An introduction to Systematic conservation planning with prioritzr

Martin Jung & Louise O'Connor

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Preface

Welcome to the training course in systematic conservation planning with the prioritzr. This training course was originally held at the 2024 European Congress of Conservation biology in Bologna, although the materials found here will be preserved even after the conference and be openly available to everyone.

What you will learn

- The basic concepts of Systematic conservation planning (SCP) and Integer Linear Programming (ILP) in particular
- How to prepare your input data for a Conservation planning project
- How to setup and run your first prioritization
- How outputs can be analysed and interpreted.
- How to adding complexity factors and changing your conservation planning outcomes
- Advanced topics such as accounting for connectivity and management zones

Completing all course materials will take you on average 120 minutes, although people who have been exposed to similar methods or introduction before might take less. training materials before might less amount of time.

In this training course a number of different terms will be used. Whenever there are uncertainties with regards to definitions, see the Glossary.

If you have already heard before about the basic concepts of SCP and ILP (For example from the lecture then feel to jump to section 2 and data preparation Chapter 2.

> **i** Before you start…
>
> In order to run the materials on this course website, some preparatory steps need to be taken. Please see the installation instructions in Appendix A if you have never used **prioritizr** before!

Part I

Introduction to SCP

1 Introduction

Welcome to this short introduction to systematic conservation planning with prioritizr! On this page you will learn about the basic concepts of systematic conservation planning (SCP) and more specifically algorithmic solutions identifying planning outcomes.

Course info

If you have taken part in person to the introduction on the day, you might want to skip this section and directly start with handling and preparing data at Chapter 2 .

1.1 Systematic conservation planning

The classical definition of Systematic conservation planning (SCP) is that of a structured, scientific approach to identifying and prioritizing areas for conservation (REFs). Its goal is to ensure that biodiversity is maintained and ecosystems are protected in a way that maximizes ecological, economic, and social benefits. Although SCP has been conceived specifically for creating and expanding reserve networks (usually protected areas), it can be used for much more including for example the identification of restoration, land-use planning or monitoring options.

It is also a common misconception that a project implementing SCP is only about prioritization (the algorithm part). Rather, it describes a whole framework typically ranging from

1. Defining Conservation goals and objectives
2. Eliciting pathways to impact and theory of change with stakeholders
3. Compiling and preparing data
4. Identifying targets, constraints and costs
5. Formulating a planning problem and identifying priorities for it
6. Evaluating said priorities through robust performance metrics
7. Implementing the priorities in exchange with stakeholders

8. Monitoring the performance and adapting plans where necessary.

1.1.1 Key concepts

1.2 Exact algorithms and integer programming

See Hanson *et al.* (2019) for additional discussion of optimality in linear programming.

1.3 Tools and software

We stress that prioritizr is not the only software available

Part II

Problem creation

2 Preparing input data

2.1 Planning units

Say something about what a PU file is, load and plot from the example data

2.2 Features

Explain what features are and plot

2.3 Costs

Explain what costs are and how they are used

2.4 Other constraints (Protected areas)

Showcase a protected area file and exclusion areas as example

2.5 Other data for the prioritization

Mention weights, targets, etc and give example for each

2.6 Preparing data in different formats

Showcase different dataformats as input alternative

```
library(tidyverse)
trees |>                                                    ①
  mutate(
  volume_girth = volume * girth                             ②
  )
```

① Take dataset and mutate
② Update with interaction term

3

Part III

Solving a problem

4 Solving a conservation planning problem

4.1 Ensure that a solver is available

4.2 Create a solution

4.3 Plot the solution

5 Interpret and analyse outputs

5.1 Plot the solution

5.2 Calculate performance evaluation metrics

Area statistics, Mean representation, Target shortfall

5.3 Irreplaceability

Calculater ferrier irreplacibility and RWR

Part IV

Adding complexity

6 Objective functions

6.1 The need for targets

6.2 Minimum set

6.3 Maximum coverage

6.4 Creating ranked priority maps

7 Adding complexity to conservation planning

7.1 Decision variables

7.2 Adding (socio-economic) costs

7.3 Feature weights

7.4 Linear penalities

Part V

Advanced topics

8 Connectivity

Conservation planning can be used to obtain area-based solutions to identify options for (improved) conservation of species. In reality however many seemingly 'optimal' solutions in terms of complementarity (e.g. covering the best areas for conserving selected features) might not work for species that persist only in isolated populations, which are thus more prone to extinction. Here a strategy is not to identify (and conserve) a single site, but manage a network of sites that are ideally as much as possible connected.

What this imply for area-based conservation planning? It means ideally sites are selected in a way that not only maximizes complementarity but also results in compact and/or structurally and functionally connected areas.

The aim of this section is to describe different way of 'directly' considering connectivity in area-based conservation planning with *prioritizr*. For a comprehensive overview on the general principles of considering connectivity in area-based planning we recommend several recent reviews and perspectives (Daigle *et al.* 2020) (Beger *et al.* 2022) (Hanson *et al.* 2022).

> **!** Note
>
> Much of the code examples in this section might take quite a bit of time to run and requires knowledge of how to set up a problem formulation. We suggest to try these options only as you are familiar with modifying problem formulations and altering outputs.
> For demonstration purposes we focus on the Alpine region for these examples. You can obtain a shapefile of their outline here.

Although by no means comprehensive, we broadly consider four commonly applied but different ways of considering connectivity in prioritzr.

1. Boundary penalties that prefer larger compared to smaller sites (Ball *et al.* 2009).
2. Connectivity penalties that penalize (unconnected) solutions (Alagador *et al.* 2012).
3. Connectivity constraints to (hard) constrain solutions to certain criteria such as proximity (Hanson *et al.* 2022).

4. Connectivity features such present/future layers or connectivity layers (Kujala *et al.* 2013).

8.1 Boundary penalties

The inclusion of boundary penalties is one of the oldest and most widely applied ways of forcing a prioritization output (Ball *et al.* 2009). By setting a boundary length modifier (BLM) or penalty constant, we effectively penalize solutions that result in overly fragmented patches. Since it is a penality it does not fully prevent them however.

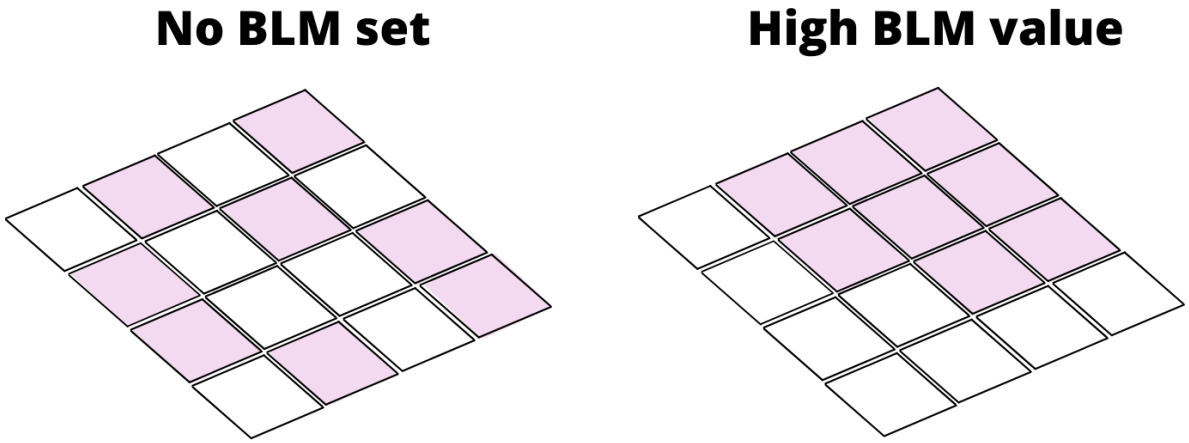


Figure 8.1: Boundary length modifier (BLM), which is effectively a penalty (Source: Marxan solutions)

Unfortunately, and similar to other penalty values, there are no specific guidelines of what might work or not, so often it might be worth exploring a few options.

As in previous tutorials we first load our data. However as noted above, we focus on the Alpine region only to make this interpretable. To do so we first crop and mask our PU and feature data to the alps.

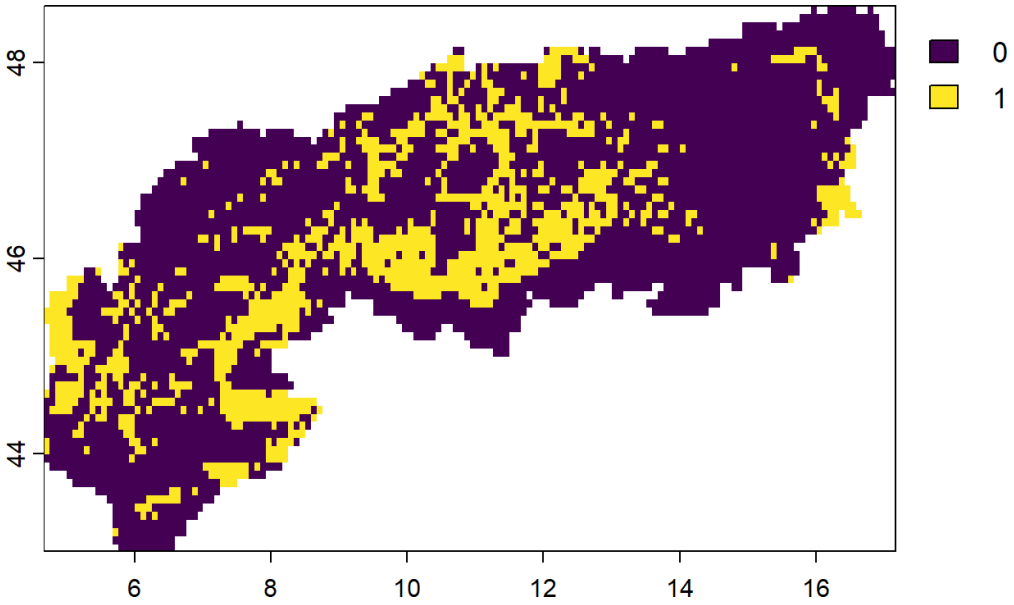
```
# Crop. Focus on the alps here
alps <- sf::st_read('extdata/boundary_alps/AlpineConvention.shp') |>
  sf::st_transform(crs = sf::st_crs(4326))

PU <- PU |> terra::crop(alps) |> terra::mask(alps)
spp <- spp |> terra::crop(alps) |> terra::mask(alps)
```

Now we can create a conservation planning problem for this region.

```
p <- problem(PU, spp) |>                                    ①
  add_min_set_objective() |>                                ②
  add_relative_targets(targets = 0.3) |>                    ③
  add_binary_decisions() |>                                 ④
  add_default_solver()                                      ⑤
```

① A problem with the cropped data (Planning units and features)
② Using a minimum set operation here.
③ Arbitrary targets of 30% of the feature distribution
④ Binary decisions
⑤ Use the fastest solver installed/available (usually Gurobi or cbc)



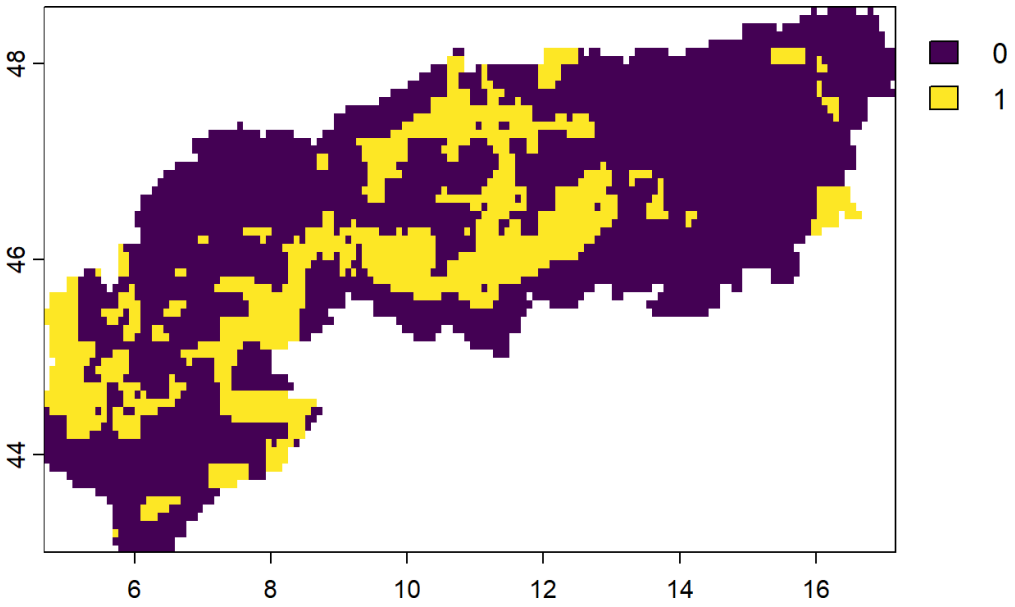
Now lets add some boundary constraints to the same problem.,

```
# First we precompute the boundary matrix (large matrix of neighbourhoods)
bm <- boundary_matrix(PU)
# Then we rescale it for better performance
bm <- rescale_matrix(bm)

# Now create a new problem using the settings from above, but with a boundary penality
s_blm <- p |>
```

```
  add_boundary_penalties(penalty = 1e-4, data = bm) |>                    ①
  solve()
```

① Specify a boundary penalty. Usually this requires some trial-and-error.



As you can see the solution is effectively more '*clumped*'. But what about the area selected? Do we need more area to get the best complementary solution here?

```
# calculate costs (sum of area)
dplyr::bind_rows(
  eval_cost_summary(p, s),
  eval_cost_summary(p, s_blm)
)

# Answer is...?
```

> **Performance**
>
> Boundary length penalties generally solve faster with simpler objective functions, such as a minimum set objective function.

8.2 Connectivity penalties

Another more direct way to ingest some connectivity into a problem formulation is to use a certain auxillary layer, for example green infrastructure, (inverse) costs of transversal or connectivity estimates run through software like Circuitscape, as linear penalty. When including connectivity estimates as penalties in conservation planning we usually distinguish between symmetric and asymmetric penalties.

8.2.1 Symmetric connectivity penalties

Symmetric connectivity penalties describe information that is non-directional, in other words the same penalties apply when for example a species moves from west to east or from east to west across the study region (see also (Alagador *et al.* 2012)).

In the following example we again define a minimum set problem as before. We then load a pressure layer (the Human modification index) under the assumption that higher human modification values reduce the (structural) connectivity value of a landscape. Again we require a penalty term and it is advised to carefully calibrate this constant in practice.

```
# Define a minimum set problem
p <- problem(PU, spp) |>
  add_min_set_objective() |>
  add_relative_targets(targets = 0.3) |>
  add_binary_decisions() |>
  add_default_solver()


# Load the Human Modification index and clip to the alps
HM <- rast("extdata/gHM.tif") |> terra::crop(alps) |> terra::mask(alps)

# Now prepare the connectivity matrix and rescale
bm <- connectivity_matrix(PU,HM)                                    ①
# rescale matrix
bm <- rescale_matrix(bm)                                            ②

# Update the problem formulation and solve with a small penalty.
s_con1 <- p |>
  add_connectivity_penalties(penalty = 1e-4, data = bm) |>          ③
  solve()
```

```
plot(s_con1)
# It also possible to evaluate the connectivity values via
eval_connectivity_summary(p,s_con1, data = bm)
```

① This command calculates a cross-product between the Planning unit and a pressure layer
② Rescaling is usually necessary to achieve better convergence
③ The Penalty constant chosen reflects the magnitude of influence dedicated to this layer.

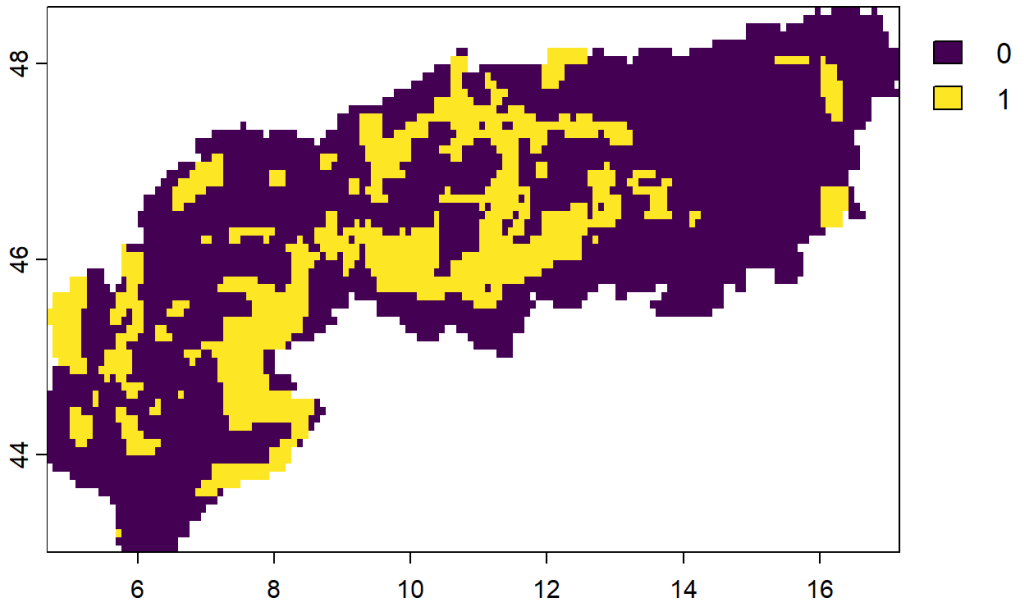


Figure 8.2: Prioritization with symmetric connectivity penalties

Influence of penalty values

Try changing the penalty parameter. How do the results change? If you encounter unusual results (all values identical) the reason is often an inappropriate penalty.
In real world example it usually recommended to calibrate such quite parameters so as to ensure realistic outcomes. See this vignette for more information on how to do so.

Another alternative approach could be to not use a separate layer, but constrain the area-based prioritization by some prior knowledge about minimum or maximum distance constraints. For example, one can envisage a case where we know that most species are unlikely to disperse further than 10 km from any selected patch. In this case it can be beneficial to avoid prioritizing such areas for conservation to avoid further fragmentation and possibly extinction of local populations.

Let's try it out (Note: this can take quite a bit longer to solve):

```
# Here we precompute a proximity matrix with maximum distance of about ~10km (WGS84 projecti
cm <- proximity_matrix(PU, distance = 0.1)                                          ①
# rescale boundary data
cm <- rescale_matrix(cm)

# Do one with boundary constraints
s_con2 <- p |>
  add_connectivity_penalties(penalty = 1e-4, data = cm) |>
  add_cbc_solver(time_limit = 240,first_feasible = TRUE) |>
  solve()

plot(s_con2)
```

① Note the different command compared to before. This calculates proximity constraints.

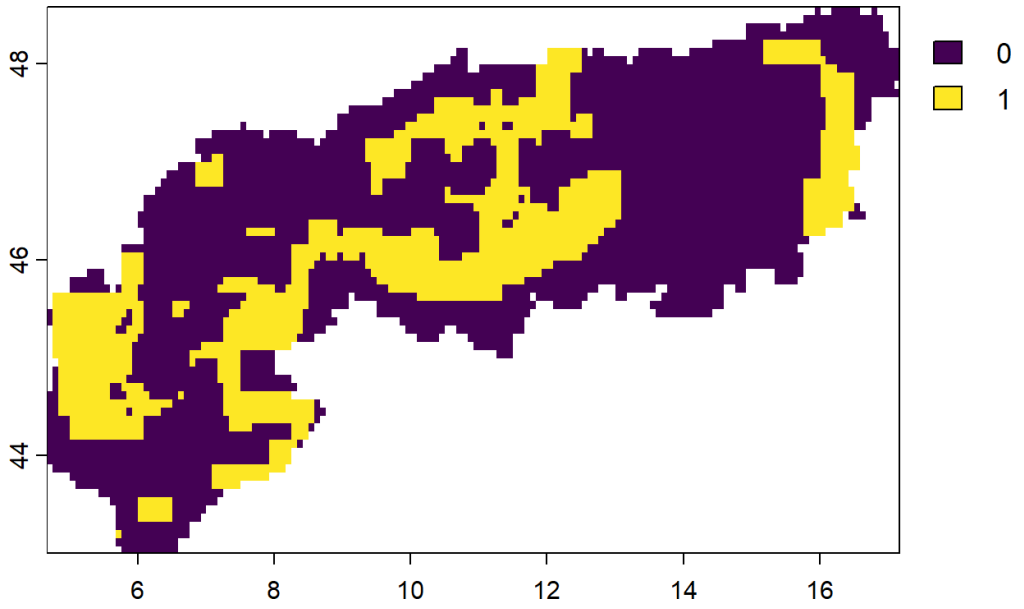


Figure 8.3: Proximity penalties(10km)

> **Tip**
>
> There is also a matrix function called 'adjacency_matrix()'. Can you imagine what this one does?

8.2.2 Asymmetric connectivity penalties

Opposed to symmetric connectivity penalties (Section 8.2.1), asymmetric penalties have some kind of directionality. For example in situations where species can only move down PU such as rivers blocked by a dam, or for planning problems with migration corridors (south to north) ((Beger *et al.* 2010)). Adding this penalty to a problem penalizes solutions that have low directional connectivity among PU.

```
# Make a directional dummy layer based on the cell numbers
dummy <- PU
dummy[!is.na(PU)] <- terra::cells(dummy)

# Now prepare the connectivity matrix and rescale
cm <- connectivity_matrix(PU, dummy)                                    (1)
# rescale matrix
cm <- rescale_matrix(cm, max = 1)                                       (2)

# We only use the diagonal for this simple example, thus going north to south
cm <- Matrix::triu(cm)                                                  (3)

# Update the problem formulation and solve with a penalty.
s_asc <- p |>
  add_asym_connectivity_penalties(penalty = 1, data = cm) |>            (4)
  solve()

plot(s_asc)
```

(1) We again create a connectivity matrix using the dummy cell numbers
(2) Rescale and make sure values are from 0 to 1 for better convergence.
(3) We take only the diagonal for simplicity. This effectively removes one geographical dimension (top to bottom).
(4) Solve the solution. Note the higher penalty for this dummy example.

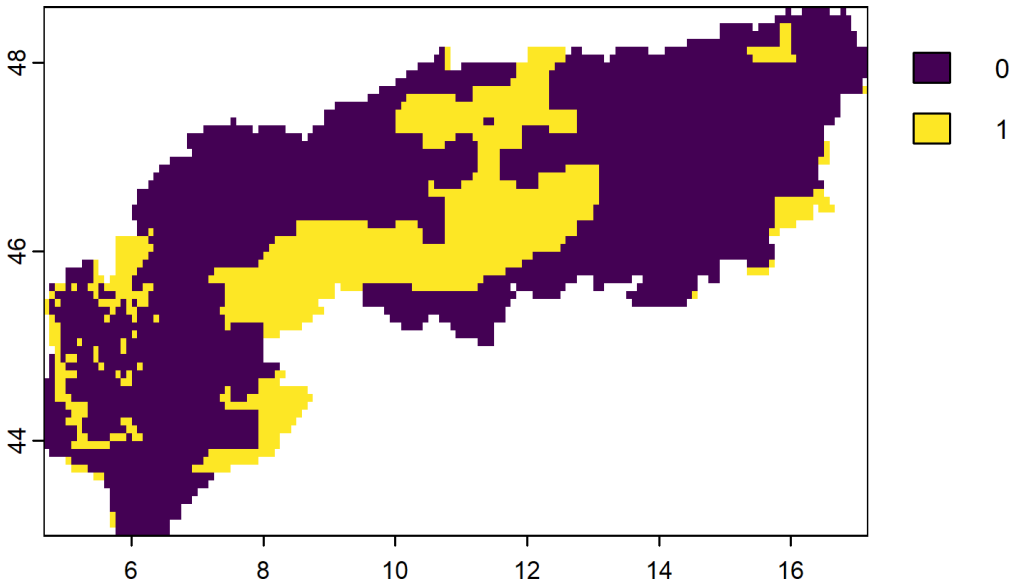


Figure 8.4: Asymmetric connectivity penalty from North to South

8.3 Connectivity constraints

So far we have made use of penalties to *nudge* solutions into to being more connected or less fragmented. Penalties however can not guarantee *per se* that a solution satisfies the desired criteria for example having only a few rather than many continuous patches. Constraints force a solution to, regardless of the optimality gap used to generate a prioritization, always exhibit the intended characteristics (or being infeasible).

8.3.1 Neighbour constraints

This simply constraint specifies that each selected PU has to have at least X neighbours in the solution.

```
# Define a problem
p <- problem(PU, spp) |>
  add_min_set_objective() |>
  add_relative_targets(targets = 0.3) |>
  add_binary_decisions() |>
  add_default_solver()
```

```
# Obtain only solutions with PU that have at least 2 neighbouring PU
s <-
  p %>%
  add_neighbor_constraints(k = 2) %>%                                    ①
  solve()

plot(s)
```

① Try changing the k parameter to 3 or 4. What happens?

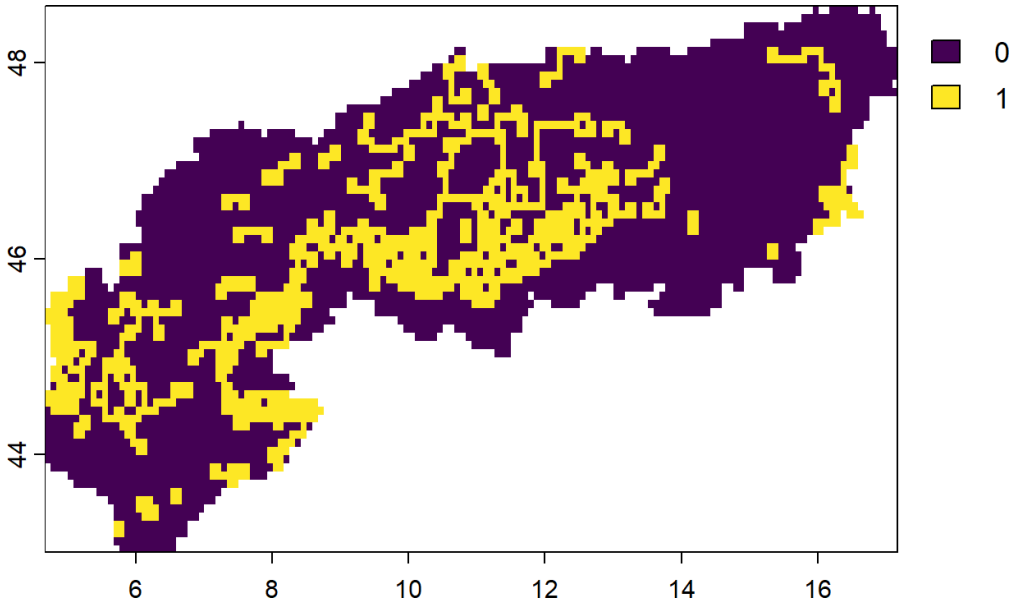


Figure 8.5: A solution with a hard connectivity constraint of having at least 2 neighbouring PUs

8.3.2 Contiguity constraints

On the extreme end of the SLOSS (Single large vs several small) debate are single continuous reserves. Such planning solutions can be beneficial for example when the aim is to adequately conserve the most area under large budget constraints. For such cases prioritizr supports so called contiguity constraints, which form a single large reserve instead of multiple.

Contiguity constraints are very time-consuming to solve and an installation of a commercial solver (like Gurobi) is highly advised.

```
# create problem with added contiguity constraints and solve it
s2 <-
  p |>
  add_contiguity_constraints() |>
  add_relative_targets(targets = 0.1) |>
  add_gurobi_solver(time_limit = 2400, first_feasible = TRUE) |>
  solve()
```

8.3.3 Linear constraints

Linear constraints are not directly linked to connectivity, but can in theory used for this purpose (and more). Linear constraints simply specify that the solution has to satisfy a criteria, such as for example having at least XX% of area or covering at least YY% of 'connectivity' features. They are thus quite similar to including connectivity as a feature (Daigle *et al.* 2020) (see also below for connectivity features), but are implemented directly as constraints.

For example, in this problem formulation we constrain the solutions to only those that also contain a certain (admittedly) arbitrary amount of 'greenness' (quantified by the NDVI).

```
# Load and clip the ndvi layer
ndvi <- rast("extdata/ndvi.tif") |> crop(alps) |> mask(alps)

# The threshold for linear constraints. We want at least this much!
threshold <- global(ndvi, "sum", na.rm = TRUE)[[1]] * 0.3

# Update the solution.
s3 <-
  p |>
  add_linear_constraints(
    data = ndvi, threshold = threshold, sense = ">="                    ①
  ) |>
  solve()

plot(s3)
```

① We specify a greater/equal sense here. Different directions such < or <= are also possible.

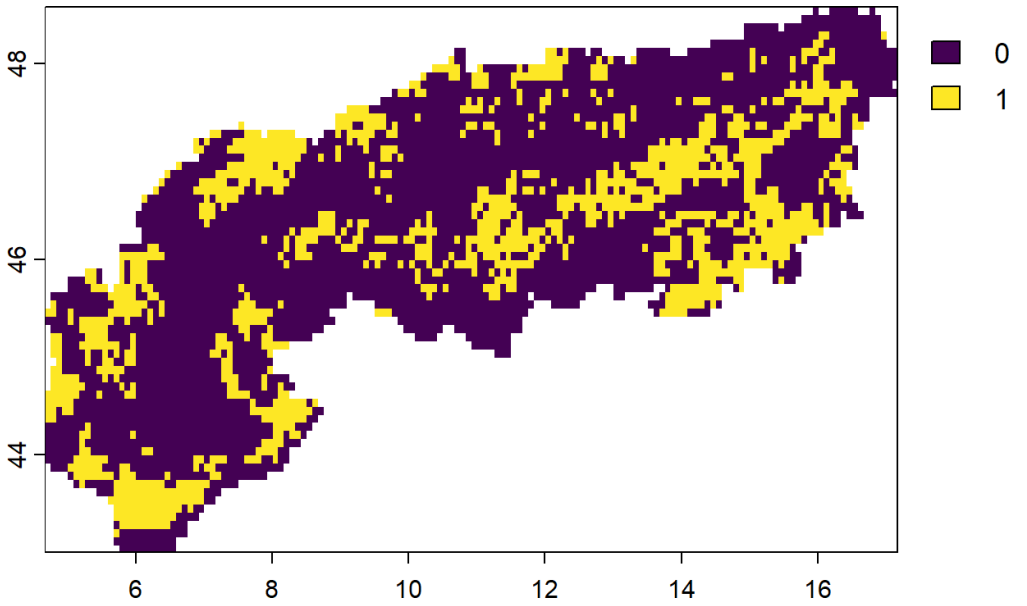


Figure 8.6: A prioritization including certain minimal amounts of greenness as constraint

Can you think of a reason why it might be beneficial to modify the input layers beforehand? Consider that it can incurs costs (in terms of area) to select PU as part of the solution.

> **Tip**
>
> Linear constrains are extremely flexible and can be used to constrain priorities into many directions. For example, with them it is easily feasible to obtain a solution that satisfies at least 10% of total area over the studyregion, while maximizing target achievement.

8.4 Connectivity features

Another, relatively straight forward way, to 'account' for connectivity is to directly add features representing connectivity *per se* and ensure that solutions conserve not only the areas a species occurs in but also the area it transverse through. For example (Kujala *et al.* 2013) considered both current and future projected distributions of species (constrained by dispersal distance) to identify potential stepping stones or refugia in response to climate change. For a comprehensive overview see also the recent work on climate-smart metrics for conservation planning (Buenafe *et al.* 2023).

As an example here we aim to identify the top 'priorities' that account for present as well as future distributions of species in a simplified manner. This approach can certainly be improved further, for example by considering dispersal constraints or weights of present against future distributions (discounting), but illustrates the concept.

```
budget.area <- round(0.3 * length(cells(PU))) ##  30 percent

# Identify the solution for a maximum coverage problem and contemporary only
s0 <- problem(PU, spp) |>
  add_max_features_objective(budget = budget.area) |>
  add_relative_targets(targets = 0.3) |>
  add_binary_decisions() |>
  add_default_solver() |>
  solve()

# Now add the future distributions of the species as well as their
spp.list <- list.files(path = "extdata/SpeciesDistributions/", full.names = T, recursive = T
sppf <- rast(spp.list[grep("rcp85", spp.list)])
# Crop and mask
sppf <- sppf |> terra::crop(alps) |> terra::mask(alps)

# Add to stack
s1 <- problem(PU, c(spp, sppf)) |>
  add_max_features_objective(budget = budget.area) |>
  add_relative_targets(targets = 0.3) |>                                    ①
  add_binary_decisions() |>
  add_default_solver() |>
  solve()

# Overlay and compare
comb <- s0+s1 |> as.factor()                                                ②
levels(comb) <- c("no priority", "current/future only", "current and future")
plot(comb, legend = "bottom")
```

① Note that we specify identical targets for present/future. Ideally targets are specified by feature rather than flat as done here.

② Since the decision variable is binary, we can simply sum the result.

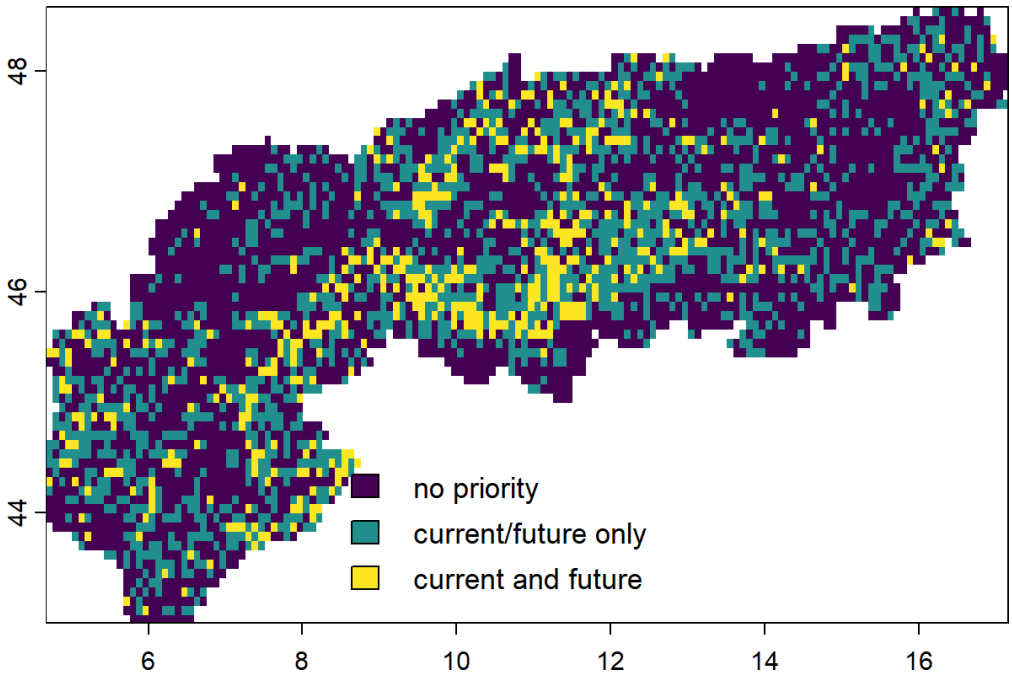


Figure 8.7: Vertical connectivity with future projections

9 Adding zones

The technical prioritization in SCP with prioritizr is primarily about allocating area for a given objective to a range of planning units (PUs). Yet in many (if not most) situations there is a need to not only allocate land to a single but multiple outcomes. For example, when we aim to prioritize areas across realms (land and sea) both of which are affected by different costs, features and penalties. Similarly, land could be directly prioritized to certain land system classes (forests, croplands, wetlands) instead of all land, thus increasing interpretability as well as control over the outputs. The concept of having different allocations in the same problem formulation is commonly known as 'zoning' and has been popularized by Marxan (Watts *et al.* 2009).

The prioritizr website contains an excellent tutorial about how different (management) zones can be added to a planning problem, thus we will only cover the essentials here using the testing data that comes with the training course.

For demonstration purposes we focus on the Alpine region for these examples. You can obtain a shapefile of their outline here.

We consider a situation in which we have limited resources (financially or logistically) and would like to identify different priorities for areas with low or with high human modification. To do so we effectively separate our study region into low and high modified management zone.

Targets can be specified per zone individually, but in the solution each PU needs to be allocated to one of the zones or not be selected at all.

```
# Prepare the various layers we use here
alps <- sf::st_read('extdata/boundary_alps/AlpineConvention.shp') |>
  sf::st_transform(crs = sf::st_crs(4326))

hmi <- rast("extdata/gHM.tif") |> terra::crop(alps) |> terra::mask(alps)
ndvi <- rast("extdata/ndvi.tif") |> terra::crop(alps) |> terra::mask(alps)
pa <- rast("extdata/protectedareas.tif") |> terra::crop(alps) |> terra::mask(alps)
PU <- PU |> terra::crop(alps) |> terra::mask(alps)
spp <- spp |> terra::crop(alps) |> terra::mask(alps)
```

```r
# Budget total of 30% totally
barea <- terra::global(PU,"sum",na.rm=TRUE)[,1]*0.3

# Respecify targets equal to the number of features
tr <- matrix(nrow = terra::nlyr(spp),ncol = 2)
tr[,1] <- 0.3 # Low use zone target
tr[,2] <- 0.1 # High used zone target

tr[c(10,20,30,40,50),2] <- 0                                          (1)
tr[c(1,2,3,4,5),1] <- 1                                               (2)

# create problem
p <- problem(c(PU,PU),                                                (3)
             zones(                                                   (4)
               "low_hmi" = spp,
               "high_hmi" = spp*hmi)                                  (5)
             ) |>
  add_max_features_objective(budget = barea) |>
  add_relative_targets(targets = tr) |>
  add_binary_decisions() |>
  add_default_solver()

s0 <- solve(p)
s0p <- category_layer(s0) |> as.factor()                              (6)
levels(s0p) <- c("not selected", "low_hmi", "high_hmi")
```

(1) Some features in the highly used zone might also not receive any benefit at all
(2) While for others in the low-used zone we aim to conserve as much as possible (target= 100%)
(3) The same PU layer is used. This could also be separated by zones with different costs.
(4) Here we specify the feature (amount) contributing to each zone.
(5) Note that for highly modified zone we reduce the amount of suitable habitat by the amount of modified land.
(6) To display the multi-zone layer as a single categorical raster.

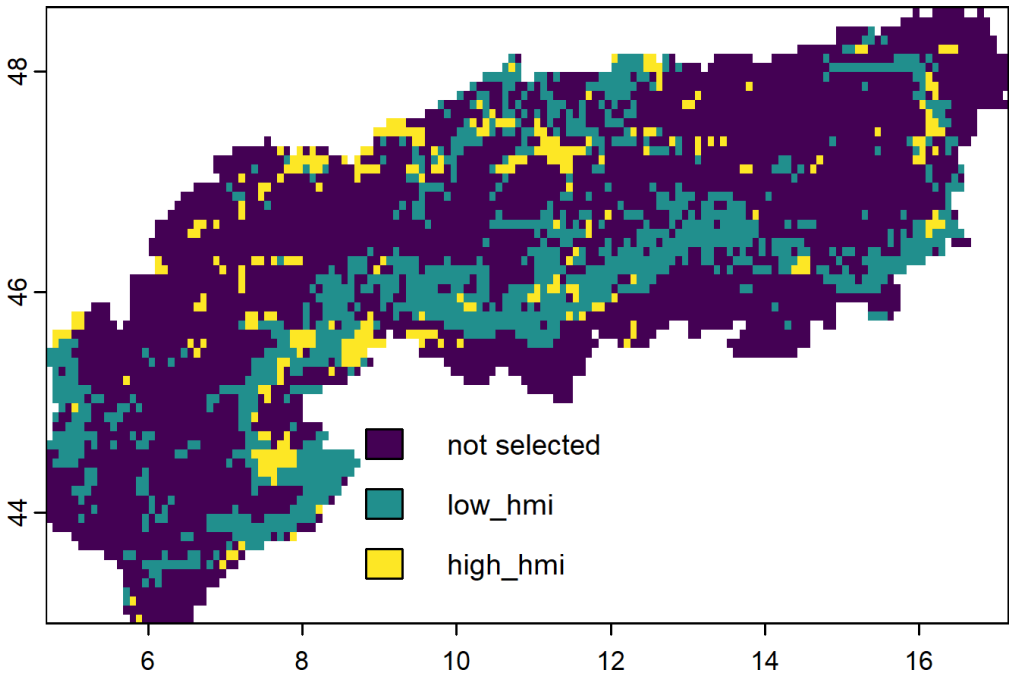


Figure 9.1: Selected features per zone

What do we achieve with each zone? Here we can calculate the representation by zone in terms of the absolute held amount (related also to the total or zone amount of area).

```
reps <- eval_feature_representation_summary(p, s0)

# Apparently some species benefit more than others from co-benefits (distribution covered be
ggplot(reps,
       aes(x = feature, y= absolute_held, fill= summary)) +
  geom_bar(stat = "identity") +
  facet_wrap(~summary)
```

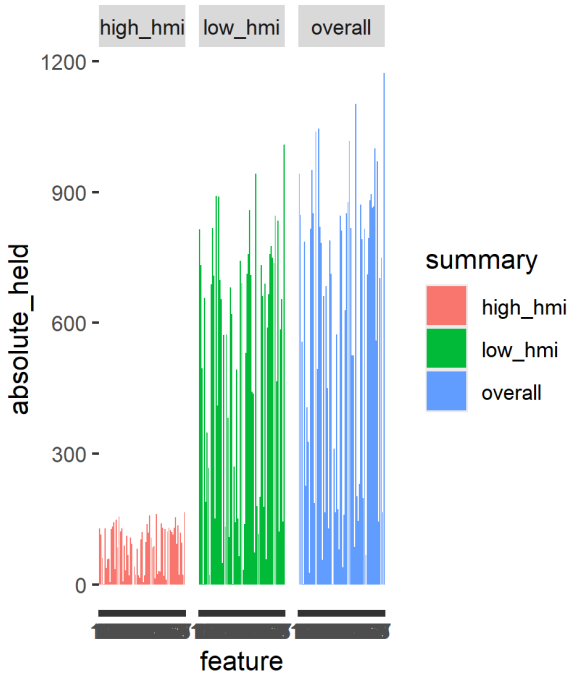


Figure 9.2: Relative amount held overall and per zone

9.1 Zoning for PA expansion and green infrastructure.

Finally, Let's think of a another example where the aim is to expand the current protected area network, while conserving as much biodiversity and green infrastructure as possible. We again define 2 management zones, one for current protected areas and expansions thereof and one for the remaining land (green infrastructure).

```
# Make a manual bounded constraint data.frame to account for
# fractional shares of current protected areas
mcon <- data.frame(pu = c( terra::cells(PU), terra::cells(PU) ),
                   zone = c(
                     rep("protected_area", length(terra::cells(PU))),
                     rep("gi", length(terra::cells(PU)))
                   ),
                   lower = 0, upper = 1
```

```
)
# Respecify the lower and upper amount of area
mcon$lower[mcon$zone=="protected_area"] <- terra::values(pa, dataframe=T) |> tidyr::drop_na(

# Budget total of 30% totally for the PA zone, 100% for the rest
barea <- c(
  terra::global(PU,"sum",na.rm=TRUE)[,1] * .3,
  terra::global(hmi,"sum",na.rm=T)[,1]
)

# Respecify targets
tr <- matrix(nrow = terra::nlyr(spp)+1, ncol = 2)                    ①
tr[,1] <- 0.3 # Protected area zone flat target
tr[,2] <- 1   # Green infrastructure zone, everything goes
tr[nrow(tr),1] <- 0                                                  ②

# create problem
p <- problem(c(PU,PU),
             zones(
               "protected_area" = c(spp,ndvi),                       ③
               "gi" = c(spp*hmi,ndvi)
             )
             ) |>
  add_min_shortfall_objective(budget = barea) |>
  add_manual_bounded_constraints(data = mcon) |>
  add_relative_targets(targets = tr) |>
  add_proportion_decisions() |>
  add_default_solver()

# Solve
s <- solve(p)

plot(s)
```

① Note the addition plus one here for the greenness layer.
② This specifies a target of 0 for NDVI and the protected area zone, thus no benefits can be gained here
③ Note the addition of NDVI to the features. Also a simple discounting of modified land for the species features

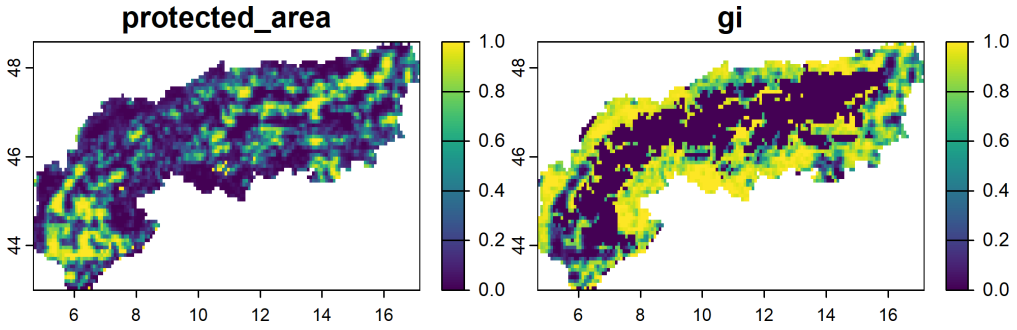


Figure 9.3: Expanding protected areas to 30% and the remainder to Green infrastructure

This solutions expands from the currently protected land in the alps (29%) to (30%). Obviously not much but this also demonstrates that often the level of policy ambition - when focussing on area alone - can be relatively modest. Although in practice even small expansions can be quite challenging in implementation.

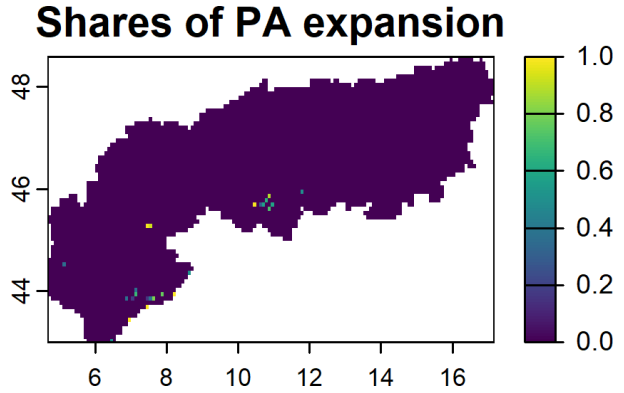


Figure 9.4: Subset of shares that increase from current protected areas

Note that a very similar and more elegant way can be to use linear constraints (add_linear_constraints()) applied per zone to limit the allocation of area per zone.

Glossary

Table 9.1: A glossary of key terms used in this Training course

Term	Abbreviation if any	Definition
Boundary Length Modifier	BLM	A penalty constant added to a conservation problem that penalizes selecting isolated patches. Results in overall more compact solutions.
CARE	CARE	A often used abbreviation that stands for ***C****onnectivity*, ***A****dequacy*, ***R****epresentation*, and ***E****ffectiveness* which key principles that should be considered when designing a conservation network. See the Marxan website for more information.
Conservation Prioritization		The computational process of identifying (spatial) priorities for a given conservation objective (such as for identifying protected areas). Usually comes in in the form of a map.
Constrain		A (often linear) constant or parameter that limits the selection of certain PU as part of the solution.
Integer		In programmatic terms a full number (e.g. -1, 1, 2, 3, …)
Integer Linear Programming	ILP	Mathematical problem formulation using Linear Programming (ILP) where the variables are integer values and the objective function and equations are linear.
Penalty	p	In the context of SCP commonly referring to a constant parameter used to penalize solutions. For example a costing or connectivity matrix.
Planning unit	PU	The fundamental unit at which decisions in SCP are realized. Can be of multiple formats such as grid cells or farms

Term	Abbreviation if any	Definition
Systematic Conservation Planning	SCP	A framework and step-wise approach towards mapping conservation areas. Usually involves multiple steps such as the identification of a problem and the theory of change, data collection and preparation, conservation prioritization, evaluation and finally implementation. See Margules & Pressey (2000)

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A Installation of all required software

Opposed to other conservation planning software (e.g. Zonation 5) using prioritizr requires prior knowledge on how to use **R**.

A.1 Install R

R is a programming language and environment specifically designed for statistical computing and graphics. It is widely used among statisticians and data analysts for its extensive capabilities in data manipulation, statistical modelling, and graphical representation.

To install R, please go to the following website, then:

1. Click on the link at the top for your respective operating system
2. Recommended is the **base** version of R particular for new users. Select the latest version 4.4, download and execute.
3. Follow the instructions in the installation popup.

> ℹ Although older R-versions can work as well (e.g. R 4.3), we recommend the latest version with which the training materials have been tested.

In addition, we also recommend the installation of **RTools** on the same website (here for example for Windows). RTools contains a range of code compilation software, such as a C++ compiler. These software are often necessary to install additional R-packages, particular when they are not available in binary format.

To download RTools, click the "Rtools44 installer" link, download and execute and follow the instructions.

A.2 Install a IDE such as Rstudio

By default R is terminal based, meaning inputs are parsed as entered. To create reproducible scripts we recommend the use of an integrated development environment (IDE) and here in particular Rstudio. Of course other alternative IDEs can also be used such as for example Visual Code. It is free to use in its basic version and available for most operating systems, including Windows 10/11, Linux and MacOS distributions.

To download and install Rstudio follow the instructions on this website.

A.3 Install a solver in R

To use prioritizr and solve a conservation problem, we require a solver. Solvers are specialized algorithms or software designed to find the best solution (or an optimal solution) to a mathematical problem that involves maximizing or minimizing a particular function subject to certain constraints. For different mathematical problems, for example linear or mixed programming, different solvers are often necessary or perform better.

Many state-of-the-art solvers are proprietary and often used by large companies to solve problems related to supply chain or financial risk managements. Although freely available and open-source solver slowly catch up, they usually cannot compete with proprietary such as Gurobi or CPLEX. For a comprehensive overview of different available and supported solvers a detailed vignette can be found on the prioritizr website.

For new users we recommend the use of the *HiGHS* solver, which is free to use and can be installed across a range of operating systems. To enable it run the following code and make sure it runs through without issues.

```
install.packages("highs")
```

If for some reason the installation of he package fails, another option could be the *cbc* solver, which can currently only be installed directly from the developers Github repository. For this to work you likely need to have RTools installed (see A.1 above).

```
if (!require(remotes)) install.packages("remotes")
remotes::install_github("dirkschumacher/rcbc")
```

Gurobi

The Gurobi solver is among the fastest supported ones for prioritizr. Unfortunately it is not openly available and purchasing it can be quite costly. However for academic users (those with an academic email) and researchers it is possible to obtain a time-limited (usually 12 months) license for research projects. This License can also be renewed. For further information see the installation vignette on the prioritizr homepage!

A.4 Install required R packages

In addition to the R and the solver packages above, we need to install several packages related to (spatial) data handling. These include for example *dplyr*, *terra* and sf, but also *ggplot2* for plotting.

To install please run the following code in your R terminal:

```
install.packages("dplyr")
install.packages("terra")
install.packages("sf")
install.packages("ggplot2")
install.packages("tidyterra")
```

Make sure that every line executes without an error. If you see an error, check first online for potential solutions (google) and afterwards get in touch with the course organizers.

B Frequently asked questions (FAQ)

On this page we list some answers to possible issues or problems encountered when running. See the sub headers for more information.

> **Note**
>
> This page will be updated during the day in case new issues are discovered. In case any issue can not be answered by the information on this site, please get in touch with the course organizers (Martin or Louise).

B.1 I don't understand the outputs

If you can not interpret the outputs based on the course materials and instructions, please see the help pages of the function (enter ??command in the R console or F1 on your keyboard).

The Prioritizr homepage can also be a quite valuable resource for looking up parameters and instructions. If nothing else, get in touch with the coordinators!

B.2 I can't install any software

To install R, RStudio and often also R-packages on any Computer (Windows/Linux/MacOS) usually requires adminstrator (or *sudo*) rights.

If you are not able at all to install any or all of the software listed in the installation instructions (@sec-installation), please **get in touch with the course organizers** and we will try our best to find a way forward!

B.3 My Computer is freezing

Solving particular large conservation planning problems can take quite some computational resources. This becomes especially an issue with larger conservation problems, for example when planning over larger area or more highly resolved planning units (*i.e.* spatial scale).

By solving your planning problem the entire dataset can be bigger than you might anticipate (Number of features times number of planning units times number of constraints) and needs to be processed as a whole. Because of this the amount of memory available on your operating system is usually the limitation. For example, in a global prioritization effort done with ~10km planning units ((Jung *et al.* 2021)), at least 140GB of RAM (Computer memory) was needed to solve the conservation problems.

If - during the solving - your computer suddenly starts to freeze, then you likely don't have enough computational resources to solve the problem formulation. In this case I would recommend to subset the features and PU to a smaller extent, for example using the outline of the Alps from here.

Then subset as follows:

```
alps <- sf::st_read("layer")
layer |> terra::crop(alps) |> terra::mask(alps)
```

B.4 Solving the problem takes too long

Other than using a faster solver or simplifying the problem (see also suggestion above), there are few options available directly with the solver:

- (Parameter gap in the solver) Increase the gap (Default is 0.1) to a larger estimate. This can result in suboptimal but still feasible solutions which are usually very close.
- (Parameter time_limit in the solver) Increasing this number caps the computation time. Units are in seconds.
- (Parameter first_feasible in the solver) Setting this to TRUE makes the solver return the first feasible solution, which might not be optimal one, but is usually quite close.