1 Introduction

Many ecosystems respond linearly and smoothly to environmental drivers. However, in many other cases the response can be fast and abrubt, even following a tiny perturbation (?). Of course, these transitions can have dramatic consequences for populations depending on the ecosystem at hand.

For example, shallow lakes are a well-known case of such a transition. These lakes can stay in a clear water state up to a certain threshold value of nutrient input. Once this threshold is reached, the lake becomes rapidly turbid, with opaque and less-oxygenated waters, even if the added amount of nutrient was small. Ecological models and experiments on lakes suggest that these transitions are related to the presence of a bifurcation point, at which the stable equilibria of an ecosystem change abruptly. Shallow lakes can exhibit multiple stable states for a range of nutrient input (alternative stable states). As the nutrient threshold is crossed, the clearwater state becomes unstable and the lake becomes turbid.

Due to the inherent complexity of ecosystems, it remains unclear how general this state-and-shift behavior is nature, and pinpointing the exact points at which shifts happen remains difficult. However, theoretical work on ecological models suggests that some ecosystem properties could be used to identify and anticipate those transitions, despite a lack of complete understanding of its behavior.

For example, as an ecosystem approaches a bifurcation point where a transition occurs, it is expected to ”slow-down”, that is, take more time to recover from perturbations. A population of a given species close to a threshold could take more time to recover from the loss of a fraction of individuals, when compared to the same population far from a threshold. These properties are expected to yield a specific signature on their temporal and spatial dynamics. For example, systems close to thresholds should exhibit higher variance, skewness and spatial autocorrelation.

These ”early-warning” signals have gathered much attention in the past years. The challenge ahead relies in knowing how general these type of transitions are and how preciselypkg we can identify thresholds. One way forward is to generalize the use of these early-warning signals by making them available so that a wider audience can contribute to this effort. To this end, we developed the `R` package `*spatialwarnings* which goal is to facilitate the computation of spatial indicators and assess their significance. This package contains a set of functions that can be readily applied on spatial raster datasets such as aerial imagery.`

An early-warning signals workflow

`Many indicators have been used to detect ecological transtions, but not every indicator is applicable to any dataset. To ensure that the computed indicator reflects the distance to a transition point, one must make sure the spatial patterns are not blurred by other processes. ? provides a guiding workflow to carry out a relevant analyses in` spatially-structured ecosystems. We recall its main lines in the following paragraph but the reader is kindly advised to refer to their publication for further discussion.

Based mostly on research done in semi-arid ecosystems, two types of pre-transition patterns can be contrasted. For ecosystems that show periodic patterns, authors have suggested that the shape of the patterns (patches, bands, etc.) could be used as an indicator of transition (?). Ecosystems that do not show these patterns require other indicators such as a monitoring of summary statistics (e.g. variance) and/or patch-size distributions (?). Usually, deciding whether an ecosystem responds in a periodic or aperiodic way is straightfoward to detect visually on aerial images. However, a metric-based approach can be used by computing the radial spectrum of the dataset to estimate whether a dominant periodic scale emerges (see Section. 2.2).

The *spatialwarnings* package works with raster data as represented by a matrix object. To read common image files, we recommend the user image-reading functions provided by packages *png* (function readPNG) or *jpeg* (function readJPEG). Non-raster spatial datasets need to be converted first through (e.g.) interpolation in order to compute indicators.

The functions in the package are divided into several "tasks", each one corresponding to the computation, the display and the assessment of a small family of indicators. Each of those tasks is essentially divided into three steps:

1. Use the task function to compute the indicator values. All task functions have the suffix _spews (as in SPatial Early-Warning Signals) to make their role apparent.

2. Assess the significance of these indicators using the indictest generic function on the returned object

3. Review the results by calling the print() and plot() methods on the object returned by indictest

The following sections the rationale behind each task and how they can be performed using the package *spatialwarnings*, for non-periodic and periodic spatial patterns.

2 Indicators for non-periodic patterns

2.1 Generic indicators

Any dynamical system approaching a transition point exhibits a phenomenon called Critical Slowing Down (CSD) (?). This means that for a given perturbation, a system will take more time to recover when close to a threshold than far from a threshold. As a result, it will depart further from its equilibrium (higher variance), have a stronger temporal autocorrelation and exhibit a higher skewness. Since these indicators only depend on simple properties of dynamical systems, they can, in principle, exist in many different systems, hence the adjective "Generic" (?).

This family of indicators can be computed using the generic_spews function. We work out an example below using data obtained from an ecological model of forest gaps dynamics (?). This model is a cellular automaton with three parameters, α, δ and d.

The forestdat dataset included with the package is the result of ten simulations with different values of δ. It is a list of two components. The component parameters is a data frame containing the parameters used for ten the simulations. The component matrices is a list of ten boolean matrices representing a snapshot of the state of the cellular automaton around equilibrium (whether the cell is occupied by trees or not).

```
R>   data(forestdat)
R>   str(matrices)
```

```
List of 10
 $ : logi [1:100, 1:100] TRUE TRUE TRUE TRUE TRUE TRUE ...
  ..- attr(*, "class")= chr [1:2] "binary_matrix" "matrix"
 $ : logi [1:100, 1:100] TRUE TRUE TRUE TRUE TRUE TRUE ...
  ..- attr(*, "class")= chr [1:2] "binary_matrix" "matrix"
[...]
  ..- attr(*, "class")= chr [1:2] "binary_matrix" "matrix"
 $ : logi [1:100, 1:100] FALSE TRUE TRUE TRUE FALSE FALSE ...
```

```
R>   head(forestdat$parameters)
```

```
  simu alpha      delta    d
1    1   0.2 0.00000000 0.01
2    2   0.2 0.02222222 0.01
3    3   0.2 0.04444444 0.01
4    4   0.2 0.06666667 0.01
5    5   0.2 0.08888889 0.01
6    6   0.2 0.11111111 0.01
```

Given the parameters, the model is known to exhibit a transition for a value of delta close but superior to 0.2. Let's compute the generic spatial indicators and display the result:

```
R>   gen_indic <- generic_spews(forestdat$matrices)
R>   summary(gen_indic)
```

```
Generic Spatial Early-Warnings
```

```
 10 matrices (size: 100x100)

 Mat. #  Mean Moran's I Skewness Variance
      1 0.947   0.00265   -0.987  0.00340
      2 0.945   0.02904   -1.057  0.00348
      3 0.938   0.04076   -0.876  0.00389
      4 0.925   0.06376   -1.064  0.00577
      5 0.916   0.06873   -0.980  0.00636
      6 0.900   0.10533   -0.804  0.00725
      7 0.887   0.11271   -0.905  0.00955
      8 0.847   0.13693   -0.766  0.01265
      9 0.799   0.16556   -0.669  0.01779
     10 0.667   0.17228   -0.346  0.02616

Use as.data.frame() to retrieve values in a convenient form
```

The next step is to assess the significance of the indicator values. This is done by calling the indictest generic:

```
R>   gen_test <- indictest(gen_indic)
R>   print(gen_test)
```

```
Generic Spatial Early-Warnings

 Mat. #  Mean Moran's I P>null     Skewness P>null     Variance
      1 0.947   0.00265  0.328       -0.987  0.524      0.00340
      2 0.945   0.02904  0.000 ***   -1.057  0.806      0.00348
      3 0.938   0.04076  0.000 ***   -0.876  0.479      0.00389
      4 0.925   0.06376  0.000 ***   -1.064  0.990      0.00577
      5 0.916   0.06873  0.000 ***   -0.980  0.973      0.00636
      6 0.900   0.10533  0.000 ***   -0.804  0.923      0.00725
      7 0.887   0.11271  0.000 ***   -0.905  0.996      0.00955
      8 0.847   0.13693  0.000 ***   -0.766  0.997      0.01265
      9 0.799   0.16556  0.000 ***   -0.669  0.999      0.01779
     10 0.667   0.17228  0.000 ***   -0.346  0.971      0.02616
 P>null
  0.072 .
  0.108
  0.097 .
  0.000 ***
  0.000 ***
  0.000 ***
  0.000 ***
  0.000 ***
  0.000 ***
  0.000 ***
```

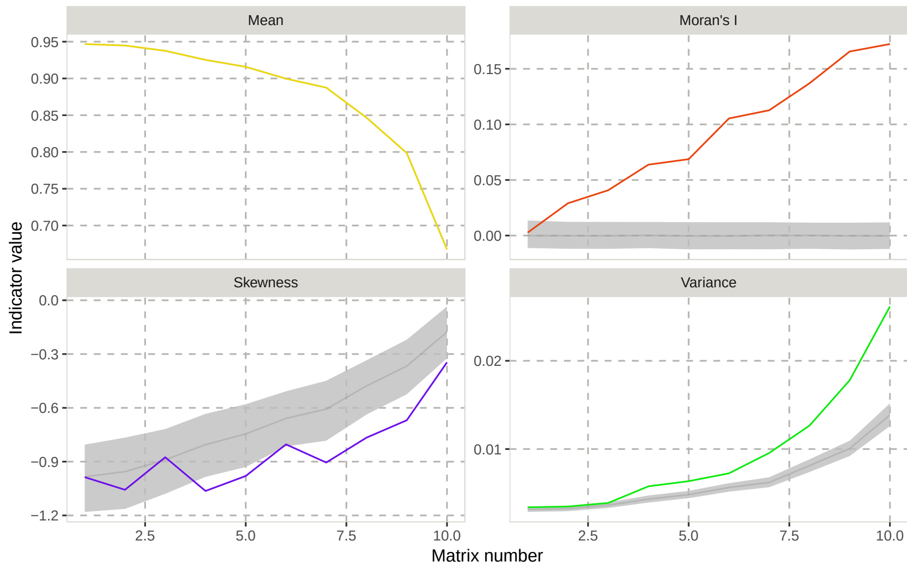

Figure 1: Generic indicator values for Kubo's forest-gap model. The line shows the trend and the grey enveloppe the 5% and 95% quantiles of the null distribution.

```
Significance tested against 999 randomly shuffled matrices
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

This object can then by plotted to display the indicator trends with the obtained null distribution: Fig. 1.

2.2 Spectral indicators

2.3 Patch-based indicators

3 Using the package: additional remarks

3.1 Leveraging on plyr's abilities

3.1.1 Progress report

3.1.2 Parallel processing

Acknowledgments

References