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

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fasterRaster: GIS in *R* using *GRASS* for large rasters and vectors

Abstract [150 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* seamlessly connects to *GRASS* 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 objects, *fasterRaster* can be several times faster, and for very large objects, can succeed where other solutions fail. A *pkgdown* website contains documentation and a tutorial: https://adamlilith.github.io/fasterRaster/index.html.

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

Main text [3938 words including main text, acknowledgements, figure captions, and table]

Introduction

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. Thus, there is a need for tools that can process large rasters and vectors in an efficient manner.

The *R* ecosystem provides a flexible set of tools for analysis of geographic data. These include the *sf* package for vectors (Pebesma, 2018; Pebesma & Bivand, 2023), and *terra* and *stars* packages for both rasters and vectors (Hijmans, 2025; Pebesma & Bivand, 2023). Of note, the *terra* package achieves significant gains in speed and memory management by processing through compiled C++ code and, where possible, by leaving large rasters and vectors on disk to be called in chunks 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 and specialty GIS operations through

"tools" (functions). These can be called via a command line, or through the built-in graphical user interface.

Users familiar with *terra*, *sf*, and *stars* face barriers to harnessing the performance gains of *GRASS*. Within *R*, users can call *GRASS* tools through the *rgrass* package (Bivand et al., 2025). However, this requires users to become familiar with *GRASS* syntax, file organization, and data "templates". To start, users would first need to create a *GRASS* "project," which is a working folder in which support files and rasters and vectors with the same coordinate reference system are stored. If GIS objects with a different coordinate reference system are used, a new project needs to be created, and *GRASS* needs to be prompted to switch to the new project. Each project also contains one or more "mapsets," which are subfolders in which rasters and vectors are stored. Mapsets must thus also be managed. Finally, each project has a "region," which is a dynamic, gridded object like a raster that has an extent and resolution. Most *GRASS* tools that operate on rasters will automatically crop and resample the output to the extent and resolution of the active region. Users must therefore track the region and modify it to ensure outputs have the expected properties. Users of *terra*, *sf*, and *stars* do not have to manage analogous file organization systems and data templates. Together, these differences create barriers to combining the respective strengths of *terra*, *sf*, and *stars* with *GRASS*.

Here I present the *fasterRaster* package for *R*, which allows users of *R* to take advantage of the capabilities of *GRASS*. *fasterRaster* uses *rgrass* as a backend to connect to *GRASS* (Bivand et al., 2025), and so obviates the need to learn *GRASS*-specific syntax and file organization. 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 developed 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.

Interoperability: The large majority of *fasterRaster* methods (functions) share the same name and functionality as methods in *terra*, and most share the same arguments. *fasterRaster* uses *R*'s object-oriented programming system so users can use *terra*, *sf*, *stars*, and *fasterRaster* in the same *R* session without conflict between methods that have the same name.

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, calculates 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.

Simplicity: *fasterRaster* makes using *GRASS* in *R* simple. Users do not need to manage or even be aware of *GRASS*-specific data constructs like projects, mapsets, or regions. These are managed dynamically and automatically in the background.

Ease-of-use: *fasterRaster* makes *GRASS* tools easy to use. Functions have R help pages, each with worked examples. The package has its own *pkgdown* website (Wickham et al., 2025) with documentation and vignettes, including a "getting started" tutorial (https://adamlilith.github.io/fasterRaster/index.html).

Functionality

fasterRaster can be installed from the Comprehensive R Archive Network (CRAN), with development versions available from the GitHub repository at https://github.com/adamlilith/fasterRaster.

After attaching the package using `library(fasterRaster)`, users must tell *fasterRaster* where *GRASS* is installed on their system using the `faster()` function. (Help for this function and any other can be obtained using `?functionName`.) After this, the first function call that uses *GRASS* as a backend will start *GRASS.* Invisible to the user, *fasterRaster* creates a *GRASS* "project" which is by default in the operating system's temporary directory. *GRASS* will store here all files it needs to do processing.

fasterRaster rasters and vectors are S4 objects called "GRasters" and "GVectors" (collectively, "G-objects"). GRasters can contain integers, double-floating point numeric values, or categorical data such as land cover classes. GVectors can have data tables, where each row corresponds to a particular "geometry" (point, line, or polygon) in the vector. The `fast()` function can be used to directly load from disk rasters or vectors in common file formats (e.g., GeoTIFF, Esri shapefiles, or Open Geospatial Consortium GeoPackages). `fast()` can also convert rasters and vectors from *terra* or *sf* packages to G-objects, although loading files from disk will always be faster than coercing them from objects created by other packages. GRasters and GVectors are *R* objects that contain pointers to *GRASS* files in the temporary *GRASS* project folder. Once the *R* session is stopped, this temporary directory is typically emptied and the files within them will no longer be available. To use G-objects in later analyses, users must save them using `writeRaster()` or `writeVector()`, both of which can write files in a variety common file formats.

Users can apply any of >200 methods, including functions for cropping, buffering, masking, projecting between coordinate reference systems, and otherwise creating and manipulating G-objects. All of these methods can be perused through the package index using `?fasterRaster` or on the *pkgdown* website. Of note, the package includes methods that draw on *GRASS*'s deep array of specialty tools. For example, `geomorphons()` identifies topographic features from an

elevation raster (e.g., flat areas, pits, valleys, footslopes, spurs, peaks, etc.; Stepinski & Jasiewicz, 2011; Jasiewicz & Stepinski, 2013). The `flow()`, `flowPath()`, and `streams()` functions conduct hydrological analysis of watershed basins and stream flow. An array of functions create rasters *de novo* with, for example, fractal geometry, random walks, normally distributed values, or spatial dependence (`fractalRast()`, `rWalkRast()`, `rNormRast()`, and `rSpatialDepRast()`, respectively). The `vegIndex()` function calculates 17 different vegetation indexes including the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI and EVI2), normalized difference water index (NDWI; Gao 1996), and the modified soil adjusted vegetation index (MSAVI; Qi et al. 1994). `bioclims()` generates the 19 BIOCLIM variables representing climatic extremes and averages (Booth et al., 2014) plus an extended set of 20 additional BIOCLIM variables such as temperature or precipitation of the quarters following the warmest/coldest quarters (i.e., fall or spring) and the hottest/coldest/wettest/driest months or quarters. The `fragmentation()` function classifies degrees of habitat fragmentation (i.e., patch, perforated, transitional, edge, interior; Riitters et al. 2000).

Workflows focused on "small" rasters and vectors (i.e., small number of cells and/or number of vector features) will almost always run faster using *terra* functions, but *fasterRaster* can make workflows faster—or at least feasible—if objects are large. To illustrate the strengths of each package, I constructed two matching workflows for assessing the relative influence of drivers and risks of forest loss in Southeast Asia. One workflow used almost exclusively *terra* methods, and the other *fasterRaster* methods, but both were otherwise the same in the inputs, function calls, order of operations, and outputs. Since actual performance will vary across different users' workflows and data, the exercise is intended to be illustrative. Nonetheless, the comparison demonstrates the relative tradeoffs between *terra* and *fasterRaster* and how to use each to best advantage.

Methods

The study region encompassed five major river basins of Southeast Asia, the Mekong, Salween, Irrawaddy, Chao Phraya, and the Sittang. In the past few decades, these regions have experienced dramatic social and environmental change yet remain bastions of biodiversity (Hughes 2017; Wang et al. 2023). Within the focal region, I used rasterized forest presence at ~30-m resolution in 2000 and 2020 from 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 across 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 other operations that did not use *terra* or *fasterRaster* functions were excluded 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 the Nam Loi subbasin of the Salween (Fig. S1). The specific regions were chosen so that the same set of functions could be applied across each (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 *terra* `distance()` function used as-is was extremely slow and so would have severely biased the comparison of runtimes. In preliminary runs of the medium-sized region, the function could take weeks to run, much longer than all of the other functions' runtimes combined. (Newer versions of *terra* released since these tests were run allow users options that can speed its operation, so may run faster than reported here). In the workflows, `distance()` was used to calculate distance between forested cell centers and rivers and roads, which are indicative of access to forest and so a risk factor (Soares-Filho et al., 2006). Since the purpose of the analyses was intended to be illustrative, not indicative, of runtimes, I used an aggregation "hack" to make comparisons fairer. For distance-based operations, I first reduced the number of cells (made cells larger) using the `aggregate()` function, called `distance()` on the coarse-resolution raster and respective vector, and then used `disaggregate()` to return the output to the original resolution. Reducing the number of cells to which distances needed to be calculated greatly sped *terra*'s `distance()` operation. However, aggregation also induced spatial distortion in the predictors based on distance to roads and rivers (Fig. S2). This "hack" was used only for the `distance()` operations.

Code for the benchmarking exercise is archived at https://github.com/adamlilith/fasterRaster_benchmarking. For these exercises, I used *terra* version 1.8-54 and *fasterRaster* version 8.4.1.0 connected to *GRASS* 8.4. All tests were run on a Windows 11 Enterprise desktop computer with a Intel Xeon® 2592 MHz processor with 20-cores and 40 logical processors, 512 GB RAM, and a 4-TB SSD. However, the workflows limited both packages to using 4 cores and 64 GB of RAM, so neither package was allowed to harness the full capacity of the system.

Results

The three study regions differed in size by orders of magnitude, with the largest containing >1.26 billion non-`NA` cells (Table 1). Based on the results from the large study region (run with the *fasterRaster*-based workflow and no aggregation "hack" before application of the `distance()` function), the risk of forest loss in 2000 was greatest in Cambodia (Fig. S1). Hereafter, I focus on the relative runtimes of a *terra*- versus *fasterRaster*-based workflows.

Table 1. Number of 30×30-m cells in each study region.

Region	Non-`NA` cells
Small	17,189,027
Medium	180,001,073
Large	1,266,543,912

The large study region encompassing all five river basins was not workable for *terra*. The *terra* `focal()` function worked for a 3-cell window but failed when the window was increased to 33 cells, causing *R* to crash. Multiple attempts were made. The `focal()` operation was implemented before the `distance()` function was required, so for the *terra* workflow, the aggregation "hack" was superfluous. In contrast, *fasterRaster* was able to complete the workflow for the large region and did not need the cell aggregation "hack" to apply the `distance()` function. The "entire" *fasterRaster* workflow runtime (with no cell 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 the medium extent, the "entire" *fasterRaster* workflow was about 30% faster than the *terra* workflow (Fig. 1). *fasterRaster* took less than 13 days (307 hr 4 min), whereas *terra* required almost 19 days (453 hr 58 min). The `distance()` function was the slowest in the *terra* workflow even after applying the aggregation "hack" in which larger cells were created from composites of 512×512 cells. The `extract()` function took the most time in the *fasterRaster* workflow. The "fold-averaged" *fasterRaster* runtime was twice as fast as the *terra* runtime (Fig. 2).

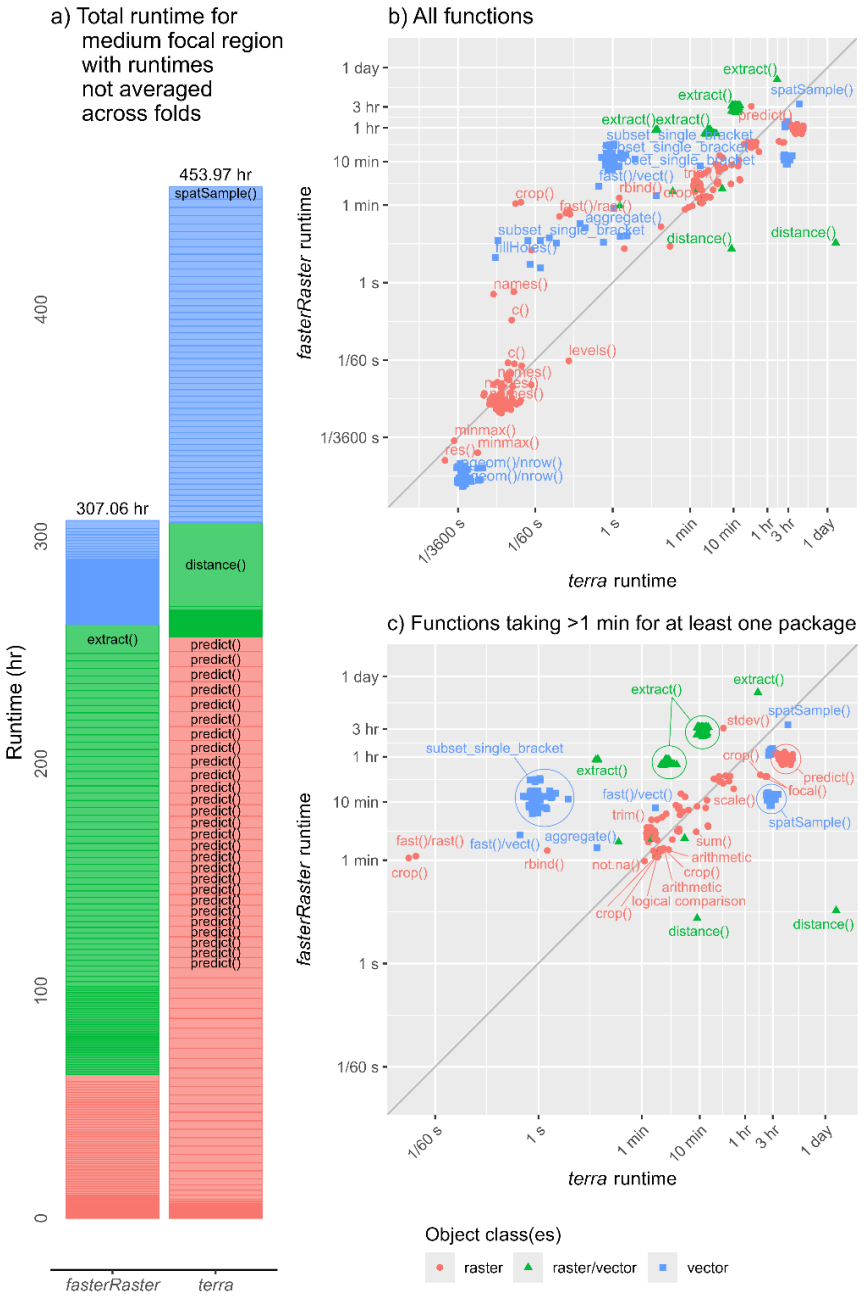

Figure 1. Comparison of runtimes for the "entire" workflow for the medium study region extent. In each panel, colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function, and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

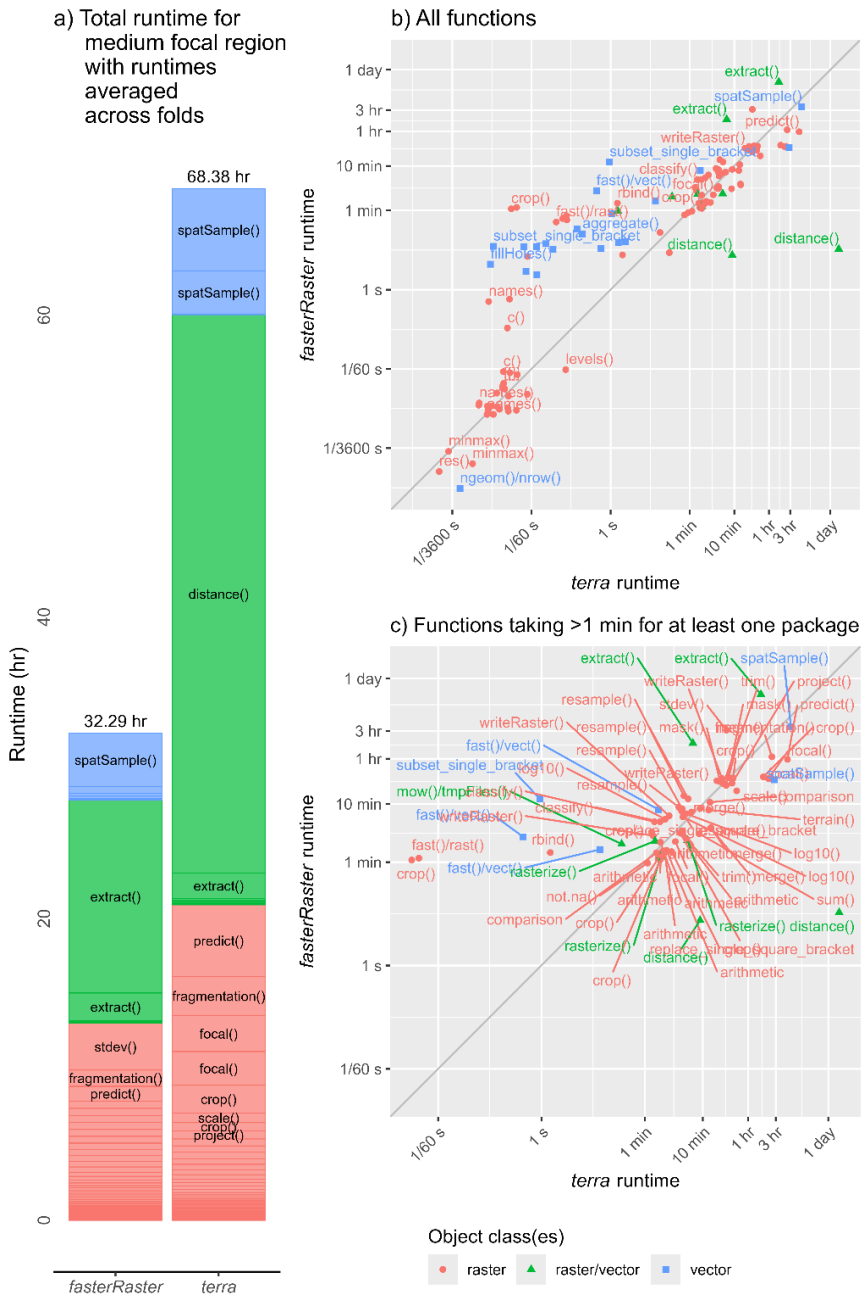

Figure 2. Comparison of "fold-averaged" runtimes for the medium study region extent. In each panel, colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function, and sorted from slowest to fastest. Functions that took ≥15 min to execute are labeled. Total runtime is shown at the top of each bar. (b) Comparison of runtime of the same functions in the *terra* and *fasterRaster* packages. (c) Runtime of functions that took at least 1 min to run in at least one workflow. Cells were aggregated by a factor of 512 to speed the call of *terra*'s `distance()` function.

For workflows analyzing the small extent, the "entire" *fasterRaster* workflow was more than three times slower than the *terra* workflow (Fig. 3). The *fasterRaster* workflow took nearly a day (22 hr 39 min) to complete, whereas the *terra* workflow took less than a third of a day (7 hr 10 min). The `extract()` function was slowest in the *fasterRaster* workflow , and `distance()` the slowest in the *terra* workflow. Since `extract()` was called once per fold, averaging runtimes across crossvalidation folds 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. 4). These results are for cases where the `distance()` function "hack" used an aggregation factor of 128. Aggregating cells by a factor of 32 caused the "entire" and the "fold-averaged" *fasterRaster* runtimes to be much shorter than the *terra* runtimes, while aggregating by 512 led to a 2- to 6-fold lead of *terra* over *fasterRaster* (Figs. S3, S4, S5, and S6).

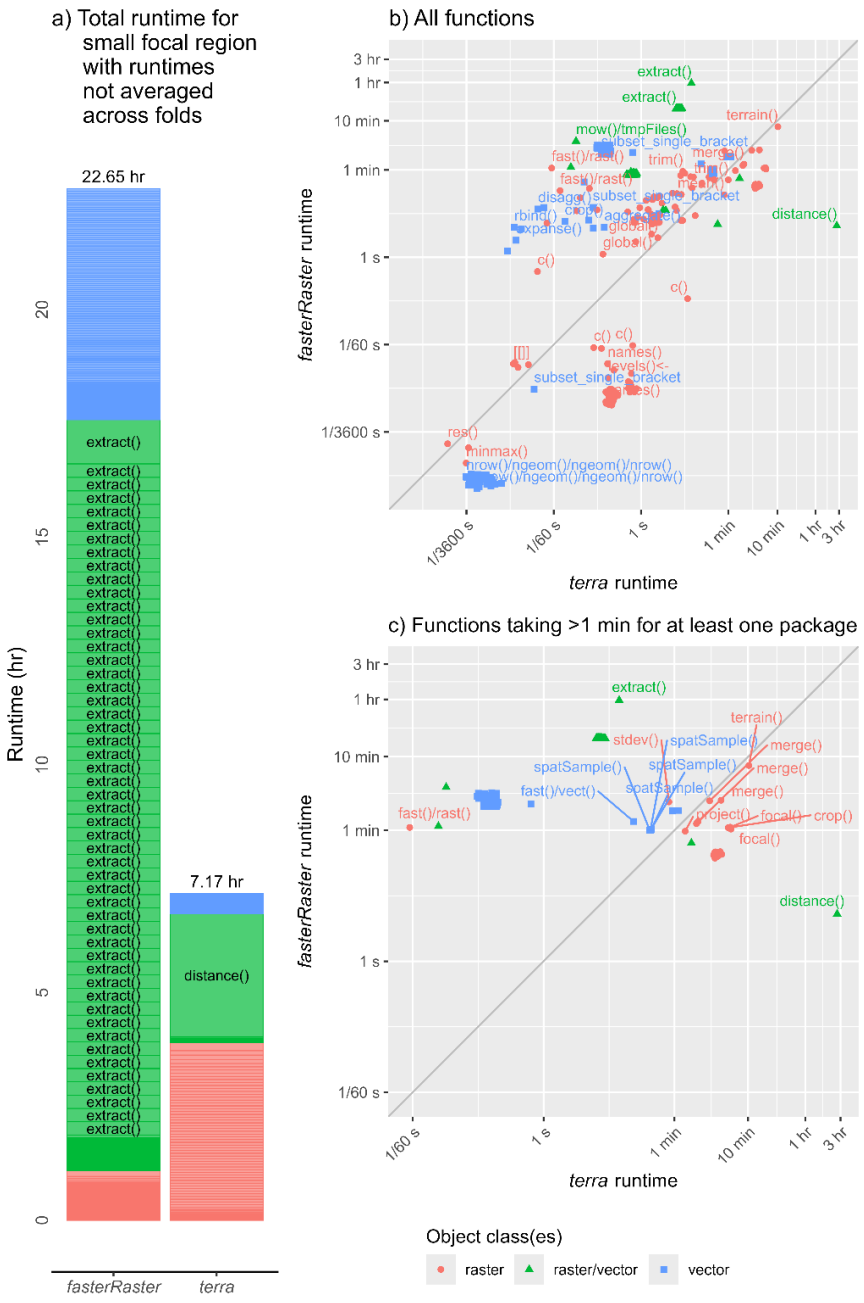

Figure 3. Comparison of runtimes for the "entire" workflow for the small study region. In each panel, colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function, and sorted from slowest to fastest. 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) Comparison of runtimes of the same function from each package. (c) Runtime of functions that took at least 1 min to run in at least one workflow. Cells were aggregated by a factor of 128 to speed the call of *terra*'s `distance()` function.

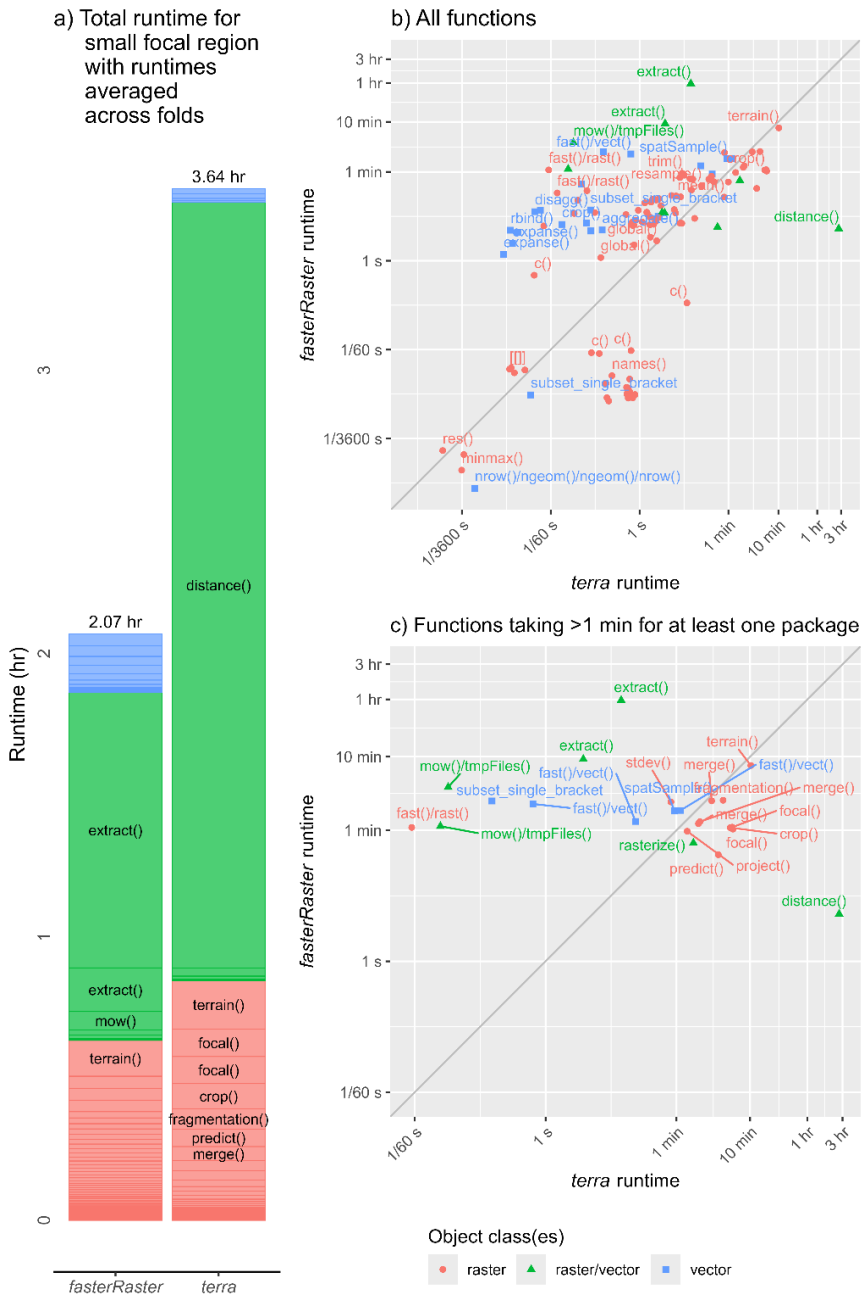

Figure 4. Comparison of runtimes for the "fold-averaged" workflow for the small study region. Runtimes of functions called across folds are averaged. In each panel, colors represent whether functions were run on rasters (red), vectors (green), or both (blue). (a) Comparison of total runtime. Bars are divided into smaller rectangles, one per function, and sorted from slowest to fastest. Functions that took ≥15 min to execute are labeled. Total runtime is shown at the top of each bar. (b) Comparison of runtime of the same functions from the two packages. (c) Runtime of functions that took at least 1 min to run in at least one workflow. Cells were aggregated by a factor of 128 to speed the call of *terra*'s `distance()` function.

Conclusions

The *fasterRaster* package brings the power of *GRASS* to *R* while facilitating interoperability with *terra* and other geospatial *R* packages. The exercise demonstrated that in cases when spatial objects are large (many cells or fine spatial detail), *GRASS*-based analysis through *fasterRaster* can achieve significant performance gains.

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. 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).

Despite its strengths, *fasterRaster* does differ from *terra* in ways users should be aware. First, many methods may have the same name and general functionality, but will not necessarily produce the exact same outputs. For example, *terra*'s `distance()` function by default calculates the distance from the center of a raster cell to the closest part of a lines vector (Hijmans, 2025). In contrast, the *fasterRaster* `distance()` function 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. (Newer versions of terra's `distance()` have an option to use this same procedure). Differences have also been observed in `resample()`, `project()`, and other functions, though discrepancies can be data-specific. As a result, users should not expect *fasterRaster* functions to be exact replacements of those in *terra*. Second, *fasterRaster* relies on temporary files (as does *terra*), but these have less protection from automated disk-cleaning tools found on some operating systems like MS Windows 11's "Storage Sense." If left running, these tools can delete temporary files and "break" GRasters and GVectors. Relatedly, the disadvantage of a disk-heavy processing system like *GRASS* is that while it may reduce memory requirements, it can fill the disk with lots of unused temporary files. To address this, *fasterRaster* contains automated routines to remove most of these temporary files. However, users can also manually call the `mow()` function to remove extraneous files, though it must be done carefully to avoid breaking existing G-objects.

Future development will focus on expanded functionality and ease of use. *GRASS* has a wealth of additional tools that do not yet appear in *fasterRaster*. These include tools for 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). All of these represent opportunities for further development. *fasterRaster* syntax mirrors that of *terra*, but depending on demand, future development may also create *sf*-analogous functions so users familiar with that package can more easily switch between it and *fasterRaster*.

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, issues, and feature requests can be reported on the *fasterRaster* GitHub repository at https://github.com/adamlilith/fasterRaster.

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

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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 response raster)	WGS84	Continuous	OSM, 2024
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

4

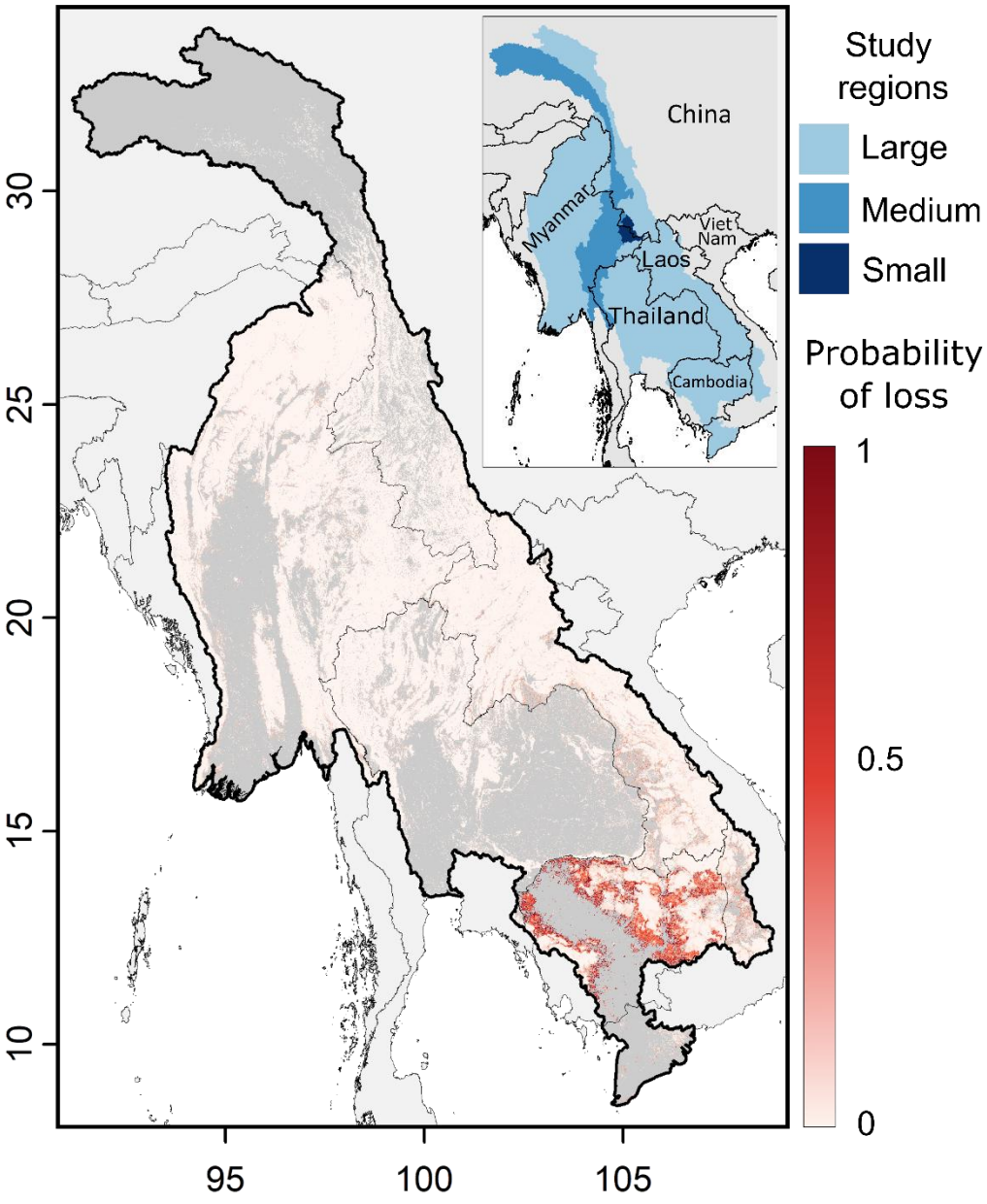

Figure S1. Study region and predicted probability of forest cover loss between 2000 and 2020 based on analysis of the large study region. The map of forest loss probability was created using the *fasterRaster* workflow without the aggregation "hack" to accommodate the `distance()` function.

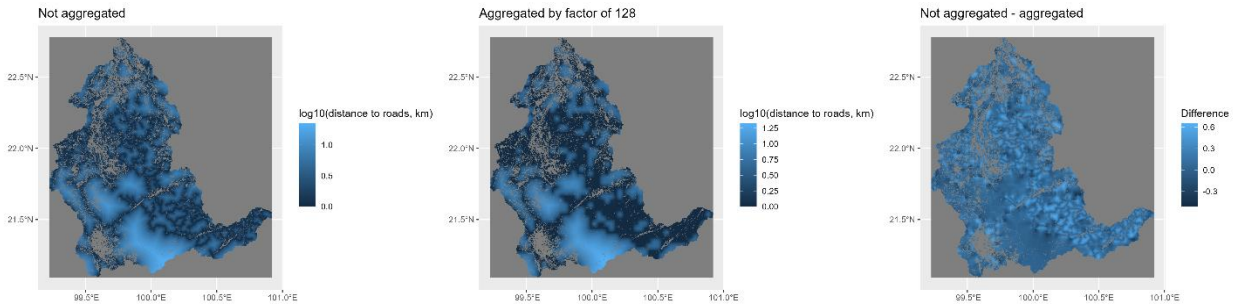

Figure S2. Effect of aggregating cells to speed the call of *terra*'s `distance()` function which would otherwise dominate the runtimes. Cell aggregation, then resampling, induces artifacts in the output. The small study region (subbasins of the Salween river basin) are shown for illustration. Here, 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.

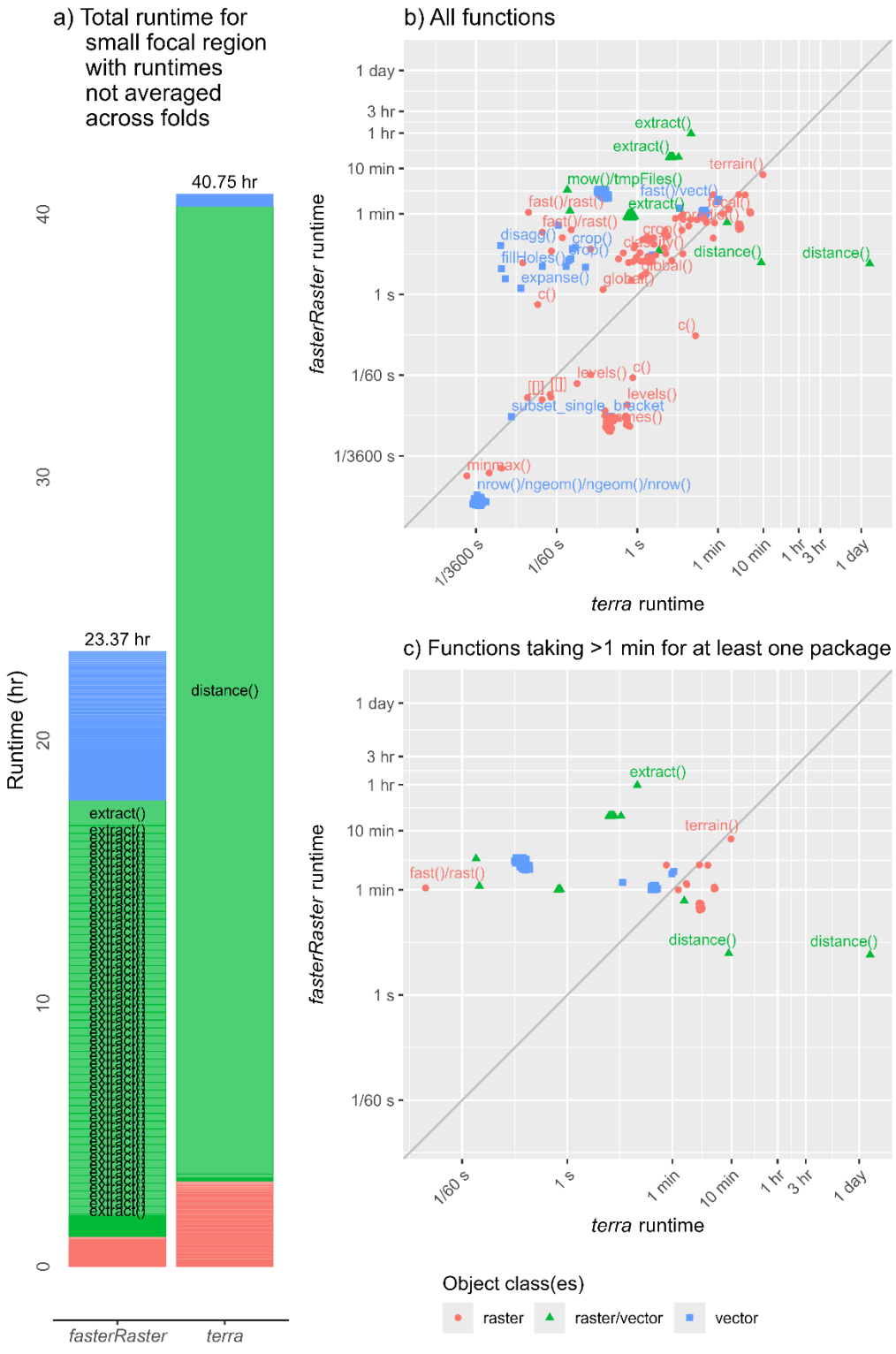

Figure S3. Comparison of runtimes "**entire**" workflow for the **small** study region extent when cells were aggregated by a factor of **32**.

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

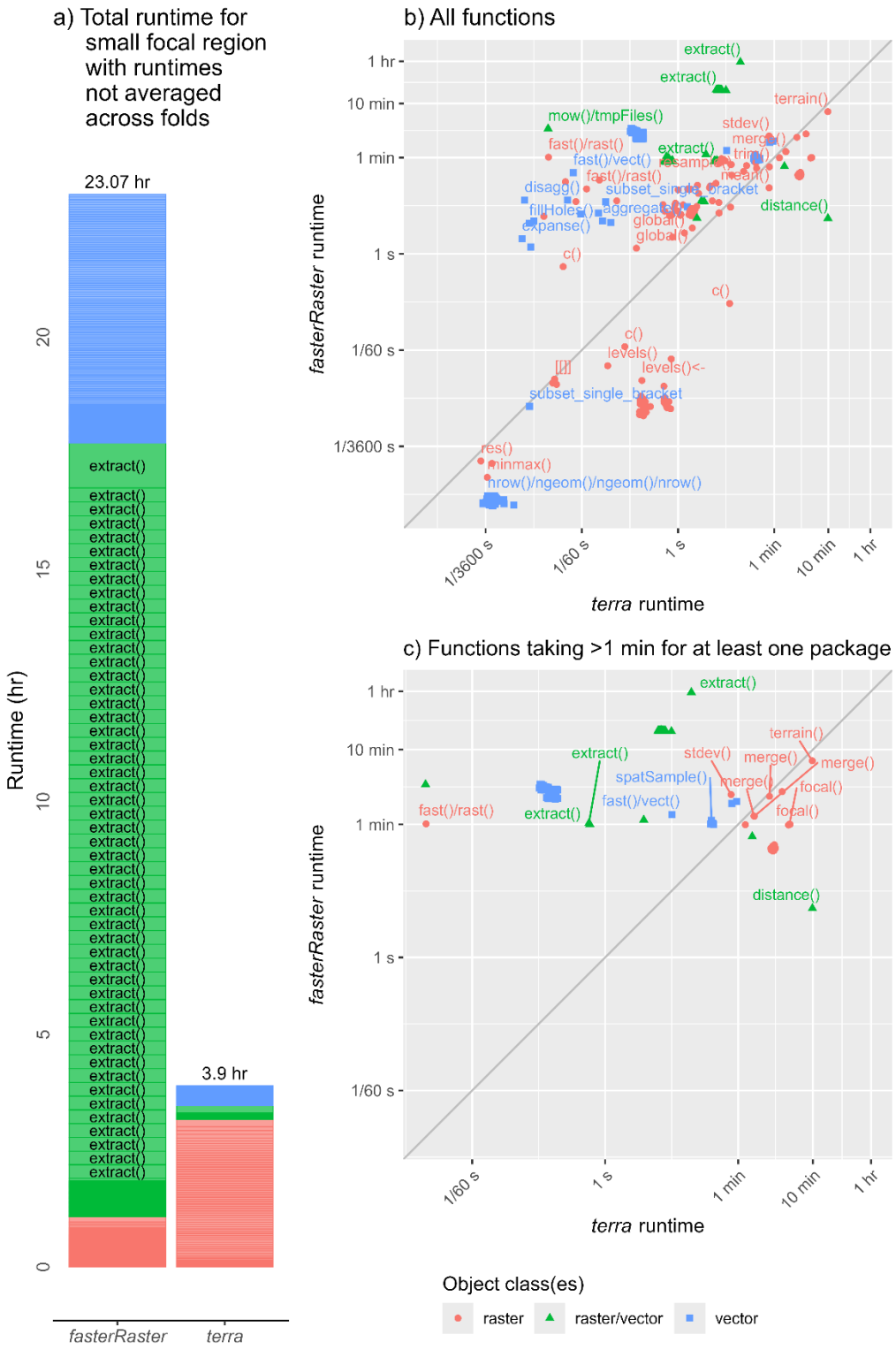

Figure S5. Comparison of runtimes "**entire**" workflow for the **small** study region extent when cells were aggregated by a factor of **512**.

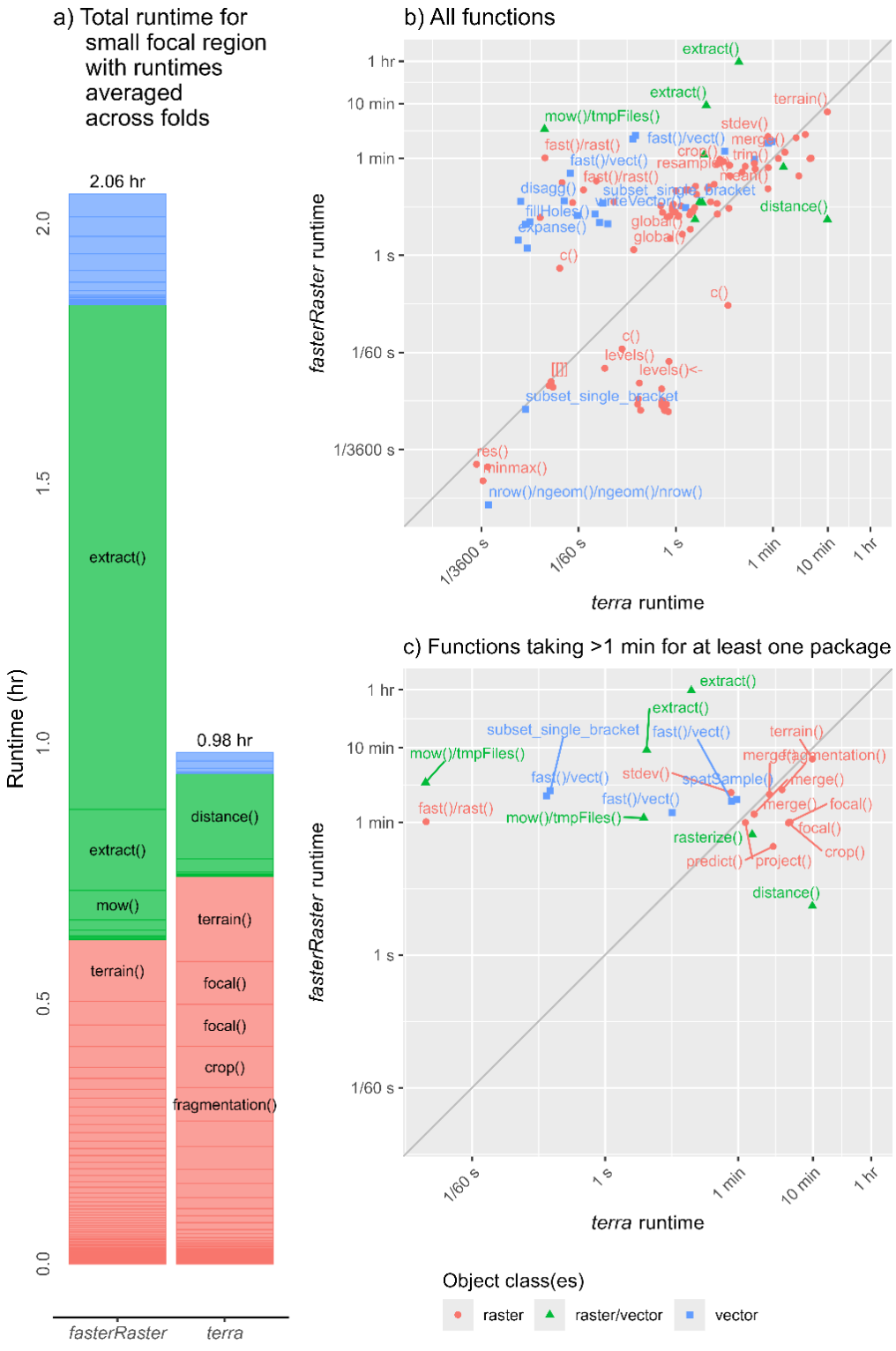

Figure S6. Comparison of runtimes "**fold-averaged**" workflow for the **small** study region extent when cells were aggregated by a factor of **512**.

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