

Course Introduction

Michael Noonan

DATA 589: Spatial Statistics



1. Course Overview
2. Why Spatial Statistics?

Course Overview

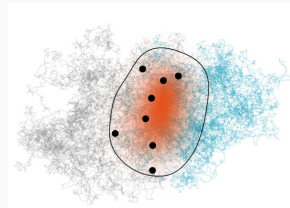
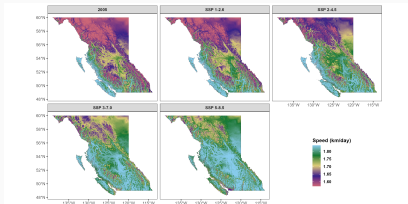
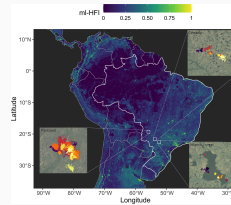
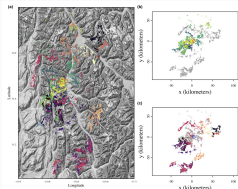
Name: Michael Noonan

Office: SCI 379

Email: michael.noonan [at] ubc.ca (use subject heading DATA589 in all email communication)

Office Hours: TBD, or by appointment arranged via email.

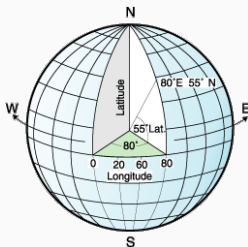
Course Resources: Canvas & GitHub



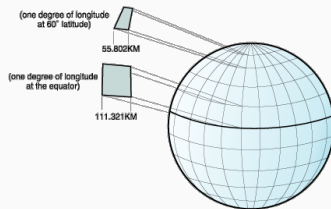
- Focus is on modelling spatial data (i.e., combining data with models to generate descriptions of spatial processes).
- You'll learn methods for handling the most common types of spatial data (Ripley's K, point processes, Kriging, regression with correlated errors, etc...).
- How to work with and visualise spatial data (not as straightforward as other data types).
- How to use open source software (R) to apply these analyses (traditional carried out in ArcGIS; \$1,370/yr).

- Basic statistics (concepts like means, medians, variances, probability distributions, regression, covariance should be familiar to you).
- Remote sensing.
- Computer programming (we will be using R, but the course is not focused on 'how to code').
- Methods for handling *ad hoc*, corner cases.
- ArcGIS, QGIS, or cartography.

The Earth is spherical.



Flattening it to two dimensions is challenging.



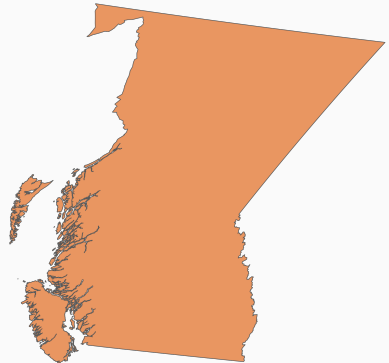
We use “projected coordinate systems” to project maps of the Earth’s spherical surface onto a two-dimensional plane.

Each projected coordinate system will result in a different two-dimensional map... which can have large impacts on any downstream analyses.

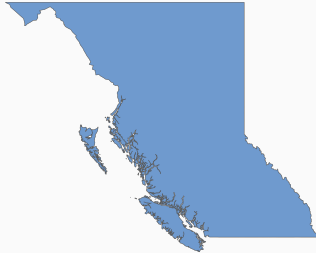
Latlong Projection



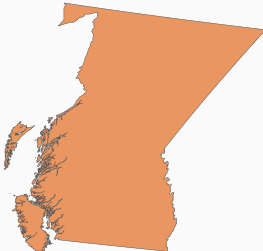
Winkel Tripel projection



Latlong Projection



Winkel Tripel projection



Projection systems are not a focus of this course.

Different projections have different use cases (global, continental, city), so the choice should be guided by the study scope/aims (there are many resources to help you with this).

If you work on spatial data in the future, ensure you use a consistent projection system throughout your workflow.

- For each topic, there will be a core lecture and an associated lab assignment.
- Lectures will cover the core concepts of the course. Lecture slides will be posted the evening prior to the lecture. You are encouraged to take notes, and to ask questions in the lectures. All lectures will be recorded and made available to you.
- The labs use structured tutorials to guide you on the use of the open-source software program R for applying the methods learned in the lectures to data. The lectures and labs are designed to be *complementary* and not all the material in the practicals will be covered in the lectures and vice versa.

Lab practicals (3)	39%	Due at the end of each lab.
Group Presentation	30%	In class during final week (Apr 22).
Final Exam	31%	In class during final week (Apr 24).
Total	100%	

There will be a total of 3 lab assignments (1 for each lab) to be completed throughout the course.

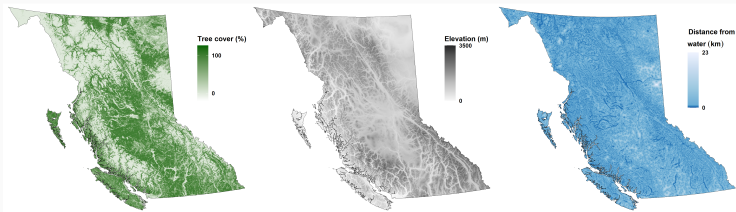
The course GitHub page and Canvas will host the labs and assignment templates, and the various datasets. The lab assignments are designed to build skills in working with and analysing spatial data.

Grading: Each lab assignment is worth a total of 13% of your total grade with some points coming from answering the questions correctly, and some from the cleanliness and documentation of your code.

Working in groups of 4, students will be required to complete a data analysis assignment and give a presentation describing their work.

Each group must select a species of their choosing and download the occurrence records from GBIF data repository (<https://www.gbif.org/>).

Groups will be provided with a set of environmental variables, and must use these to describe trends in the observed point data.



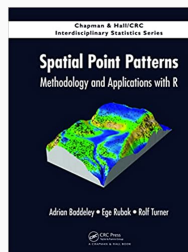
The final exam will consist of a set of question designed to assess students' understanding of the core concepts covered in the course.

The exam will be comprehensive, and any material covered in the lectures and labs will be testable.

Grading: The final is worth a total of 31% of your total grade.

There is no textbook for this course, but if you are interested in expanding your knowledge beyond what is covered in lectures, the following textbook is recommended:

- Baddeley A, Rubak E, Turner R.
Spatial Point Patterns: Methodology
and Applications with R. 2015. CRC.
~ \$120



Week	Lecture Topics
1	Course introduction; Spatial Intensity
2	Spatial Correlations; Poisson Point Processes Models
3	PPP Model Validation; Spatial Autocorrelation; Variograms
4	Kriging; Co-Kriging; Regression-Kriging; Correlated Errors

Why Spatial Statistics?

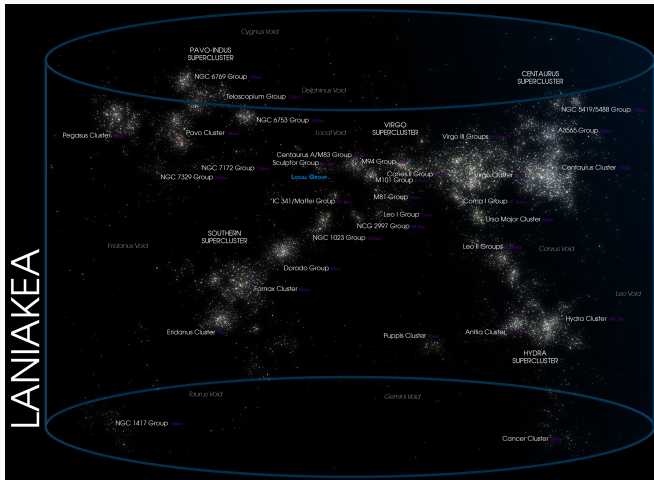
Science is a process of learning about the world around us. As scientists, we weigh competing ideas about how the world works (hypotheses) against observations (data).

But our descriptions of the world are almost always incomplete, our observations have error, and important data are often missing... So, how do we accurately compare what we observe with what we hypothesize without bias?

Statistics

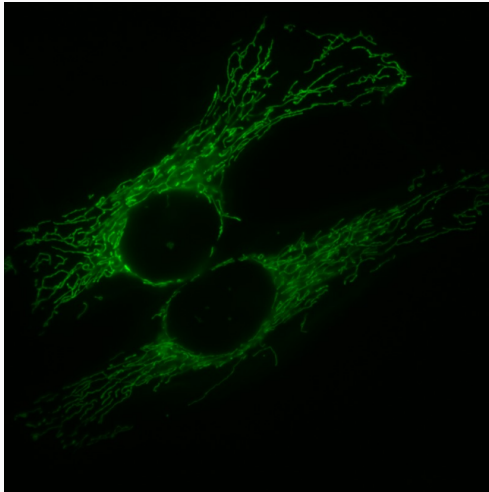
... but we exist in a physical world and everything happens 'somewhere'.

Stars are found in clusters.



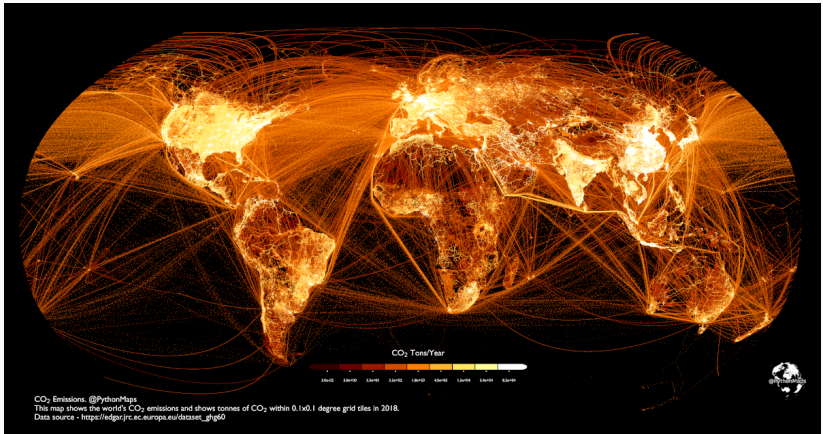
Source: Wikipedia

Mitochondria are located in certain areas of cells.

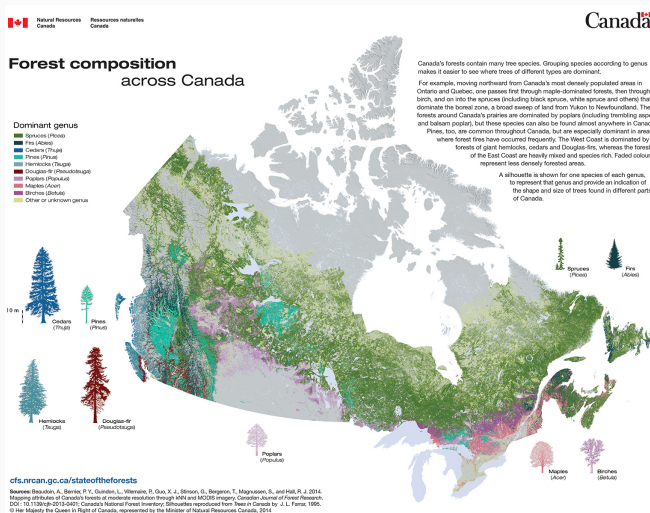


Source: Illinois Science Council

Carbon emissions are high in some places, low in others.



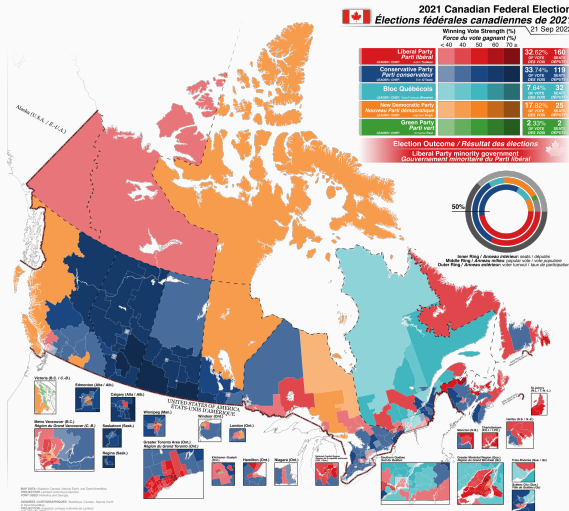
Trees of the same species are often found in the same areas



... but have non-uniform patterns in their local distribution.



Election results are clustered in space.

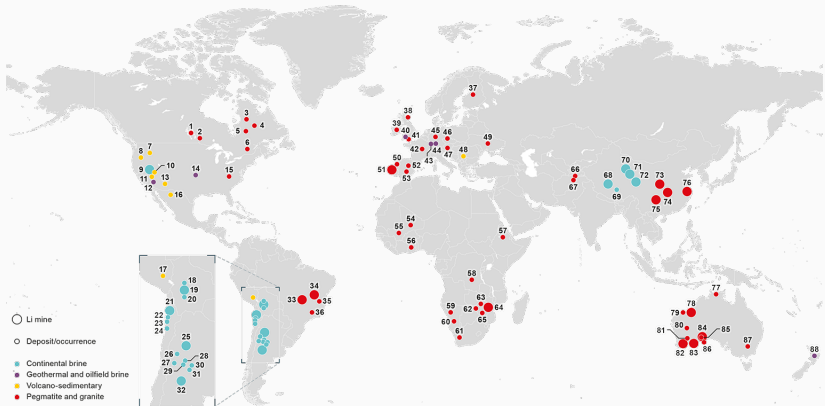


Lithium deposits only occur in certain areas.

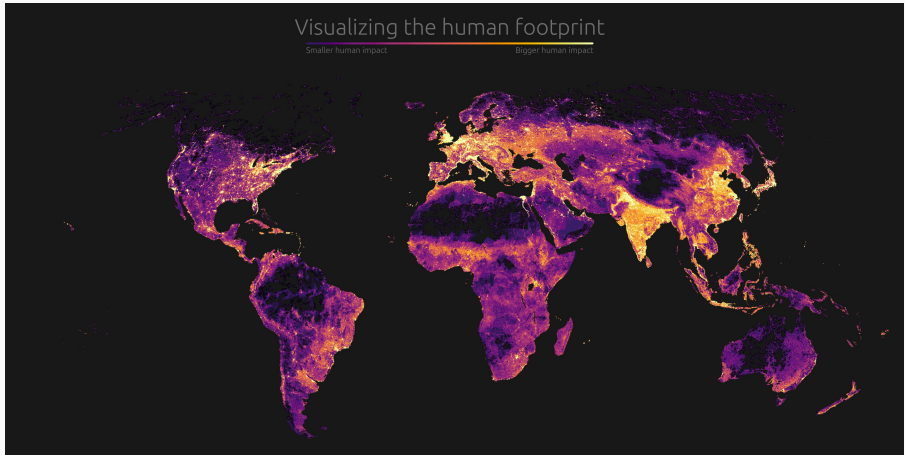
Global lithium (Li) mines,
deposits and occurrences (November 2021)



British
Geological
Survey

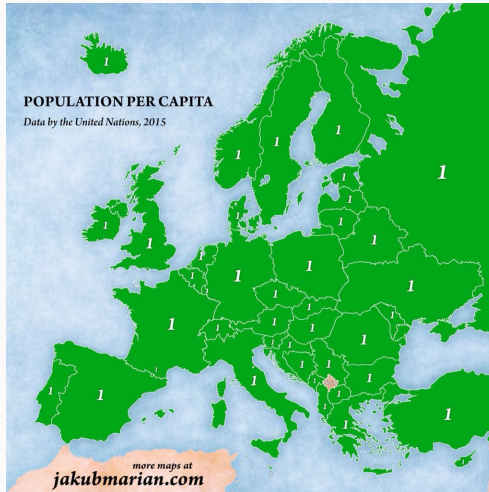


Maps are also engaging, effective ways to display data and convey messages.

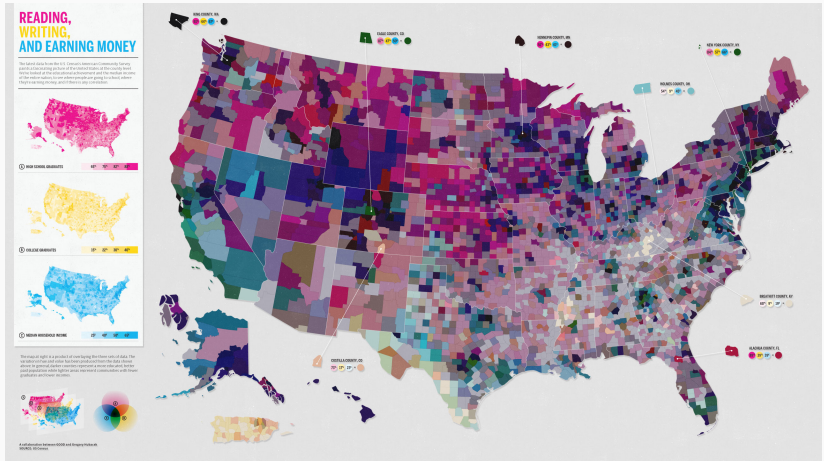


Source: Visual Capitalist

...but only if the information contained in them is meaningful



...or if meaningful information is conveyed effectively.



Source: American Community Survey

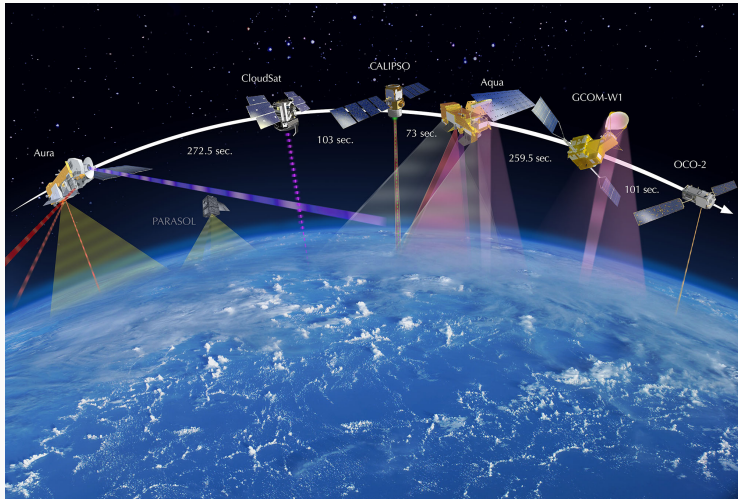
We are also in a 'Golden Age' for collecting and working with spatial data.

Historically, surveying, mapping, and spatial data collection were slow, painstaking processes.



Source: 1722 edition of William Leybourn's *The Compleat Surveyor*.

Satellites can remotely measure environmental characteristics.



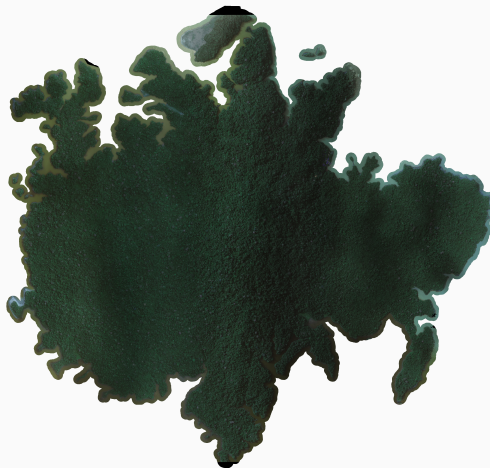
Source: Wikipedia

Camera equipped drones can help us find animals in the wild.



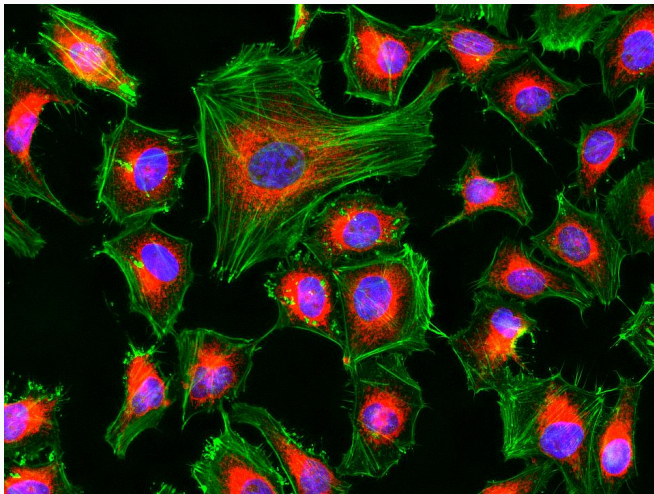
Source: RoboticsBiz.com

Lidar equipped drones can produce high-resolution maps.

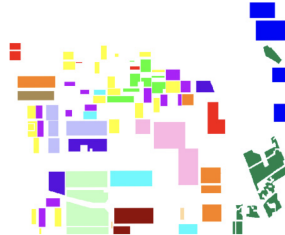
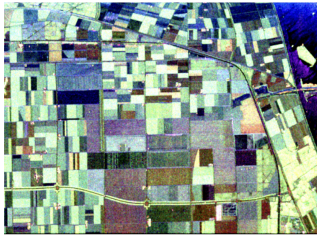


Source: Noonan *et al.* (2021)

Microscopes can localise microscopic cellular structures.



Machine learning algorithms can sift through these large volumes of data.



Source: Zhang *et al.* (2017)

Cluster computing reduces computing time (important for spatial data).



Source: CERN

The spatial context of data carries important information for understanding how processes operate.

The spatial arrangement of points in a dataset is often a surrogate for unobserved variables (e.g., soil fertility and the locations of trees), or can provide us with information on unrecorded historical events (e.g., cosmological evolution).

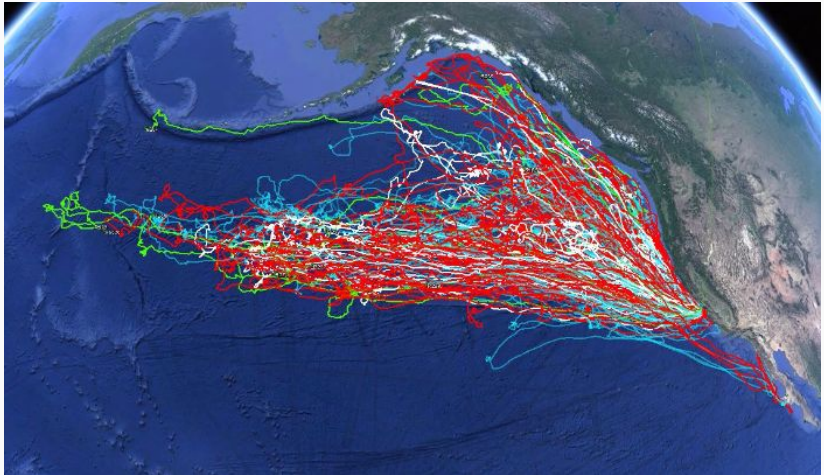
Spatial patterns can also influence the outcomes of other processes (e.g., the distribution of schools can drive housing prices).

So how do we study spatial phenomena?

Sometimes plotting the data is enough to learn something new.

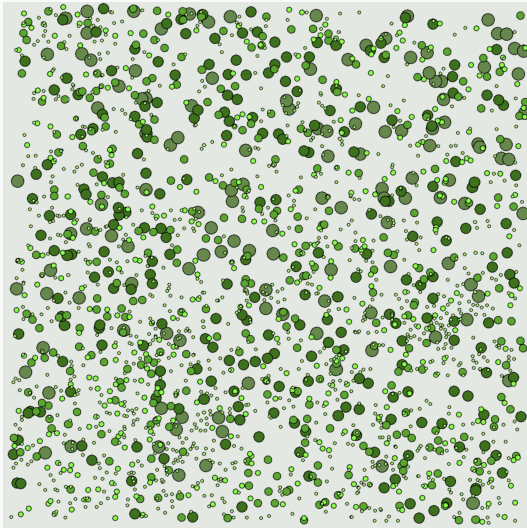


Sometimes plotting the data is enough to learn something new



Source: UC Santa Cruz

...but not always

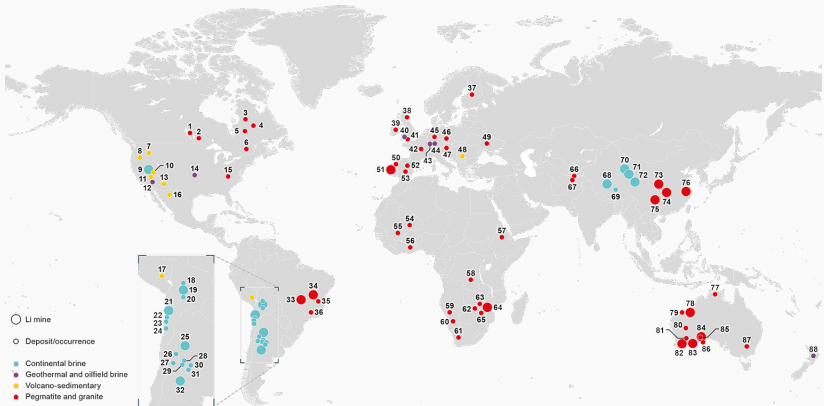


...and we can't make predictions from simple figures.

Global lithium (Li) mines,
deposits and occurrences (November 2021)



British
Geological
Survey



Sometimes visualising the data is enough to learn something new... but in most cases the patterns are difficult to see and simple visualisations can be uninformative, or even misleading.

So instead, we rely on

Spatial Statistics

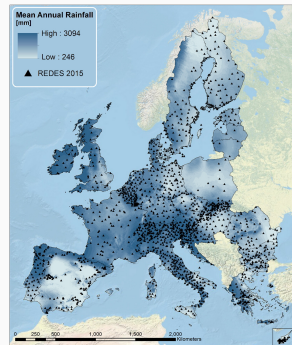
A set of formal techniques for studying processes using their spatial properties.

In general, there are two types of spatial data:

Point data where the location conveys information about the process.



Measurements where the sampling locations are artefactual.

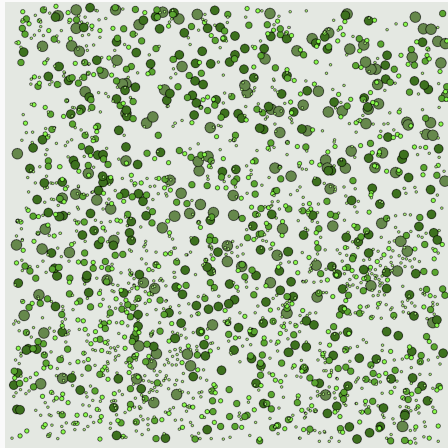


The analysis of point data requires a special set of statistical tools that fall under a general umbrella termed ‘point pattern processes’.

This family of methods treats the locations as informative and attempts to identify patterns in the spatial arrangement of the locations, as well as underlying causes for these patterns (usually by relating them to covariates).

The first half of the course will be focused on this family of methods.

Point data typically look like this, and our goal is usually to describe and understand how/why this pattern emerged.



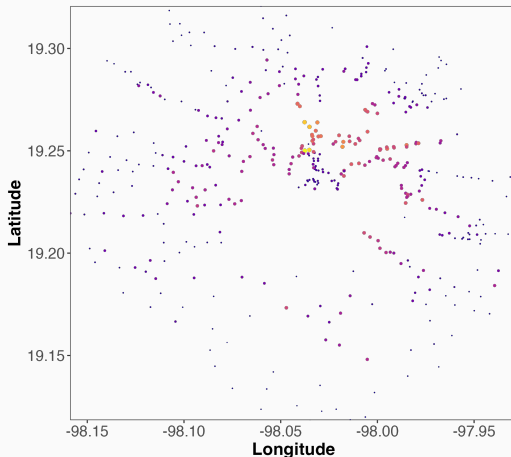
Source: Conservation Biology Institute

The second type of spatial data are measurements of 'things' taken across space.

This family of methods treats the measurement as informative and attempts to identify patterns in the spatial arrangement of the values by modelling the spatial autocorrelation structure (i.e., points measured close together in space will usually have more similar values than points measured further apart in space).

The second half of the course will be focused on this family of methods.

Spatial measurements typically look like this, and our goal is usually to interpolate the values or relate them to covariates.



Source: Fusaro *et al.* (2019)

We use statistics to interpret data and make inference about the world around us.

Spatial statistics is a branch of statistics that is focused on studying processes based on their spatial properties.

Spatial data are very diverse and there is no one-size-fits-all approach for working with them (need to match the tools to the study questions and the properties of the data).

Next lecture we will begin to learn how to work with 'point' data.

References

- Fusaro, C., Sarria-Guzmán, Y., Chávez-Romero, Y.A., Luna-Guido, M., Muñoz-Arenas, L.C., Dendooven, L., Estrada-Torres, A. & Navarro-Noya, Y.E. (2019). Land use is the main driver of soil organic carbon spatial distribution in a high mountain ecosystem. *PeerJ*, 7, e7897.
- Noonan, M.J., Martinez-Garcia, R., Davis, G.H., Crofoot, M.C., Kays, R., Hirsch, B.T., Caillaud, D., Payne, E., Sih, A., Sinn, D.L. *et al.* (2021). Estimating encounter location distributions from animal tracking data. *Methods in Ecology and Evolution*, 12, 1158–1173.
- Zhang, Z., Wang, H., Xu, F. & Jin, Y.Q. (2017). Complex-valued convolutional neural network and its application in polarimetric sar image classification. *IEEE Transactions on Geoscience and Remote Sensing*, 55, 7177–7188.