

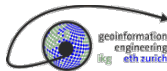
Meaningful Spatial Statistics

Edzer Pebesma

joint work with Simon Scheider, Ben Gräler, Christoph Stasch

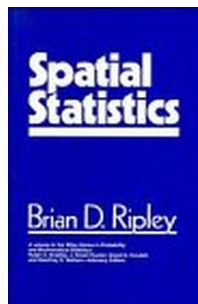


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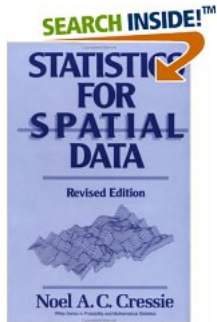
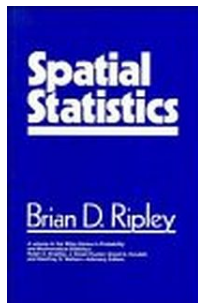


ETH Zürich, Nov 19, 2015

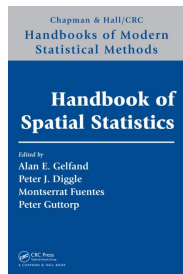
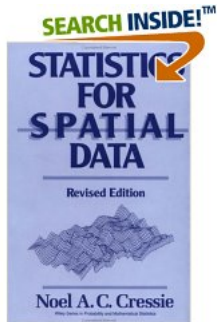
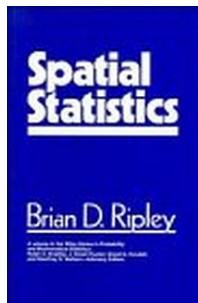
Spatial Statistics is...



Spatial Statistics is...



Spatial Statistics is...



but also...



but also...



but also...



but also...



<http://www.spatialstatistics.info/>



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Environmental Modelling & Software

Volume 51, January 2014, Pages 149–165



Meaningful spatial prediction and aggregation

Christoph Stasch^a, , Simon Scheider^a, , Edzer Pebesma^{a, b}, , Werner Kuhn^a,

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Highlights

- We introduce a new notion of meaningfulness of spatial prediction and aggregation.
- Observation, prediction, and aggregation procedures are formalized as functions.
- We show how datasets can be described as results of executing such procedures.
- We propose formal checks of meaningfulness based on functional correspondence.

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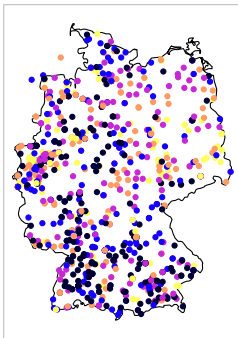


runmycode

RunMyCode

Code and data

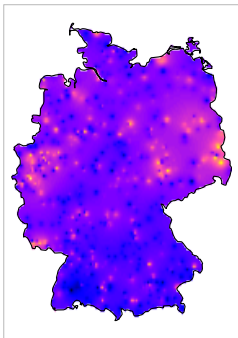
CO₂ emissions of power plants



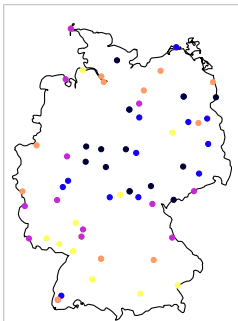
Sum of CO₂ emissions



Interpolated CO₂ emissions



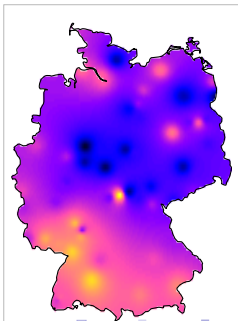
PM₁₀ measurements



Sum of PM₁₀ measurements



Interpolated PM₁₀ measurements



Overview

1. Spatial Statistics
2. Discovery
3. Provenance
4. What is data?
5. Basic types
6. Data generation procedures
7. Derivation operations
8. Examples: derivation graphs
9. Potential, further work
10. Conclusions

1. Spatial Statistics

- ▶ Statistics is the science of uncertainty
- ▶ statistics (plural) vs. Statistics (singular)
- ▶ Spatial Statistics: a collection of methods/tools for analyzing spatial data (estimation, inference, prediction, simulation)
- ▶ Spatial Statistics usually adopts some kind of random field model
- ▶ Omni-presence of spatial correlation was described by Fisher (1936, *The Design of Experiments*), long before Tobler 1953 explained this to geographers.
- ▶ Fisher suggested to cope with it by randomizing sampling designs
- ▶ this rules out interpolation and flexible aggregation
- ▶ aren't all data spatial?

The classical types of Spatial Statistics

1. Point pattern analysis: focus on observed patterns
 - ▶ are these (crime, disease) cases clustered?
 - ▶ which process generated this pattern?
2. Geostatistics: focus on predicting missing values
 - ▶ how do I interpolate a variable at a new (point, area)?
 - ▶ how/where should I sample, to improve interpolation?
3. Areal (lattice) data analysis: focus on patterns and relations
 - ▶ Are these area values spatially correlated? Or clustered?
 - ▶ how can I analyze regression models, given this correlation?
 - ▶ (neighbours; SAR/CAR models)

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 - ▶ extend previous themes to space-time, but also
 - ▶ state-space models, (S)PDE's
 - ▶ feature tracking, analysis of movement/trajectories

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Cognitive dissonance?

GI Science has:

- ▶ fields (coverages), and
- ▶ objects (features).

Spatial Statistics has:

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- ▶ lattices (areal data).

1. is this a cognitive dissonance between Spatial Statistics and GI Science?
2. is there more cognitive dissonance between them?

Research article

Modelling spatio-temporal information generation

Simon Scheider^{a*}, Benedikt Gräler^b, Edzer Pebesma^b, and Christoph Stasch^{b,c}

^a*Institut für Kartographie und Geoinformation, ETH Zürich, Switzerland;*

^b*Institute for Geoinformatics, University of Münster, Germany;* ^c*52°North GmbH*

(Received 00 Month 200x; final version received 00 Month 200x)

Maintaining knowledge about the provenance of data, i.e., about how it was obtained, is crucial for its further use. Contrary to what the overused metaphors of “data mining” and “big data” are implying, it is hardly possible to use data in a meaningful way if information about its sources and types of conversions are discarded in the process of data gathering. A generative model of data derivation could not only help automating the description of derivation

2. Discovery

How do you discover data?

2. Discovery

How do you discover data?

Why is discovery important?

2. Discovery


How do you discover data?

Why is discovery important?

Impact.

3. Provenance


PROV-O¹: “Provenance is information about entities, activities, and people involved in producing a piece of data or thing, which can be used to form assessments about its quality, reliability or trustworthiness.

¹<http://www.w3.org/TR/2012/WD-prov-overview-20121211/> 

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The PROV Family of Documents defines a model, corresponding serializations and other supporting definitions to enable the inter-operable interchange of provenance information in heterogeneous environments such as the Web. ”

¹<http://www.w3.org/TR/2012/WD-prov-overview-20121211/> 

4. What is data?

“data are not just numbers, they are numbers with a context²”

²George W. Cobb and David S. Moore. "Mathematics, statistics, and teaching." *American Mathematical Monthly* (1997): 801-823.

4. What is data?

“data are not just numbers, they are numbers with a context²”

To give context, to numbers, we need

- ▶ reference systems: SI, units of measurement, datums, calendars, identifiers
- ▶ coherence: when/where/what (meaning)
- ▶ maybe also: who/why/how (intention, pragmatics)

²George W. Cobb and David S. Moore. "Mathematics, statistics, and teaching." *American Mathematical Monthly* (1997): 801-823.

5. Basic types

Basic reference system types and simple derivations thereof. Each type needs to go along with its reference system (RS).

\mathcal{P} denotes the power set (set of all subsets).

Symbol	Definition	Meaning	Description
S		\mathbb{R}^3	Set of possible spatial locations with RS.
T		\mathbb{R}	Set of possible moments in time with RS.
D		\mathbb{N}	Set of possible discrete entity identifier with RS.
Q		\mathbb{R}	Set of possible observed values with RS.

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R	S set	$\mathcal{P}(S)$	Set of regions: bounded by polygons, or collection of isolated locations and combinations thereof.
I	T set	$\mathcal{P}(T)$	Set of collections of moments in time: continuous intervals or a set of moments in time or combinations thereof.
D set	D set	$\mathcal{P}(D)$	Sets of object identifiers
Q set	Q set	$\mathcal{P}(Q)$	Sets of quality values.

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D set	D set	$\mathcal{P}(D)$	Sets of object identifiers
Q set	Q set	$\mathcal{P}(Q)$	Sets of quality values.
bool		$\{T, F\}$	Boolean, also used to express predicates for selection
Extent	$R \times I$	$R \times I$	set of spatio-temporal extent as the orthogonal product of the spatial and temporal projections
Occurs	$(S \times T)$ set	$\mathcal{P}(S \times T)$	set of spatio-temporal subsets, occurrences of events and objects, but also of certain values or conditions in a field; footprint, support

Transitions

Symbol	Type definition	Description
Select	$\text{Extent} \Rightarrow S \times T$	select the centroid (or alike) of an extent
SSelect	$R \Rightarrow S$	select the centroid of a region
TSelect	$I \Rightarrow T$	select the centroid of a time interval
Tessel	$S \times T \Rightarrow \text{Extent}$	map spatio-temporal locations to their corresponding spatio-temporal extent
STessel	$S \Rightarrow R$	map spatial locations to regions
TTessel	$T \Rightarrow I$	map time stamps to time intervals
QPartition	$Q \Rightarrow Q \text{ set}$	map quality values to ranges of qualities
Qstat	$(Q \Rightarrow \text{bool}) \Rightarrow Q$	summarize quality values (e.g., mean, median)

6. Generation procedures: Fields

Symbol	Type definition	Description
Field	$S \times T \Rightarrow Q$	spatio-temporal field
SField	$S \Rightarrow Q$	spatial field
TField	$T \Rightarrow Q$	temporal field (time series)

Generation procedures: Lattices

Symbol	Type definition	Description
Lattice	$R \Rightarrow I \Rightarrow Q$	spatio-temporal lattice
LatticeS	$R \Rightarrow T \Rightarrow Q$	temporal spatial lattice
LatticeT	$S \Rightarrow I \Rightarrow Q$	spatial temporal lattice
SLattice	$R \Rightarrow Q$	spatial lattice
TLattice	$I \Rightarrow Q$	temporal lattice

Generation procedures: Events

Symbol	Type definition	Description
Event	$D \Rightarrow S \times T$	spatio-temporal events
RegionalEvent	$D \Rightarrow R \times T$	events affecting a set of locations
IntervalEvent	$D \Rightarrow S \times I$	events lasting for some time interval
BlockEvent	$D \Rightarrow \text{Extent}$	events affecting a set of locations and lasting for some time interval
SEvents	$D \Rightarrow S$	events' locations
TEvents	$D \Rightarrow T$	events' timestamps
MarkedEvent	$D \Rightarrow S \times T \times Q$	spatio-temporal marked events

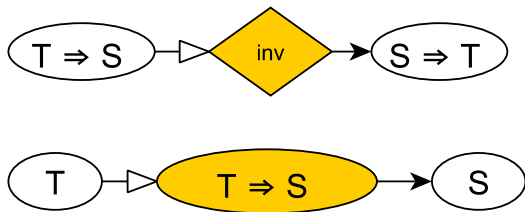
Generation procedures: Trajectories

Symbol	Type definition	Description
Trajectory	$T \Rightarrow S$	trajectory
RegionalTrajectory	$T \Rightarrow R$	trajectory of regions
IntervalTrajectory	$I \Rightarrow S$	trajectory over temporal intervals
BlockTrajectory	$I \Rightarrow R$	trajectory over temporal intervals of regions
MarkedTrajectory	$T \Rightarrow S \times Q$	marked trajectory

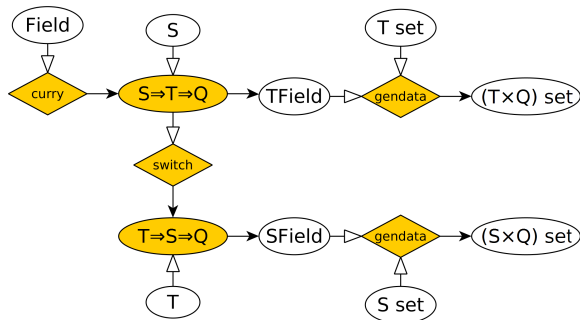
Generation procedures: Objects

Symbol	Definition	Description
Objects	$D \Rightarrow T \Rightarrow S$	objects in time and space
RegionalObjects	$D \Rightarrow T \Rightarrow R$	objects in space and time defined over regions
IntervalObjects	$D \Rightarrow I \Rightarrow S$	objects in time and space defined for collections of moments in time
BlockObjects	$D \Rightarrow I \Rightarrow R$	objects in space and time defined over regions and collections of moments in time
OjectTimeSeries	$D \Rightarrow T \Rightarrow Q$	time series associated with each object
MarkedObjects	$D \Rightarrow T \Rightarrow S \times Q$	marked object trajectories

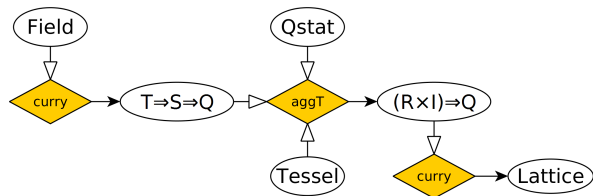
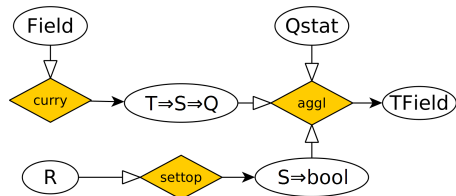
7. Data derivation



8. Data derivation graphs: generating field data

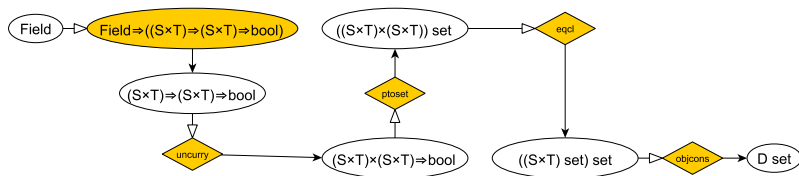


Data derivation: spatial/temporal aggregation

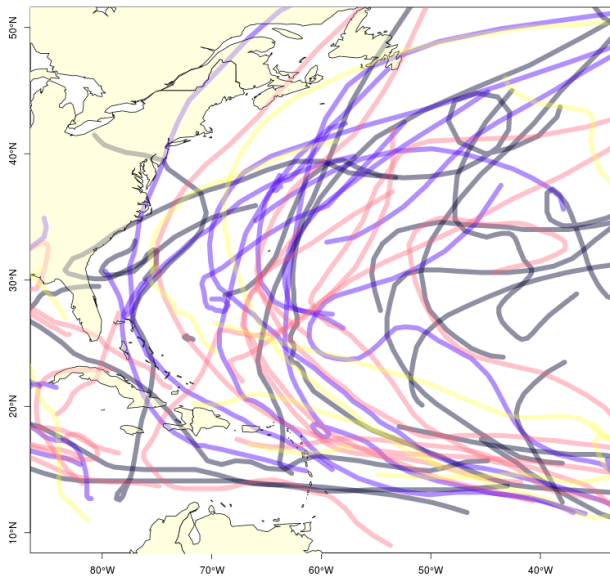


see paper for definitions of curry, aggl, agglT and settop

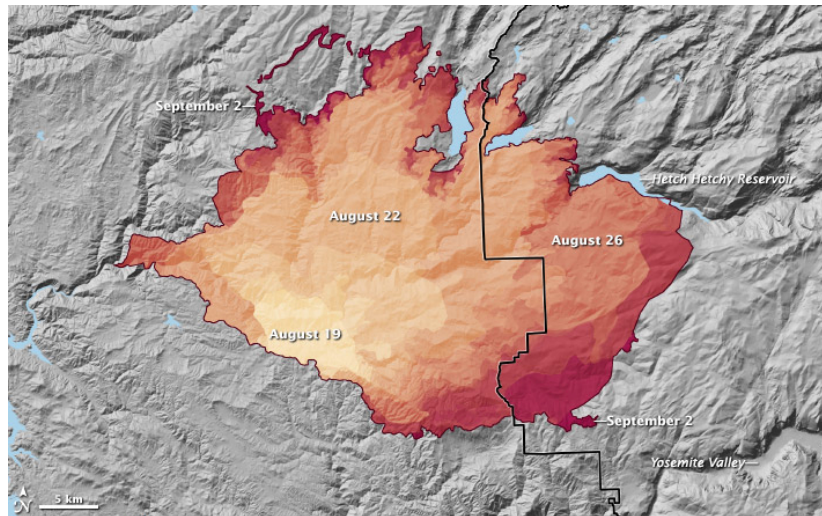
Data derivation: deriving objects from fields

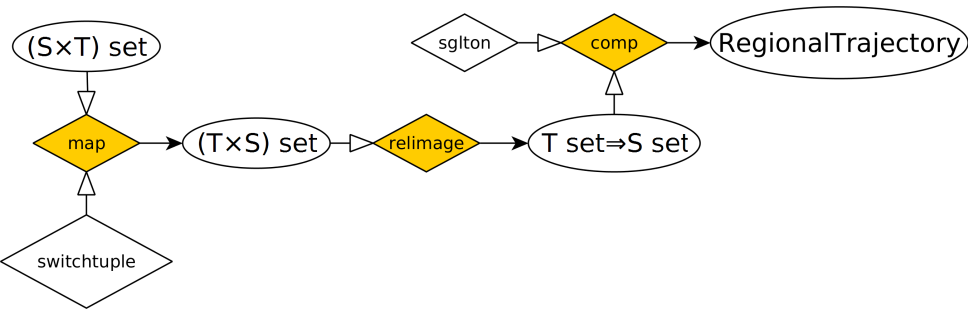


Storms: Trajectories from fields



Forest fires: Regional Trajectories





ArcGIS - enviroCar tracks overview

KARTE ÄNDERN | Anmelden

Details | Bearbeiten | Grundkarte

Freigeben | Drucken | Messen | Adresse oder Ort suchen

Info | Inhalt | **Legende**

Legende

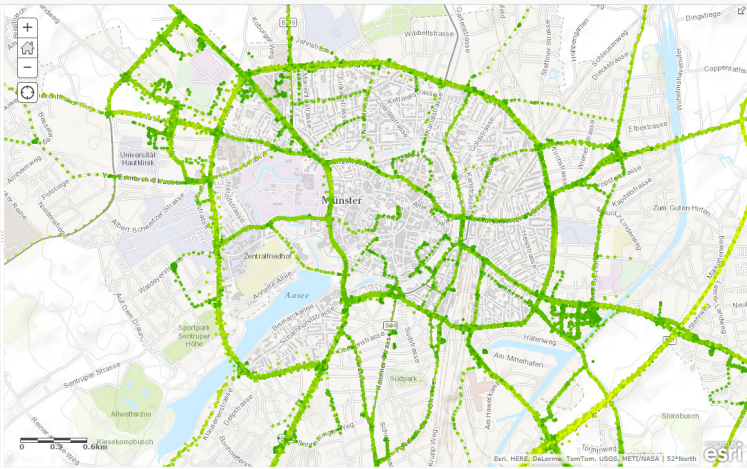
enviroCarTracks - enviroCarTrack

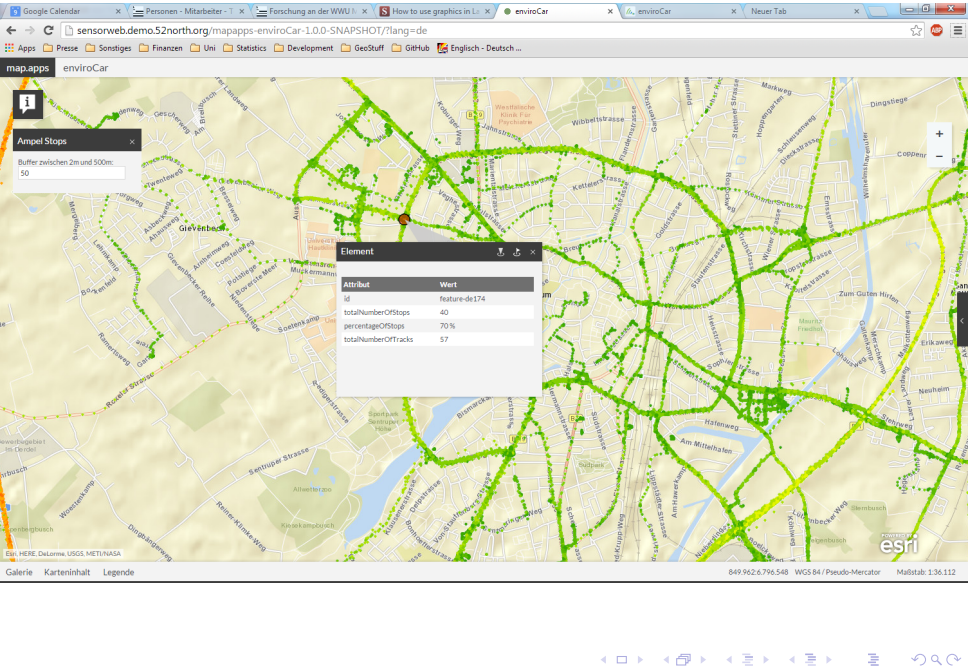
- < 10 km/h
- 10 - 30 km/h
- 30 - 50 km/h
- 50 - 70 km/h
- 70 - 90 km/h
- 90 - 100 km/h
- 100 - 130 km/h
- 130 - 150 km/h
- 150 - 180 km/h
- > 180 km/h

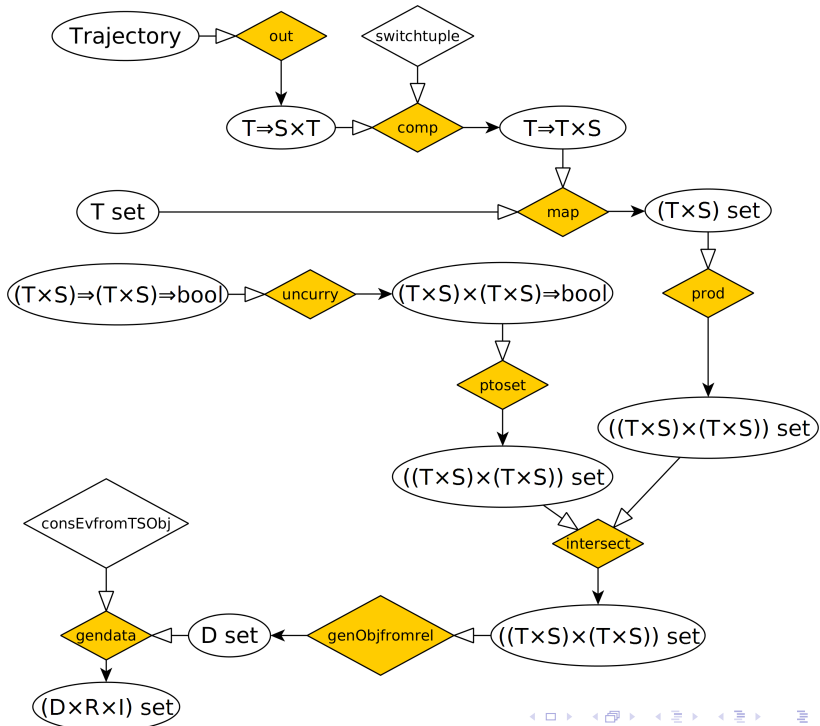
enviroCarTracks

enviroCar speed map

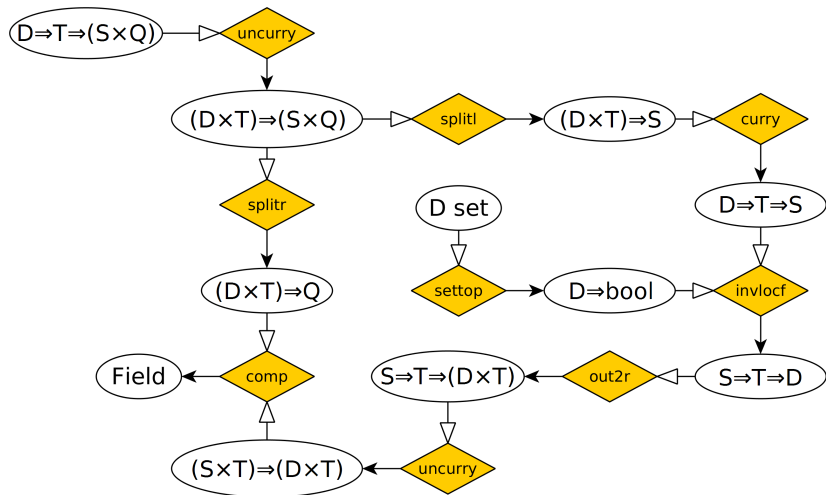
- < 10 km/h
- 10 - 30 km/h
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- 50 - 70 km/h
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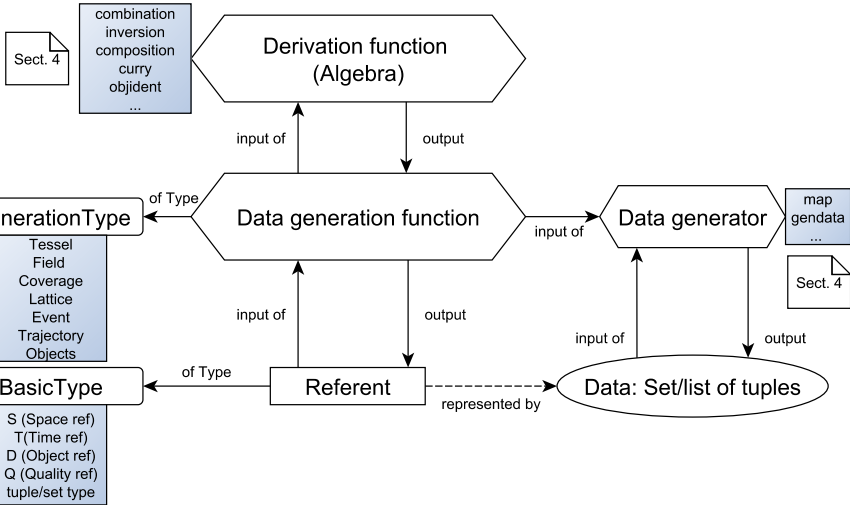




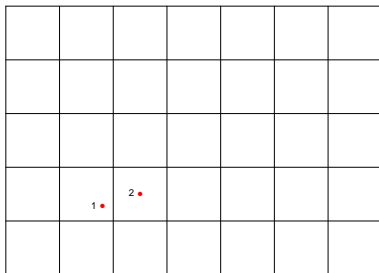


Generating a field from marked trajectories

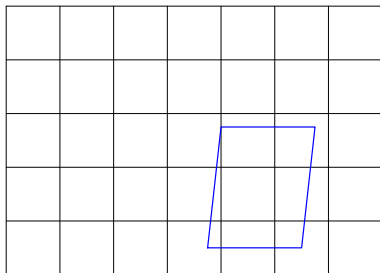
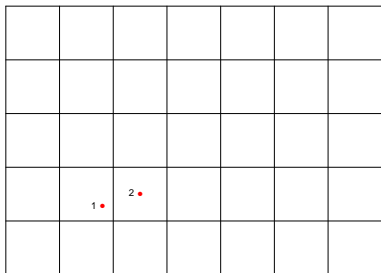




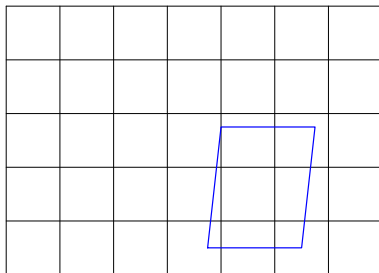
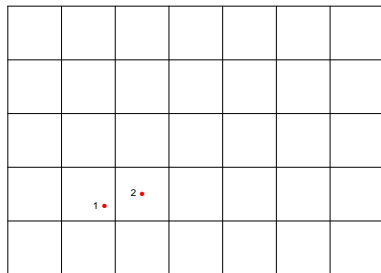
Retrieving information from raster maps



Retrieving information from raster maps



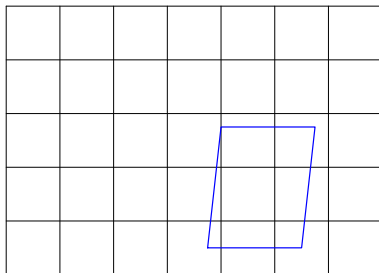
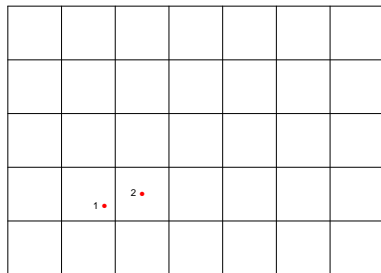
Retrieving information from raster maps



Three simplest cases:

point	cell is point	cell is constant	cell is aggregation
1	NA	cell value	NA
2	cell value	cell value	NA

Retrieving information from raster maps



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2	cell value	cell value	NA

how *can* software decide what to do?

9: Potential, further work

- ▶ Discovery:
 - ▶ the theory³ works, but does it solve problems in practice?
 - ▶ translate the abstract syntax of our algebra into tools
 - ▶ annotate data sets with derivation graphs
 - ▶ publish data with derivation graphs
 - ▶ develop discovery mechanisms (linked data, annotation tools)

³[http:](http://www.geographicknowledge.de/vocab/AlgebraReferenceSystems.thy)

9: Potential, further work

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 - ▶ develop discovery mechanisms (linked data, annotation tools)
- ▶ Generation:
 - ▶ reason about space of possible derivations
 - ▶ reason about compatibility
 - ▶ develop recommender systems

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10. Conclusions – I

- ▶ We propose a generative algebra for spatio-temporal information that describes how data is generated in a variety of derivation processes, expressed as derivation graphs.
- ▶ Data generation procedures are expressed as functions on basic types *S*, *T*, *Q*, *D*
- ▶ Possible derivations can be expressed as chains of function applications, where each function is either an operation of the algebra or a spatio-temporal data generation procedure.
- ▶ Types of data generation include tessellations, fields, coverages, lattices, events, objects, trajectories.
- ▶ We illustrate how they can be converted into each other.
- ▶ Our algebra can be used for publishing provenance of data sets in terms of a derivation graph and on a level of detail that distinguishes types of spatio-temporal information.
- ▶ Our algebra makes explicit the **support** of data, i.e. whether values refer to aggregated values or constant values over regions or time periods.

Conclusions – II

The dominant GI types in use (simple features, coverages) do not inform **how** non-geometry attributes Q relate to geometry S, T :

- ▶ are they *constant*,
- ▶ do they refer to an aggregate for the feature *as a whole*?
- ▶ do they refer to a single (central) location?
- ▶ are they the result of another convolution over a signal?

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- ▶ do they refer to a single (central) location?
- ▶ are they the result of another convolution over a signal?

For spatial analysis, all this matters.

Thank you.

Spatial statistics

Functional types

GIS



OGC

