheds (Koltsida et al., 2023).

### 2.5 Sensitivity analysis and calibration

The Rock Creek models (Case #2) used parameters calibrated with a Latin hypercube approach (to generate a large number of potential parameter sets; Abbaspour et al., 2004) to the SWAT model with growing season Dynamic World 2016 inputs, using R-SWAT software (Nguyen et al., 2022). R-SWAT is an open source, graphic interface, parallelizable, and user-friendly tool to calibrate the SWAT model and analyze results (Nguyen et al., 2022). The parameters optimized during the Latin hypercube approach, which had 2,500 iterations, are shown in Table S3. Calibration and evaluation data were complete monthly streamflow (n=108 months) and nitrogen (n=10 months) data from the USGS station 01648010 (concentrations converted to loads by multiplying by streamflow), split with the first half for calibration and the latter half for evaluation. The years 2013-2021 were used in the simulations as these were the years the USGS station had been active for streamflow, and there was a 3 year model warm-up period (2010-2012) to reduce the influence of initial states. The calibrated parameter set was chosen as having the best performing Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) values for streamflow and nitrogen yield out of the sample of parameter sets.

For Case #3, sensitivities of Difficult Run Watershed SWAT model performance to specific parameters were analyzed using the density-based PAWN method in the Sensitivity Analysis for Everybody (SAFE) toolbox (Pianosi and Wagener, 2015; Pianosi et al., 2015; Zadeh et al., 2017). Eight thousand SWAT model runs with growing season Dynamic World 2016 data were used for the sensitivity analysis. We analyzed the sensitivity of 35 parameters and then chose the top 10 parameters with sensitivities greater than the dummy parameter to use in the calibration (Table 1 and Figure S1). We then calibrated the Difficult Run Watershed SWAT models at the daily time step using the AMALGAM optimization algorithm (Vrugt and Robinson, 2007) with 3200 iterations and NSE as the objective function (the metric that the algorithm aims to maximize) and observed daily streamflow from USGS station 01646000 (with the first half for calibration and latter half for validation; Figure S2). In addition to NSE, metrics for Kling-Gupta Efficiency (KGE; Gupta et al., 2009) and refined Index of Agreement ($d_r$; Willmott et al., 2012) were calculated to confirm our interpretations, with higher values implying better model performance.

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**Table 1:** Parameters used in SWAT model streamflow calibration for Difficult Run Watershed (Case #3), for models input with growing and non-growing season Dynamic World 2016 data, as well as the model with NLCD 2016 input.

| Symbol | Definition † | Lower Limit | Upper Limit | Calibrated Growing | Calibrated Non-growing | Calibrated NLCD 2016 |
|---|---|---|---|---|---|---|
| CH_KII.rte | Channel hydraulic conductivity (mm/h) (v) | 0.1 | 150 | 0.11 | 3.86 | 0.14 |
| ALPHA_BNK.rte | Bank flow recession constant (v) | 0.01 | 1 | 0.14 | 0.27 | 1.00 |
| CN_F.mgt | Runoff curve number (r) | -0.2 | 0.2 | -0.17 | -0.20 | -0.08 |
| SNO50COV.bsn | Fraction of SNOCOVMX for 50% cover (v) | 0.01 | 0.8 | 0.03 | 0.03 | 0.25 |
| ESCO.hru | Soil evaporation compensation coef. (v) | 0.01 | 1 | 0.01 | 0.03 | 0.35 |
| CH_NII.rte | Manning's n value for main channel (v) | 0.01 | 0.30 | 0.30 | 0.30 | 0.30 |
| SOL_BD.sol | Soil moist bulk density (r) | -0.2 | 0.2 | -0.19 | -0.01 | 0.00 |
| SNOCOVMX.bsn | Snow depth above which is 100% cover (mm) (v) | 0 | 500 | 471 | 496 | 205 |
| SFTMP.bsn | Snowfall temperature threshold (°C) (v) | 0 | 3 | 0.95 | 0.98 | 1.02 |
| SOL_AWC.sol | Available Water Capacity (r) | -0.25 | 0.25 | -0.23 | -0.25 | -0.23 |

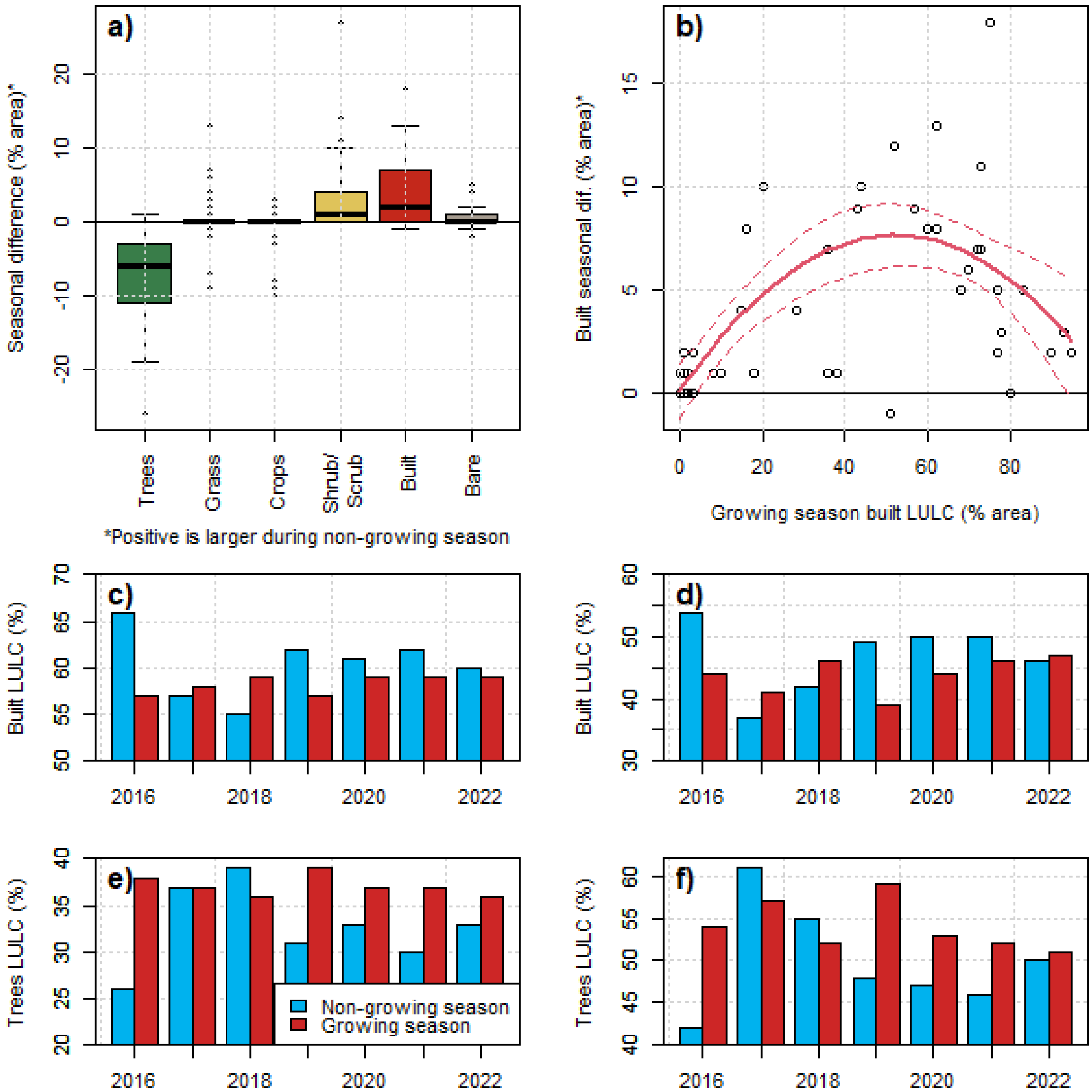
† A 'v' indicates that the original parameter from QSWAT was replaced by the calibrated value, in the same unit. An 'r' indicates that the original parameter was modified relatively, multiplying it by 1 + the calibrated value (e.g. a value of -0.2 reduces the original parameter by 20%).

## 3 Results and discussion

### 3.1 Seasonal landcover comparisons

The Dynamic World 2016 data classified a greater area of the 55 watersheds as trees during the growing season than during the non-growing season, typically by 5-10% of watershed area (Figure 3a). During the non-growing season, some areas classified as trees during the growing season were instead given built or shrubland LULC classes. Differences in seasonal LULC classifications in Dynamic World data were strongest in mixed-LULC watersheds (i.e., watersheds with 15% to 85% of the area classified as built LULC), and weaker in very low built or very high built percentage watersheds ($R^2$=0.49, df=52, F=24.82, p<0.001; Figure 3b). There was a relative mean absolute difference (RMAD) of 9.0% of watershed area between

NLCD 2016 developed (including open space, low, medium, and high intensity) and Dynamic World 2016 growing season built data (5.9% using non-growing season built data) for the 37 currently monitored watersheds (Figure S3 and Table S4).




170 **Figure 3:** All using Dynamic World 2016: a) Difference between growing and non-growing season LULC for 55 watersheds (classes of water, flooded vegetation, barren, and snow/ice were approximately 1% of watershed area so omitted; boxplots show median, interquartile range (IQR), and outliers outside 1.5 * IQR), b) Quadratic relationship between built area and the seasonal difference in built area for 55 watersheds, with 95% confidence intervals as dashed lines, c) and d) Time series of built area estimates for the Rock Creek and Difficult Run Watersheds, respectively, and e,f) same as above but for tree area.

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The differences between seasons were not limited to a single year of data or watershed. For instance, our study watershed for the LULC change simulation (Case #2, Rock Creek) showed a 9% increase in built LULC, and a 12% decrease in tree area, in non-growing season relative to growing season Dynamic World data from 2016. Meanwhile, our study watershed for the independently calibrated models (Case #3, Difficult Run) showed a 12% decrease in tree cover and a 10% increase in built areas in the non-growing season compared to the growing season Dynamic World 2016. Over the entire time period of available Dynamic World estimates for these watersheds, growing season LULC estimates generally had more tree area, while non-growing season had more built area (Figure 3c-f). However, in some years (e.g., 2017-2018) the relationship could be reversed, highlighting that further research is needed about the year-to-year variability of seasonal LULC estimates and impacts of using different years of seasonal LULC in environmental models.

Changes in LULC estimates between seasons were often concentrated along forested edges of mixed-LULC areas (Figure S4). In these deciduous areas, such as the edges of mixed residential/forested zones, leaf cover decreases during the non-growing season, which could be exposing other types of LULC underneath, or making forest more difficult to distinguish from surrounding built area for the classifications. Actual on-the-ground changes from built LULC to other types, or from other LULC types to trees (e.g., succession), are not likely to be occurring within the short (seasonal) time interval between our LULC composites (Cai et al., 2014).

### 3.2 Case #1: Water quality regressions

Median stream water specific conductance (SC) was positively correlated with 2016 Dynamic World built LULC during both seasons (Figure 4; Table 2). This relationship is expected and confirms that urban development has a strong positive effect on surface water salinization (Utz et al., 2022; Kaushal et al., 2005). The model for growing season built LULC vs. median SC had a slope of 6.41, while the same model for non-growing season LULC had a slope of 6.06, and the AIC's for both models were within 1 AIC unit (484 and 483, respectively), which suggests similar performance. For perspective, a model created with developed classes from NLCD 2016 had a slope of 6.19 and AIC of 486 (Table 2), with a similar fit as both seasonal models ($R^2$ ranging from 0.65-0.68), supporting that Dynamic World could be relevant for identifying LULC forcings affecting water quality particularly where regional products such as NLCD are not available.

**Table 2:** Regression models for specific conductance for the growing vs. non-growing seasons of Dynamic World 2016 built data and the NLCD 2016 developed classes model (df=35). LCI and UCI: upper and lower 95% confidence intervals of slope.

| LULC | Intercept | Slope | $R^2$ | F | p-value | LCI | UCI | AIC |
|---|---|---|---|---|---|---|---|---|
| Dyn. World growing season | 152.38 | 6.41 | 0.67 | 70.42 | <0.001 | 4.86 | 7.96 | 484 |
| Dyn. World non-growing season | 140.31 | 6.06 | 0.68 | 74.97 | <0.001 | 4.64 | 7.48 | 483 |
| NLCD 2016 | 106.56 | 6.19 | 0.65 | 64.20 | <0.001 | 4.62 | 7.75 | 486 |

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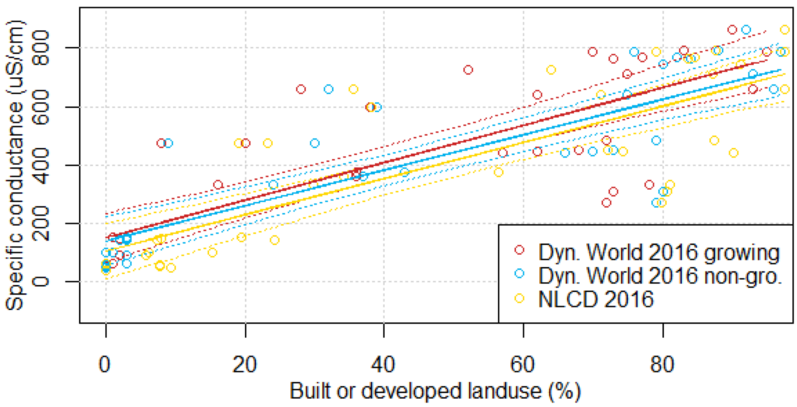


**Figure 4:** Modeled median specific conductance (SC) for 37 watersheds comparing Dynamic World 2016 growing and non-growing season built and NLCD 2016 developed LULC, with 95% confidence intervals as dashed lines.

### 3.3 Case #2: Hydrologic and nitrogen yield models

Our Rock Creek Watershed SWAT model for streamflow and nitrogen yield, developed and calibrated using Dynamic World 2016 growing season data, performed with a streamflow calibration NSE of 0.56 (validation NSE of 0.65), nitrogen yield calibration NSE of 0.45 (validation NSE of 0.80), and nitrogen yield calibration percent bias (PBIAS, where <0 implies overestimation bias; Gupta et al., 1999) of 14.6% (validation PBIAS of 1.6%) (Table 3). Therefore, we concluded that the model developed with Dynamic World 2016 growing season data was reliably simulating real conditions at the monthly time step (Figure 5a,b; red circles). When the calibrated parameter adjustments were transferred to the SWAT model developed with non-growing season LULC (as could be done when simulating an actual LULC change), streamflow performance decreased by approximately 0.30 NSE units and nitrogen yield PBIAS became -34.4% to -57.4%, implying overestimation of nitrogen (Table 3; Figure 5a,b; blue circles). Also, the model simulated 50% greater nitrogen yield over the entire 2013-2021 time period when non-growing season Dynamic World 2016 data was used as the LULC input, rather than growing season LULC (Figure 5c). These discrepancies between model outputs are not negligible. In relative terms, this difference is greater than the current pollutant load reduction target for Chesapeake Bay of 17% total nitrogen load (Maryland Department of Environment, 2019). Therefore, we advise to take the potential seasonal variability of Dynamic World LULC estimates into consideration if used to design water quality improvement efforts, particularly when decision making is involved, or an LULC change is being simulated. A model could be fit to one season of LULC, but have bias if transferred to a different time period of LULC estimates due to temporal inconsistencies.

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**Table 3:** Model performance metrics for the calibrated Rock Creek hydrologic model (Case #2) for streamflow and nitrogen yield, based on Nash Sutcliffe Efficiency (NSE), mean absolute error (MAE), and percent bias (PBIAS, where <0 implies overestimation bias), at the monthly time step.

| SWAT LULC input | Period | Streamflow NSE | N yield NSE | N yield MAE (kg) | N yield PBIAS |
|---|---|---|---|---|---|
| Dyn. World 2016 growing season | Calibration | 0.65 | 0.45 | 713 | 14.6% |
| Dyn. World 2016 growing season | Validation | 0.56 | 0.80 | 909 | 1.6% |
| Dyn. World 2016 non-growing season | Calibration | 0.35 | -0.53 | 1177 | -34.4% |
| Dyn. World 2016 non-growing season | Validation | 0.21 | -2.00 | 3205 | -57.4% |
| NLCD 2016 | Calibration | 0.71 | -1.14 | 1694 | -7.8% |
| NLCD 2016 | Validation | 0.85 | -0.33 | 2364 | 22.1% |

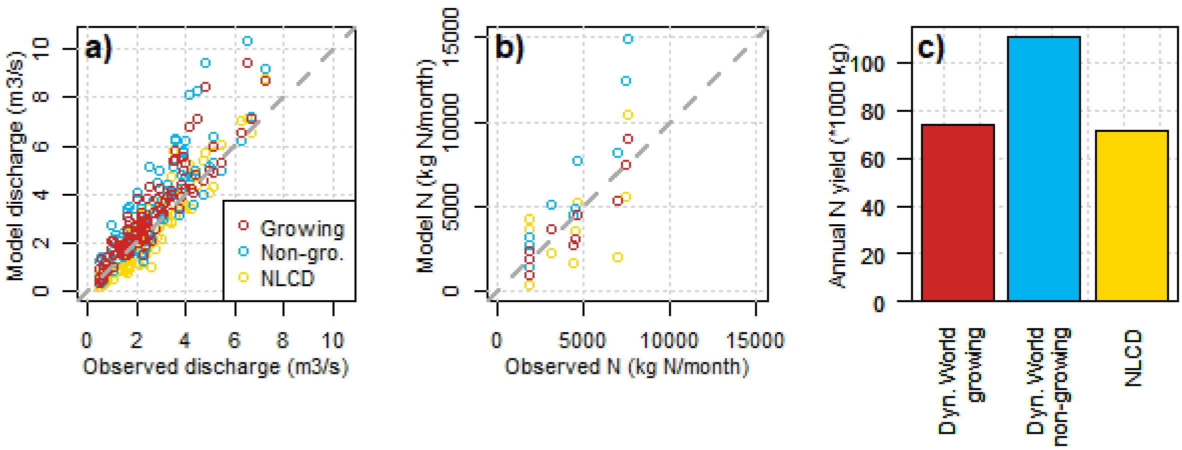


**Figure 5:** a) Observed vs. simulated monthly discharge for the Rock Creek Watershed comparing Dynamic World 2016 growing and non-growing season built and NLCD 2016 developed LULC, b) Same for monthly nitrogen (N) yields for Rock Creek, and c) Modeled average annual nitrogen yields for Rock Creek.

The differences observed between models using Dynamic World LULC were due to the 9% increase in built areas in non-growing season Dynamic World 2016 data, which have more impervious surfaces, a higher runoff curve number, and generate proportionally more water and nutrient runoff than the forested areas which were classified during the growing season. This could be particularly problematic when using computationally more efficient SWAT models that assign subbasin conditions based on the dominant HRU, as a change in dominant LULC type in a watershed could result in different subbasin conditions in the model greater than the proportional change in LULC. Future work could evaluate how Dynamic World data influences Earth System Models that spatially aggregate rainfall-runoff over a coarser grid cell and/or without flow routing between cells (Clark et al., 2015). For perspective, the nutrient outputs for the SWAT model with Dynamic World 2016

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growing season LULC were similar to those simulated by the SWAT model with NLCD 2016 LULC input using the same parameter adjustments (Figure 5c).

### 3.4 Case #3: Independently calibrated hydrologic models

The individually calibrated SWAT models using growing season vs. non-growing season Dynamic World 2016 LULC input for the Difficult Run Watershed had comparable performance when simulating streamflow, despite the differences in LULC inputs (10% increase in built areas and 12% decrease in tree cover for the non-growing season LULC input). NSE performance metrics at the daily time step were between 0.52 and 0.54 for each model with Dynamic World LULC over the calibration and validation time periods, Kling-Gupta Efficiency (KGE) was between 0.61 and 0.75, and refined Index of Agreement ($d_r$; which by not squaring errors provides a better measure of low flow performance) only ranged between 0.68 and 0.70 (Table 4; scatterplots in log scale to show daily baseflows and time series are presented in Figure 6a-d). For perspective, the SWAT model calibrated with NLCD 2016 LULC had an NSE of 0.48 for the calibration period and 0.47 over the validation period (Table 4).

**Table 4:** Comparison of streamflow performance for calibrated SWAT models developed independently with Dynamic World 2016 growing season LULC input, Dynamic World 2016 non-growing season LULC input, and NLCD 2016, at the daily time step for the Difficult Run Watershed (Case #3). Performance indices are $R^2$, NSE, Kling-Gupta Efficiency (KGE), and refined Index of Agreement ($d_r$).

| SWAT landuse input | Period | $R^2$ | NSE | KGE | $d_r$ |
|---|---|---|---|---|---|
| Growing season | Calibration | 0.54 | 0.53 | 0.61 | 0.69 |
| Non-growing season | Calibration | 0.54 | 0.54 | 0.65 | 0.70 |
| NLCD 2016 | Calibration | 0.49 | 0.48 | 0.56 | 0.69 |
| Growing season | Validation | 0.56 | 0.53 | 0.73 | 0.68 |
| Non-growing season | Validation | 0.57 | 0.52 | 0.75 | 0.68 |
| NLCD 2016 | Validation | 0.53 | 0.47 | 0.69 | 0.68 |

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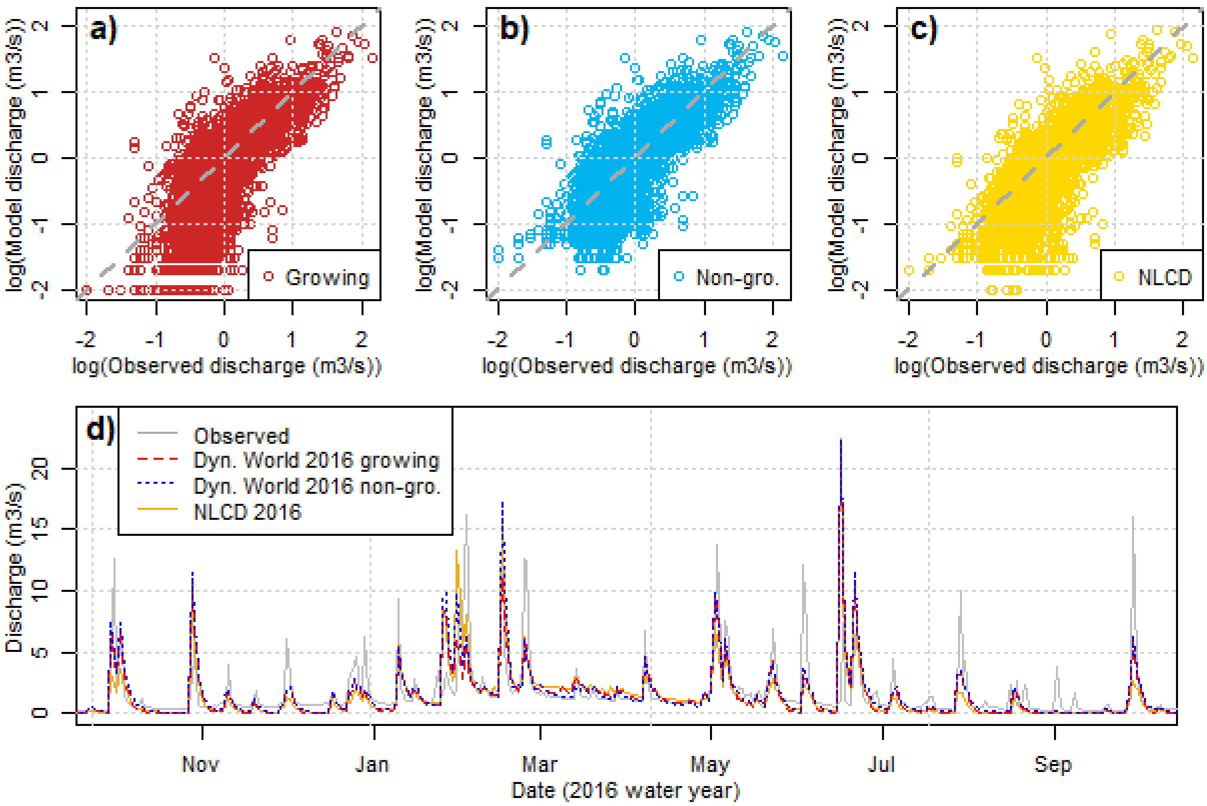


**Figure 6:** Daily discharge models for the Difficult Run Watershed displaying base-10 log, so that daily baseflows and low flows are visible, comparing independently calibrated models with a) Dynamic World 2016 growing season LULC, b) Dynamic World 2016 non-growing season LULC, and c) NLCD 2016. Also d) Time series of Difficult Run modeled discharge.

The most sensitive parameters for the Difficult Run Watershed case were channel hydraulic conductivity (CH_KII), bank flow recession coefficient (ALPHA_BNK), and runoff curve number (CN_F) (Figure S1). Among these and other sensitive parameters, there were differences in optimized values depending upon the SWAT LULC input (Table 1). For example, the CN_F adjustment optimized to -0.17 for growing season Dynamic World 2016, -0.20 for non-growing season Dynamic World 2016, and -0.08 for NLCD 2016 inputs, suggesting that the optimization adjusted runoff processes to compensate for the different proportions of LULC. The difference in forests of 12% of watershed area between growing and non-growing season Dynamic World 2016 data for Difficult Run (Table S4) is as large a difference as real changes in forests that have been found to cause these sensitivities in model parameters (Li et al., 2019), but was likely caused by classification variation rather than an actual cycle from trees to built area and back (Hermosilla et al., 2018). It is critical to consider that the differences in parameter values create the potential for the models to respond differently to future changes in LULC or climate change due to variations in unmeasured water balance outputs (Myers et al., 2021a).

## 4 Conclusions

When seasonal changes in LULC data occur, due to classification difficulties such as vegetation cycles (e.g., deciduous leaf cover in mixed-LULC areas), hydrologic and water quality models developed using growing season LULC inputs could behave differently from those using non-growing season LULC (Figure 7), with meaningful differences for environmental efforts such as pollutant load reduction targets. The cause in temperate watersheds is primarily a sensitivity to changes from built to forest LULC proportions that affect modeled runoff and nutrient yields, representing temporal classification inconsistencies rather than actual succession or restoration (Cai et al., 2014; Hermosilla et al., 2018). Environmental and geospatial researchers should be aware of this sensitivity when developing models and assessing changes in LULC as they relate to water quantity and quality, especially when considering the use of different seasons of available Dynamic World LULC data in a model. The seasonal variation in Dynamic World LULC data we identified is pertinent for environmental models of future climates, biodiversity, habitat loss, land management, ecology, and biogeochemistry that are dependent on precise assessments of LULC change that could be affected by the seasonal classification variation (Hu et al., 2021; Baumgartner and Robinson, 2017; Yang et al., 2022; Di Vittorio et al., 2018). With a limited geographic scope (e.g., temperate watersheds) and small sample of models, our work does not intend to show definitively when, where, or in what model configurations these sensitivities would occur, but that they are a possibility that modelers should be aware of, and supports that further research is needed.

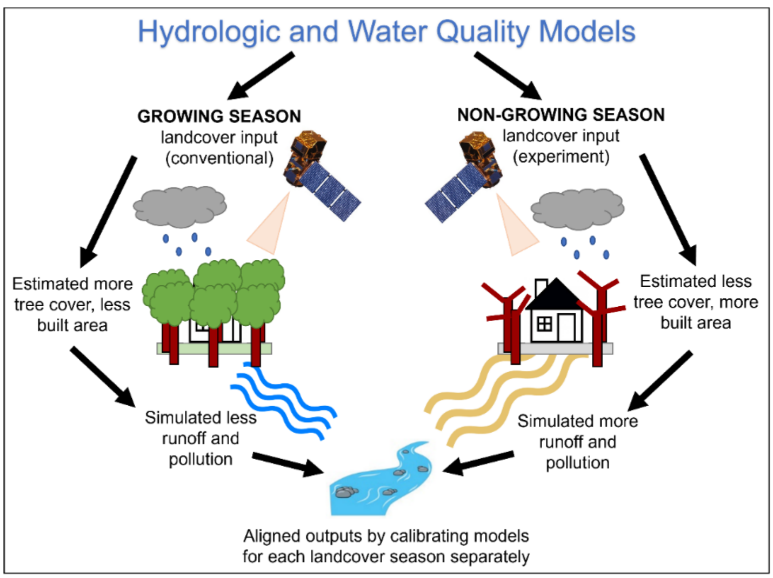


**Figure 7:** Conceptual diagram of the conclusions of the study in temperate watersheds of the eastern United States.

Future research building on our findings could investigate:

1. How seasonal LULC classification inconsistencies could affect assessments of habitat, biodiversity, land management, ecology, and future climate based on LULC change,
2. How seasonal LULC classification inconsistencies influence models outside our temperate study area (e.g., mountainous, arid, tropical, high-latitude, savannah, Mediterranean, continental),
3. The use of high-frequency monitoring data (Zhang et al., 2023) to investigate the influence of high temporal resolution LULC on water quality patterns,
4. Whether a modification to environmental models such as time varying parameters (Li et al., 2019) could account for the seasonal differences in Dynamic World LULC classifications,
5. The incorporation of LULC pixel probabilities from the Dynamic World dataset (Brown et al., 2022; Small and Sousa, 2023) into environmental models,
6. Post-processing approaches for high temporal resolution LULC products to address seasonal inconsistencies (Sexton et al., 2013; Liu and Cai, 2012; Hermosilla et al., 2018),
7. Which seasons of LULC data are most accurate for different purposes, such as vegetation or impervious surface classification,
8. Whether near real-time LULC data could be used in LULC change models (e.g., Hood et al., 2021) to improve the temporal precision of interpolations between discrete LULC images, and
9. To what extent year-to-year inconsistencies in seasonal LULC estimates could affect environmental models simulating LULC change over years.

## Code and data availability

Data from this study, including the LULC images, water quality data, and model outputs from each case, are available from Mendeley Data at https://doi.org/10.17632/bbb9xbpv22.3 (Myers et al., 2022). Codes from this study, including Google Earth Engine scripts and those to reproduce figures and analyses, are available on GitHub at https://github.com/Danmyers901/Calibration/tree/master/Landcover.

## Supplementary information

Supplementary material for this article is available online for Figures S1-S4 and Tables S1-S4.

## Author contribution

D.T.M. contributed to conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft, writing – review & editing, and visualization. D.J. contributed to conceptualization, methodology, resources, writing – original draft, writing – review & editing, formal analysis, and investigation. D.O.V contributed to conceptualization, methodology, resources, writing – original draft, writing – review & editing, supervision, project administration, and funding acquisition. J.P.S. contributed to conceptualization, methodology, resources, writing – original draft, writing – review & editing, formal analysis, and investigation. D.L.F. contributed to methodology, validation, investigation, writing – original draft, and writing – review & editing. X.Z. contributed to methodology, validation, investigation, writing – original draft, and writing – review & editing.

## Competing interests

The authors declare that they have no conflict of interest.

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