Ability of spatial indicators to detect geographic changes (shift, shrink and split) across biomass levels and sample sizes

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Running title:

Indicators and geographic changes

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Abstract

Spatial indicators are widely used to monitor species and are essential to management and conservation. In the present study, we tested the ability of 11 spatial indicators to quantify changes in species' geographic patterns: (1) spatial displacement of a patch of biomass ('shift'), (2) a spatial decrease in a patch, accompanied either by a loss of biomass ('shrink0') or (3) a relocation of the same biomass ('shrink1'), and (4) splitting of a patch into smaller patches ('split'). The geographic changes were simulated by manipulating the spatial distributions of the demersal species (observed during bottom trawl surveys). Hence, the spatial distributions of the latter being used as input data on which the manipulations were done. Additionally, other aspects of the indicators affecting the responses to the geographic changes were also tested, (1) homogeneous increase in biomass throughout the patch and (2) different sample sizes.

The center of gravity (defined by latitude and longitude) was the only indicator that accurately detected the 'shift' in biomass. The index of aggregation identified a decrease in the area and biomass of the main biomass patch ('shrink0'), while the Gini index, equality area and spreading area were accurately identified a decrease in the area of the main biomass patch when total biomass did not decreased ('Shrink1'). Inertia and isotropy responded to all geographic changes, except for those in biomass or distribution area. None of the indicators successfully identified 'split' process. Likewise, one of the indicators were sensitive to a homogeneous increase in biomass or the type of spatial distribution. Overall, all indicators behaved similarly well when sample sizes exceeded 40 stations randomly located in the area. The framework developed provides an accessible and simple approach that can be used to evaluate the ability of spatial indicators to identify geographic processes using empirical data and can be extended to other indicators or geographic processes. We discuss perspectives of the development of spatial indicators especially within the application of EU's Marine Strategy Framework Directive.

Keywords: spatial metrics; monitoring; marine conservation; fisheries management;

1. Introduction

All life in Earth is both product and contributor to its place in space and time (David Attenborough, launch of 'Our Planet', 2019). Spatial indicators have been developed to represent and summarize species spatial patterns and their dynamics. They are often used in management (e.g. assess the state of species and ecosystems) (Bock et al., 2005; Greenstreet et al., 2012; Modica et al., 2016; Piet and Jennings, 2005; Rochet and Trenkel, 2009), and in ecology (e.g. to understand a species' relationship with its environment, in face of habitat and climate change (Persohn et al., 2009; Yalcin and Leroux, 2017). Thus, the ability of indicators to identify an underlying geographic process accurately is crucial for their appropriate use in practical situations.

Selecting indicators from the large list of those available is not straightforward and usually only a few indicators can be used. Previous studies have attempted to identify a small set of indicators that identified most of the spatial patterns observed and have better statistical properties (e.g. robust to outliers and changes in the distribution, regardless of abundance, Bock et al., 2005). Further, most indicators' results are often highly statistically correlated with each other, and thus may be redundant. For example, Rufino et al. (2018) suggested grouping indicators into three categories that, reflect the main ecological patterns of species spatial distribution: occupancy, aggregation and quantity. Doing so would reduce the number of indicators to only three, each representing one category.

Another important aspect of indicators that can influence their selection is their ability to identify spatial or geographic change. To our knowledge, one aspect of sampling design that has been poorly addressed when using empirical data is the number of samples required to identify a change in species distribution. However, Rindorf and Lewy (2012) analyzed the properties of several indicators analytically and by simulating abundance-occupancy relationships, in response to changes in species distribution and sample size.

The aim of the current study was to determine the ability of several spatial indicators to identify changes in geographic patterns of demersal species, when the species main biomass patch moves (shift), when a larger patch splits into smaller ones (split) or when the area of highest biomass decreases (shrink, with a decrease in or relocation of biomass). The indicators were also assessed at higher levels of biomass (two and five times as high) and multiple sample sizes (20-160 stations). Conclusions are then drawn about management applications, especially in the European Union’s Marine Strategy Framework Directive (2008/56/EC) (MSFD), which requires that species and ecosystems be monitored using indicators that are operational and have clearly defined targets.

2. Materials and Methods

2.1. Data used

The data analyzed came from a bottom trawl fishery survey (EVHOE)(Evaluation Halieutique de l’Ouest Européen, EVHOE cruise, RV Thalassa, IFREMER, Leaute and Pawlowski, 2015) that was performed in Autumn 2015 in the Bay of Biscay and the Celtic Seas. The survey covered a bathymetric range 20 up to 700 m deep and consisted of 148 randomly stratified sampling stations (Fig. 2). The distribution of the biomass of 29 demersal species (Supplementary material 1) was interpolated onto a grid with 15 km × 15 km resolution that covered all species distributions, using ordinary kriging (see further details in Rufino et al., 2019). This interpolated area was the input data manipulated and from which the indicators were calculated.

2.2. Geographical manipulation

To determine whether the indicators were sensitive to the main geographic changes in species distributions, four types of naive spatial manipulation were performed: 1) shift; 2) shrink0 3) shrink1 and 4) split (Fig. 1). With this objective, an area was selected within the geographic distribution of each species and then manipulated to simulate the four geographic changes. More precisely, a rectangular area was extracted from the total area interpolated for all 29 species. The geographic range of this rectangular area was -10.482 to -7.145 in latitude and 48.289 to 51.439 in longitude, represented as 23 rows × 14 columns, on a grid with 15 km × 15 km resolution) (Supplementary material 1, Fig. S1, S2).

These raster grids were subjected to an initial treatment in which the biomass in a target area of nine rows in the center was left unchanged, while those in the remaining rows at the top and bottom were replaced with randomly generated values close to zero (i.e. mean equal to the 10% quantile of the biomass of the target area) and low variability (half the standard deviation of the target area). This treatment was performed to remove any patterns present in the top and bottom sections of the species distributions and to ensure that any differences in the indicators would be due only to the geographic changes simulated. Thus, the target area corresponded to nine contiguous rows with the highest biomass (Fig. S3). This area was then subjected to the four geographic manipulations: shift, split and shrink (with and without a decrease in biomass) (Fig. 2, Fig. S4).

The ‘shift’ process illustrates when the center of a species distribution moves in a certain direction, without a change in biomass (e.g., as expected under climate change). This is not a change in the species distribution but simply reflects that the biomass has relocated. For this process, starting from the initial state, the target area was successively shifted, towards the bottom of the rectangle (south), by one row seven times (to the bottom of the raster rectangle). Each shift of one row corresponded to a ~ 4% shift in the species distribution.

The 'split' manipulation mimics the process in which a larger patch with higher biomass is broken into smaller patches, without changing the total biomass. For this, starting from the initial state, the target area was split into thirds, and the three top and bottom rows were shifted successively towards the top and bottom of the rectangle, respectively five times.

The 'shrink' process reflects a decrease in species distribution, (i.e. when a large biomass patch decreases in size). For this, starting from the initial state, the two edge rows of the target area were successively replaced with randomly low values four times, until only one row of the target was left. Two shrink processes were considered: (1) total biomass decreases due to the decrease in the distribution areas (shrink.0, i.e. some of the population emigrated) and (2) the biomass of the reduced areas was randomly distributed in the complete area (shrink.1), representing relocation of the same population.

2.3. Spatial indicators

Eleven spatial indicators were calculated for each manipulated spatial distribution (Table 1). The indicators selected were not intended to be exhaustive, but rather to represent the three main categories identified by Rufino et al., (2018). Since the data were interpolated on a regular grid, the areas of influence of each data point were set to 1 for simplicity. Thus, indicators representing an area were expressed as a number of grid cells rather than in units of surface area. We denoted $x_i, i = 1, \ldots, N$ the geographic location of data points. In two dimensions, this corresponds to $(longitude_i, latitude_i)$. Fish biomass was denoted $z(x_i) = z_i, i = 1, \dots, N$.

Center of Gravity also called center of mass, indicates the mean spatial location of the population (Bez and Rivoirard, 2001)(Supplementary material 2). Given the manipulations performed, we considered longitude and latitude of the center of gravity separately:

$$CG.lon = \frac{\sum_{i=1}^{N} z_i longitude_i}{\sum_{i=1}^{N} z_i}$$

$$CG.lat = \frac{\sum_{i=1}^{N} z_i latitude_i}{\sum_{i=1}^{N} z_i}$$

This indicator is sensitive to the spatial locations of data points.

The **Gini index** is defined as the two times the area between the 1:1 line and the Lorenz curve (Supplementary material 2). It is considered a measure of statistical concentration since it is not sensitive to the spatial location of the data points (Petitgas, 1998, 1997; Reuchlin-Hugenholtz et al., 2015) . When applied to fish density, the x-axis of Lorenz curve represents the area occupied by cumulative fish densities (ranked by increasing density) while the y-axis represents the corresponding percentage of the total population biomass. For fish density equally distributed among the samples, the Lorenz curve follows the 1:1 line. As the distribution of fish density becomes increasingly uneven (i.e., more concentrated) the Lorenz curve deepens. Gini index ranges from 0-1, the higher its value, the more concentrated the biomass is in fewer samples.

The **level of aggregation** (Bez and Rivoirard, 2001) is calculated as follows:

$$L_{agg} = \frac{\sum_{i=1}^{N} z_i^2}{\sum_{i=1}^{N} z_i}$$

It corresponds to the mean fish density at the location where an individual fish is randomly sampled from the population. This index is not sensitive to the spatial location of the data points.

The **index of aggregation** is calculated by standardizing the level of aggregation by Q the total biomass (Bez and Rivoirard, 2001). While the areas of influence of each sample have been set to 1:

$$I_{agg} = \frac{L_{agg}}{Q} = \frac{\sum_{i=1}^{N} z_i^2}{N(\sum_{i=1}^{N} z_i)^2} = \frac{1}{eqarea}$$

From this equation, the **equivalent area** represents the area covered by a population with constant density equal to the level of aggregation (Bez and Rivoirard, 2001).

Spreading area measures whether the positive fish biomasses are statistically concentrated around their mean (Woillez et al., 2007; Supplementary material 2). It is the Gini index of the positive sample and thus related to the Gini index.

Inertia represents the spatial dispersal of the population around its center of gravity, i.e. the mean square distance between individual fish and the center of gravity (Bez and Rivoirard, 2001; Supplementary material 2).

$$Inertia = \frac{\sum_{i=1}^{N} z_i \cdot (x_i - CG)^2}{\sum_{i=1}^{N} z_i}$$

Isotropy/anisotropy represents the shape (symmetry) of the inertia, i.e. round or ellipsoid, and equals the ratio of the two principal axes of inertia (Supplementary material 2).

The **index of dispersion** and c**oefficient of dispersion** also called variance-to-mean ratio (σ^2:μ) or relative variance, measure the aggregation of individuals (Taylor, 1961).

2.4. Procedure

To determine whether the indicators were sensitive to a homogeneous increase in biomass (e.g. to represent a year with good environmental conditions overall, in which biomass increases proportionally at all points), the geographically manipulated raster was multiplied by two and five before the geographic manipulation (biomass effects, three levels, 1, 2 and 5) and the indicators were estimated again.

To determine whether the indicators were sensitive to sample size (i.e. the number of samples required to detect the geographic changes), 20 -160 random samples (in steps of 20) were taken from each of the manipulated raster’s (sample size effect, nine levels), and the indicators were estimated again using these data.

Thus, the indicators differed as a function of the initial state, (1) the geographic manipulation (shift, split or shrink), (2) the level of biomass, and (3) the sample size. The difference in indicator value between the initial state and each configuration was calculated for each species and summarized (mean and 95% confidence interval estimated by bootstrap). Thus, a total of 3132 simulations were performed (29 species distribution × 4 manipulations × 3 biomass levels × 9 sample sizes).

All analysis and plotting were performed using R software (R Core Team, 2014). Indicators were estimated using the RGeostats (Renard et al., 2017) and ineq (Zeileis, 2014) packages of R, while rasters were manipulated using the raster package (Hijmans, 2016).

3. Results

The latitude of the center of gravity accurately identified the southward shift of the species biomass, although its relative change was smaller than that of the corresponding number of grid rows shifted (i.e. a 20% shift in latitude, for a 30% shift in rows, i.e. 7 out of 23 in the target area). No change was detected for the shrink or split processes (Fig. 3; Table

1). The longitude of the center of gravity did not change for the shift and split processes, but did changed slightly (by 0.02) for both shrink processes (shrink0 and shrink1), especially at higher levels of shrinkage (target area decreased by >50%, by 2-4), thus independent of total biomass.

The Gini index, did not change for the shift or split processes, but progressively increased by up to 20% as the species distribution main occupied area decreased, when total biomass was redistributed (shrink.1) (Fig. 3; Table 1). However, when the biomass of the reduced area was lost (shrink0), the Gini index decreased slightly and then increased slightly (by ~5%) as the level of shrinkage increased. A similar but opposite pattern was observed for the equivalent area and spreading area.

The index of aggregation showed an opposite pattern, increasing progressively up to 0.03 units (shrink0) but not when the total biomass was maintained (shrink1) (Fig. 3; Table 1).

The inertia and isotropy decreased progressively with an increasing level of each geographic manipulation considered, although to a greater extent for the shrink1 and split (Fig. 3; Table 1).

The index of dispersion, level of aggregation and the coefficient of dispersion all responded mainly to the increase in total biomass in the rectangular area, and only slightly to the geographic manipulations (Fig. 3; Table 1).

For most indicators the influence of sample size on the ability to identify the underlying geographic manipulation was inconsistent when only 20 stations were considered (Fig. 4; Table 1). The indicators showed a consistent response to changes in geographic patterns when the sample size reached 40 stations, except for the level of aggregation, which required 80 stations. Only equivalent area and spreading area had increasing ability to identify changes as the level of manipulation and sample size increased.

Inertia and isotropy were generally sensitive to all geographic manipulations, although to a higher degree for shrink1 and split, and were not sensitive to changes in total biomass. The shift manipulation was detected only by the respective coordinate of the center of gravity, which was also relatively insensitive to a homogeneous increase in the biomass level. The shrink manipulation, in which the main biomass patch decreased, was identified by the Gini index, index of aggregation, equality area and spreading area. For shrink0, (i.e. total biomass decreases), the index of aggregation was more effective. For shrink1 (i.e. biomass missing from the decrease in the area is relocated over the entire area), the Gini index (increased), equality area (decreased) and spreading area (decreased) were more effective; however, the latter two were highly sensitive to smaller sample sizes. The 'split' manipulation was not detected by any of the indicators.

Three indicators were not sensitive to any of the manipulations but did change with the increase in total biomass: coefficient of dispersion, index of dispersion and level of aggregation.

4. Discussion

A good suitable indicator should be calculated by a simple direct equation and clearly interpret the underlying process (Baddeley et al., 2015). Although previous studies recommend including multiple indicators (Petitgas and Poulard, 2009; Woillez et al., 2007b), monitoring programs, such as the MSFD often require parsimonious and non-redundant indicators. It is thus necessary to select few indicators, if possible, using objective criteria. We tested the ability of several indicators to detect the main geographic processes that are observed in species distributions and their sensitivity to changes in total biomass, and sample size.

For the interpretation to remain unambiguous, each indicator should respond to only one change. However, if only one indicator can be used, one that is sensitive to several geographic changes can help identify spatial changes that can be investigated in detail in future studies. the indicator can be used as a preliminary signal to indicate that a population experienced a spatial change. For these situations, the inertia and isotropy indicators are the most adequate since they responded to all of the geographic processes considered: shift, shrink and split, although they did not respond to the level of biomass or the spatial distribution.

The center of gravity was the only indicator that responded only to the 'shift' process (i.e. a patch of higher biomass moves in a certain direction without changing the total biomass or range. It is widely recognized that species are modifying their distributions due to climate change and other anthropogenic impacts (Hermant et al., 2010). Most previous studies on biogeography, however, use presence/absence data, and thus measure only species distributions. The center of gravity (through its coordinates) can accurately spot and quantify a biomass geographic shift of a species, when the species distribution does not change. Additionally, this indicator was not influenced by homogeneous changes in biomass. Nevertheless, the center of gravity can be highly sensitive to the presence of other patches within the sampled area or outliers and to non-homogeneous changes in biomass (data not shown).

Four indicators responded only to the shrink process (i.e. a decrease in the size of the main biomass patch). If biomass is lost along with the decrease in the area, (shrink0), the index of aggregation should be used. However, if the biomass is relocated (i.e. total biomass does not change), Gini index, equivalent area and spreading area were more effective, although the latter two were highly sensitive to the sample size.

None of the indicators detected a split of the main biomass patch into smaller patches. Other indicators, such as the number of patches or a geostatistical variogram model (through its range parameter, also known as patch size) may do so. Nether was included in the current study, however, because the former varies greatly depending on the parameters chosen for calculation, while the latter had no spatial structure to analyze, since the distribution was broken during manipulation. Additionally, it is difficult to identify a spatial model for many distributions because they are not visible for some species or years. Nevertheless, this aspect requires further study.

For simplicity, we studied a rectangular sampling area, however, this is rarely possible in real world situations which are hindered by an irregular topography. For example, the areas sampled in coastal surveys are often long and narrow, with extremely irregular shapes (Brind'Amour et al., 2014; Rufino et al., 2017, 2010). In such cases, irregularities in the sampling area can move the center of gravity outside the surveyed area and cause the inertia and isotropy indicators to calculate non-real distances. Artificially dividing the sampling area into several sub-areas may sometimes resolve this problem (Tableau et al., 2016). Nevertheless, future studies are required to develop indicators that are for areas with irregular shapes.

One approach to address the sampling area issue is to split study areas into smaller spatial management units. When large areas, such as ocean, are sampled, several processes are combined that are difficult to distinguish. In this case it becomes essential to divide the areas into spatial management areas, which can then be monitored using indicators. For example, several fishery surveys are conducted on an annual basis in European waters. If indicators are to be used to monitor such a large area, spatial management areas are required. We recommend that the scales of underlying processes be identified as well as the methods to establish spatial management areas for relevant application of indicators.

Empirical data on species distribution was used instead of simulated data to avoid making assumptions about factors, such as distribution parameters. Species distributions were then manipulated to specify define the spatial changes studied. This approach is generalizable to all indicators and case studies because it is simple, effective and available to all researcher.

The MSFD criterion associated with the spatial distribution of species (D1C4) requires indicators that can identify two main processes: (i) species distribution range and, where relevant, (ii) pattern within this range. We chose three geographic changes that likely match the spatial processes highlighted in the MSFD. Hence, we suggest using the indicators that respond to the geographic 'shift' to assess species distribution and using those that respond to shrink (0 or 1) or split changes to assess the pattern within the species distribution. Based on Rufino et al. (2018), who classified indicators into three categories we suggest that 'occupancy-related' indicators would correctly identify shift changes (i.e. distributional range) and 'aggregation-related' indicators would correctly identify shrink and split changes (*i.e.* pattern within the distribution).

In conclusion this approach is a simple and straightforward way to determine the ability of indicators to identify certain spatial processes. Based on the indicators studied, the center of gravity (for shift process), Gini index, index of aggregation (for a shrink process), with more than 60 samples were the best indicators for options to identify the geographic processes underlying. Inertia and isotropy were two indicators that were sensitive to all processes, so can be used to trigger a spatial change in the species or community.

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TABLES

Table 1: Response of the spatial indicators to the handled distributions and biomass change (no change, vs. doble and quintuple).

Indicator	Description	Manipulation					
		Shift	Shirnk.0	Shrink.1	Split	Biomass	Spatial distribution
		Migration of a species southward (without changing the species range)	Decrease in the area occupied and biomass	Decrease in the area occupied, with biomass relocated	Split of the main occupied area in three smaller areas		
	Expectations	Increase or decrease depending on the indicator	Increase or decrease depending on the indicator	Increase or decrease depending on the indicator	Increase or decrease depending on the indicator	No change	No change
Latitude of the centre of Gravity (CG.lat)	Mean geographic location of the population (lat/long coordinates).	Increase up to 20%	Stable	Stable	Stable	No influence	No influence
Longitude of the Centre of Gravity (CG.long)		Stable	Stable but increase variability	Stable but increase variability	Stable	No influence	Influence for RFo and TPS, in ‘shrink’
Gini (Lorenz curve)	Represents the difference between the observed distribution and a distribution where every sample contains the same individuals [0-1].	Stable	Small decrease (<10%; stable)	Increased	Stable	No influence	Small influence only in ‘shrink’
Equivalent area (eqarea)	The area that would be covered by the population if all individuals had the same density, equal to the mean density per individual [0-PosA](nmi^2)	Stable	Small increase (stable)	Decreased	Stable	No influence	Small influence only in ‘shrink’
Spreading area (sparea)	Index related to the Gini index, but which has the advantage of having no contribution from zero values of density (nmi^2).	Stable	Small increase (stable)	Decreased	Stable	No influence	Small influence only in ‘shrink’
Index of aggregation (Iagg)	Describes the level of aggregation independent of total abundance.	Stable	Decreased	Small increase (stable)	Stable	No influence	Small influence only in ‘shrink’
Inertia	Describes the dispersion of the population around its center of gravity (nmi^2)	Decreased	Decreased	Decreased	Decreased	No influence	Small influence
Isotropy	Measures the elongation of the spatial distribution of the population.dispersion shape (symmetry) of the inertia around the center of gravity (i.e.	Decreased	Decreased	Decreased	Decreased	No influence	Small influence

	round or ellipsoid), and it is the ratio between the two inertia axes. [0-1]						
Index of dispersion (contagion)(MeVa)	Used to measure the distributional pattern within the range (MSFD)	Stable	Stable	Stable	Stable	Changed	Small influence only in 'shrink'
Level of aggregation (Lagg)	Mean density per individual, used to describe the level of aggregation.	Stable	Stable	Stable	Stable	Changed	Small influence only in 'shrink'
Coefficient of dispersion (σ^2/mean ratio)(VaMe)	This index gives indications on over or under dispersion compared to a Poisson distribution.	Stable	Stable	Stable	Stable	Changed	Small influence only in 'shrink'

FIGURE LEGENDS:

Summary of the process used to evaluate spatial indicator's ability.

Figure 1: Mean response and respective bootstrap 95% confidence intervals of spatial indicators as a function of three geographic manipulations Shift, Shrink, with biomass decrease (0) or biomass relocation (1) and Split) and of a a homogeneous increase in biomass (0 no increase, 2 two times and 5 five times) of the area analysed. Spatial indicators (Table 1): center of gravity latitude (CG.lat) and longitude (CG.long), Gini, equivalent area (earea), spreading area (sparea), index of aggregation (Iagg), inertia, isotropy (iso), index of dispersion (MeVa), level of aggregation (Lagg) and coefficient of dispersion (VaMe). The 'd.' preceding the indicator's name means 'difference' from its value for the initial state.

Figure 2: Mean response and respective bootstrap 95% confidence intervals of the spatial indicators as a function of three geographic manipulations manipulations (Shift, Shrink, with biomass decrease (0) or biomass relocation (1) and Split). Indicators are defined as in Figure 1.

Figure 3: Mean response and respective bootstrap 95% confidence intervals of the spatial indicators as a function of sample size (20-160) and three geographic manipulations (Shift, Shrink, with biomass decrease (0) or biomass relocation (1) and Split). Indicators are defined as in Figure 1.

FIGURES:

Graphical abstract.

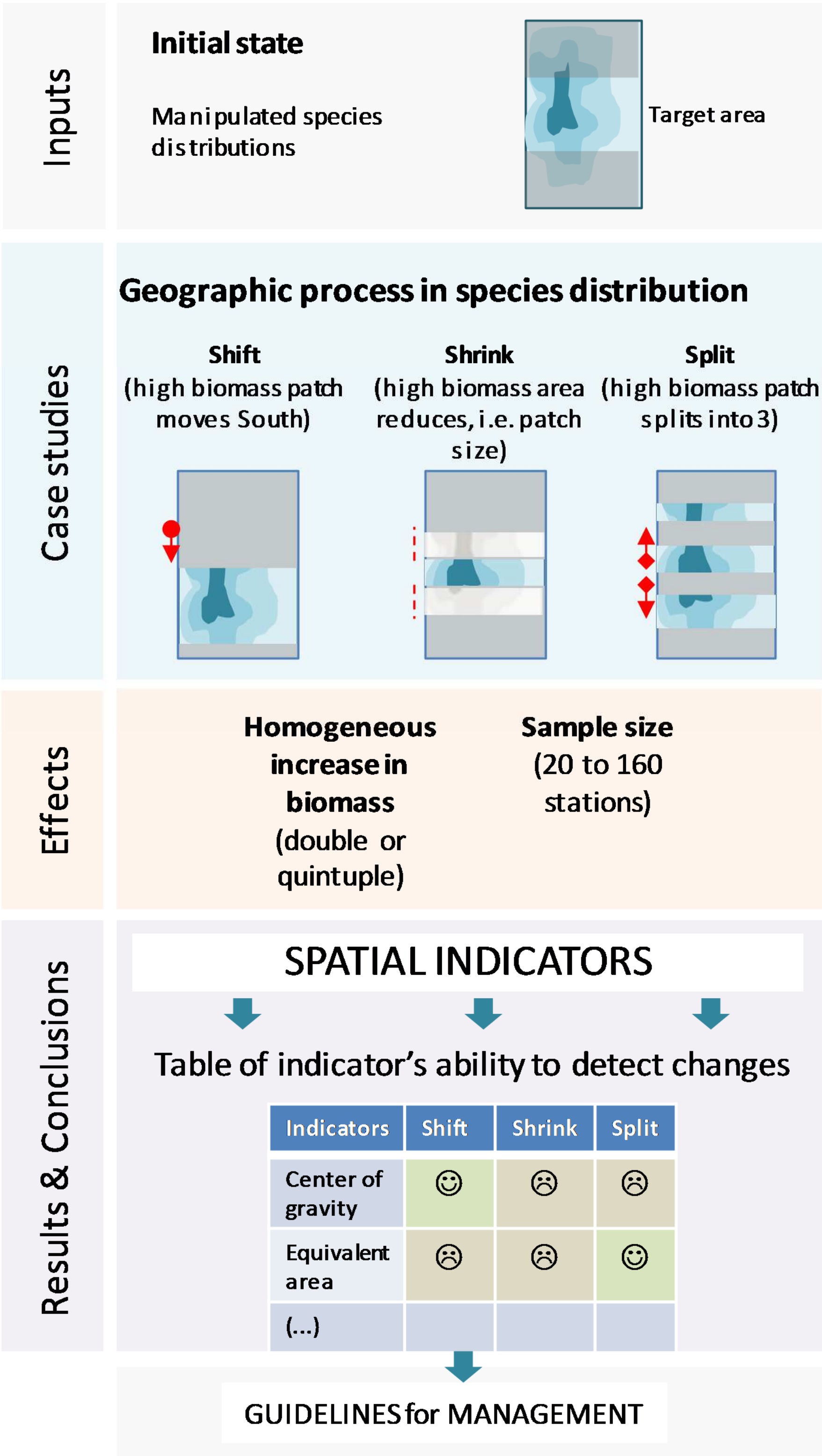

Figure 1: by biomass level

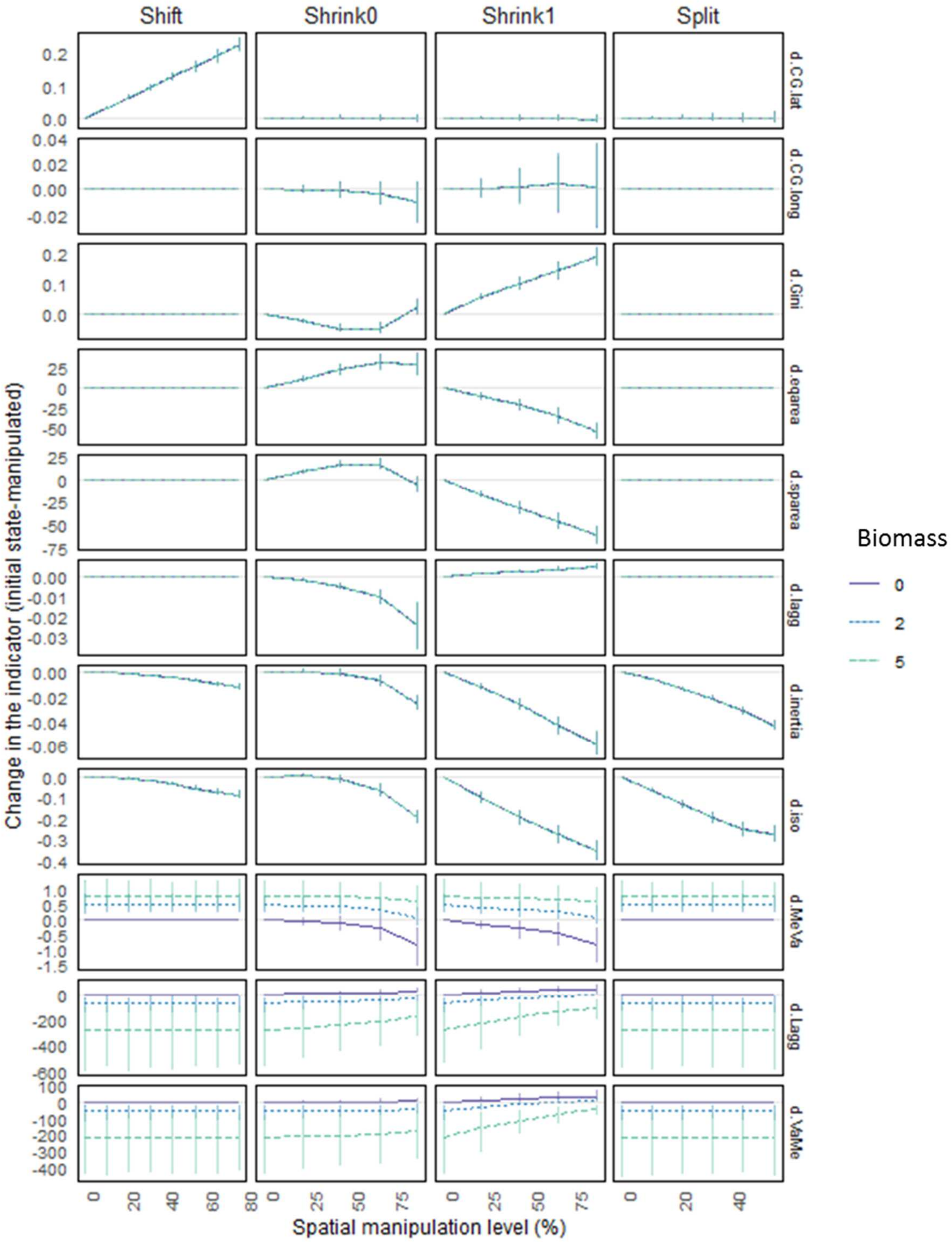

Figure 2: by method

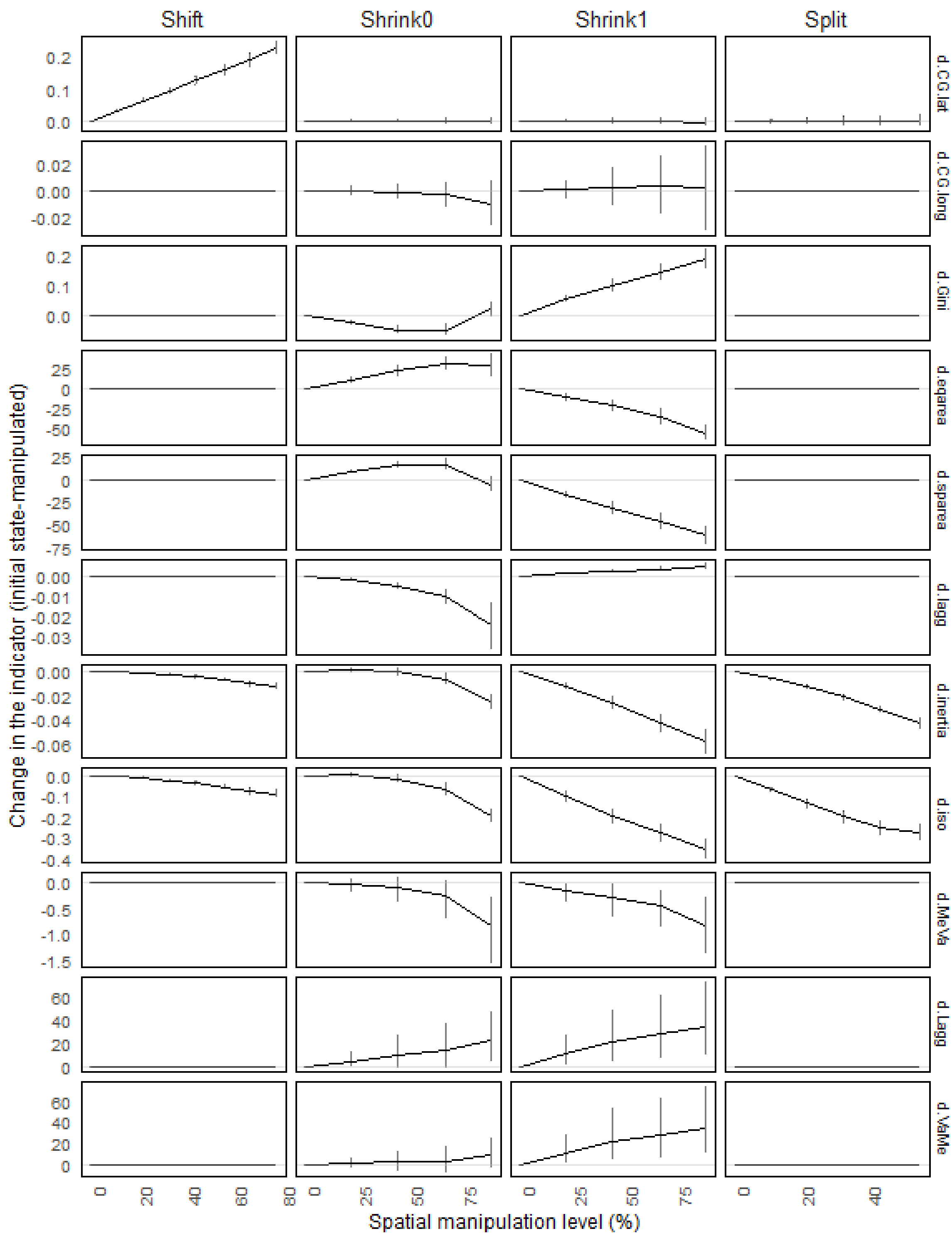

Figure 3: by sample size