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Title: *fasterRaster*: GIS in *R* using *GRASS* for large rasters

Running title: *fasterRaster*: GIS in R for large rasters

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Abstract [149 words of 150]

Within the *R* ecosystem, packages like *terra* and *sf* are the go-to solutions for most geospatial analyses, yet can struggle with large rasters and vectors. The Geographic Resources Analysis Support System, or *GRASS*, offers solutions that are often more efficient for large data. However, using *GRASS* through *R* requires users to become familiar with *GRASS*-specific syntax and data constructs. The *fasterRaster* package for *R* connects to *GRASS* seamlessly and enables analysis of large data sets. Modeled after the functions in *terra*, *fasterRaster* possesses over 200 methods for processing rasters and spatial vectors. *fasterRaster* also contains a growing number of specialty functions for hydrological, remote sensing, and topographical analysis. For small spatial objects, *terra* and *sf* will nearly always be faster, but for larger ones, *fasterRaster* can be several times faster, and for very large spatial objects, can succeed where other solutions fail. A *pkgdown* website documents the project: https://adamlilith.github.io/*fasterRaster*/index.html.

Keywords: geographic information system; geomorphology; hydrology; open source; geospatial; scalability; memory management

Introduction [3444 words up excluding literature cited, tables, and figure captions]

The growth in information-dense geographic data sets has enabled the asking and answering of key questions in the environmental sciences, while at the same time demanding increasing compute power. Rasters with very fine resolution and broad extents, and spatial vectors with many features and fine-scale detail can take substantial time to process and often surpass the capacity of most personal computing systems. While high-performance computing can address these challenges, access to clusters is limited and requires a specialized skillset. Thus, there is still ample need for local processing of large rasters and vectors.

The *R* ecosystem provides a flexible set of tools for analysis of geographic data, especially in the *sf* package, which supports vectors (Pebesma, 2018; Pebesma & Bivand, 2023), *terra*, which supports both rasters and vectors (Hijmans, 2025), and *stars*, which also supports raster and vector and especially those with temporal dimensions (Pebesma & Bivand, 2023). Of note, the *terra* package achieves significant gains in speed and memory management through most of the code being written in C++ and, where possible, by having large rasters reside on disk as original or temporary files to be called as-needed (Hijmans, 2025). Together, *terra*, *sf*, and *stars* provide the basis for many dependent packages, and so form the mainstay for nearly all analyses of geographic data within *R*. Nonetheless, large rasters and vectors can surpass the capacity of these tools, and otherwise take substantial time to process when they do work.

Geographic Resources Analysis Support System (*GRASS*) is a powerful, open-source geographic information system that handles raster and vector data (Neteler et al., 2012; *GRASS* Development Team 2025a and b). *GRASS* supports many standard GIS operations through "tools" (functions). These can be called via a command line, or through the built-in graphical user interface. The *rgrass* package also provides access to *GRASS* tools in *R* through a set of "calling" functions (Bivand et al., 2025). Using *GRASS* through *rgrass* requires users to establish a connection to *GRASS* and construct and manage a set of data structures and "templates". These include creation of *projects*, which are sets of spatial data objects in the same coordinate reference system; *mapsets*, which are subsets of projects, and *regions*, which serve as templates for the extent and resolution of most raster operations. Users call *GRASS* tools though the *rgrass* "calling" functions, which require becoming familiar with *GRASS* syntax and arguments of each tool. For example, projecting rasters from one coordinate reference system to another requires users to track the source and destination projects and mapsets, and to establish a proper region in the destination project so that resampling is conducted in a desirable way. In contrast, the *terra* and *sf* packages do not have analogous frameworks and do not require users to explicitly manage membership of data objects with the same coordinate reference system. As a result, users familiar with how *R* works face barriers to harnessing the performance gains of *GRASS*.

Here I present the *fasterRaster* package for *R*, which builds on the *terra* package, and uses *rgrass* as a backend to connect *R* to *GRASS* (Bivand et al., 2025; Hijmans, 2025). Importantly, *fasterRaster* is a complement, not a replacement, to *terra*, *sf*, and *stars*. Indeed, *terra* and *sf* will often be more efficient for processing small- or medium-sized spatial objects. However, for large rasters and vectors, *fasterRaster* can achieve significant performance gains and enable analyses that are not otherwise possible using these tools.

Software design

fasterRaster was written with five design principles in mind:

Value-added: *fasterRaster* was written to add value to existing tools, not to supplant them. The *rgrass* package already provides a convenient bridge between *R* and *GRASS*, and *fasterRaster* further facilitates this connection.

Familiarity: The large majority of *fasterRaster* methods (functions) share the same name and functionality as methods in *terra*, and most share the same argument names and definitions.

Comparability: *fasterRaster* functions are designed to yield output as similar as possible to methods of same name in *terra*. For example, the *terra* function `focal()`, run with the `fun = 'sd'` argument, can be used to calculate the sample standard deviation across a moving window of cells. The equivalent tool in *GRASS*, `r.neighbors`, calculates the population standard deviation. However, the *fasterRaster* version of `focal()`, by default, has been engineered to calculate the sample standard deviation, though it also offers the option to calculate the population standard deviation. Nonetheless, differences can remain in how functions operate, owing to choices made by developers when creating in algorithms. Hence, exact correspondence between output from *terra* and *sf* with *fasterRaster* is not guaranteed in every case.

Simplicity: *fasterRaster* makes using *GRASS* in *R* simple. Users do not need to manage *GRASS*-specific data constructs like projects, mapsets, or regions. *fasterRaster* creates, tracks, and updates these constructs automatically so users do not have even be aware of them.

Ease-of-use: Finally, *fasterRaster* makes *GRASS* tools easy to use. Help pages are written in *R*, and each method has ample examples. The package has its own *pkgdown* website (Wickham et al., 2025) with documentation and vignettes (https://adamlilith.github.io/fasterRaster/index.html). One especially noteworthy vignette provides tips for making *fasterRaster* even faster.

Getting started

To get started with *fasterRaster*, users must download the package from CRAN within *R* and attach it:

```
install.packages("fasterRaster", dependencies = TRUE)
library(fasterRaster)
library(terra)
library(sf)
```

Users must also supply the folder in which *GRASS* is installed on their system. The folder will depend on the operating system and version of *GRASS*, but will usually look something like:

```
gr_dir <- "/Applications/GRASS-8.4.app/Contents/Resources"
gr_dir <- "C:/Program Files/GRASS GIS 8.4"
gr_dir <- "/usr/local/GRASS"
```

for macOS, Windows, Linux, respectively.

Users must then provide the name of this installation folder to *fasterRaster* using

```
faster(grassDir = gr_dir)
```

This needs to be done just once per workflow, before any *fasterRaster* function that uses *GRASS* will work. Users can use `faster()` to change other settings, such as the maximum memory and number of processor cores *GRASS* uses.

In *R*, *GRASS* rasters and vectors are S4 objects called "GRasters" and vectors "GVectors" (collectively, "G-objects"). GRasters can contain integer or double-floating point numeric values, or represent categorical data with an associated table matching raster cell values to labels. GVectors can have data tables, where each row corresponds to a particular "geometry" in the vector.

The workflow illustrated below begins by loading a set of example rasters (SpatRasters) and vectors (*sf* objects) that ship with *fasterRaster*. This is done using the `fastData()` function, but most users will not use this function unless they run the examples in the package function hekp files where example data is employed. The workflow illustrates how to convert SpatRasters, SpatVectors, and *sf* objects into G-objects using the `fast()` function. Users can also directly load rasters and vectors using `fast()`, with the first argument in this case being the file path and name of the data object on disk. This latter approach is faster than coercing SpatVectors, SpatRasters, and *sf* objects to G-objects.

In this example, `madElev` is an integer raster that represents elevation, `madCover` a categorical raster of land cover classes, and `madRivers` a "lines" vector that depicts major rivers in the region. To begin, we load the example data into *R*:

```
madElev <- fastData("madElev")

madCover <- fastData("madCover")

madRivers <- fastData("madRivers")
```

…then, coerce them to GRaster and GVector objects:

```
elev <- fast(madElev)

cover <- fast(madCover)

rivers <- fast(madRivers)

plot(elev, main = "Elevation")

plot(rivers, col = 'blue', add = TRUE)
```

Invisible to the user, a *GRASS* project is created in the operating system's temporary directory. *GRASS* will store here all files it needs to do processing. Once the *R* session is stopped, this specific temporary directory is emptied and no longer available. GRasters and GVectors are actually *R* objects that contain pointers to these *GRASS* files. Hence, users cannot expect to save a GRaster or GVector object using, for example, `save()` or `saveRDS()`, and be able to restore it later (neither would saving a *terra* SpatRaster object using these functions work). However, using `writeRaster()` and `writeVector()`, users can save platform-independent versions of these files (e.g., GeoTIFFs for rasters, or ESRI shapefiles or GeoPackages for vectors).

GRasters and GVectors contain metadata about the objects they represent. For example, entering the name of a *fasterRaster* object displays metadata about the GRaster,

```
elev
```

and the GVector,

```
rivers
```

yields metadata on each object (output not shown). Metadata can also be retrieved using "getter" functions that will be familiar to users of *terra*. These include, for example, `crs()` for obtaining the coordinate reference system; `ext()`, `N()`, `S()`, `E()`, and `W()` for extent; `res()` for resolution; `dim()`, `nrow()`, `ncol()`, `ncell()` for dimensions; `levels()` for the values and corresponding labels of categorical raster "levels"; `minmax()` for minimum and maximum values, and `names()` for raster layer names or the names the columns of a table attached to a vector.

GRasters with the same extent and resolution can be "stacked" using the `c()` function as in `c(raster1, raster2)`. GVectors of the same type (points, lines, or polygons) can also be combined using `rbind()` as in `rbind(vector1, vector2)` or by using the "`+`" operator. If the vectors have compatible data tables (i.e., same columns and classes), these will also be `rbind()`'ed and attached to the output.

Users can apply any of >200 methods to G-objects, including `crop()` to clip the extent of a raster or vector to another spatial object, `buffer()` to "grow" the size of a GVector or "fill" NA cells around non-NA cells in a GRaster, `global()` to calculate summary statistics across all cells of each layer of a GRaster, `resample()` and `aggregate()` to change the spatial resolution of rasters, and `project()` to transform a G-object into a different coordinate reference system. Some functions operate on a stack of rasters, calculating values across each set of matching cells. These include `sum()`, `mean()`, `stdev()`, `quantile()`, and `range()`, amongst others.

fasterRaster also includes functions that draw on *GRASS*'s deep array specialty tools. These include, for example, the `geomorphons()` function for identifying 12 classes of topographic features from an elevation raster (e.g., flat areas, pits, valleys, footslopes, spurs, peaks, etc.; Stepinski & Jasiewicz, 2011; Jasiewicz & Stepinski, 2013); `flow()`, `flowPath()`, and `streams()` for hydrological analysis of watershed basins and stream flow; plus an array of functions for creating rasters patterns with fractal patterns, random walks, normally distributed values, and spatial dependence between cells in functions `fractalRast()`, `rWalkRast()`), `rNormRast()`, and `rSpatialDepRast()`, respectively. The `vegIndex()` function calculates 17 different vegetation indexes including the normalized difference vegetation index (NDVI), enhanced vegetation index, versions 1 and 2 (EVI and EVI2), normalized difference water index (NDWI; Gao 1996); and the modified soil adjusted vegetation index, versions 1 and 2 (MSAVI; Qi et al. 1994).

fasterRaster also comes with several functions pertinent to analysis of ecological and environmental patterns. For example, `bioclims()` calculates the 19 BIOCLIM variables representing climatic extremes and averages (e.g., temperature or precipitation of the warmest or coldest quarter, variability in precipitation or temperature, etc.; Booth et al., 2014) plus an extended set of 20 other BIOLCIM variables such as temperature or precipitation of the quarters following the warmest/coldest quarters (i.e., fall or spring), the hottest/coldest/wettest/driest months or quarters, and greatest decrease/increase in temperature or precipitation between successive months across the 12-month cycle. The `fragmentation()` function calculates a forest (or more generally, landscape) fragmentation index that classifies pixels (i.e., patch, perforated, transitional, edge, interior). The `bioclims()` and `fragmentation()` functions can also operate on SpatRasters without needing to connect to *GRASS*.

To demonstrate some of these methods, we could calculate the frequency of geomorphons within 1 km of major rivers in the region from the example above:

```
river_buff <- buffer(rivers, 1000)
elev_mask <- mask(elev, river_buff)
geomorphs <- geomorphons(elev_mask)
plot(geomorphs, main = "Geomorphons")
geomorph_freqs <- freq(geomorphs)
print(geomorph_freqs)
```

Methods

To illustrate the capacities of *fasterRaster* vis-à-vis *terra*, I constructed two matching workflows for assessing the relative influence of drivers and risks of forest loss in five major river basins of southeast Asia (the Mekong, Salween, Irrawaddy, Chao Phraya, and the Sittang). Forest presence at 30-m resolution in 2000 and 2020 was used to identify areas where forest cover was lost or persisted (Hansen et al., 2013). From these rasters, two states (persistent versus lost) were scored (forest gain was negligible, so was ignored). A variety of predictors demonstrated to influence forest loss and persistence were collated, including distance to roads and rivers, elevation, slope, human population density, presence of agriculture, country, protected areas status, and forest fragmentation class (Table S1). Generalized linear models were constructed for 50 cross-validation folds, and the resulting prediction rasters averaged to create a map of the risk of forest loss.

The two workflows relied either primarily on *terra* or *fasterRaster*, with minimal use of the opposing package in each package's workflow. The workflows employed a variety of common geographic operations. For rasters, these included projecting, resampling, merging, cropping, masking, and mathematical operations on rasters, plus focal (neighborhood) analyses, and "burning" model predictions onto a raster. They also used vector operations to define and mask the focal region, project, subset, buffer, convert to raster format (rasterize), locate random points, and extract raster values at these points. Each workflow was designed to match the other as closely as possible—i.e., in nearly all cases, a call of one function in one workflow matched a call of a function with the same functionality on the equivalent data object in the other package. The exceptions to this involved removal of temporary files and saving of specific rasters so they did not get erased during temporary file deletion. These additional operations, plus any others that did not invoke *terra* or *fasterRaster* functions were not included in the final comparison of workflow runtimes.

I implemented the same workflow on three regions of nested extents—a large region, encompassing the entire area covered by the five river basins, a medium region focused on just the Salween basin, and a small region on a subbasin of the Salween (Table 1, Fig. S1). The specific regions were chosen to require the same sets of functions (e.g., converting country border vectors and vectors representing protected areas to raster format, etc.).

Since the workflow involved 50 sets of functions repeated for each of the cross-validation folds, I report overall timing for 1) the "entire" workflow (including all 50 cross-validation folds), and 2) the "fold-averaged" workflow after averaging runtimes of functions used repeatedly across the folds. Of note, the `distance()` function was used to calculate the distance between centers of cells forested in 2000 and "lines" vectors representing roads or rivers. The *terra* `distance()` function calculates the distance from the center of a raster cell to the closest part of a lines vector (Hijmans, 2025). The `distance()` function in *fasterRaster* uses *GRASS*'s `R.grow.distance` tool, which first rasterizes the vector so each cell is demarked as "occupied" or "unoccupied" by a line segment, then calculates the distance between a focal cell's center and the center of the nearest occupied cell. As a result, *fasterRaster*'s `distance()` output can differ from *terra*'s by up to the linear dimensions of a cell, but operation is also much faster. To accommodate this difference and not overly weigh the total runtime in *fasterRaster*'s favor on this account, for distance-based operations in the workflows I aggregated cells by a factor of 1 (no aggregation) to 512 times (depending on the size of the focal region), calculated distances, then resampled them to the original resolution. Aggregation reduced the number of cells to which distances needed to be calculated, so greatly sped *terra*'s `distance()` operation. However, aggregation also induced spatial distortion in the predictors based on distance to roads and rivers (Fig. S2).

Results

The three study regions differed in size (number of non-NA cells) by orders of magnitude (Table 1). Based on the results from the large study region (run with the *fasterRaster*-based workflow and no aggregation before application of the `distance()` function), the risk of forest loss in 2000 was greatest in Cambodia (Fig. S1). Here, I focus on the relative runtimes of a *terra*- versus *fasterRaster*-based workflows.

The large extent encompassing all five river basins was not workable for *terra*. *terra*'s `focal()` function, which was used here to sum the amount of area across a 33-cell window, caused *R* to crash. Multiple attempts were made. In contrast, *fasterRaster* was able to complete the workflow and did not need cell aggregation to speed application of `distance()`. The "entire" *fasterRaster* workflow (with no aggregation) took ~27.5 weeks (4629 hr 52 min). Split across multiple *R* instances on the same computer, this required about one month of wall time. These are sizable runtimes, but attest to *GRASS*'s ability to manage very large-in-memory/large-on-disk spatial objects.

For workflows analyzing the medium extent and that aggregated cells by a factor of 512 for implementing the `distance()` function, the "entire" *fasterRaster* workflow was about 30% faster than *terra* workflow (Fig. 3). The *terra* workflow required almost 19 days (453 hr 58 min), whereas the *fasterRaster* workflow took less than 13 days (307 hr 4 min). Again, the `distance()` function was the slowest in the *terra* workflow, whereas the `extract()` function took the most time in the *fasterRaster* workflow. The "fold-averaged" *fasterRaster* workflow was twice as fast as the *terra* workflow (Fig. 4).

For workflows analyzing the small extent and that aggregated cells by a factor of 128 for implementing the `distance()` function, the "entire" *fasterRaster* workflow was more than three times faster than the *fasterRaster* workflow (Fig. 2). The *terra* workflow took just less than a third of a day (7 hr 10 min) to complete, whereas the *fasterRaster* workflow took nearly a day (22 hr 39 min). The `distance()` function was the slowest in the *terra* workflow, whereas the `extract()` function was slowest in the *fasterRaster* workflow. Since `extract()` was called once per fold, averaging runtimes across equivalent function calls greatly reduced the total runtime required by *fasterRaster*'s `extract()`. As a result, the "fold-averaged" *fasterRaster* workflow was 1.76 times faster than the "fold-averaged" *terra* workflow (Fig. 2). Aggregating cells by smaller factors (e.g., 32 or less) caused the "entire" and the "fold-averaged" *fasterRaster* workflows to take much less time than the *terra* workflows (Figs. S3 and S4).

Conclusions

The *fasterRaster* package brings the power of *GRASS* to *R* while making transitions between *terra* and other packages easier for *R* users. As of the time of writing, the package contains >200 methods for raster and vector object, most of which recreate functionality in the *terra* package. However, *GRASS* has a wealth of additional tools that are so far little represented within *fasterRaster*. These include tools for analyses in remote sensing, hydrology, time series, and LiDAR data, among others. Moreover, the *GRASS* software has been under constant development since its inception 1982, with new tools and functionality added each sub-minor version (*GRASS* history website, no date).

Aside from aside from *terra*, *sf*, and *stars*, *fasterRaster* shares the remit of several other *R* packages (reviewed on CRAN Task View: Analysis of Spatial Data; https://cran.*R*-project.org/web/views/Spatial.html), but is nonetheless unique in its capabilities. *fasterRaster* relies heavily on *rgrass*, but *rgrass* can be used as-is to call *GRASS* tools. However, this requires users to know and understand the *GRASS* syntax and keep track of the *GRASS*-specific data structures discussed above. Package *qgisprocess* connects to QGIS to conduct GIS operations, and like *fasterRaster*, provides a fully-featured GIS platform (Baghdadi et al., 2018). However, like *rgrass*, users need to understand the special syntax of each tool to call it, and this can vary quite widely from syntax familiar to users of *R*. Package *gdalraster* has special capacity to manage large raster and vector datasets, but also requires more technical knowledge to run usefully (Toney, 2023).

The *fasterRaster* package is versioned in a manner to assist users in tracking which version of *GRASS* interfaces with the package. Namely, *fasterRaster* versions will look something like 8.4.1.2, or more generally, *M1.M2.S1.S2*. Here, *M1.M2* mirror the version of *GRASS* for which *fasterRaster* was built and tested. For example, *fasterRaster* version 8.4.x.x will work using *GRASS* 8.4 (and backwards with version 8.3). The values in *S1.S2* refer to "major" and "minor" versions of *fasterRaster*. That is, a change in the value of *S1* (e.g., from x.x.1.0 to x.x.2.0) indicates changes that potentially break older code developed with a prior version of *fasterRaster*. A change in *S2* refers to a bug fix, additional functionality in an existing function, or the addition of an entirely new function. The M1.M2 and S1.S2 values increment independently. For example, if the version changes from 8.4.1.5 to 8.5.1.5, then the new version has been tested on *GRASS* 8.5, but code developed with version 8.4.1.x of *fasterRaster* should still work.

Contributions, bugs, and feature requests can be reported on the *fasterRaster* GitHub repository at [https://github.com/adamlilith/*fasterRaster*](https://github.com/adamlilith/fasterRaster).

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Table 1. Number of non-NA cells in each study region.

Region	Cells
Small	17,189,027
Medium	180,001,073
Large	1,266,543,912

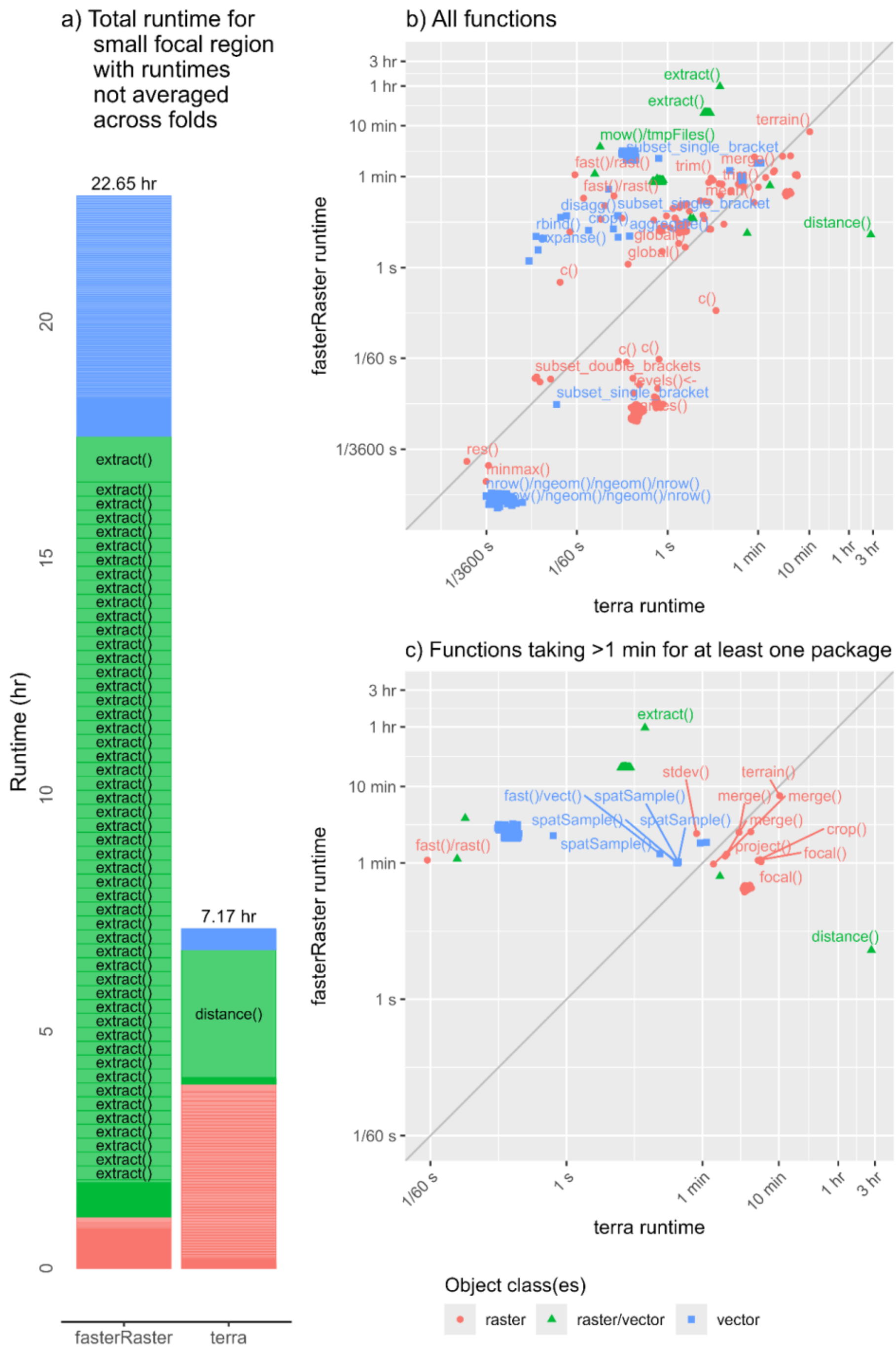

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Figure 1. Comparison of runtimes for the "entire" workflow for the small study region extent when cells were aggregated by a factor of 128 to speed the call of *terra*'s `distance()` function. In each panel colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function. Functions that took ≥15 min to execute are labeled. The `extract()` function was repeated across 50 crossvalidation folds and took the longest time the *fasterRaster* workflow. Total runtime is shown at the top of each bar. (b) Runtime of individual functions. (c) Runtime of functions that took at least 1 min to run in at least one workflow.

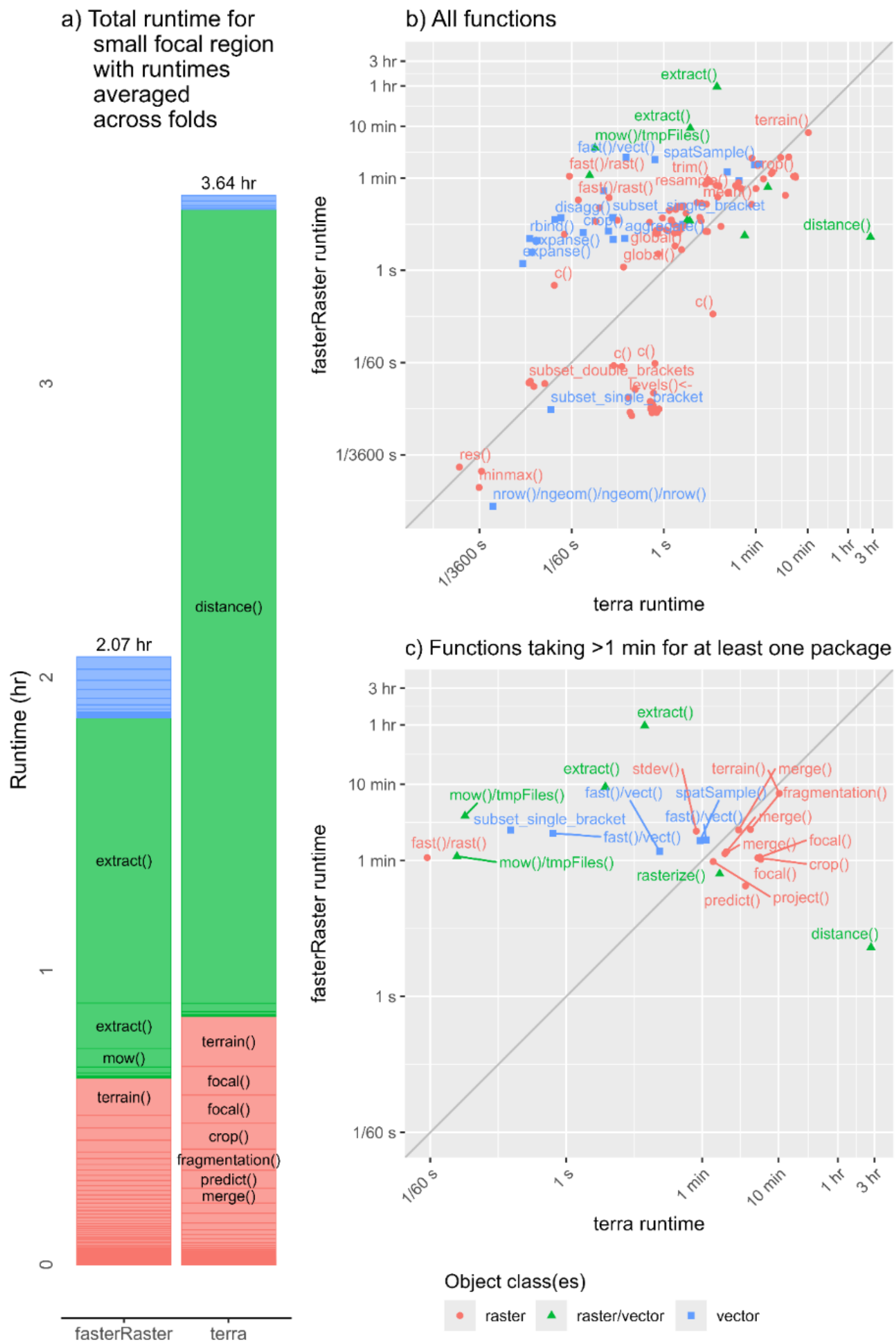

Figure 2. Comparison of runtimes for the "fold-averaged" workflow for the small study region extent when cells were aggregated by a factor of 128 to speed the call of *terra*'s `distance()` function. Runtimes of functions called across folds are averaged. In each panel colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function. Functions that took ≥15 min to execute are labeled. Total runtime is shown at the top of each bar. (b) Runtime of individual functions. (c) Runtime of functions that took at least 1 min to run in at least one workflow.

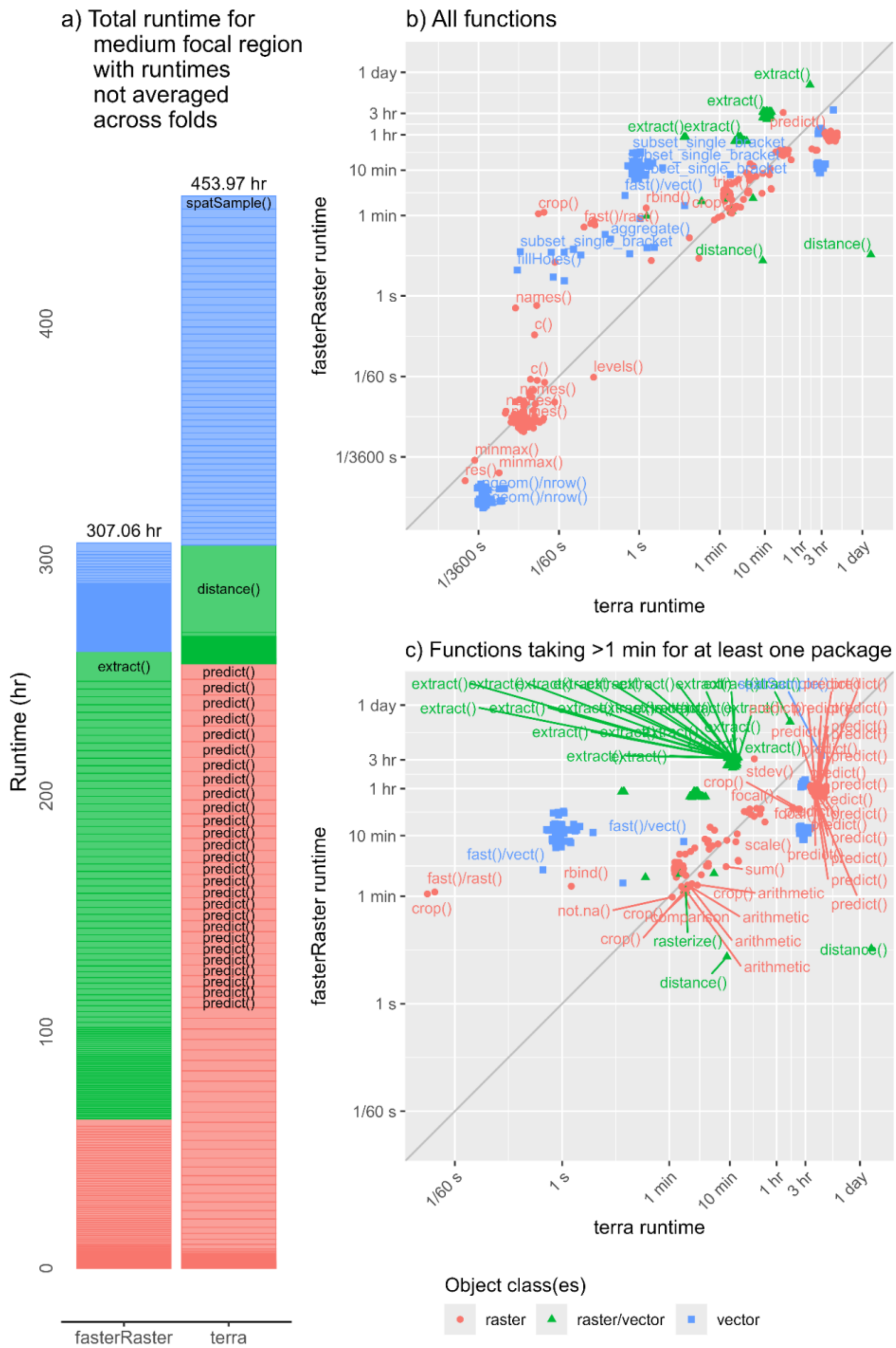

Figure 3. Comparison of runtimes for the "entire" workflow for the medium study region extent when cells were aggregated by a factor of 512 to speed the call of *terra*'s `distance()` function. In each panel colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function. Functions that took ≥15 min to execute are labeled. The extract() function was repeated across 50 folds and took the longest time the *fasterRaster* workflow. Total runtime is shown at the top of each bar. (b) Runtime of individual functions. (c) Runtime of functions that took at least 1 min to run in at least one workflow.

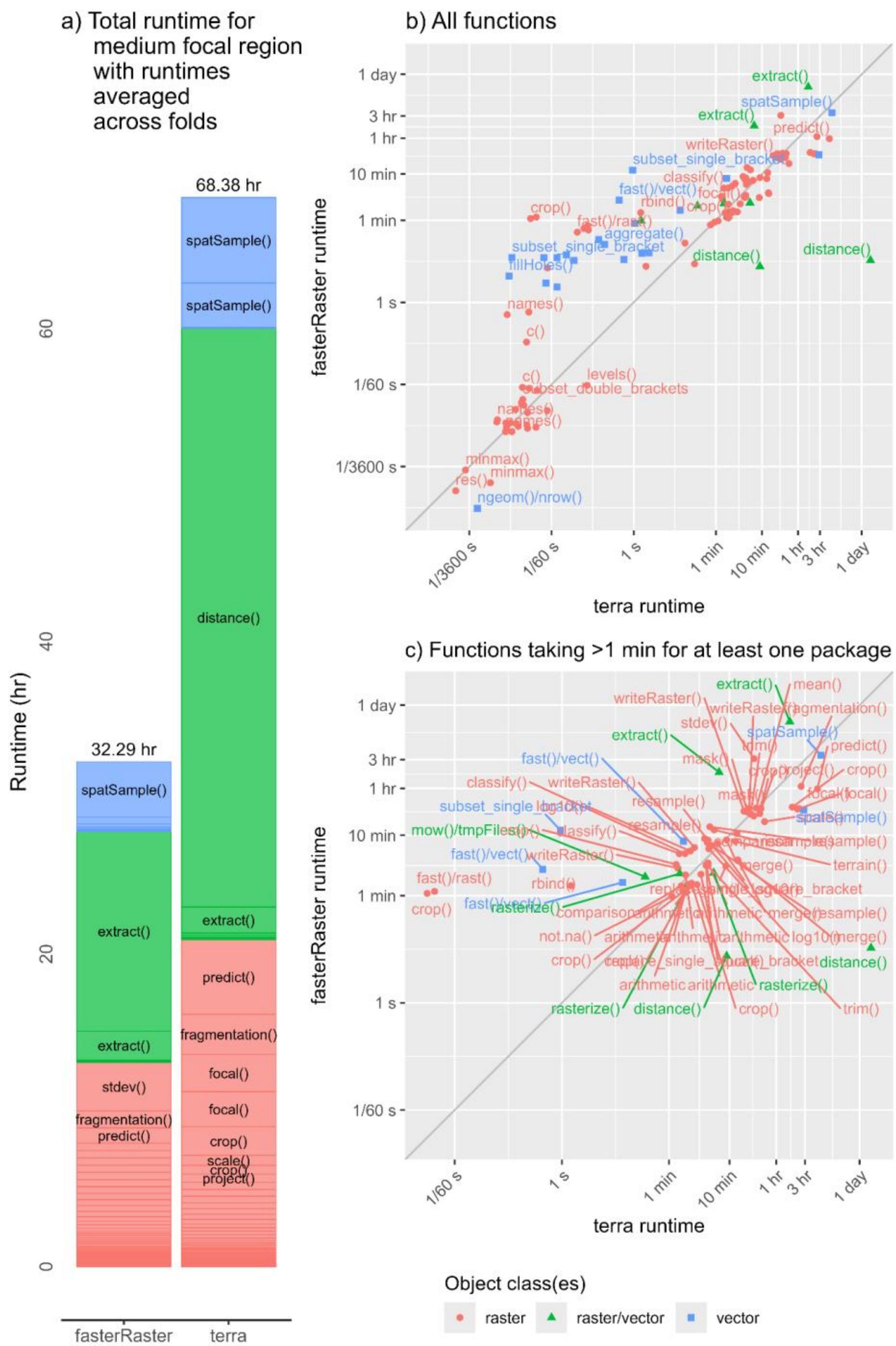

Figure 4. Comparison of runtimes for the "fold-averaged" workflow for the medium study region extent when cells were aggregated by a factor of 512 to speed the call of *terra*'s `distance()` function. In each panel colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function. Functions that took ≥15 min to execute are labeled. Total runtime is shown at the top of each bar. (b) Runtime of individual functions. (c) Runtime of functions that took at least 1 min to run in at least one workflow.

Supplement to: *fasterRaster*: GIS in R using GRASS for large rasters

Adam B. Smith

Table S1. Source and characteristics of predictors and response variable included in the workflows used to assess performance of *fasterRaster*.

	Original				
Input	Derived from	Resolution	CRS	Values	Source
Watershed basin polygons	Watershed basins polygons (vector)	—	WGS84	—	FAO, 2022a
Forest loss/persistence (response variable)	Forest cover for 2000 and 2020 (raster)	0.00025° × 0.00025°	WGS84	Integer (0/1)	Potapov et al., 2021
Forest density, 33×33-cell neighborhood (P)	Forest cover in 2000 (raster)	0.00025° × 0.00025°	WGS84	Integer (0-1089)	Potapov et al., 2021
Forest fragmentation class in 3×3-cell neighborhood (P)	Forest cover in 2000 (raster)	0.00025° × 0.00025°	WGS84	Factor	Potapov et al., 2021 & Riitters et al., 2000
Elevation (P)	Elevation (raster)	0.0003282° × 0.0003282°	WGS84	Continuous	MapZen (n.d.)
Slope, fine-scale (P)	Elevation, fine-scale (raster)	0.0003282° × 0.0003282°	WGS84	Continuous	MapZen (n.d.)
Slope, coarse-scale (P)	Elevation, coarse-scale (raster)	0.0052579° × 0.0052579°		Continuous	MapZen (n.d.)
Short vegetation in 33×33-cell neighborhood (P)	Land use/land cover (raster)	0.00025° × 0.00025°	WGS84	Integer (0-1089)	Potapov et al., 2022
Human population density in 33×33-cell neighborhood (P)	Population density in 2000 (raster)	100 × 100 m	Mollweide	Continuous	European Commission, 2023
Distance to nearest major river (P)	Rivers (vector)	(Calculated from response raster)	WGS84	Continuous	FAO 2022b
Distance to nearest major road (P)	Roads (vector)	(Calculated from	WGS84	Continuous	OSM, 2024

		response raster)			
Protected area (P)	Protected areas (vector)	(Calculated from response raster)	WGS84	Binary factor	UNEP-WCMC & IUCN, 2024
Country (P)	Countries (vector)	(Calculated from response raster)	WGS84	Factor	GADM, 2022
Protected area × country	From protected areas and countries (vectors)	(Calculated from response raster)	WGS84	Factor	UNEP-WCMC & IUCN, 2024; GADM, 2022

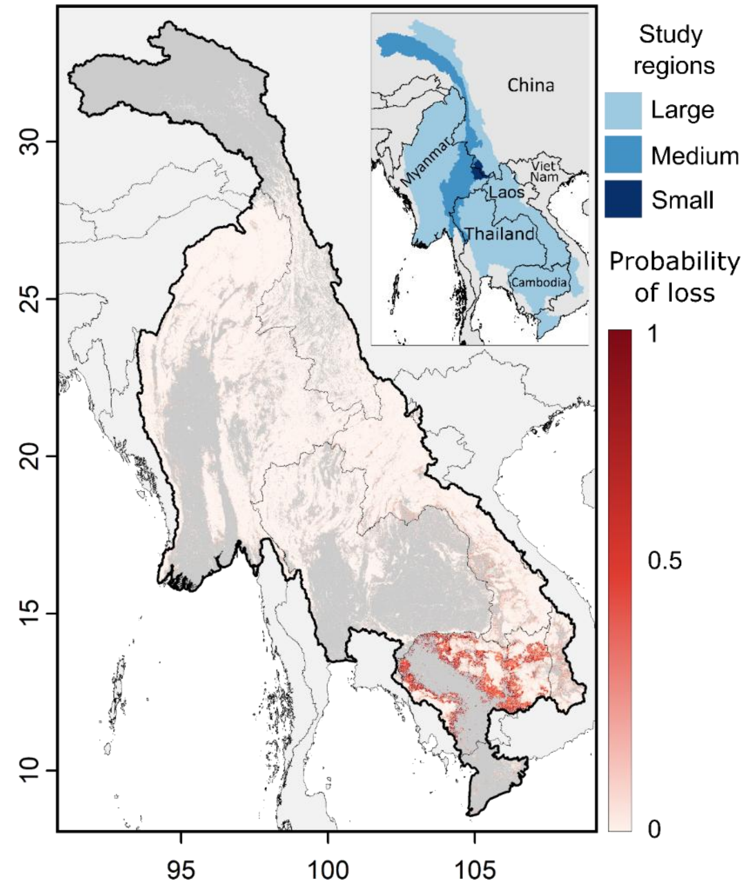

Figure S1. Study region and predicted probability of forest cover loss in 2000 based on analysis of the large study region without aggregation of cells to accommodate the `distance()` function.

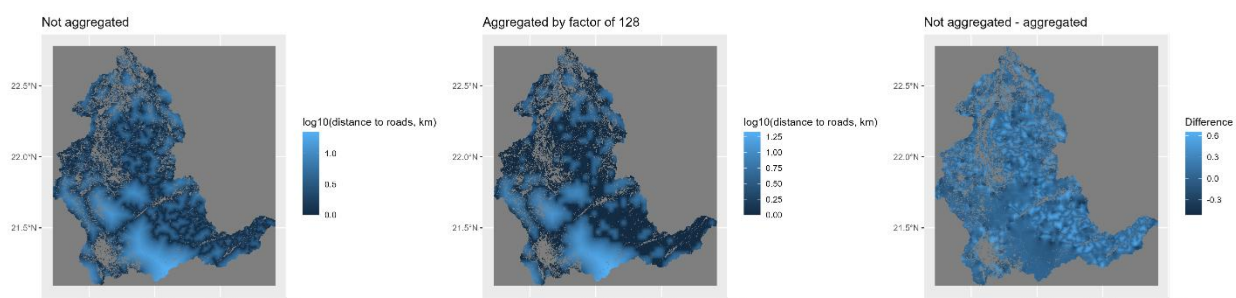

Figure S2. Effect of aggregating cells to speed the call of *terra*'s distance() function which would otherwise dominate the runtimes. Cell aggregation, then resampling, induces artifacts in the output. The small study region (subbasins of the Salween river basin) are shown for illustration. Here, cells were aggregated by a factor of 128, the effect of which is visible in the map on the right which displays the difference between the two maps to its left.

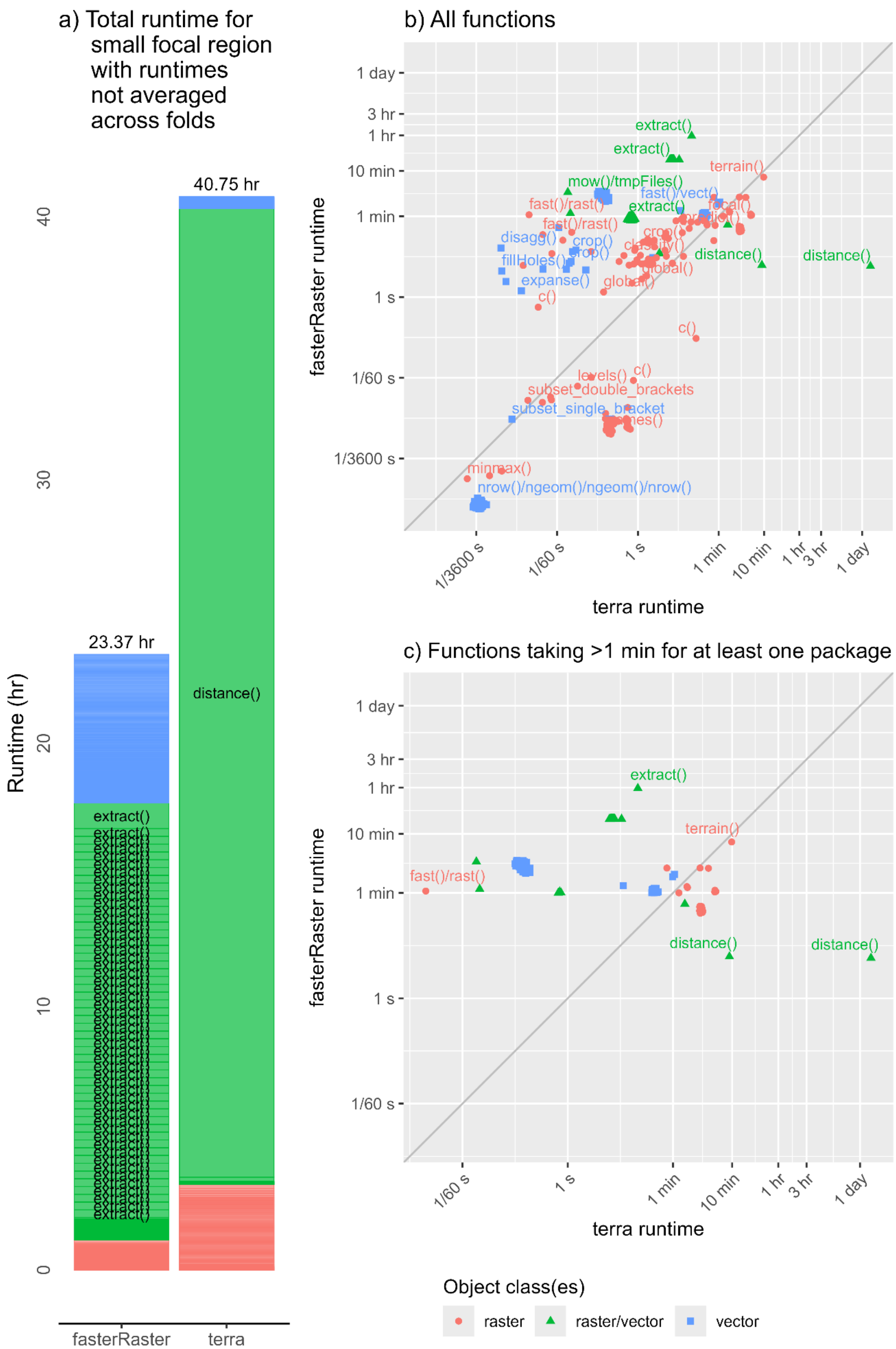

Figure S3. Comparison of runtimes "**entire**" workflow for the small study region extent when cells were aggregated by a factor of **32**.

Figure S4. Comparison of runtimes "**fold-averaged**" workflow for the small study region extent when cells were aggregated by a factor of **32**.

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