Processing Large Rasters using Tiling and Parallelization: An R + SAGA GIS + GRASS GIS Tutorial

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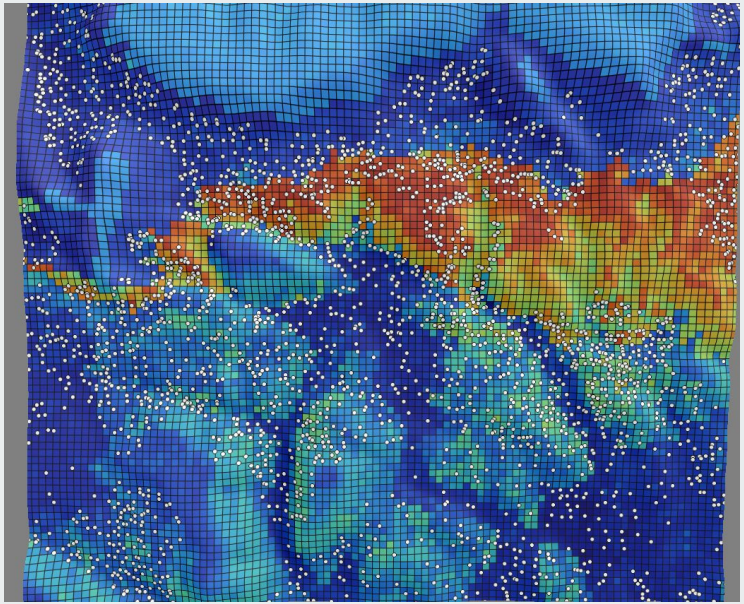
Overview



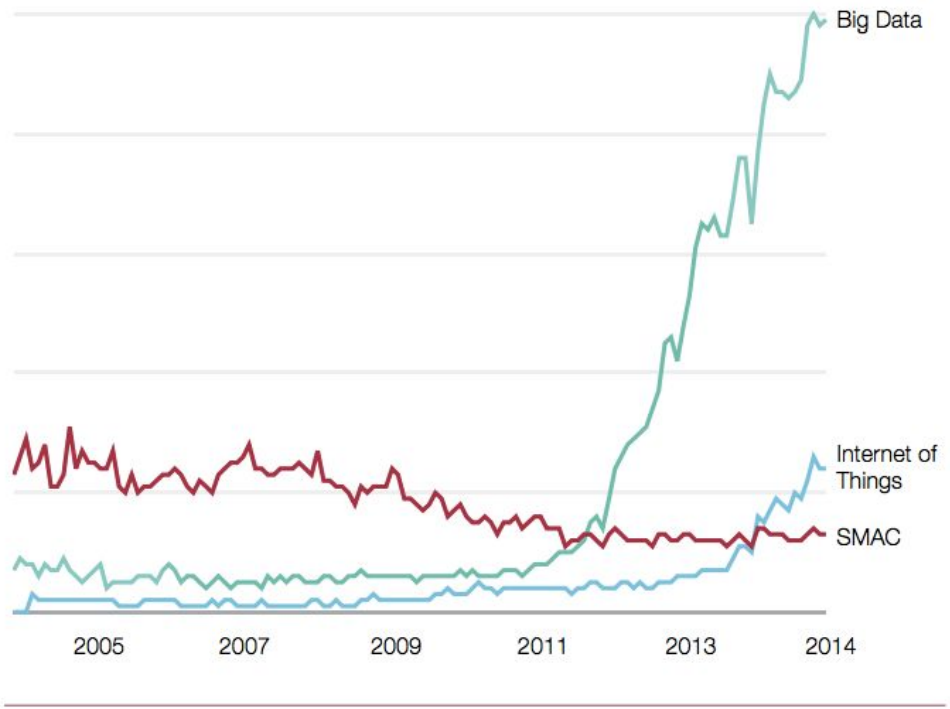
1. General concepts
    a. A systematic approach,
    b. Parallelization — basic principles,
2. Example 1
    a. processing global land cover data,
3. Example 2
    a. processing elevation data and DEM analysis,
4. Conclusions
    a. What to expect and what not to expect,
    b. Some work-arounds

3V's of big data

1. Volume (input output data size)
2. Velocity (read / write / compute)
3. Variety (e.g. millions of variables)

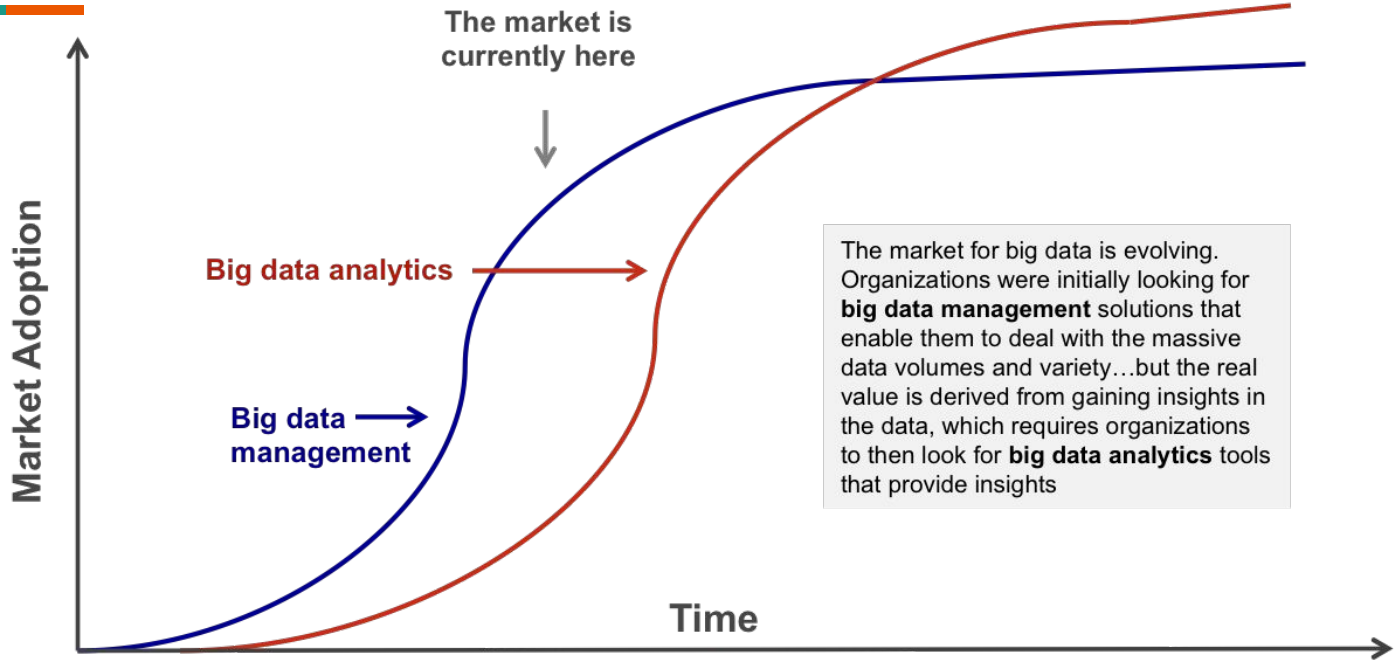
3V's of big data

Figure 1: Interest over Time for Specific Tech Trends, 2004-2014, Google Trends



Source: Google Search Trends accessed in December 2014

BData management vs BData analytics



The market for big data is evolving. Organizations were initially looking for **big data management** solutions that enable them to deal with the massive data volumes and variety…but the real value is derived from gaining insights in the data, which requires organizations to then look for **big data analytics** tools that provide insights

Big Data Management

Primary focus: manage and federate the increasingly massive volume, variety and velocity of data?

Big Data Analytics

Primary focus: Derive business value and provide insight from all the data that is being federated and managed?

First important realization

Programming with "big data" is really a different type of game — expect exponentially more complexity / get ready to boost your programming skills

SoilGrids250m

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

SoilGrids250m: Global gridded soil information based on machine learning

Tomislav Hengl, Jorge Mendes de Jesus, Gerard B. M. Heuvelink, Maria Ruiperez Gonzalez, Milan Kilibarda, Aleksandar Blagotić, Wei Shangguan, Marvin N. Wright, Xiaoyuan Geng, Bernhard Bauer-Marschallinger, Mario Antonio Guevara, Rodrigo Vargas, Robert A. MacMillan, [...], Bas Kempen [view all]

Published: February 16, 2017 • https://doi.org/10.1371/journal.pone.0169748

Abstract

This paper describes the technical development and accuracy assessment of the most recent and improved version of the SoilGrids system at 250m resolution (June 2016 update). SoilGrids provides global predictions for standard numeric soil properties (organic carbon, bulk density, Cation Exchange Capacity (CEC), pH, soil texture fractions and coarse fragments) at seven standard depths (0, 5, 15, 30, 60, 100 and 200 cm), in addition to predictions of depth to bedrock and distribution of soil classes based on the World Reference Base (WRB) and USDA classification systems (ca. 280 raster layers in total). Predictions were based on ca. 150,000 soil profiles used for training and a stack of 158 remote sensing-based soil covariates (primarily derived from MODIS land products, SRTM DEM derivatives, climatic images and global landform and lithology maps), which were used to fit an ensemble of machine learning methods—random forest and gradient boosting and/or multinomial logistic regression—as implemented in the R packages `ranger`, `xgboost`, `nnet` and `caret`. The results of 10–fold cross-validation show that the ensemble models explain between 56% (coarse fragments) and 83% (pH) of variation with an overall average of 61%. Improvements in the relative accuracy considering the amount of variation explained, in comparison to the previous version of SoilGrids at 1 km spatial resolution, range from 60 to 230%. Improvements can be attributed to: (1) the use of machine learning instead of linear regression, (2) to considerable investments in preparing finer resolution covariate layers and (3) to insertion of additional soil profiles. Further development of SoilGrids could include refinement of methods to incorporate input uncertainties and derivation of posterior probability distributions (per pixel), and further automation of spatial modeling so that soil maps can be generated for potentially hundreds of soil variables. Another area of future research is the development of methods for multiscale merging of SoilGrids predictions with local and/or national gridded soil products (e.g. up to 50 m spatial resolution) so that increasingly more accurate, complete and consistent global soil information can be produced. SoilGrids are available under the Open Data Base License.

Subject Areas

Shannon index | Forecasting | Machine learning | Trees | Agricultural soil sci... | Remote sensing | Glaciers | Soil ecology

Nutrient Cycling in Agroecosystems
September 2017, Volume 109, Issue 1, pp 77–102 | Cite as

Soil nutrient maps of Sub-Saharan Africa: assessment of soil nutrient content at 250 m spatial resolution using machine learning

Authors Authors and affiliations

Tomislav Hengl, Johan G. B. Leenaars, Keith D. Shepherd, Markus G. Walsh, Gerard B. M. Heuvelink, Tekalign Mamo, Helina Tilahun, Ezra Berkhout, Matthew Cooper, Eric Fegraus, Ichsani Wheeler, Nketia A. Kwabena

Open Access | Original Article
First Online: 02 August 2017

Abstract

Spatial predictions of soil macro and micro-nutrient content across Sub-Saharan Africa at 250 m spatial resolution and for 0–30 cm depth interval are presented. Predictions were produced for 15 target nutrients: organic carbon (C) and total (organic) nitrogen (N), total phosphorus (P), and extractable—phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sulfur (S), sodium (Na), iron (Fe), manganese (Mn), zinc (Zn), copper (Cu), aluminum (Al) and boron (B). Model training was performed using soil samples from ca. 59,000 locations (a compilation of soil samples from the AfSIS, EthioSIS, One Acre Fund, VitalSigns and legacy soil data) and an extensive stack of remote sensing covariates in addition to landform, lithologic and land cover maps. An ensemble model was then created for each nutrient from two machine learning algorithms—random forest and gradient boosting, as implemented in R packages ranger and xgboost—and then used to generate predictions in a fully-optimized computing system. Cross-validation revealed that apart from S, P and B, significant models can be produced for most targeted nutrients (R-square between 40–85%). Further comparison with OFRA field trial database shows that soil nutrients are indeed critical for agricultural development, with Mn, Zn, Al, B and Na, appearing as the most important nutrients for predicting crop yield. A limiting factor for mapping nutrients using the existing point data in Africa appears to be (1) the high spatial clustering of sampling locations, and (2) missing more

JOURNAL OF GEOPHYSICAL RESEARCH
Atmospheres
AN AGU JOURNAL

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16 March 2014
Pages 2294-2313

Research Article | Open Access

Spatio-temporal interpolation of daily temperatures for global land areas at 1 km resolution

Milan Kilibarda, Tomislav Hengl, Gerard B. M. Heuvelink, Benedikt Gräler, Edzer Pebesma, Melita Perčec Tadić, Branislav Bajat

First published: 03 February 2014 | https://doi.org/10.1002/2013JD020803 | Cited by: 34

Abstract

Combined Global Surface Summary of Day and European Climate Assessment and Dataset daily meteorological data sets (around 9000 stations) were used to build spatio-temporal geostatistical models and predict daily air temperature at ground resolution of 1 km for the global land mass. Predictions in space and time were made for the mean, maximum, and minimum temperatures using spatio-temporal regression-kriging with a time series of Moderate Resolution Imaging Spectroradiometer (MODIS) 8 day images, topographic layers (digital elevation model and topographic wetness index), and a geometric temperature trend as covariates. The accuracy of predicting daily temperatures was assessed using leave-one-out cross validation. To account for geographical point clustering of station data and get a more representative cross-validation accuracy, predicted values were aggregated to blocks of land of size 500×500 km. Results show that the average accuracy for predicting mean, maximum, and minimum daily temperatures is root-mean-square error (RMSE) =±2°C for areas densely covered with stations and between ±2°C and ±4°C for areas with lower station density. The lowest prediction accuracy was observed at high altitudes (>1000 m) and in Antarctica with an RMSE around 6°C. The model and predictions were built for the year 2011 only, but the same methodology could be extended for the whole range of the

Metrics

Citations: 34

Am score 2

Details

Keywords

spatio-temporal kriging
spatio-temporal interpolation
daily air temperature
MODIS LST

Publication History

Issue Online:
08 April 2014

Environmental Research Letters

LETTER • OPEN ACCESS • FEATURED ARTICLE

A global map of mangrove forest soil carbon at 30 m spatial resolution

Jonathan Sanderman[1,21], Tomislav Hengl[2], Greg Fiske[1], Kylen Solvik[1], Maria Fernanda Adame[3], Lisa Benson[5,6], Jacob J Bukoski[7], Paul Carnell[8], Miguel Cifuentes-Jara[9], Daniel Donato[19], Clare Duncan[4,8], Ebrahem M Eid[10,20], Philine zu Ermgassen[17,18], Carolyn J Ewers Lewis[8], Peter I Macreadie[8], Leah Glass[5], Selena Gress[11], Sunny L Jardine[12], Trevor G Jones[5,13], Eugéne Ndemem Nsombo[14], Md Mizanur Rahman[15], Christian J Sanders[16], Mark Spalding[17] and Emily Landis[17] Hide full author list

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Environmental Research Letters, Volume 13, Number 5
Focus on The Role of Forests and Soils in Meeting Climate Change Mitigation Goals

Article PDF

Figures References

Article information

Abstract

With the growing recognition that effective action on climate change will require a combination of emissions reductions and carbon sequestration, protecting, enhancing and restoring natural carbon sinks have become political priorities. Mangrove forests are considered some of the most carbon-dense ecosystems in the world with most of the carbon stored in the soil. In order for mangrove forests to be included in climate mitigation efforts, knowledge of the spatial distribution of mangrove soil carbon stocks are critical. Current global estimates do not capture enough of the finer scale variability that would be required to inform local decisions on siting protection and restoration projects. To close this knowledge gap, we have compiled a large georeferenced database of mangrove soil carbon measurements and developed a novel machine-learning based statistical model of the distribution of carbon density using spatially comprehensive data at a 30 m resolution. This model, which included a prior estimate of soil carbon from the global SoilGrids 250 m model, was able to capture 63% of the vertical and horizontal variability in soil organic carbon density (RMSE of 10.9 kg m^{-3}). Of the local variables, total suspended sediment load and Landsat imagery were the most important variable explaining soil carbon density. Projecting this model across the global mangrove forest distribution for the year 2000 yielded an estimate of 6.4 Pg C for the top meter of soil with an

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Global mapping of potential natural vegetation: an assessment of Machine Learning algorithms for estimating land potential

Research article | Biogeography | Computational Biology | Plant Science | Data Mining and Machine Learning | Spatial and Geographic Information Science

Tomislav Hengl[1], Markus G Walsh[2], Jonathan Sanderman[3], Ichsani Wheeler[4], Sandy P Harrison[5], Iain C Prentice[6]

March 30, 2018

Author and article information

Abstract

Potential Natural Vegetation (PNV) is the vegetation cover in equilibrium with climate, that would exist at a given location non-impacted by human activities. PNV is useful for raising public awareness about land degradation and for estimating land potential. This paper presents results of assessing Machine Learning Algorithms (MLA) for operational mapping of Potential Natural Vegetation (PNV). The following MLA were considered: neural networks (nnet package), random forest (ranger), gradient boosting (gmb), K-nearest neighborhood (class) and cubist. Three case studies were considered: (1) global distribution of biomes based on the BIOME 6000 data set (8057 modern pollen-based site reconstructions), (2) distribution of forest tree taxa in Europe based on detailed occurrence records (1,546,435 ground observations), and (3) global monthly Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) values (30,301 randomly-sampled points). A stack of 160 global maps representing biophysical

Three options:

1. Use software that handles large data (internal parallelization)
2. Make your own functions
3. Use infrastructure optimized for large data

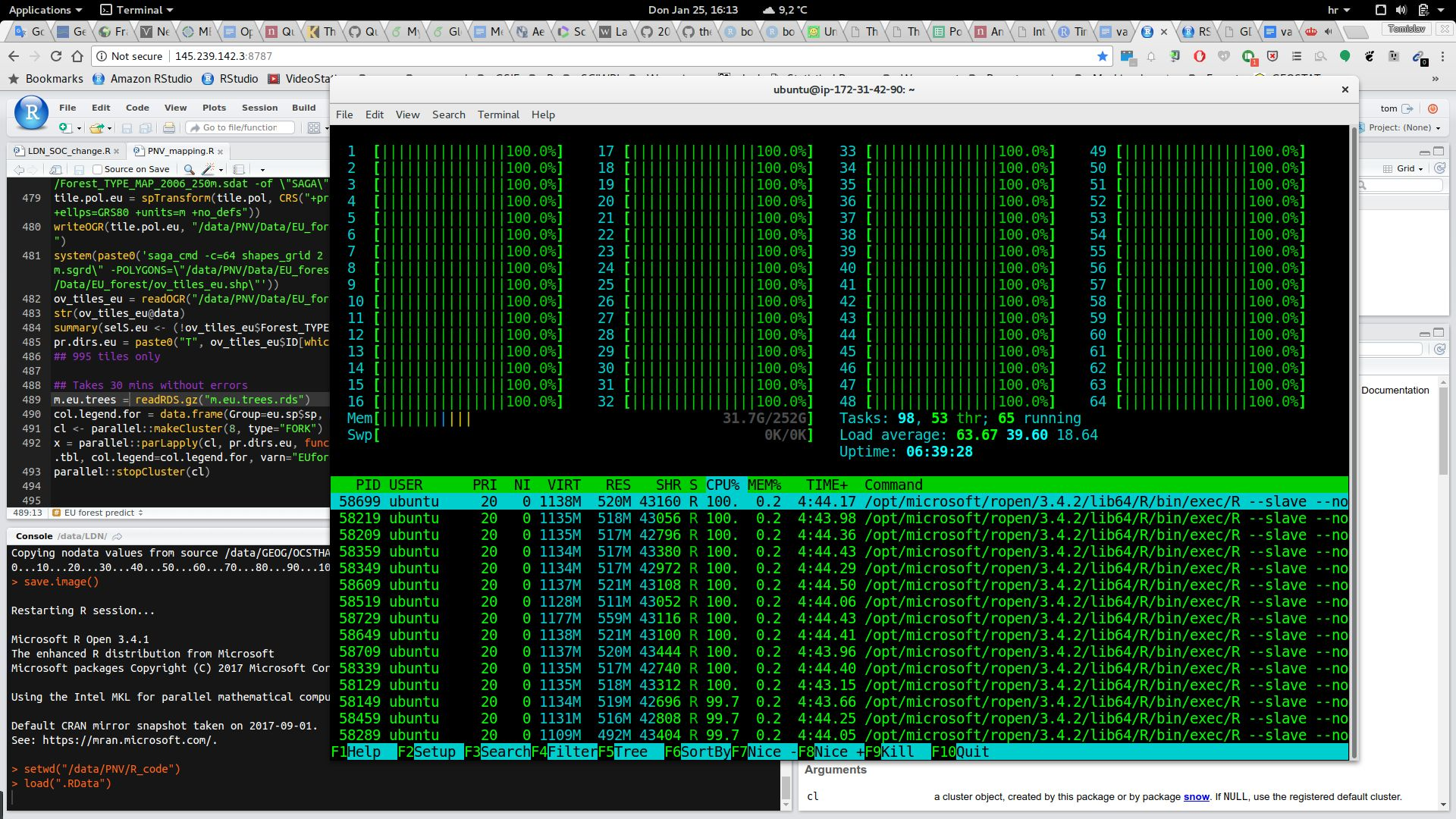
Learning parallelization is rewarding!

It is of course better if you can learn how to solve things by making your own functions

What can go wrong

1. You optimize almost everything, but then one bottleneck leaves you hanging.
2. You do not plan carefully and examine read/write times, memory handling, computing etc — and which results in a serious loss of time.
3. You leave computer computing for a very excessive amount of time without really knowing the progress.

once you get a bit better at it, it starts looking something like this...


Applications
Terminal
Don Jan 25, 16:13
9,2 °C
hr
Not secure
145.239.142.3:8787
Bookmarks
Amazon RStudio
RStudio
ubuntu@ip-172-31-42-90: ~
File Edit View Search Terminal Help
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16 [|||||||||||||100.0%] 32 [|||||||||||||100.0%] 48 [|||||||||||||100.0%] 64 [|||||||||||||100.0%]
Mem[|||||||||| 31.7G/252G]
Swp[0K/0K]
Tasks: 98, 53 thr; 65 running
Load average: 63.67 39.60 18.64
Uptime: 06:39:28
PID USER PRI NI VIRT RES SHR S CPU% MEM% TIME+ Command
58699 ubuntu 20 0 1138M 520M 43160 R 100. 0.2 4:44.17 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58219 ubuntu 20 0 1135M 518M 43056 R 100. 0.2 4:43.98 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58209 ubuntu 20 0 1135M 517M 42796 R 100. 0.2 4:44.36 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58359 ubuntu 20 0 1134M 517M 43380 R 100. 0.2 4:44.43 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58349 ubuntu 20 0 1134M 517M 42972 R 100. 0.2 4:44.29 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58609 ubuntu 20 0 1137M 521M 43108 R 100. 0.2 4:44.50 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58519 ubuntu 20 0 1128M 511M 43052 R 100. 0.2 4:44.06 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58729 ubuntu 20 0 1177M 559M 43116 R 100. 0.2 4:44.43 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58649 ubuntu 20 0 1138M 521M 43100 R 100. 0.2 4:44.41 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58709 ubuntu 20 0 1137M 520M 43444 R 100. 0.2 4:43.96 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58339 ubuntu 20 0 1135M 517M 42740 R 100. 0.2 4:44.40 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58129 ubuntu 20 0 1135M 518M 43312 R 100. 0.2 4:43.15 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58149 ubuntu 20 0 1134M 519M 42696 R 99.7 0.2 4:43.66 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58459 ubuntu 20 0 1131M 516M 42808 R 99.7 0.2 4:44.25 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
58289 ubuntu 20 0 1109M 492M 43404 R 99.7 0.2 4:44.05 /opt/microsoft/ropen/3.4.2/lib64/R/bin/exec/R --slave --no
F1Help F2Setup F3SearchF4FilterF5Tree F6SortByF7Nice -F8Nice +F9Kill F10Quit
File Edit Code View Plots Session Build
LDN_SOC_change.R
PNV_mapping.R
Source on Save
/Forest_TYPE_MAP_2006_250m.sdat -of \"SAGA\"
tile.pol.eu = spTransform(tile.pol, CRS("+pr
+ellps=GRS80 +units=m +no_defs"))
writeOGR(tile.pol.eu, "/data/PNV/Data/EU_for
")
system(paste0('saga_cmd -c=64 shapes_grid 2
m.sgrd\" -POLYGONS=\"/data/PNV/Data/EU_fores
/Data/EU_forest/ov_tiles_eu.shp\"'))
ov_tiles_eu = readOGR("/data/PNV/Data/EU_for
str(ov_tiles_eu@data)
summary(sels.eu <- (!ov_tiles_eu$Forest_TYPE
pr.dirs.eu = paste0("T", ov_tiles_eu$ID[whic
995 tiles only
Takes 30 mins without errors
m.eu.trees = readRDS.gz("m.eu.trees.rds")
col.legend.for = data.frame(Group=eu.sp$sp,
cl <- parallel::makeCluster(8, type="FORK")
x = parallel::parLapply(cl, pr.dirs.eu, func
.tbl, col.legend=col.legend.for, varn="EUfor
parallel::stopCluster(cl)
489:13
EU forest predict
Console /data/LDN/
Copying nodata values from source /data/GEOG/OCSTHA
0...10...20...30...40...50...60...70...80...90...10
> save.image()
Restarting R session...
Microsoft R Open 3.4.1
The enhanced R distribution from Microsoft
Microsoft packages Copyright (C) 2017 Microsoft Cor
Using the Intel MKL for parallel mathematical compu
Default CRAN mirror snapshot taken on 2017-09-01.
See: https://mran.microsoft.com/.
> setwd("/data/PNV/R_code")
> load(".RData")
Documentation
Arguments
cl
a cluster object, created by this package or by package snow. If NULL, use the registered default cluster.

Some lessons I've learned:

(a) Plan carefully,

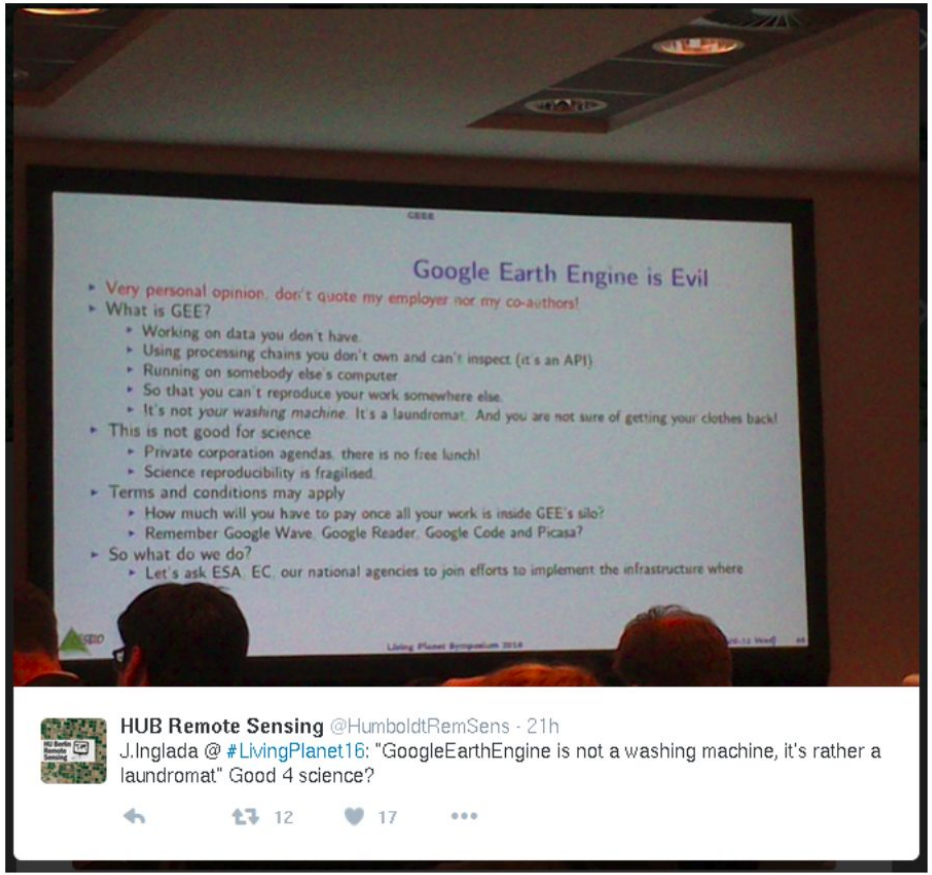
(b) Invest in hardware / storage,

(c) Use appropriate tiling (linear, hierarchical),

(d) Implement full parallelization (optimize code so it uses hardware to maximum)

(e) Make "scalable" code (it would work with N elements running on P cores),

Google Earth Engine



Software: fast reading of data

```
> ## CSV files:
> df <- data.table::fread("test.csv")
> ## shapefiles:
> f = system.file("shape/nc.shp", package="sf")
> pnt <- sf::st_read(f)
> ## rasters:
> r <- raster::stack(list.files)
```

read raster data in parallel

August 18, 2012

By Tim Salabim

(This article was first published on **metvurst**, and kindly contributed to R-bloggers)

Use library(parallel) to read raster data in parallel fashion

Recently, I have been doing some analysis for a project I am involved in. In particular, I was interested what role pacific sea surface temperatures play with regard to rainfall in East Africa. I spare you the details as I am currently writing all this up into a paper which you can have a look at once published.

For this analysis, however, I am processing quite an amount of raster files. This led me to investigate the possibilities of the `parallel` package to speed up the process.

Here's a quick example on how to read in raster data (in this case 200 global sea surface temperature files of 1° x 1° degree resolution) using `parallel`

First, lets do it the conventional way and see how long that takes

```
system.time({

    library(raster)
    library(rgdal)
```

This code will work just fine and will need approximately 2min to execute for smaller rasters (4000x4000px). However, imagine you have 100 rasters you would like to process. Here using multiple cores will save you a lot of time. And this is how you do it:

Example with parallelisation

```
library(raster)
library(doParallel)  #Foreach Parallel Adaptor
library(foreach)     #Provides foreach looping construct

#Define how many cores you want to use
UseCores <- detectCores() -1

#Register CoreCluster
cl       <- makeCluster(UseCores)
registerDoParallel(cl)

path       <- "Downloads/Stacks/"
stack_list <- list.files(path, pattern=".tif$", full.names=T)

#Use foreach loop and %dopar% command
foreach(i=1:length(stack_list)) %dopar% {
library(raster)

img  <- stack(stack_list[i])
ndvi <- (img[[4]]-img[[3]]) / (img[[4]]+img[[3]])

outname <- sub(pattern     = ".tif",
               replacement = "_ndvi.tif",
               x           = stack_list[i])

writeRaster(ndvi,
            filename  = outname,
            overwrite = T)

}
```

GDAL

```
> ## gdal warp in parallel:
> system(paste0('gdalwarp AW3D30_30m.vrt AW3D30_dem_100m.tif -co \"BIGTIFF=YES\" -wm 2000 -co \"COMPRESS=DEFLATE\" -multi -wo \"NUM_THREADS=ALL_CPUS\"'))
```

Reading large geotif tile by tile

```
> fn = system.file("pictures/SP27GTIF.TIF", package =
"rgdal")
> obj <- rgdal::GDALinfo(fn)
> tiles <- GSIF::getSpatialTiles(obj, block.x=5000,
return.SpatialPolygons = FALSE)
> tiles.pol <- GSIF::getSpatialTiles(obj, block.x=5000,
return.SpatialPolygons = TRUE)
> tile.pol  <- SpatialPolygonsDataFrame(tiles.pol, tiles)
> plot(raster(fn), col=bpy.colors(20))
> lines(tile.pol, lwd=2)
```

Reading and writing RDS files in parallel

```
> saveRDS.gz <- function(object,file,threads=parallel::detectCores()) {
  con <- pipe(paste0("pigz -p", threads, " > ", file), "wb")
  saveRDS(object, file = con)
  close(con)
}

> readRDS.gz <- function(file,threads=parallel::detectCores()) {
  con <- pipe(paste0("pigz -d -c -p", threads, " ", file))
  object <- readRDS(file = con)
  close(con)
  return(object)
}
```

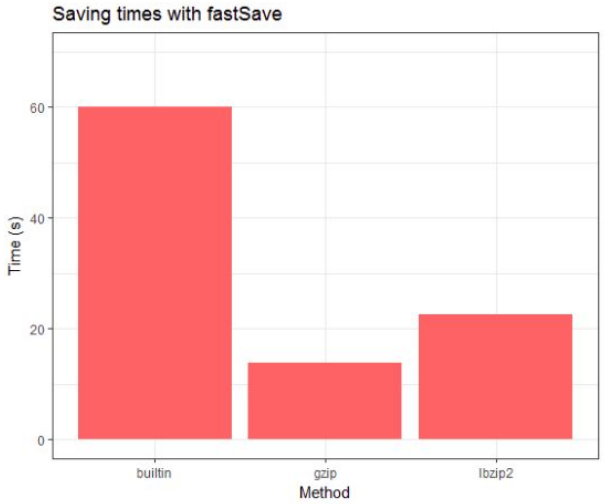
fastSave package

fastSave: Save your R sessions faster!

As the scale of the data that is processed with R increases so does time to save sessions to disks. This package allows taking advantage of parallel compression to reduce saving times.

Benchmarks

Performance comparison against built-in single-core save



3D comparison of gzip and lbzip2 algorithms

```
library(devtools)
install_github('barkasn/fastSave')
```

Use

fastSave provides the following functions:

- save.lbzip2()
- save.image.lbzip2()
- load.lbzip2()
- load.lbzip2.e()
- save.pigz()
- save.image.pigz()
- load.pigz()
- load.pigz.e()
- preserve.state()
- save.fast()
- load.fast()

SAGA-GIS Tool Library Documentation (v6.4.0)

Library Grids

Tools for spatial and geostatistical analyses.

- Author: O.Conrad, V.Wichmann (c) 2002-16
- Version: 1.0
- Menu: Spatial and Geostatistics|Grids

Tools

SAGA GIS automatically uses all cores!

```
saga_cmd [-h, --help]
saga_cmd [-v, --version]
saga_cmd [-b, --batch]
saga_cmd [-d, --docs]
saga_cmd [-f, --flags][=qrsilpxo][-s, --story][=#][-c, --cores][=#]
  <LIBRARY> <MODULE> <OPTIONS>
saga_cmd [-f, --flags][=qrsilpxo][-s, --story][=#][-c, --cores][=#]
  <SCRIPT>

[-h], [--help]   : help on usage
[-v], [--version]: print version information
[-b], [--batch]  : create a batch file example
[-d], [--docs]   : create tool documentation in current working directory
[-s], [--story]  : maximum data history depth (default is unlimited)
[-c], [--cores]  : number of physical processors to use for computation
```

GRASS GIS

M. Neteler: "You can regard GRASS GIS not as an application, but rather as an environment that provides applications (commands/modules). The idea of running GRASS in parallel is to run several GRASS commands in parallel. This kind of parallelization becomes interesting when you want to perform the same processing (say, r.fill.stats), to many different input data like time series or a tile based approach (r.tile). You will need some job scheduler, e.g. slurm or equivalent (see https://slurm.schedmd.com/rosetta.html). A single server with multiple cores can be regarded as a simple HPC system. Of course also OpenStack/docker-based job schedulers might be used which are more suitable for cloud processing."

Examples

Example 1: derivation of land cover change using global 300m resolution images

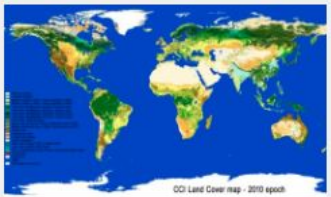
Example with the global land cover

Climate Research Data Package (CRDP)

Download CRDP user guide

Land Cover Maps - v1.6.1

Download quick user guide



3-epoch series of global land cover maps at 300m spatial resolution, where each epoch covers a 5-year period (2008-2012, 2003-2007, 1998-2002).

Each pixel value corresponds to the label of a land cover class defined using UN-LCCS classifiers.

For each epoch, the land cover map is delivered along with 4 quality flags which document the reliability of the classification:

- *qualityflag1* pixel has been processed or not,
- *qualityflag2* pixel status as defined by the pre-processing,
- *qualityflag3* number of valid observations available to derive the classification,
- *qualityflag4* level of confidence in the product (ranging from 0 to 100).

- 2008-2012 epoch - v1.6.1 (tif, 7z) - 2.8Go
- 2003-2007 epoch - v1.6.1 (tif, 7z) - 2.8Go
- 1998-2002 epoch - v1.6.1 (tif, 7z) - 1.7Go

- 2008-2012 epoch - v1.6.1 (netcdf) - 2.8Go
- 2003-2007 epoch - v1.6.1 (netcdf) - 2.8Go
- 1998-2002 epoch - v1.6.1 (netcdf) - 1.1Go

- Legend (csv)
- Symbology for ENVI (.dsr)
- Symbology for ArcGis (.lyr)
- Symbology for QGis (.qml)

Only major LC changes were detected at 1km spatial resolution and limited to a certain number of classes (see CRDP user guide).

The land cover and their quality flags can be downloaded separately at this address.

Some ideas about the data size

- ➔ at 300 m resolution: land mask about 1.4 billion pixels,
- ➔ about 6GB in size in memory (each image),
- ➔ About 80 CPU hours to compute,

Some ideas about the data size

```
> r = raster("ESACCI-LC-L4-LCCS-Map-300m-P5Y-2010-v1.6.1.tif")
> r
class       : RasterLayer
dimensions  : 64800, 129600, 8398080000  (nrow, ncol, ncell)
resolution  : 0.002777778, 0.002777778  (x, y)
extent      : -180, 180, -90, 90  (xmin, xmax, ymin, ymax)
coord. ref. : +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
data source : /data/LDN/ESACCI-LC-L4-LCCS-Map-300m-P5Y-2010-v1.6.1.tif
names       : ESACCI.LC.L4.LCCS.Map.300m.P5Y.2010.v1.6.1
values      : 0, 255  (min, max)
```

Objective: derive land cover change per pixel

Steps:

1. Prepare a tiling system,
2. Prepare functions for processing tiles,
3. Run in parallel (snowfall)
4. Generate a mosaic and build with pyramids (GDAL),

Server

1. 2 x Intel Xeon Gold 6142 @ 2.60GHz
2. Core Count: 32 / Thread Count: 64
3. RAM MEMORY: 386048MB
4. DISK: 1920GB INTEL SSDSC2KG01 + 10001GB Western Digital WD101KRYZ-01
5. File-System: ext4 / Mount Options: data=ordered errors=remount-ro relatime rw
6. OPERATING SYSTEM: Ubuntu 16.04

Optional: NAS Synology (50TB)

Prepare a function

```
make_LC_tiles <- function(...){
  out.tif = ...
  ...
  m$i = plyr::join(data.frame(NAME=m$v), comb.leg,
type="left")$Value
  writeGDAL(m["i"], out.tif, type="Int16",
options="COMPRESS=DEFLATE", mvFlag = -32768)
}
```

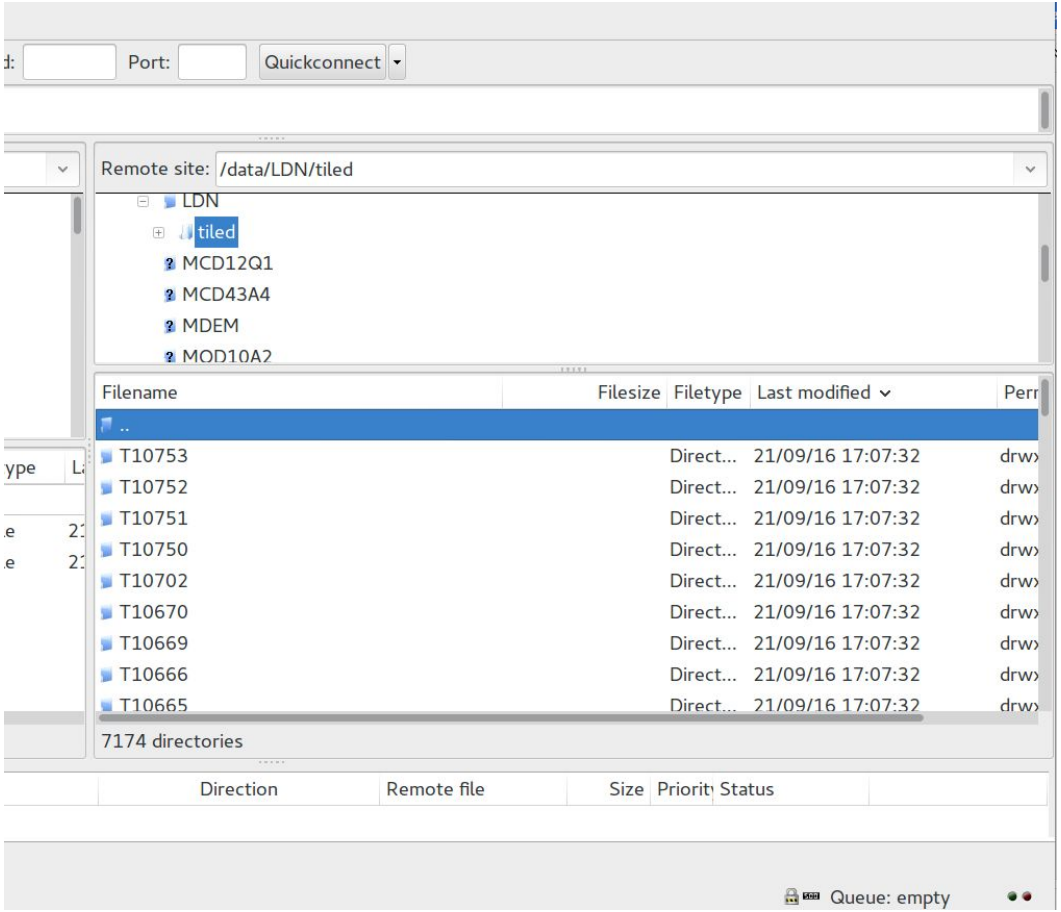
Run in parallel

```
sfInit(parallel=TRUE, cpus=64)
snowfall 1.84-6.1 initialized (using snow 0.4-1): parallel execution
on 64 CPUs.

sfExport("make_LC_tiles", "tile.tbl", "comb.leg", "cl.leg", "t.sel")
sfLibrary(rgdal)
Library rgdal loaded.
Library rgdal loaded in cluster.

sum.lst <- snowfall::sfClusterApplyLB(as.numeric(t.sel),
function(x){ make_LC_tiles(x, tile.tbl=tile.tbl) })
```

You can relax and follow generation of files...



Final step: generate mosaic

```
tmp.lst <- list.files(path="/data/LDN/tiled",
pattern=glob2rx(paste0("LandCover_CL_*.tif$")), full.names=TRUE,
recursive=TRUE)
## only 3178 tiles with values
out.tmp <- tempfile(fileext = ".txt")
vrt.tmp <- tempfile(fileext = ".vrt")
cat(tmp.lst, sep="\n", file=out.tmp)
system(paste0('gdalbuildvrt -input_file_list ', out.tmp, ' ', vrt.tmp))
system(paste0('gdalwarp ', vrt.tmp, ' LandCover_CL_300m.tif -ot
\"Int16\" -dstnodata \"-32767\" -co \"BIGTIFF=YES\" -multi -wm 2000 -co
\"COMPRESS=DEFLATE\" -r \"near\" -wo \"NUM_THREADS=ALL_CPUS\"'))
```

Activities Qgis.bin Sun Sep 18, 13:53 enz

QGIS 2.16.1-Nødebo - LDN_preview

Project Edit View Layer Settings Plugins Vector Raster Database Web Processing Help

Browser Panel

- Project home
- Home
  - bike
  - Calibre Library
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  - devel
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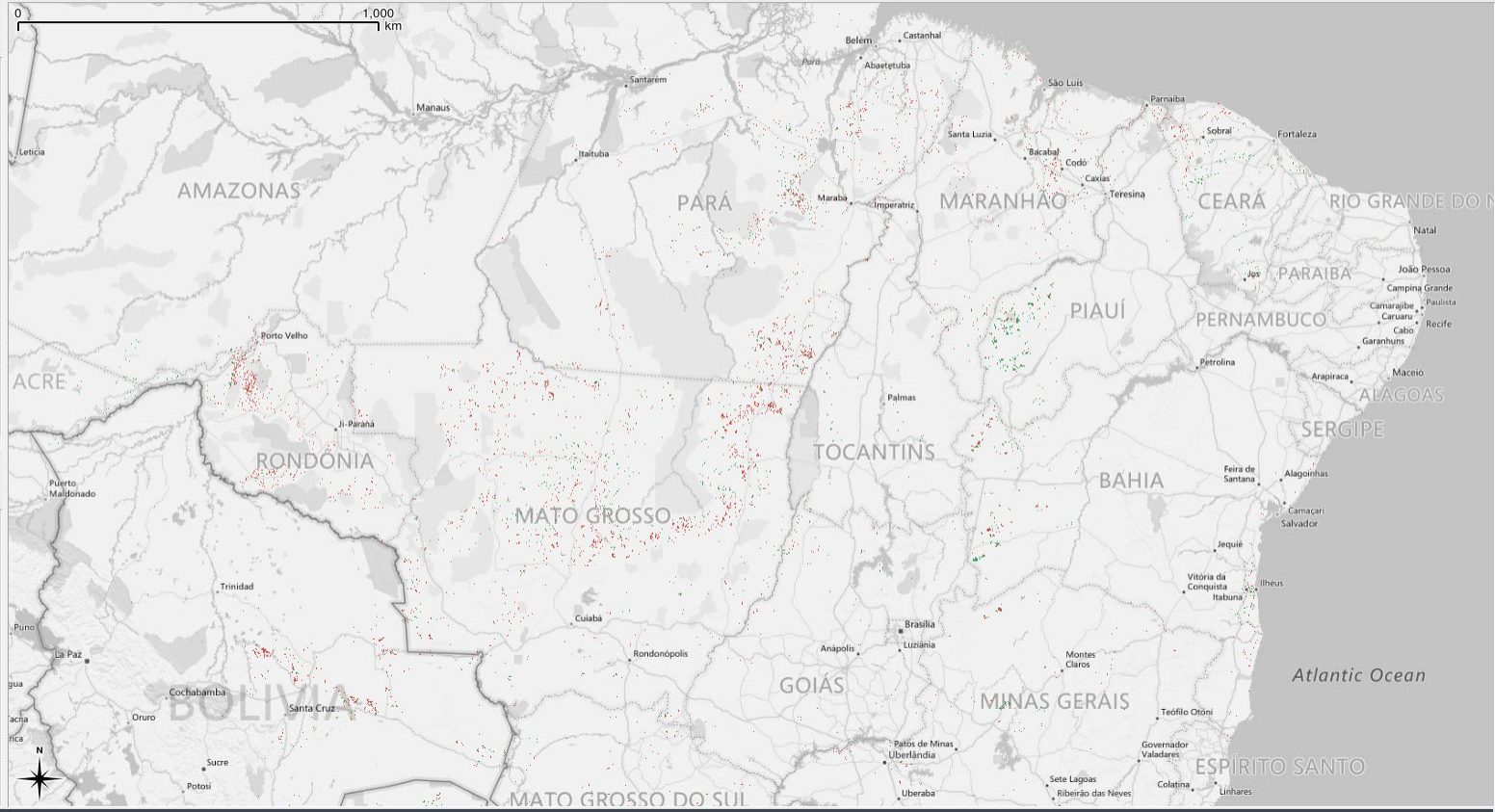
  - Downloads
  - Dropbox (ISRIC-AfSIS)
  - Envirometrix
    - LDN
      - LDN_preview.qgs
      - g2015_2014_1.zip
      - LandCover_CL_300m.t
      - My_CustomMap.kmz

Layers Panel

- 78
- 89
- 100
- OCS_CF_FactorLandUs...
  - 56
  - 67
  - 78
  - 89
  - 100
- Bing Map
- Google Satellite



Coordinate -5785766,-1147301 Scale 1:10,090,768 Magnifier 100% Rotation 0.0 Render EPSG:3857 (OTF)

QGIS 2.16.1-Nødebo - LDN_preview

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- **Bing Map**
- **Google Satellite**

Coordinate -5709297,-1166080 Scale 1:94,352 Magnifier 100% Rotation 0.0 Render EPSG:3857 (OTF)

QGIS 2.16.1-Nødebo - LDN_preview

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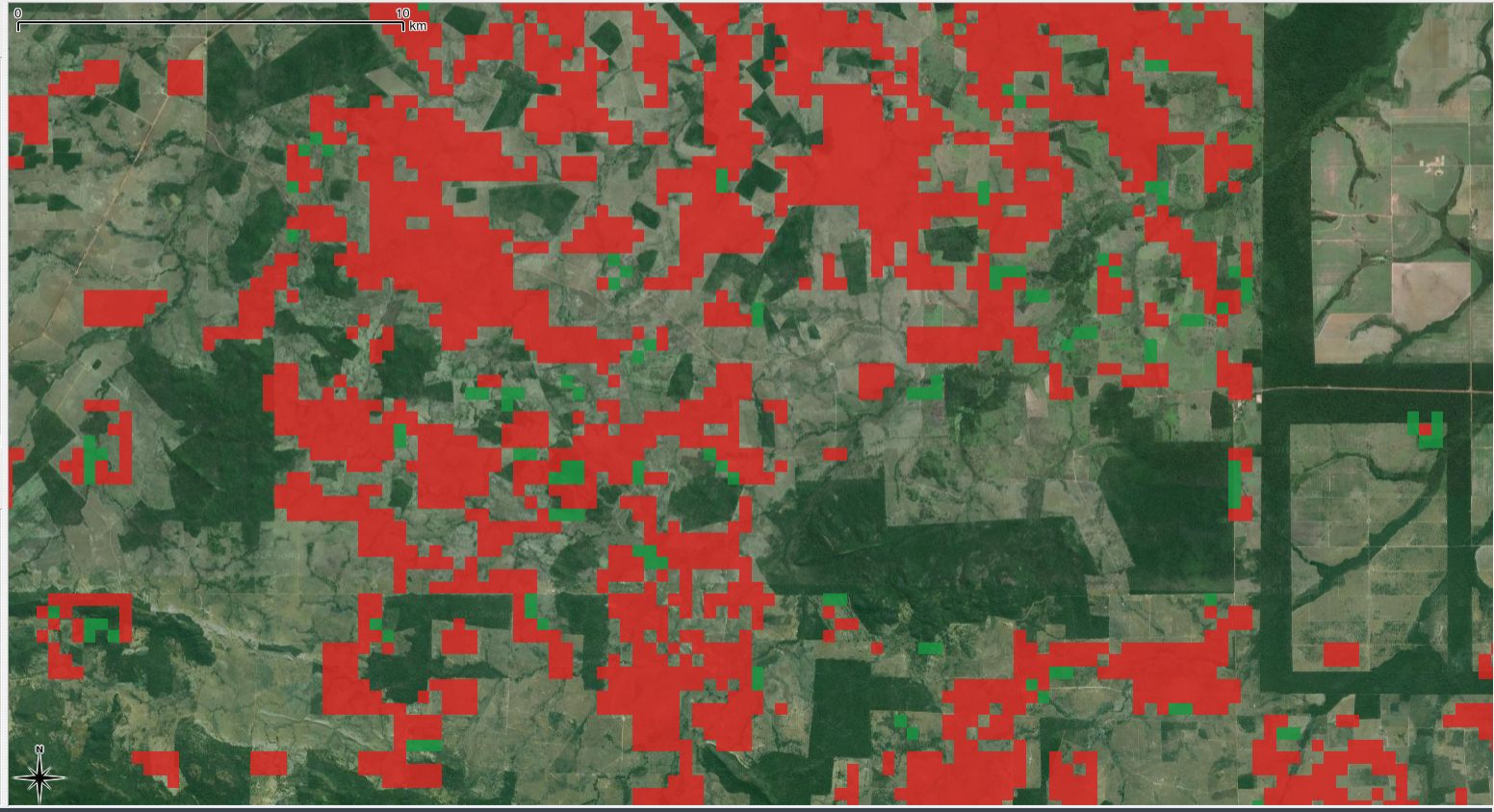

45 files downloaded. 0 caches hit.

Coordinate -5709297,-1166080 Scale 1:94,352 Magnifier 100% Rotation 0.0 Render EPSG:3857 (OTF)

Example 2: derivation of DEM surface parameters

Digital Land Surface Model

Two sources of DEM data:

- 1/3rd arc-second (10 m) National Elevation Dataset (NED)
- 1 arc-second (30 m) global ALOS AW3D30 Digital Surface Model

which one do we use?

Modeling DLSM

Use training points to build a model to merge various elevation data sources:

mDLSM = f (NED, AW3D30, NDVI, HH/HV)

two data sources, NDVI image and radar bands.

DLSM scheme

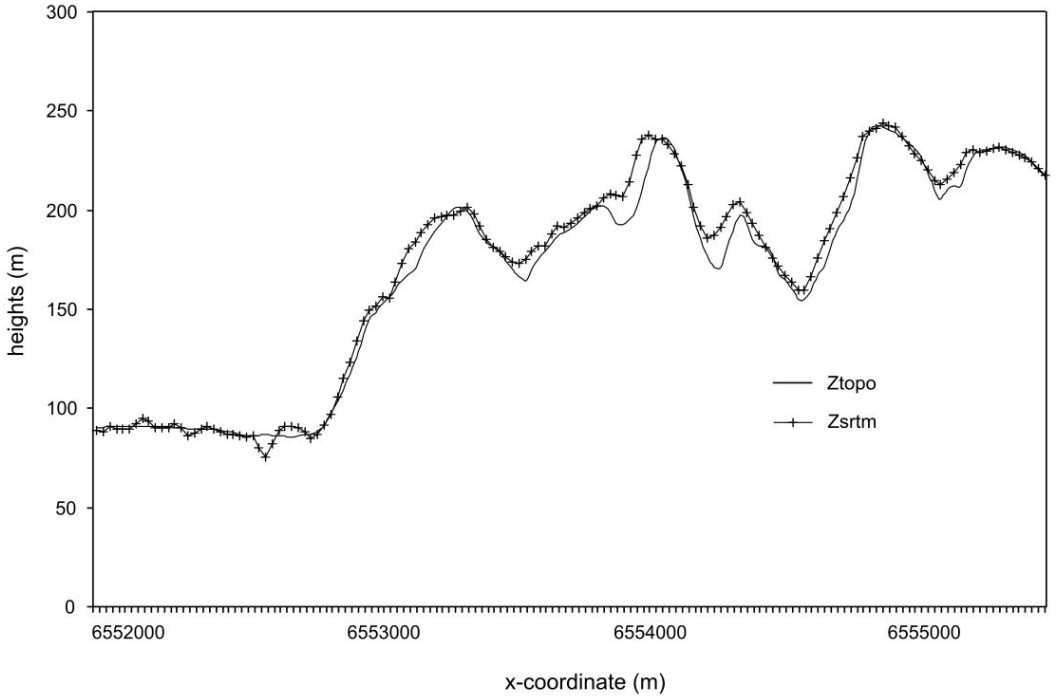

FIGURE 10 Transect of the SRTM and TOPO DEMs for Baranja Hill from West to East at $y = 5{,}073{,}012$. Note that the difference between the two DEMs can be used to map the height of canopy. In this case, we can also notice a difference between the two DEMs which is due to the foreshortening effect of the radar technology (systematic error).

Results

AW3D30

mDLSM

Conclusions I

- *Yes, you can use R (in combination with GDAL, SAGA GIS and similar) to process large rasters,*
- *Do not stop programming until you have reached the maximum usage of hardware — RAM + cores (at least 90%?),*
- *Start with smaller subsets then increase data volumes,*

Conclusions II

- *SAGA GIS is already optimized for large data (automatic parallelization),*
- *GRASS GIS is quite efficient in processing large rasters, but parallelization needs to be implemented through scripting,*
- *Even if you fully optimize/parallelize your code, investing in hardware / storage will eventually be unavoidable,*