

NeutralLandscapes.jl: a library for efficient generation of neutral landscapes with temporal change

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Soon to be a paper, maybe. TK authors, MKB,VB,RS,TP

1 Introduction

- 2 • what are neutral landscapes

3 Neutral landscapes are increasingly used in ecological and evolutionary studies to provide a null
4 expectation spatial variation of some measurement.

5 Different properties of landscapes (elevation, land cover, temperature) vary across space in non-random
6 ways. Tobler's law of geography: "everything is related to everything else, but near things are more related
7 than distant things"

8 Originally based around methods for simulating spatially auto-correlated data (Gardner *et al.* 1987; Milne
9 1992).

10 they have seen use in a wide range of fields in ecology and evolution: from landscape genetics (Storfer *et al.*
11 2007), to spatial ecology (Tinker *et al.* 2004; Remmel & Fortin 2013), and biogeography (Albert *et al.* 2017).

12 The two most popular libraries used to generate neutral landscapes are NLMR in (the R language) (Sciaini *et*
13 *al.* 2018) and NLMpy (in Python; Etherington *et al.* 2015). Here we present `NeutralLandscapes.jl`, a new
14 package for neutral landscape simulation in the Julia language. So, why create another package?

15 Here we demonstrate that `NeutralLandscapes.jl` is orders of magnitude faster than previous neutral
16 landscape packages.

17 In addition, `NeutralLandscapes.jl` implements several novel methods for simulating environmental
18 change with temporal variation. As biodiversity science becomes increasingly concerned with temporal
19 change and its consequences, its clear there is a gap in methodology in generating neutral landscapes that
20 change over time. Our model allows users to simulate time-series of any `NeutralLandscape` layer, and
21 which can produce an arbitrary distribution of change across every spatial cell, with provided levels of
22 spatial and temporal autocorrelation.

23 Software Overview

24 This software can generate neutral landscapes using several methods, enables masking and works with
25 other julia packages.

26 fig. 1 shows a replica of Figure 1 from Etherington *et al.* (2015), which shows the capacity of the library to
27 generate different types of neutral landscapes, and then apply masks and categorical classification to them.

28 [Figure 1 about here.]

29 Further, NL.jl provides methods for interacting with other julia packages, and functions for rescaling

30 **Interoperability**

31 Ease of use with other julia packages

32 Mask of neutral variable masked across quebec in 3 lines.

```
33 using NeutralLandscapes
34 using SimpleSDMLayers
35
36 quebec = SimpleSDMPredictor(WorldClim, BioClim; left=-90., right=-50., top=75., bottom=40.)
37 qcmask = fill(true, size(quebec))                # ----- TODO
38 qcmask[findall(isnothing, quebec.grid)] .= false  # should both of these lines be possible only using mas
39
40 pltsettings = (cbar=:none, frame=:box)
41
42 plot(
43     heatmap(rand(MidpointDisplacement(0.8), size(layer), mask=qcmask); pltsettings),
44     heatmap(rand(PlanarGradient(), size(layer), mask=qcmask); pltsettings),
45     heatmap(rand(PerlinNoise((4,4)), size(layer), mask=qcmask); pltsettings),
46     heatmap(rand(NearestNeighborCluster(0.5), size(layer), mask=qcmask); pltsettings),
47     dpi=400
48 )
```

49 [Figure 2 about here.]

50 **Rescaling to mimic real data**

51 Figure: Real temp (left) / Rescaled NL (right) , same unit bar

52 **Generating dynamic neutral landscapes**

53 We implement methods for generating change that are temporally autocorrelated,
54 spatially-autocorrelated, or both.

55
$$M_t = M_{t-1} + f(M(t-1))$$

56 **Models of change**

57 Two types of temporal change: (1) null change, where there is random variation in each cell across time but
58 the mean value across all cells stays constant (with some variation around this constant due to
59 randomness in change generation)

60 **Null**

61 Take an arbitrary distribution (from `Distributions.jl`) and set its mean value to 0, and apply draws from
62 that distribution to each cell at each timestep.

63 **Directional**

64 Can take an arbitrary distribution of values and set its expected-value to be the primary input into a
65 change model—the mean amount of change at each timestep. This can also be parameterized to be a
66 variable list of mean change at each corresponding timestep.

67 **Temporally autocorrelation** We generate temporally autocorrelated change using the method. We
68 take an arbitrary distribution A

69 r : rate, v : variability, U matrix of draws from standard Normal(0, 1). Here v reflects the amount of
70 temporal autocorrelation.

71 The value of a given cell (i, j) with value M_{ij}

$$M_{ij}(t + 1) = f_T(M_{ij}(t)) = r + vA_{ij}$$

72 Results in an expected value of change of r per timestep with variance v .

73 **Spatial autocorrelation** Generate a matrix δ with a NL generator.

74 r : rate, v : variability, $[Z(\delta)]_{ij}$: the (i, j) entry of the z-score of the δ matrix

75 Z-score is arbitrary and can be replaced with any dist.

76 $f_S(M_{ij}) = r + v \cdot [Z(\delta)]_{ij}$

77 **Spatiotemporal autocorrelation** Finally, to implement change this is both spatially and temporally

78 autocorrelated

79 $f_{ST}(M_{ij}) = r + v \cdot [Z(\delta)]_{ij}$

80 [Figure 3 about here.]

81 **Benchmark comparison to nlmpy and NLMR**

82 It's fast. As the scale and resolution of raster data increases, neutral models must be able to scale to match
83 those data dimensions.

84 [Figure 4 about here.]

85 How many lines of code, and what language is that code in for each pkg? NLMR contains 893 lines of R, and
86 376+51 lines of C++. nlmpy contains 386 lines of python. Julia contains 664 lines of (non-test) julia.
87 Note these numbers refer only to lines of code and not comments.

88 **Example: fitting a neutral landscape to an empirical spatial dataset using** 89 **generative modeling**

90 Here we use approximate bayesian computation to estimate the parameter of autocorrelation H for an
91 empirical raster of temperature data.

92 Why? What if we are interested in differentiating the processes that occur in this *real* landscape versus
93 landscapes with *similar statistical properties*.

94 We take a raster of mean temp around the st lawrence lowlands in QC, and use ABC to estimate the value
95 of H under the midpoint-displacement model.

96 We use the variogram as the loss function

97 [Figure 5 about here.]

98 **Discussion**

99 Why is it good that we've made this a faster thing to do? Why are models of temporal change necessary?

100 What can simulation do for spatial ecology more generally?

101 What are questions we can address with NL.jl that was not possible before?

102 **References**

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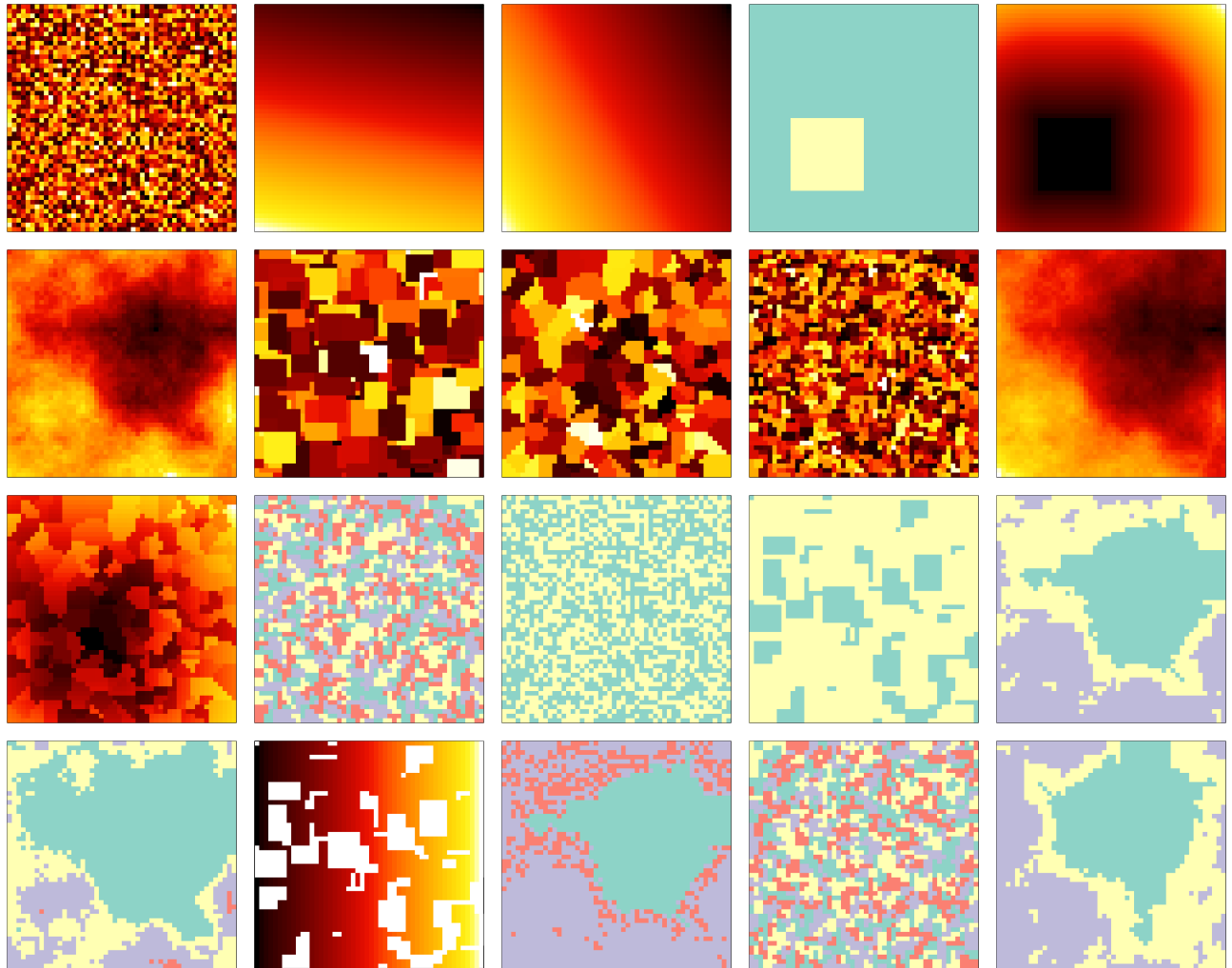


Figure 1: Recreation of the figure in `n1mpy` paper and the source, supplied in less than 40 lines of code.

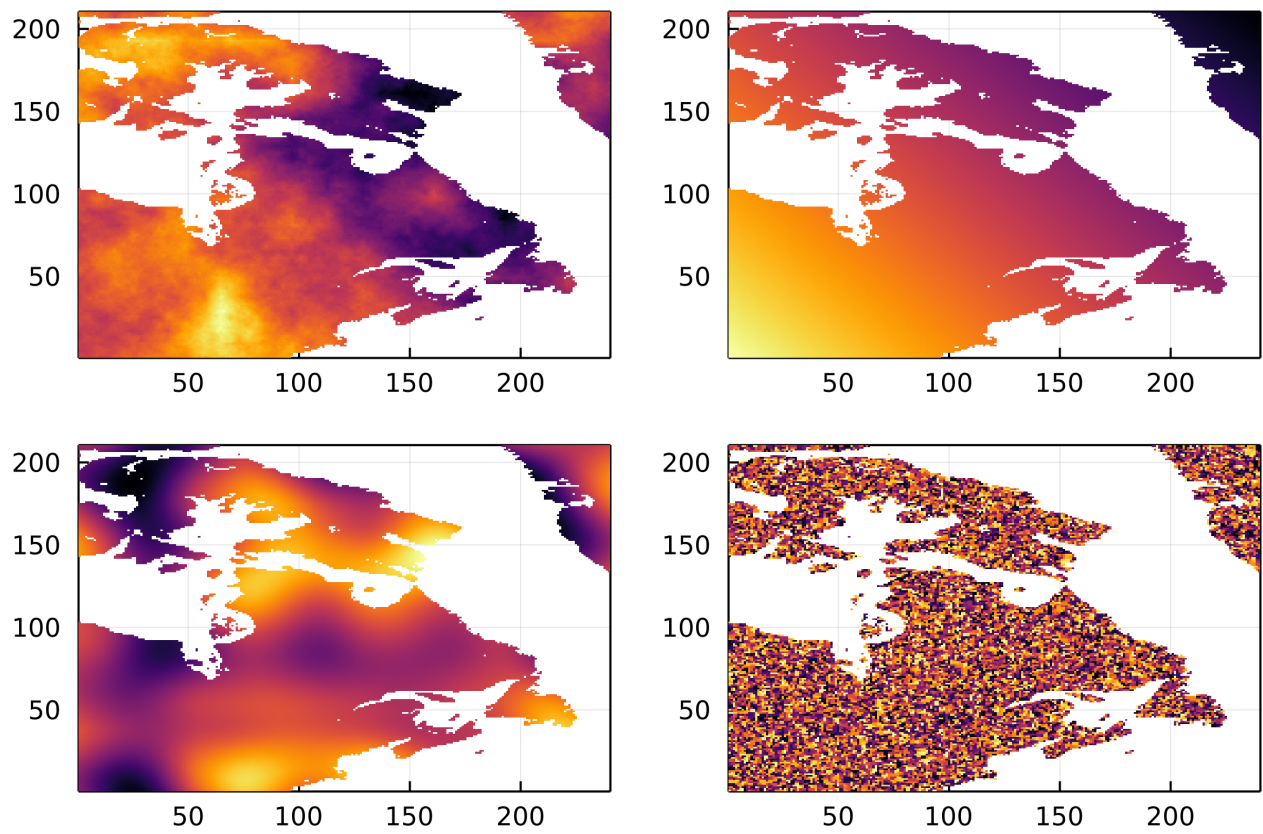


Figure 2: todo

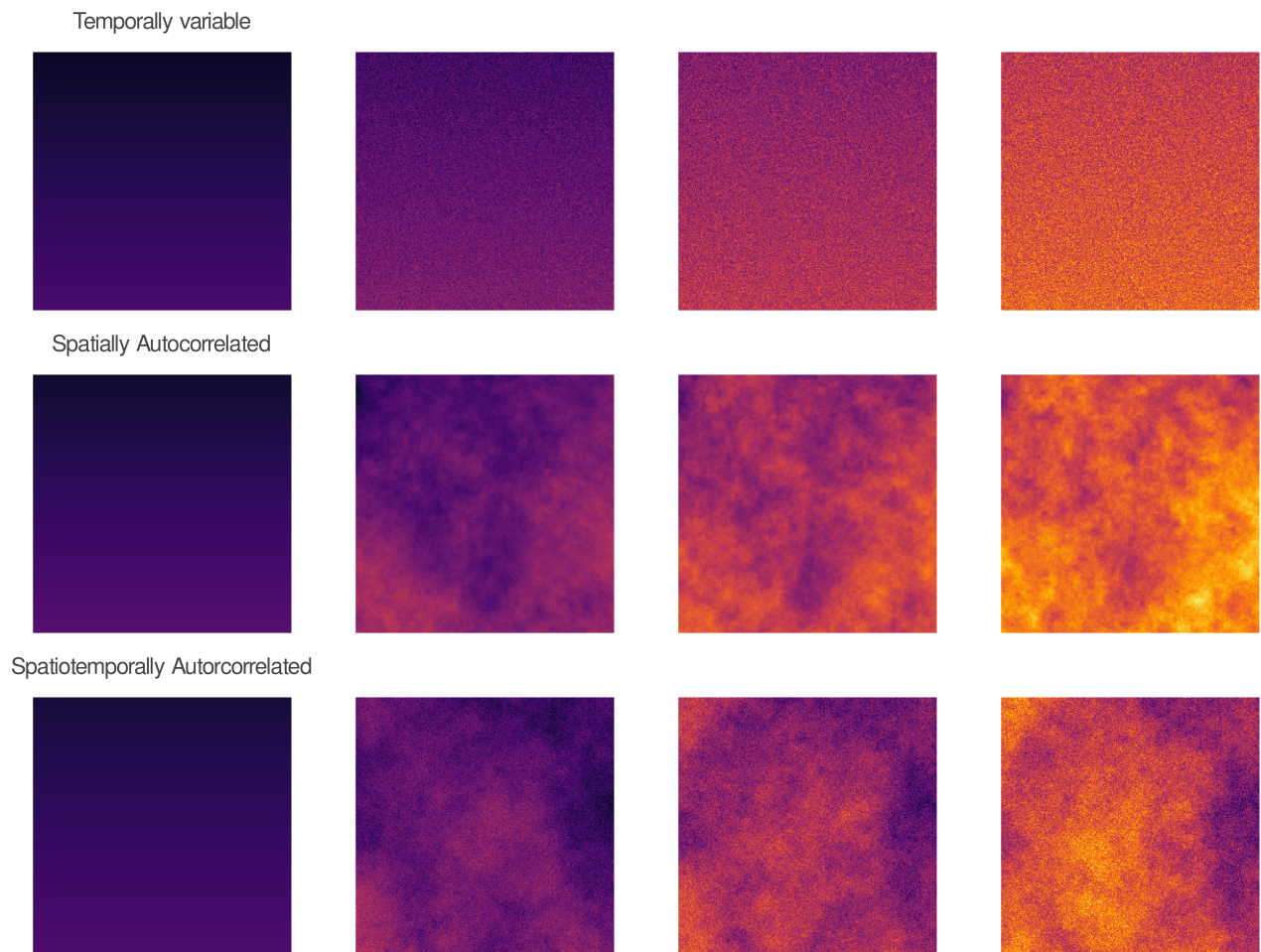


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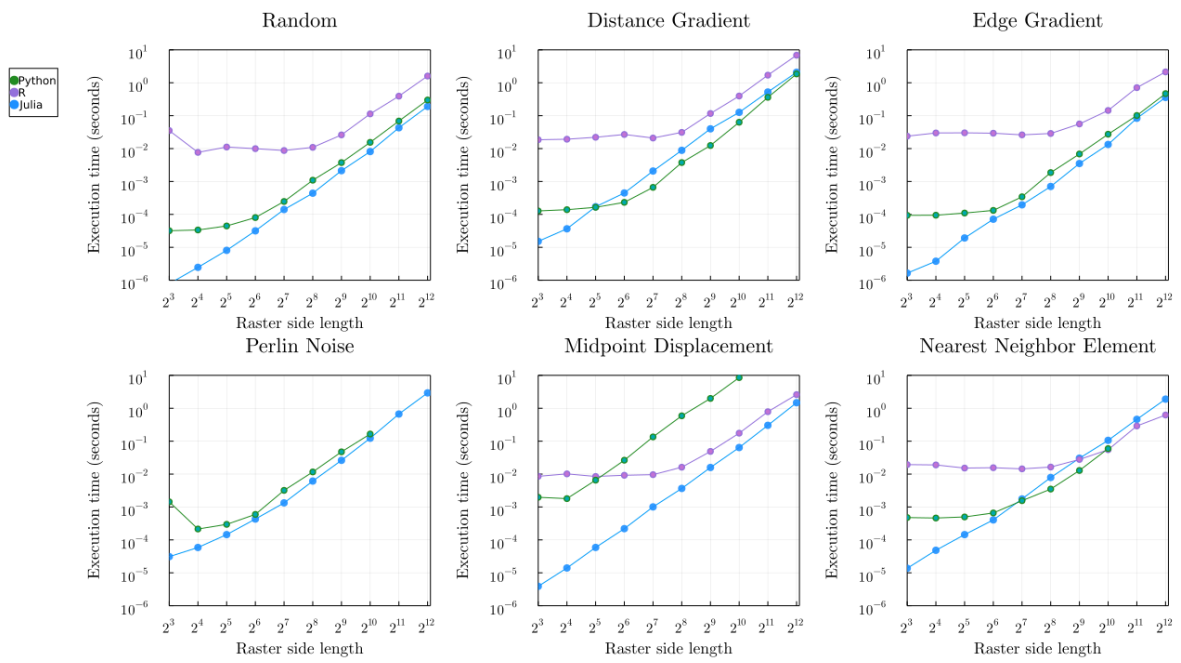


Figure 4: todo

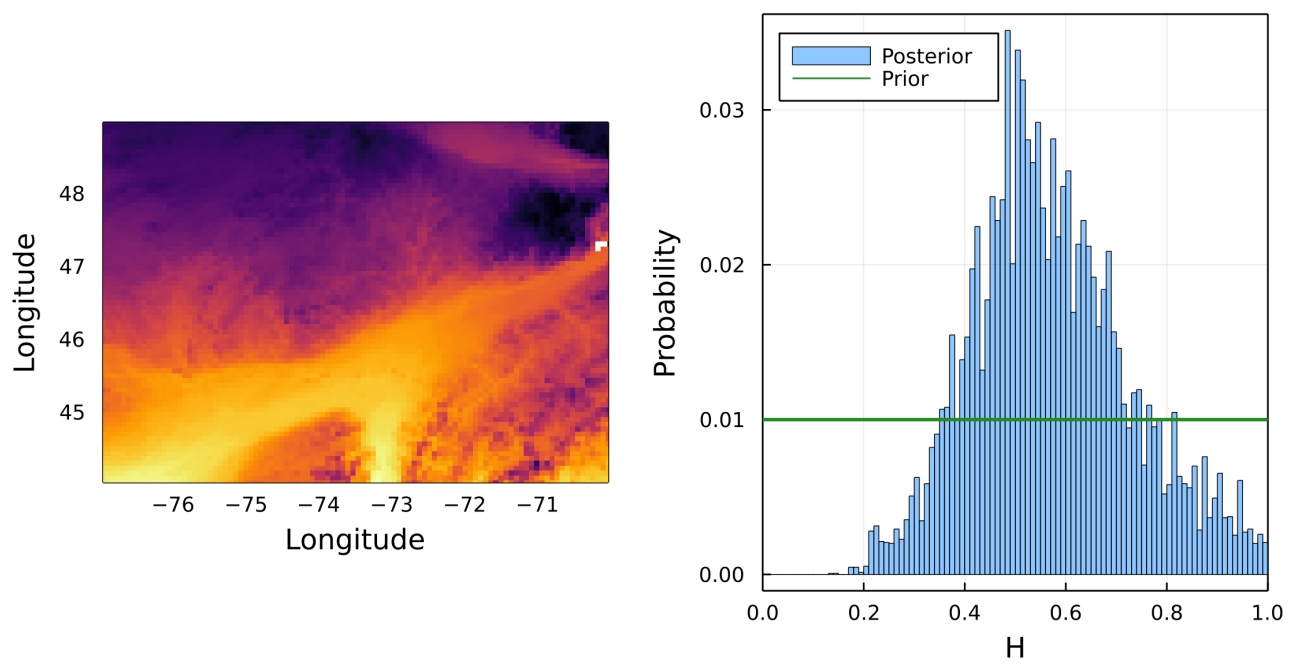


Figure 5: todo