# Abstract

The Landsat satellites provide near-global surface reflectance measurements since the early 1980s that are increasingly used to assess interannual changes in terrestrial ecosystem function. These assessments often rely on spectral indices related to vegetation greenness and productivity (e.g., NDVI). Nevertheless, multiple factors impede multi-decadal assessments of spectral indices using Landsat satellite data, including ease of data access and cleaning, as well as lingering issues with cross-sensor calibration and challenges with irregular timing of cloud-free acquisitions. To help address these problems, we developed the *LandsatTS* package for R. This software package facilitates sample-based time series analysis of surface reflectance and spectral indices derived from Landsat sensors. The package includes functions that enable the extraction of the full Landsat record for point sample locations or small study regions using the Google Earth Engine accessed directly from R. Moreover, the package includes functions for (1) rigorous data cleaning, (2) cross-sensor calibration with machine learning, (3) phenological modeling, and (4) time series analysis. For an example application, we show how *LandsatTS* can be used to assess changes in annual maximum vegetation greenness from 2000 to 2020 across a study area on Disko Island in the Greenlandic Arctic. Overall, this software provides a suite of functions to enable broader use of Landsat satellite data for assessing and monitoring terrestrial ecosystem function over the past four decades across local to global geographic extents.

# Background

Satellite remote sensing is crucial for assessing and monitoring how Earth’s terrestrial ecosystems have changed during recent decades (National Academies of Sciences 2018). The Landsat satellites are particularly valuable in this regard because they are the longest continuously running satellite program and were designed for terrestrial ecosystem monitoring at moderate spatial resolution (Wulder et al. 2019). The first Landsat satellite (Landsat 1) was launched in 1972 as a partnership between NASA and the US Geological Survey (USGS) and since that time a series of additional satellites have been launched, with the most recent being Landsat 9 in 2021. The Landsat satellites carry multispectral sensors that provide surface reflectance measurements used for a wide range scientific and land management applications (Wulder et al. 2019). These include global monitoring of forest canopy cover (Hansen et al. 2013, Sexton et al. 2013) and surface water extent (Pekel et al. 2016), as well as regional- to biome-scale assessments of how land-use and climate change are impacting terrestrial ecosystems (Pastick et al. 2019, Wang and Friedl 2019, Berner et al. 2020, Berner and Goetz 2022). Hence, the Landsat program has become a cornerstone of Earth surface monitoring, yet there are challenges that hinder use of these data by ecologists, land managers, and other non-remote sensing specialists.

Here we present the *LandsatTS* (i.e., *Landsat Time Series*) software package for R that enables users to extract, process, and analyze time series of Landsat surface reflectance measurements for sample locations anywhere on Earth. *LandsatTS* enables extraction of Landsat 5, 7, and 8 surface reflectance measurements from the full Landsat Collection 2 dataset on Google Earth Engine (GEE; Gorelick et al. 2017). Furthermore, *LandsatTS* includes functions that facilitate (1) data cleaning, (2) cross-sensor calibration, (3) phenological modeling, and (4) time series analysis of vegetation greenness (Figure 1, Table 1). This software grew out of research projects focused on vegetation dynamics across northern high-latitude ecosystems (Berner et al. 2020, Berner and Goetz 2022) and is implemented within the free, open-source, and widely used R statistical computing environment (R Core Team 2021). Below, we provide further rational for the software package, a use case example, and descriptions of each function.

It has become easier to access and process Landsat data since the archive was made publicly available in 2008 (Woodcock et al. 2008) and a copy of the archive subsequently hosted on GEE (Gorelick et al. 2017). The GEE cloud-computing platform enables users to access and process Landsat data using JavaScript and Python application program interfaces (APIs), as well as with R through the *rgee* package (Aybar et al. 2020). R is very popular among ecologists (Lai et al. 2019), yet other existing R packages only provide tools for processing individual Landsat scenes. For instance, *landsat* includes functions for radiometric and topographic correction of Landsat scenes (Goslee 2011), while *landsat8* includes functions for computing top of atmosphere reflectance, radiance, and/or brightness temperature on Landsat scenes (dos Santos 2017). Thus, the *rgee* package makes it easier for ecologists and others to use GEE and Landsat data. Nevertheless, it remains non-trivial to not only extract Landsat time series data using *rgee*, but also rigorously clean the extracted data to ensure that only high-quality measurements are used in analyses. *LandsatTS* therefore provides new tools for sample-based extraction of full Landsat data records on GEE using the *rgee* portal. Furthermore, *LandsatTS* includes tools to rigorously clean Landsat data using both pixel-level CFmask flags (e.g., cloud, water; Zhu et al. 2015) and scene-level criteria (e.g., cloud cover, solar zenith angle). *LandsatTS* helps further broaden the community of researchers who can utilize Landsat data for robust spatiotemporal analyses of terrestrial ecosystem dynamics.

Landsat time series analyses that use measurements from multiple sensors are hindered by systematic biases in individual bands and spectral indices among the Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) sensors (Ju and Masek 2016, Roy et al. 2016, Berner et al. 2020, Berner and Goetz 2022). If unaccounted for, these biases can introduce artificial trends into combined time series, such as spurious increases over time in the Normalized Difference Vegetation Index (NDVI) (Sulla-Menashe et al. 2017) and other spectral indices of vegetation greenness (Berner and Goetz 2022). Prior approaches for cross-sensor calibration focused on linear corrections for individual bands and select spectral indices (e.g., NDVI) using regional data (e.g., continental USA) from Landsat Collection 1 (e.g., Ju and Masek 2016, Roy et al. 2016). These published cross-sensor calibration models do not account for potential non-linearities, may not be suitable for other regions, and may not be appropriate for the newer Landsat Collection 2 dataset. Therefore, *LandsatTS* includes functions to cross-calibrate bands and spectral indices among Landsat 5, 7, and 8 using either random forest machine learning or non-linear regression models. These models are fit using the user’s dataset, but if the user’s dataset is too small, then the models can be fit using pre-processed data that were sampled from across the Arctic tundra and boreal forest biomes. Cross-sensor calibration is crucial to help ensure time series analyses are not affected by spurious trends.

Efforts to assess vegetation phenology using the Landsat satellites are complicated by (1) irregular timing of clear-sky acquisitions within a growing season and (2) changes in the annual number of clear-sky acquisitions across years as new satellites were launched. These challenges are especially acute in regions with short, cloudy growing seasons such as the Arctic, where the median number of clear-sky growing season measurements increased from 2 per year in 1995 to 7 per year in 2015 (Berner et al. 2020). Annual maximum vegetation greenness (e.g., NDVImax) is an important metric of vegetation phenology related to productivity (e.g., Boyd et al. 2021, Frost et al. 2022), yet this metric is sensitive to the timing and number of measurements made in a growing season. Consequently, simple calculations of this metric tend to be artificially low early in the Landsat record but less so during later years when more measurements are available, which can introduce a spurious positive trend into a time series (Berner et al. 2020). To address this issue, *LandsatTS* includes tools to estimate annual maximum vegetation greenness based on site-specific phenological modeling that iteratively fits flexible cubic splines to vegetation greenness (e.g., NDVI) time series. Users interested in other aspects of vegetation phenology could extract and process Landsat data using *LandsatTS*, but then capitalize on tools provided by other R packages. For instance, the new *phenofit* package provides state-of-the-art tools for fitting phenological models that can be used to estimate metrics such as the timing of spring onset and fall senescence (Kong et al. 2022). This compatibility with other R packages broadens the overall utility of *LandsatTS*.

*LandsatTS* includes an integrated suite of tools that were originally developed to assess long-term changes in vegetation greenness within the rapidly warming Arctic tundra and boreal forest biomes (Berner et al. 2020, Berner and Goetz 2022). This software implements a sample-based approach that we found is well-suited for assessing vegetation dynamics and evaluating ecological hypotheses in these northern biomes, while substantially reducing computational burden compared with wall-to-wall analyses. The sample-based approach is conducive to rigorous propagation of uncertainty and error using Monte Carlo simulations (Berner et al. 2020, Berner and Goetz 2022), which is important for improving confidence in remote sensing analyses but are seldom carried out partially because of computational constraints (Myers-Smith et al. 2020). Further, the sample-based approach enables comparisons between satellite and field measurements across widely distributed site networks, helping validate and interpret vegetation dynamics inferred from satellites measurements (Boyd et al. 2019, Berner et al. 2020, Boyd et al. 2021, Walker et al. 2021). These tools have also been used to assess high-latitude vegetation responses to insect outbreaks (Boyd et al. 2019, Boyd et al. 2021), wildfires (Gaglioti et al. 2021), and permafrost degradation (Verdonen et al. 2020), as well as for syntheses focused on high-latitude disturbance regimes (Foster et al. 2022) and Arctic shrubification (Mekonnen et al. 2021). In summary, *LandsatTS* enables ecologists and other researchers to extract and process Landsat time series that can then be used to analyze vegetation phenology or for other user-defined applications.

![A picture containing timeline

Description automatically generated]()

Figure 1. Schematic illustrating functions and typical workflow of the *LandsatTS* package. Each function is described in the main text and Table 1. *LandsatTS* has primary been used for assessments of interannual variability and trends in vegetation greenness. However, *LandsatTS* facilitates other Landsat time series analyses by providing tools for general data extraction and processing.

Table 1. Function names and descriptions. These are listed in the order typically used.

|  |  |  |
| --- | --- | --- |
| **Step** | **Function** | **Description** |
| Data extraction | lsat\_get\_pixel\_centers | (*Optional*) Retrieve point coordinates of all Landsat 8 pixel centers that fall within a polygon. |
|  | lsat\_export\_ts | Export full Landsat surface reflectance time series for a set of point coordinates using GEE accessed from R. |
| Data processing | lsat\_general\_prep | Prepare data exported from GEE, including parsing satellite names and renaming and scaling bands. |
|  | lsat\_clean\_data | Filter out measurements based on presence of clouds, water, shadows, oblique view angles, and other criteria. |
|  | lsat\_summarize\_data\_avail | (*Optional*) Summarize data availability at each site, such as total number and years of observations. |
|  | lsat\_neighborhood\_mean | (*Optional*) For buffered sites, compute band-wise mean surface reflectance across grid cells within the buffer. |
|  | lsat\_calc\_spec\_index | Calculate a variety of widely used spectral indices, such as the Normalized Difference Vegetation Index (NDVI). |
|  | lsat\_calibrate\_rf | Cross-calibrate bands or spectral indices from Landsat 5/8 to match Landsat 7 using Random Forests. |
|  | lsat\_fit\_phenological\_curves | Characterize seasonal land surface phenology at each site by iteratively fitting flexible cubic splines. |
|  | lsat\_summarize\_growing\_seasons | Estimate various phenological metrics from fitted cubic splines, such as annual maximum vegetation greenness. |
|  | lsat\_evaluate\_phenological\_max | (*Optional*) Evaluate estimates of annual maximum vegetation greenness with measurement availability. |
| Data analysis | lsat\_calc\_trend | Calculate temporal trends using non-parametric Mann-Kendall trend tests and Theil-Sen slope indicators. |

# Example application: Vegetation greenness trends for a landscape on Disko Island

Here we provide an example analysis of interannual changes in vegetation greenness from 2000 to 2020…

We characterize annual maximum vegetation greenness using the Normalized Difference Vegetation Index (NDVImax) derived from Landsat satellite observations. Landsat NDVImax relates to vegetation productivity and aboveground biomass in tundra ecosystems (Johansen and Tømmervik 2014, Berner et al. 2018, Berner et al. 2020). Here, we focus on the period from 2000 to 2020 because there were limited Landsat data available prior to 2000 in this region, as shown below. We provide the scripts associated with this example as supplemental files and in this section guide the reader through the analysis code with example output figures and tables that are generated by the *LandsatTS* functions (excluding Figure 2).

The following sections detail package installation and summarize the purpose and behavior of each *LandsatTS* function. Furthermore, we demonstrate the utility of *LandsatTS* with an example application focused on changes in vegetation greenness from 2000 to 2020 across a study area in the Greenlandic Arctic. For a detailed list of function descriptions, including the complete lists of arguments require by each function, please consult the helpfiles provided with the R package or refer to the list of function definitions supplied in the Supplementary Material.

*Part 1: Export Landsat time series from Google Earth Engine*

First the user needs to export Landsat time series for sample locations in the study area using GEE (Code Box 1). For this they need to prepare the environment, set the boundaries of the study area and then retrieve the Landsat pixel center coordinates using the *lsat\_get\_pixel\_centers()* function. Next, the Landsat records are exported for the pixel center locations using *lsat\_export\_ts()*. Here, we choose to export only Landsat observations between day of year 152 (beginning of June) and 273 (end of September). The user then waits for GEE to finish the exports. Progress can be monitored using the GEE task manager in the web browser (<https://code.earthengine.google.com/tasks>) or on the R console, using the *ee\_monitoring()* function provided by *rgee*. For the example, it took ~2 days to export the 19 files (totaling ~692 MB) associated with this example analysis. The CSV files containing the raw exports then need to be copied from the user’s Google Drive to the local machine that will carry out the subsequent processing using *LandsatTS*. The files can be copied manually or using the *ee\_drive\_to\_local()* function provided by *rgee*. Once the records are available locally, they need to be cleaned and processed into vegetation index time series as detailed in the next section.

Code Box 1: Export Landsat time series from Google Earth Engine

# Load required R packages

require(lsatTS)

require(rgee)

require(sf)

require(ggplot2)

require(*data.table*)

# Initialize Google Earth Engine

ee\_Initialize()

# Create sf polygon of the study area

aoi.poly <- st\_polygon(list(matrix(

c(-332950,-2243300,

-334950,-2243300,

-334950,-2245300,

-332950,-2245300,

-332950,-2243300),

ncol = 2,

byrow = T)))

*# Transform polygon to WGS84 lat long*

aoi.poly <- aoi.poly %>%

st\_sfc(crs = 3413) %>%

st\_transform(crs = 4326) %>%

st\_as\_sf()

# Get the central coordinates for each of the 4557 Landsat pixels in study area

aoi.pts <- lsat\_get\_pixel\_centers(aoi.poly)

# Export summer Landsat surface reflectance measurements for each pixel to a folder

# called “earth\_engine/lsat\_disko” on the user’s Google Drive.

lsat\_export\_ts(

pixel\_coords\_sf = aoi.pts,

startJulian = 152,

endJulian = 273,

prefix = 'disko',

drive\_export\_dir = 'earth\_engine/lsat\_disko')

## Part 2: Derive vegetation greenness time series from the raw Landsat data

To derive the vegetation greenness time series from the raw exports of Landsat time series, the records first need to be imported to R as a *data.table* object, re-formatted using *lsat\_general\_prep()* and cleaned with *lsat\_clean\_data()* to filter out clouds, snow, and water, as well as radiometric and geometric errors (Code Box 2). For the study area on Disko Island, *lsat\_clean\_data()* removed 1,817,683 of 2,452,693 observations (74.11%) in the data cleaning process. The availability of Landsat observations for all point locations (“sample.ids”) in the remaining dataset can then be visualized using *lsat\_summarize\_data\_avail*(). In the case of the pixel centers across the study area on Disko Island, the number of observations is poor before the year 2000, as highlighted by the graph that is automatically generated by the function (Figure 3). Therefore, we later limit the analysis of vegetation greenness to the years between 2000 and 2020. Finally, the NDVI is calculated using the *lsat\_calc\_spec\_index()*. The dataset is then ready for the sensor cross-calibration and phenological modelling.

Code Box 2: Derived vegetation greenness time series from the raw Landsat data

# Import CSV exported with GEE as *data.table*

data.files <- list.files(‘~/earth\_engine/lsat\_disko’, full.names = T)

lsat.dt <- do.call("rbind", lapply(data.files, fread))

# (Re-)format the imported raw data

lsat.dt <- lsat\_general\_prep(lsat.dt)

# Clean data by filtering clouds, snow, and water, as well as radiometric and geometric errors.

lsat.dt <- lsat\_clean\_data(lsat.dt)

# Summarize the availability of Landsat data for each pixel

lsat\_summarize\_data\_avail(lsat.dt)

# Compute the Normalized Difference Vegetation Index (NDVI)

lsat.dt <- lsat\_calc\_spec\_index(lsat.dt, si = 'ndvi')

Chart, scatter chart

Description automatically generated

Figure 3. Availability of quality screened Landsat observations across years for sample locations in the study area on Disko Island as returned by the *lsat\_summarize\_data\_avail()* function. Summaries are based on observations acquired between day of year 152 (beginning of June) and 273 (end of September). Note the limited availability of observations before the year 2000. Lines with points denote median counts while shaded error bands encompass the 2.5th to 97.5th percentiles of counts among sample locations.

*Part 3: Cross-sensor calibration and phenological modelling*

The derived NDVI time series need to be calibrated across the different Landsat sensors, and then NDVImax estimated using the phenological modelling approach (Code Box 3). We start by cross-calibrating the time series using *lsat\_calibrate\_rf()*. As the number of observations in the Disko Island dataset is too small to calibrate the random forest models, we use the pre-processed dataset of high latitude observations included with *LandsatTS*. The function saves the models in a specified output directory and generates a series of graphs (Figure 4) and tabular data (Table 3) that help with evaluating model performance. As desired, the calibration reduced the median bias between the Landsat 7 observations and the Landsat 5 and 8 observations visually (Figure 4) and statistically (Table 3). Next, as a step towards estimating annual NDVImax, we fit phenological models to the calibrated NDVI time series using *lsat\_fit\_phenological\_curves()*. The function automatically returns a figure with Landsat observations and fitted phenological curves for nine random sample locations in the dataset (Figure 5). Each phenological curve characterizes the seasonal progression of NDVI using observations pooled over a multi-year period (here an 11 year moving window) and should be smooth and hump-shaped. Beware of phenological curves with long straight lines that could suggest inadequate seasonal distribution of data used when fitting the curves. Once the models are fitted, the summary statistics (including the estimated NDVImax) are extracted using *lsat\_summarize\_growing\_seasons()*. The *lsat\_evaluate\_phenological\_max()* can be used to output a figure that allows for visually assessing the performance of modelled NDVImax (Figure 6). In the case of this Disko Island dataset, modeled estimates of NDVImax tendto be biased slightly low (~1%) when only one or two observations are available from a growing season (Figure 6), yet there were rarely such few observations during the period from 2000 to 2020 (Figure 3). The final step following the cross-calibration and phenological modelling is the time series analysis.

Code Box 3: Cross-calibration and phenological modelling

# Cross-calibrate NDVI among sensors using random forest models

# Outputs in Figure 4 and Table 3.

Lsat.dt <- lsat\_calibrate\_rf(

lsat.dt,

band.or.si = ‘ndvi’,

train.with.highlat.data = T,

outdir = ‘output/ndvi\_xcal\_smry/’,

overwrite.col = T)

# Fit phenological models (cubic splines) to time series at

# each sample location (Figure 5)

lsat.pheno.dt <- lsat\_fit\_phenological\_curves(lsat.dt, si = ‘ndvi’)

# Summarize spectral characteristics for each growing season

lsat.gs.dt <- lsat\_summarize\_growing\_seasons(lsat.pheno.dt, si = ‘ndvi’)

# Evaluate the estimates of annual maximum NDVI (Figure 6)

lsat.eval.dt <- lsat\_evaluate\_phenological\_max(lsat.pheno.dt, si = ‘ndvi’)

Chart

Description automatically generated

Figure 4. Relationships between Landsat 7 NDVI and both (a) Landsat 5 NDVI and (b) Landsat 8 NDVI using (left panels) original data and (right panels) data that were cross-calibrated with random forest models. Each point is a sample location from the Arctic – Boreal domain where there were temporally overlapping measurements from pairs of Landsat satellites. Orange diagonal lines depict 1:1 relationships. Model performance metrics are provided in Table 3. Note that cross-calibration substantially reduces biases between sensors but does increase scatter.

Table 3. Summary of original biases, performance of random forest models for cross-sensor calibration, and post-calibration biases in NDVI between Landsat 7 ETM+ and either Landsat 5 TM or Landsat 8 OLI. Error metrics were derived internally by the random forest using out-of-bag (OOB, i.e., withheld) data and further assessed using cross-validation, which yielded nearly identical results albeit with further information on post-calibration biases.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | **Satellite**  **sensor** | **Original Data** | |  | **OOB Error Metrics** | | |  | **Cross-Validated Error Metrics** | | | | | | **Median**  **bias** | **Median**  **% bias** |  | **r2** | **RMSE** | **N** |  | **r2** | **RMSE** | **N** | **Median**  **bias** | **Median**  **% bias** | | Landsat 5 TM | -0.04 | -6.1 |  | 0.98 | 0.03 | 4315 |  | 0.98 | 0.03 | 1438 | +0.001 | +0.1 | | Landsat 8 OLI | +0.03 | +4.6 |  | 0.97 | 0.03 | 4881 |  | 0.97 | 0.03 | 1627 | -0.001 | -0.1 | |  | |  | | |  | | | | |
|  |  |  |  |  |  |  |  |  |  |

A picture containing calendar

Description automatically generated

Figure 5. Seasonal progression of Landsat NDVI and phenological curves for nine random sample locations from the study area on Disko Island. Each point is an observation sorted by the day of year it was acquired and colored by the year of acquisition. Each phenological curve was fit to observations pooled over an 11-year window centered on each focal year.

Chart, box and whisker chart

Description automatically generated

Figure 6. Raw estimates of annual maximum NDVI (NDVImax) are biased low when few Landsat observations are available from a given growing season, whereas phenologically modeled estimates of NDVImax are minimally impacted by the availability of observations. The figure summarizes how raw and modeled estimates of NDVImax differ from observed NDVImax based on number of observations, as determined using *lsat\_evaluate\_phenological\_max().*

## Part 3: Analyze vegetation greenness time series

Finally, the trend in the NDVImax across years for each sample location (pixel center) in our study area on Disko Island is calculated using the *lsat\_calc\_trend()* function (Code Box 4). Note how we use the “yrs” argument to restrict the time series analysis to the years between 2000-2020 to avoid using the low number of observations in the record prior to the turn of the millennium. Figure 7 shows a histogram of precent change in NDVImax across the study area and a time series of annual mean NDVImax by trend category, both of which are generated by the function. These figures indicate extensive browning across the study area in recent decades*.*

Code Box 4: Analyze vegetation greenness time series

# Compute temporal trend in NDVImax (Figure 7)

lsat.trend.dt <- lsat\_calc\_trend(lsat.gs.dt, si = 'ndvi.max', yrs = 2000:2020)

Chart, histogram

Description automatically generated

Figure 7. (a) Histogram of relative change in Landsat NDVImax from 2000 to 2020 among sample locations in the study area on Disko Island. Landsat NDVImax decreased (browned) across much of the study area over the past two decades. (b) Annual mean Landsat NDVImax from 2000 to 2020 for sample locations grouped by their concomitant temporal trend. Trends were assessed for each sample location by removing temporal autocorrelation and then applying a Mann-Kendall trend test. Error bands depict ±1 standard error.

*Results from the example study*

This example analysis showed that from 2000 to 2020, annual maximum vegetation greenness (i.e., NDVImax) systematically decreased (α = 0.10; browned) across 51% of the study area on Disko Island, whereas vegetation greenness systematically increased (α = 0.10; greened) across 3% of this study area (Figure 2a and 8). There were no systematic changes across the remaining 46% of the study area (Figure 2a and 8). Overall, vegetation greenness decreased by an average of 5.7 ± 8.4% (± 1 SD) during this period. The predominance of browning in this study area contrasts with widespread greening in the Arctic (Myers-Smith et al. 2020, Frost et al. 2021), where Landsat observations indicate that average Arctic vegetation greenness increased 3.9% from 2000 to 2020 (Berner et al. 2020, Mekonnen et al. 2021). Nevertheless, browning in this study area is broadly consistent with findings from recent pan-Arctic analyses using Landsat (Berner et al. 2020) and MODIS (Frost et al. 2021) satellite data that show regional browning in southwestern Greenland. The causes of browning in southwestern Greenland warrant further investigation but are potentially linked to hotter and drier conditions suppressing shrub and other vegetation growth and, in some areas, to defoliation from moths (*Eurois occulta*) or browsing by muskoxen (*Ovibos moschatus*) (Forchhammer 2017, Gamm et al. 2018, Prendin et al. 2020). This analysis demonstrates a general workflow that can be used to not only explore long-term changes in vegetation greenness across focal landscapes, but also to perform sample-based analyses across large geographic domains.

# Package installation

The R package *LandsatTS* is publicly available through a GitHub code repository. Users will need to have installed the R software environment on their computer. The *LandsatTS* package is operating system agnostic and can be installed from within R using the *install\_github()* function from the *devtools* package:

devtools::install\_github("logan-berner/lsatTS")

The installation will compile the package from source code on the user’s computer. As the *LandsatTS* package itself is exclusively written in R code, no additional software is required.

To use the data extraction and preparation functions, users will need an account on GEE, and to have installed and configured the *rgee* package to access GEE from R. Please see the GEE (<https://earthengine.google.com/>) and *rgee* (<https://r-spatial.github.io/rgee/>) websites for details on signing up for an account and configuring *rgee*, respectively.

All other external package dependencies are configured and automatically dealt with by *devtools* during the installation. These required packages include (*LandsatTS* tested with version cited):

*crayon* v1.4.2 (Csárdi 2021), *data.table* v1.14.2 (Dowle and Srinivasan 2021), *dplyr* v1.0.7 (Wickham et al. 2021), *ggplot2* v3.3.5 (Wickham 2016), *ggpubr* v0.4.0 (Kassambara 2020), *magrittr* v2.0.1 (Bache and Wickham 2020), *mapview* v2.10.0 (Appelhans et al. 2021), *purr* v0.3.4 (Henry and Wickham 2020), *R.utils* v2.11.0 (Bengtsson 2021), *ranger* v0.13.1 (Wright and Ziegler 2017), *sf* v1.0-4 (Pebesma 2018), *stats* v4.1.1 (R Core Team 2021), *stringr* v1.4.0 (Wickham 2019), *tidyr* v1.1.4 (Wickham 2021), *zoo* v1.8.9 (Zeileis and Grothendieck 2005), *zyp* v0.10-1.1 (Bronaugh and Werner 2019).

# Data extraction

*LandsatTS* enables point sample-based extraction of full Landsat data records from GEE using the application programming interface provided by the *rgee* package. Sample locations typically represent (1) center coordinates of field sites, (2) a census of all Landsat pixels from a small area of interest, or (3) a random sample from a large region. Data extraction is conducted using the function *lsat\_export\_ts()*. If the user wishes to extract Landsat data for all pixels in a small area of interest, then the central coordinates of each pixel can be obtained using *lstat\_get\_pixel\_centers()* and then those sample locations are passed to *lsat\_export\_ts()*. Please note *lsat\_export\_ts()* has not been tested for data extractions exceeding 105 Landsat pixels (~90 km2). A recent analysis of the boreal forest biome focused on reflectance measurements acquired June through August from 1985 to 2019 for 105 Landsat pixels. This data extraction took about two weeks to run on GEE and yielded a total of ~41.6 million multispectral measurements that required ~15 Gb of hard drive storage (Berner and Goetz 2022). *LandsatTS* enables large data extractions but is not infinitely scalable.

*Export point-coordinate Landsat time series from Google Earth Engine using lsat\_export\_ts()*

The function *lsat\_export\_ts()* exports time series of Landsat 5, 7 and 8 surface reflectance measurements for each sample location by querying the Landsat Collection 2 archived on GEE. Data are exported for user-defined time periods. It is important to stress this function only works for sample locations (point coordinates) that must be supplied as a simple feature (*sf*) collection of point geometries. The function issues one or more tasks to GEE that export the data in the form of comma separated value (CSV) files to the user’s Google Drive. The number of tasks issued varies depending on the number of sample locations for which the Landsat record is to be extracted. Data extractions that involve a large number of sample locations are prone to errors and may exceed user limits set by GEE. Therefore, the function will chunk the sample locations into small groups (by default 250 sites) and for each chunk will issue a separate export task to GEE. The function returns a list of *rgee* task objects, which can be used to query the progress of the exports and subsequently retrieve the data from the user’s Google Drive.

*Optional: Get central coordinates of pixels within a polygon using lsat\_get\_pixel\_centers()*

The function *lsat\_get\_pixel\_centers()* facilitates extracting data for all Landsat pixels in a small area of interest (e.g., < 5 km x 5 km) by determining the central coordinates of all Landsat pixels that fall within a user-specified polygon. The user-specified polygon is supplied to the function as a simple feature collection. The function determines the Landsat Worldwide Reference System (WRS) scene whose center is closest to the center of the user-specified polygon. It then extracts the center coordinates for all pixels that overlap with the user-specified polygon from the first Landsat 8 scene on record available on GEE. A buffer can be specified to include additional pixels beyond the polygon boundary. The function returns the pixel centers as a simple feature object that can then be passed to the *lsat\_export\_ts()* function for the extraction of the Landsat time series. Please note this function is not designed to be used for sampling polygons that would exceed tens of thousands of Landsat pixels. The number of pixels in large polygons can quickly become too difficult to handle in the subsequent export and processing workflow, and such polygons may also extend beyond the area of the Landsat scene (185 km x 180 km) used to determine the pixel centers. For large areas, we recommend a random or regular subsampling of point locations such as done in prior studies (Berner et al. 2020, Berner and Goetz 2022).

# Data processing

## Prepare data for analysis using lsat\_general\_prep()

The function *lsat\_general\_prep()* takes the GEE exports generated by *lsat\_export\_ts()* and prepares the data for the subsequent *LandsatTS* workflow. These preprocessing tasks include parsing coordinates and other information, renaming columns, and scaling band values. The GEE exports need to be passed to the function in the form of a *data.table* object. *lsat\_general\_prep()* returns a *data.table* object that can then be passed on to *lsat\_clean\_data()* for the next step in the processing workflow. Please note that all *LandsatTS* functions handling a *data.table* object require a column called “sample.id” that uniquely identifies each location. If this column is not called “sample.id”, please modify accordingly.

## Clean surface reflectance data using lsat\_clean\_data()

The function *lsat\_clean\_data()* filters measurements to those made under clear-sky conditions. This function allows the user to filter measurements based on pixel quality flags and scene criteria. The USGS provides pixel quality flags based on the CFMask algorithm (Zhu et al. 2015) and information on each scene (e.g., cloud cover). The default settings for *lsat\_clean\_data()* will filter out measurements flagged as snow or water, as well as measurements acquired at high solar zenith angle (>60°), those with high geolocation uncertainty (>15 m), or those acquired as part of scenes with extensive cloud cover (>80%). Additionally, optional water masking is provided based on maximum surface water extent from the Landsat-based JRC Global Surface Water Dataset (Pekel et al. 2016). The main input supplied to *lsat\_clean\_data()* is a *data.table* of Landsat records for individual sample locations (specified by a sample.id column) - usually the direct output of *lsat\_general\_prep()* - and returns cleaned records in the form of an updated *data.table*, along with a console message summarizing the number and percentage of measurements removed during cleaning (generally >70%).

*Compute neighborhood mean surface reflectance using lsat\_neighborhood\_mean()*

The function *lsat\_neighborhood\_mean()* computes the mean band-specific reflectance across a neighborhood of pixels for measurements at each period in time. This is helpful when each of the user’s sample locations was buffered to include a neighborhood of Landsat pixels (e.g., 3 x 3 pixels). The main input to this function is a *data.table* of Landsat records for buffered sample locations. The function returns a new *data.table* with mean reflectance for each band at each point in time at every sample location. If used, the function should be called immediately after *lsat\_clean\_data()*.

*Summarize data availability for each site using lsat\_summarize\_data\_avail()*

The function *lsat\_summarize\_data\_avail()* takes a *data.table* of Landsat records and returns a summary *data.table* that provides information on the time period and number of observations available for each sample location. It also generates a figure showing the annual median (2.5th and 97.5th percentile) number of observations available from each satellite summarized across all sample locations. The figure is plotted to the current graphics device and can be saved by calling the function *ggsave()*.

*Calculate spectral indices using lsat\_calc\_spec\_index()*

The function *lsat\_calc\_spec\_index()* calculates a variety of common spectral indices. The function currently supports calculating 15 spectral indices, including the Normalized Difference Vegetation Index (NDVI), 2-band Enhanced Vegetation Index (EVI2), and others (Table 2). Note the function can only compute one spectral index at a time. As an input it requires a *data.table* with Landsat records and a string indicating the spectral index to be calculated. The function then returns the *data.table* updated with a new column containing the spectral index for each observation.

Table 2. Spectral indices that can be computed using the *lsat\_calc\_spec\_index()* function.

|  |  |  |  |
| --- | --- | --- | --- |
| **Name** | **Abbreviation** | **Formula** | **Citation** |
| Enhanced Vegetation Index | EVI |  | Huete et al. (2002) |
| Enhanced Vegetation Index (2-band) | EVI2 |  | Jiang et al. (2008) |
| Moisture Stress Index | MSI |  | Rock et al. (1986) |
| Near Infrared Vegetation Index | NIRv |  | Badgley et al. (2017) |
| Normalized Burn Ratio | NBR |  | Key and Benson (1999) |
| Normalized Difference Infrared Index | NDII |  | Hardisky et al. (1983) |
| Normalized Difference Moisture Index | NDMI |  | Gao (1996) |
| Normalized Difference Vegetation Index (red) | NDVI |  | Rouse et al. (1974) |
| Normalized Difference Vegetation Index (green) | gNDVI |  | Gitelson and Merzlyak (1998) |
| Normalized Difference Vegetation Index (kernel) | kNDVI | )2) | Camps-Valls et al. (2021) |
| Normalized Difference Water Index | NDWI |  | McFeeters (1996) |
| Plant Senescence Reflectance Index | PSRI |  | Merzlyak et al. (1999) |
| Soil Adjusted Vegetation Index | SAVI | 1.5 \* | Huete (1988) |
| Soil Adjusted Total Vegetation Index | SATVI |  | Marsett et al. (2006) |
| Wide Dynamic Range Vegetation Index | WDRVI |  | (Gitelson 2004) |

## Cross-calibrate spectral band or index across sensors using lsat\_calibrate\_rf()

The function *lsat\_calibrate\_rf()* will calibrate individual bands or spectral indices from Landsat 5 TM and Landsat 8 OLI to match Landsat 7 ETM+ using random forest models following the approach developed by Berner et al. (2020). Further cross-sensor calibration is needed because there are systematic differences in individual bands and spectral indices among Landsat sensors that must be addressed when combining data from multiple sensors (Ju and Masek 2016, Roy et al. 2016, Berner et al. 2020, Berner and Goetz 2022). Here, the Landsat 7 ETM+ is used as a benchmark because it temporally overlaps with the other two sensors. Cross-calibration can only be performed on one band or spectral index at a time and requires having data from 100s to preferably many 1,000s of sample locations to train the random forest models. There is an option for users to train the random forest models using pre-processed Landsat data from ~6000 randomly sampled locations across the Arctic – Boreal domain.

The overall approach involves determining the median spectral reflectance at a sample location during a portion of the growing season using Landsat 7 and Landsat 5/8 data that were collected the same years. A random forest model is then trained to predict Landsat 7 reflectance from Landsat 5/8 reflectance. Random forest models are ensembles of regression trees (Breiman 2001) that here are trained using a fast implementation provided by the *ranger* package (Wright and Ziegler 2017). If the user’s dataset includes both Landsat 5 and 8, then the function will train a random forest model for each sensor. The function evaluates model performance using both out-of-bag and cross-validated approaches. Please see Berner et al. (2020) for further details.

The main inputto *lsat\_calibrate\_rf()* is a *data.table* of Landsat records for sample locations and a string specifying the name of the band or spectral index to be cross-calibrated. By default, *lsat\_calibrate\_rf()* will return a *data.table* with a new column containing the cross-calibrated data. The function creates a user-specified output directory that contains (1) trained random forest models, (2) a CSV file with model evaluation metrics, and (3) a multi-panel figure comparing sensors pre- and post-calibration. Furthermore, model evaluation metrics are returned to the console and the figure plotted in the active graphics device. If the default setting to add a new column with the cross-calibrated data is used, then either use those data in the subsequent functions (e.g., ndvi.xcal) or, once satisfied, manually overwrite the uncalibrated data to simplify subsequent column names.

## Fit phenological curves to vegetation greenness time series using lsat\_fit\_phenological\_curves()

The function *lsat\_fit\_phenological\_curves()* provides information on the phenological timing of every Landsat observation relative to multi-year estimates of annual maximum vegetation greenness at each sample location. Specifically, the function models seasonal land surface phenology at each sample location using flexibly cubic splines iteratively fit to vegetation greenness (e.g., NDVI) time series within successive moving windows. The magnitude and timing of annual maximum vegetation greenness are determined for each time period by first pooling observations over years within each moving-window and then fitting cubic splines to observations that have been sorted by day of year. For each time period, a cubic spline is initially fit that describes vegetation greenness for each day of year during the growing season. To screen outliers, each observation of vegetation greenness is compared against the model fitted values for that day of year and if the deviation is greater than a user-specified difference (default is a 30% difference), then the observation is removed, and the cubic spline is re-fit. This is repeated until no observations exceed the user-specified threshold. The phenological status of each remaining observation is then determined relative to the modeled maximum vegetation greenness during the multi-year period. Additional details are provided in Berner et al. (2020).

The function takes as input a *data.table* with irregular time series of vegetation greenness observations at each sample location, as well as several parameters (e.g., moving window width, minimum number of observation needed to fit a cubic spline, cubic spline flexibility). The function returns a new *data.table* with phenological information for each remaining observation that occurred during a time period with adequate data for modeling surface phenology (i.e., typically fewer observations will be returned than are provided to the function). Among other output, the returned *data.table* provides for each observation the modeled estimates of (1) vegetation greenness for that day of year and for peak summer; (2) vegetation greenness for that day of year as a fraction of annual maximum vegetation greenness; (3) day of year when annual maximum vegetation greenness occurred; and (4) expected difference in vegetation greenness between that day of year and peak summer. The function also returns a figure to the current graphic device that shows seasonal progression of Landsat observations and modeled surface phenology for a random subset of nine sample locations. The user can optionally output a CSV that includes for each sample location the vegetation greenness predicted for each day of year during each time period by the cubic splines. Furthermore, the function includes an optional “test run” mode that will run the function on a random subset of nine sample locations and return a figure showing model fits, thus allowing the user to quickly experiment with different parameter settings. Note the function was designed to characterize seasonal phenology in terrestrial ecosystems with a single growing season and thus may not be suitable for use in ecosystems with multiple growing seasons. Also, the function was designed for spectral indices that are typically positive (e.g., NDVI). If using a spectral index that is typically negative (e.g., NDWI) then multiply the index by -1 before running the *lsat\_fit\_phenological\_curves()* and *lsat\_summarize\_growing\_seasons()* functions and then back-transform afterwards.

## Derive annual growing season metrics using lsat\_summarize\_growing\_seasons()

The function *lsat\_summarize\_growing\_seasons()* estimates several annual growing season metrics from vegetation greenness time series and modeled land surface phenology derived from Landsat satellite observations. The function’s main input is the *data.table* generated by *lsat\_fit\_phenological\_curves()* and user-specified parameters including the name of the spectral index and the phenological cut-off for an observation to be considered part of the growing season. Specifically, an observation is considered to be part of the growing season if the modeled vegetation greenness for that day of year is within a user-specified fraction of modeled annual maximum vegetation greenness (by default 0.75). The function returns a new *data.table* that includes for each sample location the annual mean, median, and 90th percentile vegetation greenness computed from observations during each growing season. The function also returns phenologically modeled estimates of the magnitude and timing (day of year) of annual maximum vegetation greenness. For each sample location, annual maximum vegetation greenness is estimated by first adjusting individual observations by the expected difference in vegetation greenness between that day of year and peak summer and then taking the median of phenologically adjusted values within each growing season. Please see Berner et al. (2020) for additional details.

## Assess estimates of maximum vegetation greenness using lsat\_evaluate\_phenological\_max()

The function *lsat\_evaluate\_phenological\_max()* assesses how estimates of annual maximum vegetation greenness vary with the number of Landsat observations when derived from raw observations and after phenological modeling. Raw estimates of annual maximum vegetation greenness are sensitive to the number of observations available from a growing season, but phenological modeling tends to substantially reduce this dependency (Berner et al. 2020). The main input to the function is a *data.table* with Landsat records and phenological information generated by *lsat\_fit\_phenological\_curves().* The function assumes the “actual” annual maximum vegetation greenness at a sample location is captured by having at least a user-specific number of observations (e.g., ≥ 7). For each site, the function extracts years with at least the user-specified number of growing season observations and then repeatedly compares how raw and phenologically modeled estimates of annual maximum vegetation greenness differ from actual annual maximum vegetation greenness as progressively smaller subsets of observations are used. The function returns a figure to the current graphic device that summarizes how raw and modeled estimates of annual maximum vegetation greenness differ from actual conditions when there are between 1 and n-1 Landsat observations from a single growing season. This lets the user determine how much annual estimates of maximum vegetation greenness are impacted by the number of available growing season observations.

# Data analysis

## Compute interannual trends in vegetation greenness using lsat\_calc\_trend()

The function *lsat\_calc\_trend()* computes a temporal trend in annual time series of vegetation greenness for each sample location over a user-specified time period. This function iteratively pre-whitens each time series (i.e., removes temporal autocorrelation) (Yue et al. 2002) and then computes Mann-Kendall trend tests and Theil-Sen slope indicators as implemented by the *zyp.yuepilon()* function from the *zyp* package (Bronaugh and Werner 2019). The function takes as input a *data.table* with annual time series of vegetation greenness for each sample location. The function returns (1) a new *data.table* that summarizes the interannual trend at each sample location; (2) a console message summarizing trends across all sample locations; and (3) a multi-panel figure summarizing interannual variability and trends in vegetation greenness. Specifically, the new *data.table* summarizes for each sample location the trend slope, intercept, Kendall’s tau, and p-value, as well as total absolute and relative change in vegetation greenness and other information (e.g., number of years with observations). The console message summarizes the mean (±1 SD) relative change in vegetation greenness across all sample locations, as well as the percentage of samples sites that greened, browned, or had no trend based on a user-specified critical value (default α = 0.10). The multi-panel figure provides (a) a histogram of relative change in vegetation greenness among sample locations and (b) a time series of annual mean (± 1 SE) vegetation greenness for sample locations that greened, browned, or had no trend.

# Conclusion

The *LandsatTS* package for R facilitates the extraction and processing of Landsat surface reflectance time series, as well as generating and analyzing metrics of vegetation greenness and other spectral indices. We demonstrated the functionality of this software by analyzing changes in vegetation greenness across a tundra landscape on Disko Island off the west coast of Greenland, but would like to highlight that these tools are also well suited for sample-based analyses of vegetation dynamics across large geographic regions such as whole terrestrial biomes (e.g., Berner et al. 2020, Berner and Goetz 2022). To date, *LandsatTS* has been used for ecological studies focused on Arctic tundra and boreal forest, but many of the functions could be used for studies focused on lower latitude ecosystems, especially ecosystems with a single growing season. Overall, this software provides a suite of functions to enable broader use of Landsat satellite data for assessing and monitoring Earth’s land surface over the past four decades in a sample-based framework suitable for local to global geographic extents.

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