Supplementary materials

# Interactive charts

To see the results for this paper as interactive charts, please visit and download the html files on the [github page](https://github.com/TanyaTsui/spatialClusteringWasteReuse) of this paper. If you are unfamiliar with github, click the links below to see the charts directly in your web browser.

* [Effect of cell size on Moran’s I, all materials](https://nbviewer.org/github/TanyaTsui/spatialClusteringWasteReuse/blob/main/moransI_wholeCountry_lowess_withPoints.html) - double click on a material in the legend to isolate one material.
* [P-values for Moran’s I at cell sizes, for all materials](https://nbviewer.org/github/TanyaTsui/spatialClusteringWasteReuse/blob/main/moransI_wholeCountry_pValue.html) - double click on a material in the legend to isolate one material.
* [Map of hotspots for waste reuse](https://nbviewer.org/github/TanyaTsui/spatialClusteringWasteReuse/blob/main/folium_hotspots.html), for all materials
* [3d plot of waste reuse values](https://nbviewer.org/github/TanyaTsui/spatialClusteringWasteReuse/blob/main/3dplot_minerals.html), to illustrate how Moran’s I can be used to optimize cell size

# Global Moran’s I

## Comparing values with random cases

A Monte Carlo method was used to estimate the p-value of global Moran’s I values for each material. For each material type, the Moran's I was calculated to quantify the level of clustering for the amount (kg) of waste reused with each grid cell - this is the 'observed Moran's I'. Then, in a series of random permutations, the values were randomly reassigned to other grid cells, and the Moran's I is calculated again. This process was repeated 999 times, creating 999 'permuted Moran's I's’. The p-value is an indicator comparing our observed Moran's I with a Moran's I computed from permuted data. It is here defined as the estimated probability that our observed Moran's I is larger than a Moran's I computed from permuted data. For example, a p-value of 0.05 means that 95% of Moran's I computed with permuted data are smaller than the observed Moran's I.

Figure 1 compares observed and simulated Moran’s I values for all materials, when values are aggregated to grid cell sizes of 2km. For all materials except for glass and textile, the observed Moran’s I (red line) is far from the simulated Moran's I values (blue curve), which suggests spatial dependence.

Figure 2 compares observed and simulated Moran’s I for all materials, at all cell sizes. The blue lines show how the observed Moran’s I changes as cell sizes increase, and the orange lines show how the simulated Moran’s I changes as cell sizes increase. For some materials, such as glass and textile, the blue line often intersects with the orange line. This means that it is likely that there is no spatial autocorrelation, since the simulated (randomized) and observed Moran's I values are close. It is important to clarify that for the simulated Moran’s Is (orange line), the random shuffling was done on the grid cells, rather than the individual data points themselves.

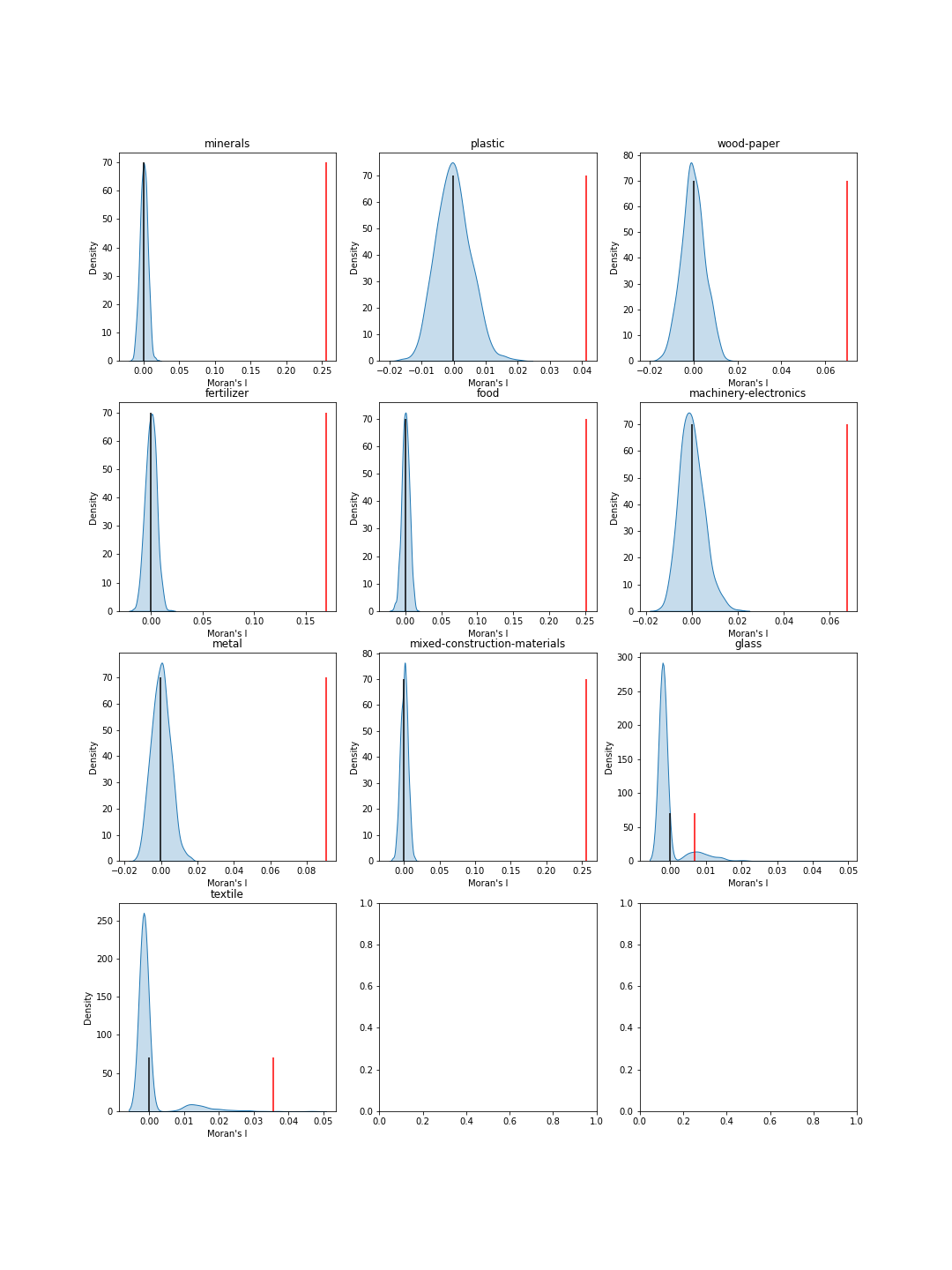


Figure 1: Comparison of observed and simulated Moran’s I values for grids with cell size of 2km. Red line = observed Moran’s I; black line = simulated Moran’s I; blue curve = kde plot of all simulated Moran’s I values

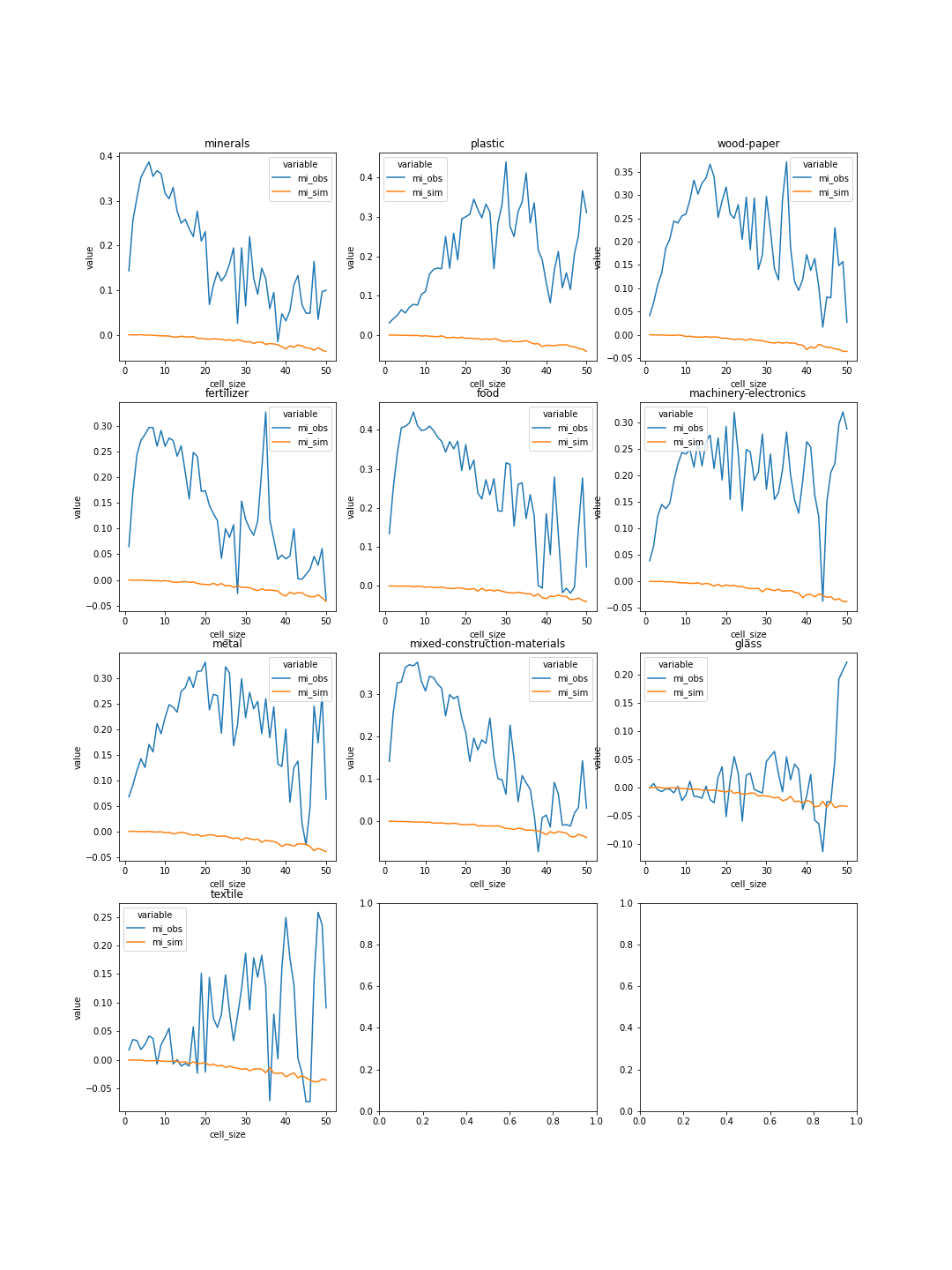


Figure 2: Comparison of observed and simulated Moran’s I values for all cell sizes. Blue line = observed Moran’s I; orange line = simulated Moran’s I

## Comparing peak Moran’s I - materials vs population

To get a better understanding of the peak Moran’s I values, a comparison was made between peak Moran’s I values of materials and the Dutch population. As seen in figure 3 below, the Moran’s I trendline for the Dutch population (in black) is higher than all the materials (except for food at cell size 7km), and the peak Moran’s I is actually when the cell size is the smallest - at 1km. As seen in figure 4 below, the p-values of the Dutch population is much lower than of material reuse, and remains consistently low at all cell sizes. This comparison suggests that the Dutch population has a higher spatial autocorrelation than material reuse.

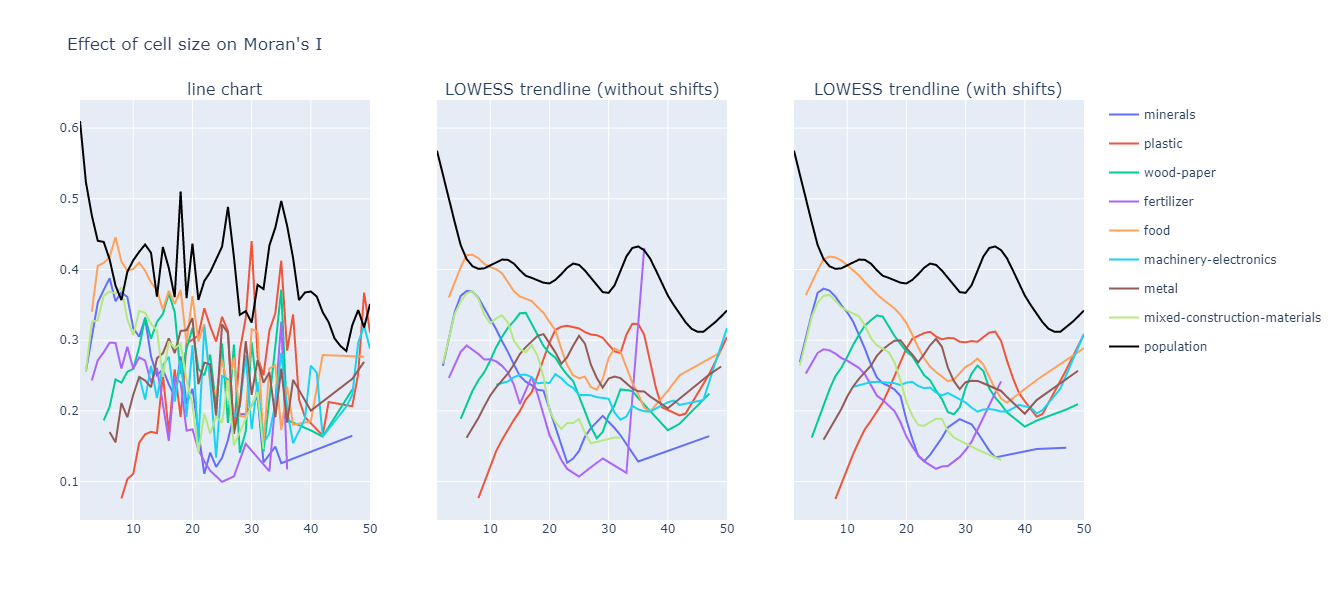


Figure 3: Moran’s I trendlines for the Dutch population (black) and for locations of material reuse

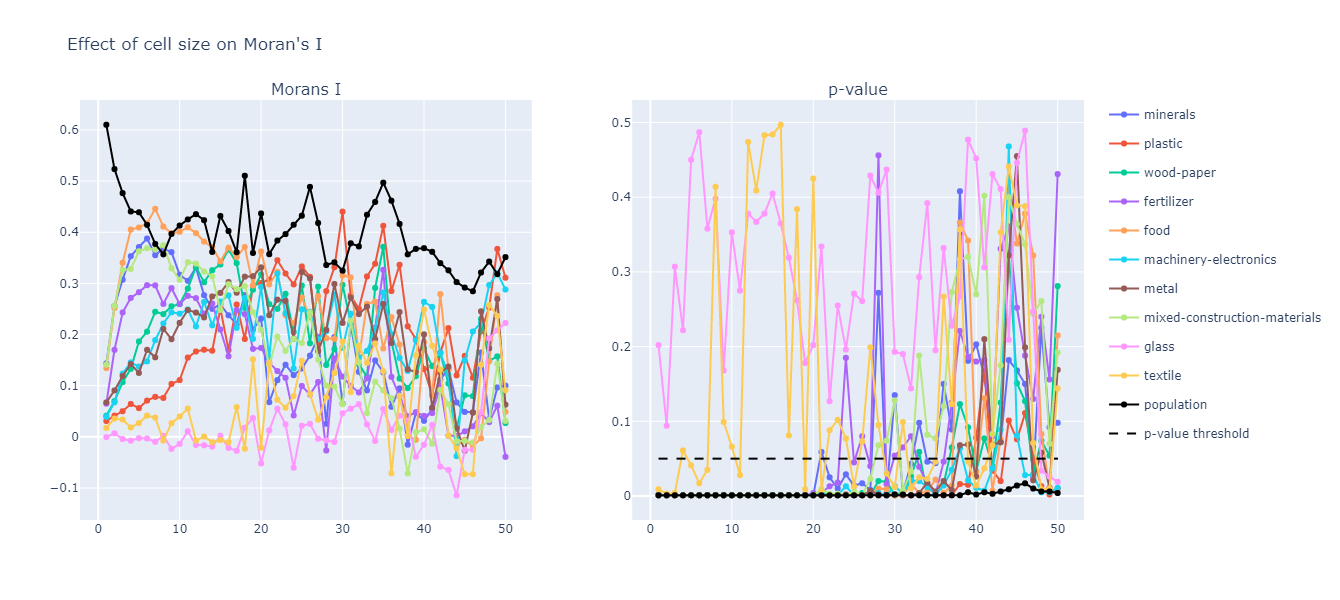


Figure 4: Comparing Moran’s I trendline for Dutch population and materials (left), and p-values for Dutch population and materials (right)

## Why multiple comparison corrections were not used for the study of Global Moran’s I

Normally, a formal statistical testing setup would require multiple comparison corrections to account for false positives due to the relatively large number of materials and cell sizes tested in this study.

In fact, the Bonferroni correction (method to counteract the multiple comparisons problem) rejects the null hypothesis only if the p-value is smaller than , where is the original accepted p-value (0.05), and is the number of tests. If we followed this correction in our case, our p-value threshold would be ; a p-value so low that none of our Moran's I values would be accepted.

On the other hand, if we decreased the number of cell sizes to 1, the p-value threshold would be much higher - , allowing for 47% of the tests to reject the null hypothesis.

Here we can see that, while decreasing the number of cell sizes would increase the validity of the statistics (by decreasing the probability of false positives), it also prevents us from understanding how Moran's I values change as cell sizes increase, which is the main aim of the study.

In fact, the theoretical aim of this study is to test an infinite number of cell sizes between a minimum and maximum: 1-50km, to find where Moran's I values 'peak' between cell sizes of 1-50km. The more cell sizes we test, the more accurately we can find the 'Moran's I peak'. But as cell sizes reach infinity, the accepted p-value threshold according to the Bonferroni correction approaches zero.

With this example using the Bonferroni correction, we hope to illustrate that it does not make sense to use multiple comparison corrections on our study, as there isn't a finite number of hypotheses we want to test. Instead, there is more of a 'continuum of hypotheses' between cell sizes of 1-50km. A very interesting concept, but would require a new theory and is out of scope for this paper.

This has consequences for our interpretation of the p-values of the results. For the p-values, we are more interested in small p-values as an indicator for spatial dependence rather than statistical significance. Despite the lack of a formal statistical framework, we conjecture that there is indeed some kind of spatial autocorrelation for most materials, following the intuition given by Figure 4.

# Research limitations

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## Limitations of analyzing waste data to generate insights for the circular economy

In general, waste data limits our perspective of the circular economy. Strategies for a circular economy can be grouped into two broad categories: product life extension and material reuse. Product life extension refers to strategies that prolong the lifetime of a product over multiple life cycles, such as reuse, repair, refurbishing and remanufacturing. Material reuse refers to strategies that recover materials of a product after it has completed all use life cycles, such as recycling. It is generally understood in circular literature, as shown in the 9R framework, that product life extension is preferred over material reuse [(Kirchherr, Reike, and Hekkert 2017)](https://www.zotero.org/google-docs/?QmAY4f).

By definition, waste data provides information on material that has completed use cycles, i.e. products that have been disposed of, which forces studies on waste data to overemphasize the importance of material reuse over product life extension. However, product life extension is not necessarily the best solution for all products / materials in all situations - some materials and products are more suited for recycling. Analysis of waste data could make a contribution to better understanding decision making in these fields [(Sileryte et al. 2022)](https://www.zotero.org/google-docs/?ejzHoP).

Categorizing materials in waste data is challenging, because of the trade-off between specificity and generalization. Unlike other flows such as energy and water which do not necessarily need to be categorized, waste data can only be meaningful when categorized into material types.

It is, however, difficult to choose the correct level of categorization, or ‘granularity’, for materials in waste data. Larger, more 'general' categories (such as metal, plastic...etc.) allow each material type to have more data points, making statistical analysis possible. However, results are less meaningful, because a general category such as 'metal' doesn't give any information on whether it's copper, steel, or gold. These distinctions are important, because different types of metals are used in vastly different industries. On the other hand, if the categories are too specific, there are not enough data points and statistical analysis cannot be conducted at all.

Additionally, typical data categorizations for waste data do not match detailed standards in the production of new products. For example, while a type of waste flow might be categorized simply as 'aluminum', new product designs typically have a higher specificity, such as requiring a specific grade of aluminum alloy. This problem could potentially be addressed by identifying materials, products, or industries that don't require such specific categorizations, although this tends to lead to ‘downcycling’.

One potential way to unify the categories of materials in the dataset is to convert the dataset's unit from kilograms to tonnes of embodied carbon. This study used weight (kilograms) as the unit of analysis, which has the danger of giving a false sense of which materials should be prioritized. For example, in the LMA dataset, construction and demolition waste takes up 80% of the total kilograms of waste produced in the Netherlands. This percentage is often quoted by researchers to justify the importance of exploring circularity for the construction industry. However, an 80% share of total weight does not equal an 80% share of environmental impact. If embodied carbon was used as a unit of analysis instead, different materials can be meaningfully compared from the lens of reducing carbon emissions.

The results of this study is further limited by the dataset used - data from the Dutch national waste registry (LMA). Firstly, the data is limited by a 'waste management' perspective. A waste flow is only recorded in the dataset if it goes through a waste management company, meaning that industrial symbiosis exchanges between non-waste management companies are excluded. As a result, most of the reuse activities analyzed in this study are associated with low-value circular economy processes such as recycling. This study is also limited by the quality of data collected by the LMA on the location of waste reuse. For many entries, the location recorded does not represent the true location of reuse, but rather the location of the headquarters of a company. Working with experts on the dataset, around 30% of flows in the construction industry were considered to be invalid. Finally, this study was limited by the geographical scope - only flows within the Netherlands have been included, whereas imports and exports of materials to and from other countries have not.