`rOPTRAM`: Implementation of the OPTRAM Algorithm in `R`

true true

01 March 2024

Abstract

While drylands supply a livelihood to much of the world's rural population, these arid and semi-arid areas are under increased pressure due to both growing demand and the current climate crisis. Maintaining a sustainable source of food for rural populations depends on reliable grazing, and the quality of grazing is in turn determined by soil moisture. Thus to ensure a sustainable food supply, soil moisture must be monitored. Classic soil moisture monitoring methods rely on sensors, inserted into the soil, that give accurate measurements at high temporal resolution, but at a point location.

However, answering the needs of populations that depend on extensive grazing lands requires a regional scale assessment of soil moisture. Point measurements, albeit accurate, do not afford the needed information to prepare for, or mitigate drought events at regional scale. To this end, remote sensing methods to estimate soil moisture have been developed. Among them, the OPTRAM model has been shown to accurately determine soil moisture over large areas. The `rOPTRAM` package in `R` has implemented that model allowing researchers and practitioners to monitor grazing potential at regional scale and long time intervals.

Introduction

Across the African Sahel tens of millions of people depend on herds of grazing animals for food security (Mbow et al. 2021; Kusserow 2017). A time series of soil moisture measurements can serve to determine the quality and potential for grazing in arid and semi-arid regions. By following seasonal variations in soil moisture, forecasts for preferred grazing lands can be prepared. *In situ* volumetric soil content typically is measured using Time Domain Reflectrometer (TDR) sensors with a high temporal resolution (Kirkham 2014). TDR sensors are recognized to be very accurate, and can collect for long periods. However these data are point measurements, and cannot cover the extensive areas needed for determining regional scale grazing potential. Cosmic Ray Neutron Scanner (CRNS) technology can acquire soil moisture measurements also at high temporal resolution, with a larger spatial scale than TDR, covering a few hectares. These instruments are, however, quite expensive, and less accurate than TDR spot measurements (Davies et al. 2022; Schrön et al. 2017). Thus soil moisture measurements at regional scale, and with long term trend estimates are lacking. Populations living in drylands need high resolution regional soil moisture predictions to prepare for and mitigate droughts.

A novel physical-based model, OPtical TRApezoid Model (OPTRAM) developed by Sadeghi et al. (2017), that uses remote sensing imagery, was recently proposed and validated (Longo-Minnolo et al. 2022) to address the need to estimate soil moisture over vast areas in watershed and regional scales. OPTRAM is based on the well known physical relationship between soil moisture and land surface temperature (LST) (Lambin and Ehrlich 1996). Less than a decade ago Sadeghi et al. (2017) showed that shortwave infrared (SWIR) Transformed Reflectance (STR) can replace the thermal band needed to derive LST. Thus the model can now be applied to various earth observation systems with visible, near-infrared, and SWIR bands such as Sentinel-2 or Landsat (Ambrosone et al. 2020; Dubinin et al. 2020).

Algorithm

`rOPTRAM` produces a large dataset of pixel values of two satellite based raster layers: a vegetation index (VI), such as Normalized Difference Vegetation Index (NDVI) and the STR layer. All pairs of pixel values, at all acquired image dates are plotted as a scatter plot. Then regression lines are extracted at both the upper ("wet") and lower ("dry") bounds of the scatter plot. The slopes and intercepts of these two regression lines are the model coefficients, used to derive a spatially explicit soil moisture map. This soil moisture map is calculated, following Sadeghi et al. (2017), using Equation 3. In his original work, Sadeghi et al. (2017) used a visual examination of the scatterplot to locate the trapezoid edges.

The new `rOPTRAM` package, on the other hand, delineates the upper and lower, "wet" and "dry" bounds of the VI/STR scatterplot programatically, through the following approach. Sentinel-2 images are acquired, through the `CDSE` package (Karaman 2023), clipped to the study area, and for the user-specified time range. The API request sent to the Copernicus DataSpace Ecosystem[1] prepares both VI and STR indices. All pixel values for both indices, and for all images along the time series are collected into a table, and plotted as a scatterplot. The VI axis of the scatterplot is divided, programatically, into a series of small intervals, and a subset of the STR values, within that narrow interval of VI is extracted . Then the top and bottom 5% quartiles of these STR values are found for each of these intervals. The upper quartile values are paired together with the VI values for each interval, thus collecting points along the "wet" trapezoid edge. Similarly the bottom quartile values, paired with VI values, make up the "dry" trapezoid edge. Each of these two sets, typically consisting of 50 to 100 points, is used to delineate the "wet" and "dry" trapezoid edges, thus offering a mathematically robust and repeatable implementation of the OPTRAM model.

One of three possible equations is fitted to each of these "wet" and "dry" sets of trapezoid edges. In the simplest cast, a linear Ordinary Least Squares (OLS) regression line is fitted to each of the sets of points. The intercept and slope of these lines gives the coefficients for calculating soil water content. Two additional fitted options are implemented in `rOPTRAM`: second order polynomial and exponential. In all cases, the fitting function returns the root mean square error (RMSE) of the fitted line to the original 5% quartile trapezoid edges, enabling evaluation of the fitted result.

Linear regression fit of trapezoid edges

$$STR_{dry} = i_{dry} + s_{dry} \cdot VI \tag{1}$$

$$STR_{wet} = i_{wet} + s_{wet} \cdot VI \tag{2}$$

where: i_{wet}, i_{dry} are the regression line intercepts, and s_{wet}, s_{dry} are the slopes

Then soil moisture can be derived from:

$$W = \frac{STR - STR_{dry}}{STR_{wet} - STR_{dry}} \tag{3}$$

Second order polynomial fit of trapezoid edges

Polynomial fitted regression lines for the "wet" and "dry" edges can be expressed as:

$$STR_{dry} = \alpha_{dry} + \beta1_{dry} \cdot VI + \beta2_{dry} \cdot VI^2 \tag{4}$$

$$STR_{wet} = \alpha_{wet} + \beta1_{wet} \cdot VI + \beta2_{wet} \cdot VI^2 \tag{5}$$

and in this case, soil moisture is derived as:

[1] https://dataspace.copernicus.eu/

$$W = \frac{STR - (\alpha_{dry} + \beta 1_{dry} \cdot VI + \beta 2_{dry} \cdot VI^2)}{(\alpha_{wet} + \beta 1_{wet} \cdot VI + \beta 2_{wet} \cdot VI^2) - (\alpha_{dry} + \beta 1_{dry} \cdot VI + \beta 2_{dry} \cdot VI^2)} \quad (6)$$

Examples

Setup

Define directories and load required packages

```
Output_dir <- tempdir()
# Edit here...
work_dir <- system.file("paper", package = "rOPTRAM")
GIS_dir <- file.path(work_dir, "GIS")
aoi_file <- file.path(GIS_dir, "lachish.gpkg")

# load libraries
remotes::install_gitlab("rsl-bidr/rOPTRAM")
pkgs <- c("knitr", "ggplot2", "rOPTRAM", "jsonlite")
invisible(lapply(pkgs, require, character.only = TRUE))
# model parameters
veg_index <- "NDVI"
from_date <- "2022-09-01"
to_date <- "2023-04-01"
max_cloud <- 5
```

Run model, linear trapezoid fitting

Acquiring images from Copernicus DataSpace requires registering and setting up an OAuth client. Refer to the documentation.

```
BOA_list <- optram_acquire_s2(aoi_file = aoi_file,
                              from_date = from_date,
                              to_date = to_date,
                              max_cloud = max_cloud,
                              veg_index = veg_index,
                              output_dir = Output_dir,
                              remote = "scihub")
VI_dir <- file.path(Output_dir, veg_index)
VI_list <- list.files(VI_dir, full.names = TRUE)
STR_dir <- file.path(Output_dir, "STR")
STR_list <- list.files(STR_dir, full.names = TRUE)
VI_STR_df <- optram_ndvi_str(STR_list, VI_list,
                                 output_dir = Output_dir,
                                 rm.low.vi = TRUE,
                                 rm.hi.str = TRUE)
# Set output_dir to GIS_dir to save the plot
rmse <- optram_wetdry_coefficients(
  VI_STR_df,
  aoi_file = aoi_file,
  output_dir = GIS_dir,
  vi_step = 0.005,
  trapezoid_method = "linear",
  edge_points = TRUE)
knitr::kable(rmse, caption = "RMSE values for wet/dry fitted lines")
```

Second run: polynomial fitted curves

Refer to Equation 6.

```
rmse <- optram_wetdry_coefficients(
  VI_STR_df,
  aoi_file = aoi_file,
  output_dir = GIS_dir,
  vi_step = 0.005,
  trapezoid_method = "polynomial",
  edge_points = TRUE)
knitr::kable(rmse, caption = "RMSE values for wet/dry fitted lines")
```


Acknowledgements

The authors wish to thank Professor Maxim Shoshany, Faculty of Civil & Environmental Engineering, Technion, Israel, for advice and assistance in supplying relevant data for testing the model and software.

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