



Applied Geodata Science I

Session 4

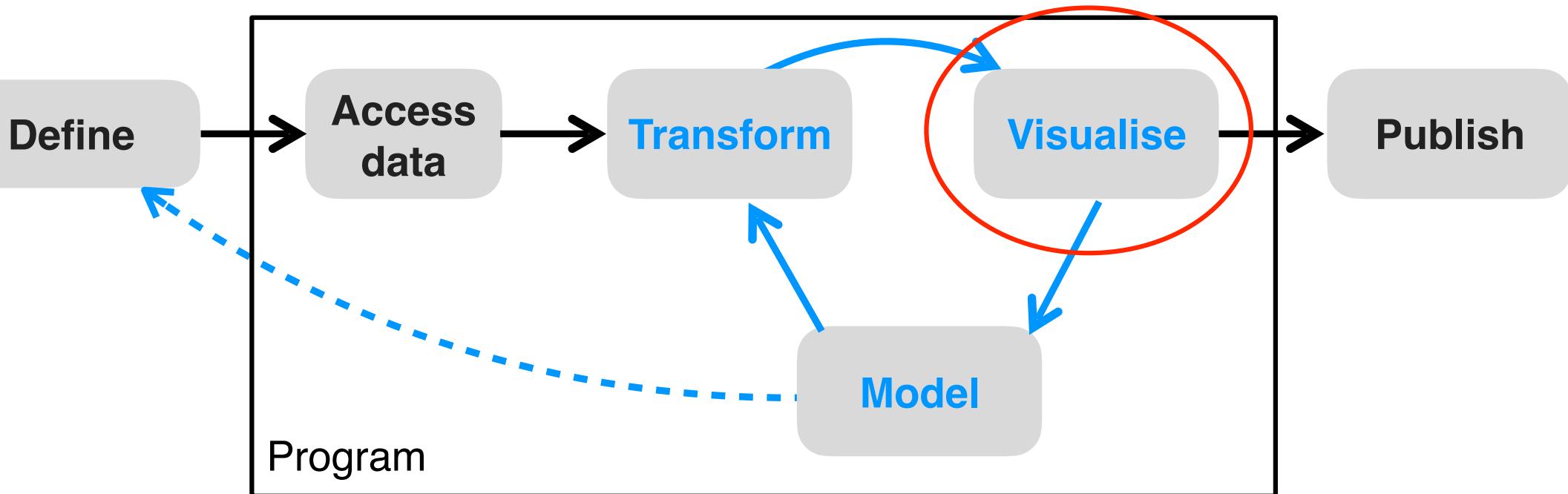
Prof. Dr. Benjamin Stocker

10.03.2025



The data science workflow

AC
GD
I



The course website: https://geco-bern.github.io/agds1_course/



Applied Geodata Science I

Introducing applications of machine learning in Geography and Environmental Sciences

AUTHOR

Benjamin Stocker

PUBLISHED

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About this course

Course description

This course introduces essential methods of the data science workflow, supported by [Geodata Science](#) and demonstrates common applications of machine learning methods in the field of Environmental Sciences by worked examples.

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Applied Geodata Science

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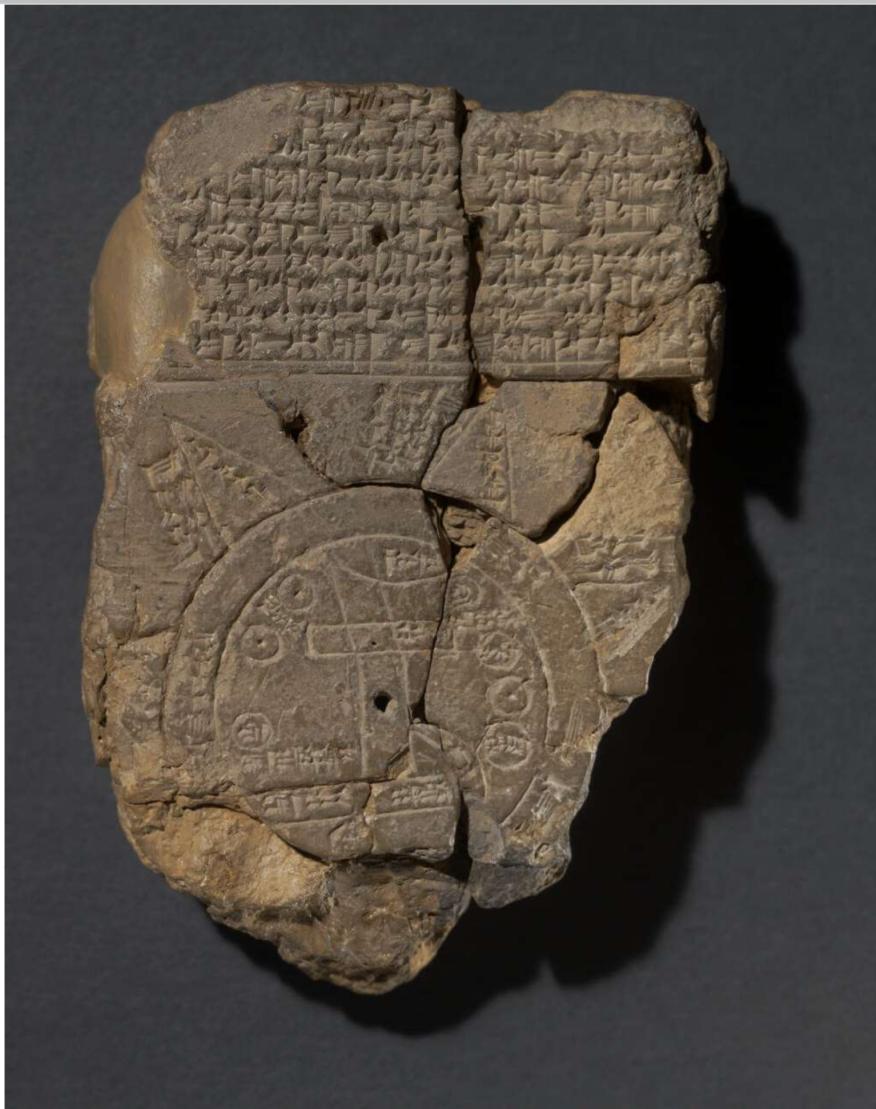
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Preface

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Earliest data visualisation?



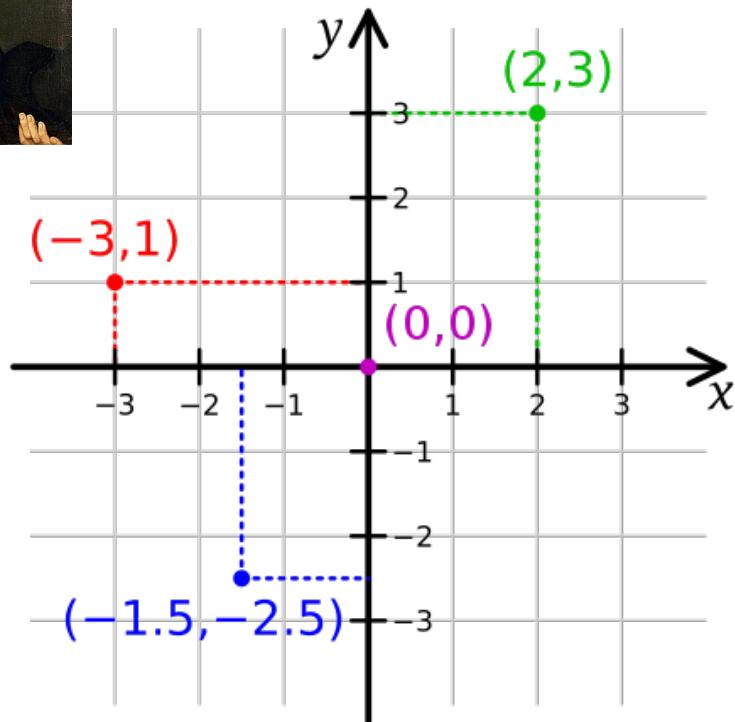
Babylon, ca. 500 BC

https://www.britishmuseum.org/collection/object/W_1882-0714-509

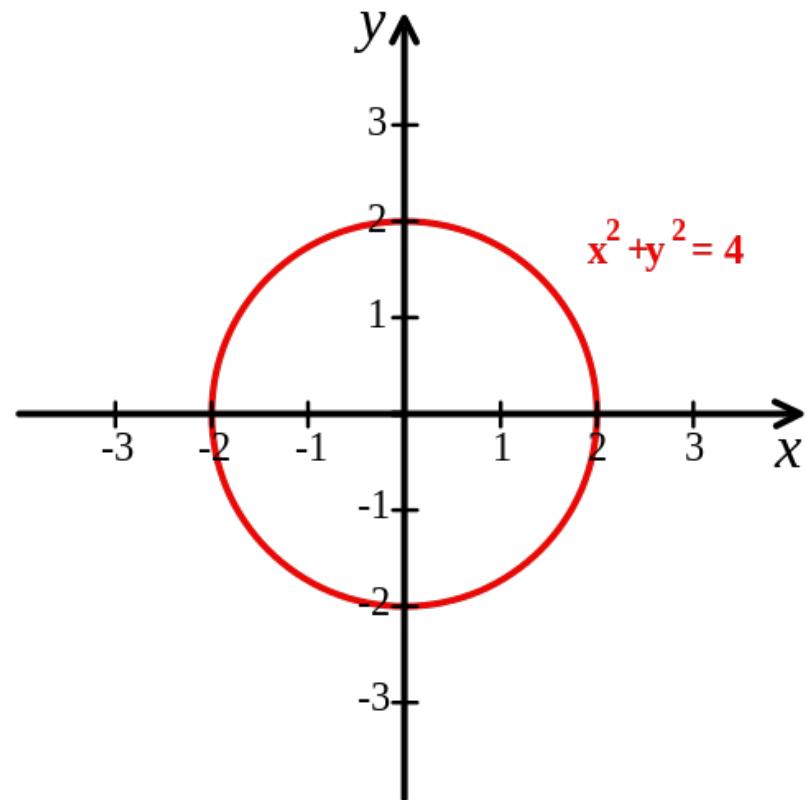
Cartesian coordinate system



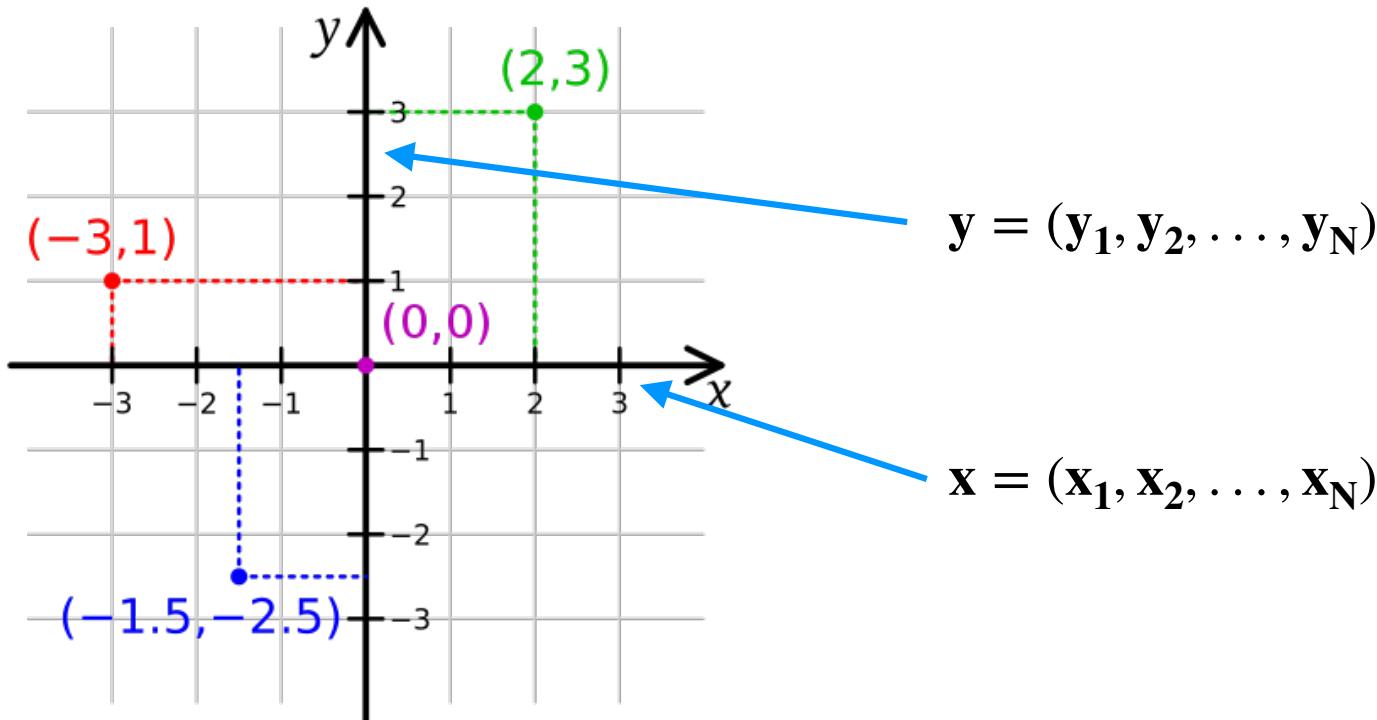
René Descartes
1596-1650



Link between geometry and algebra!

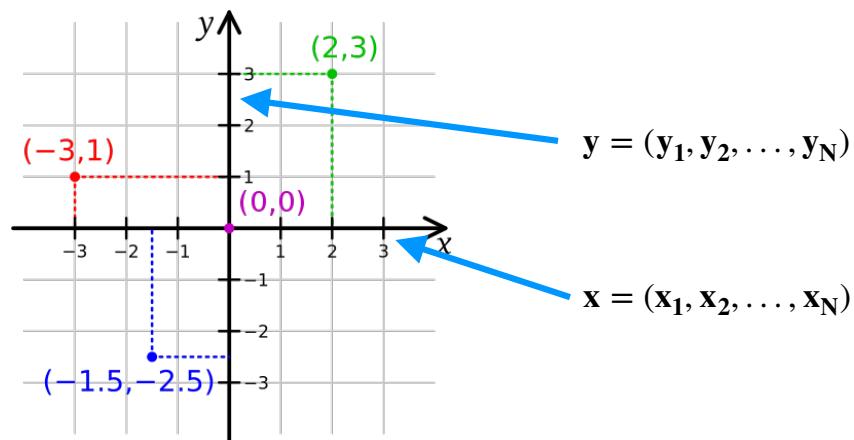


Cartesian coordinate system



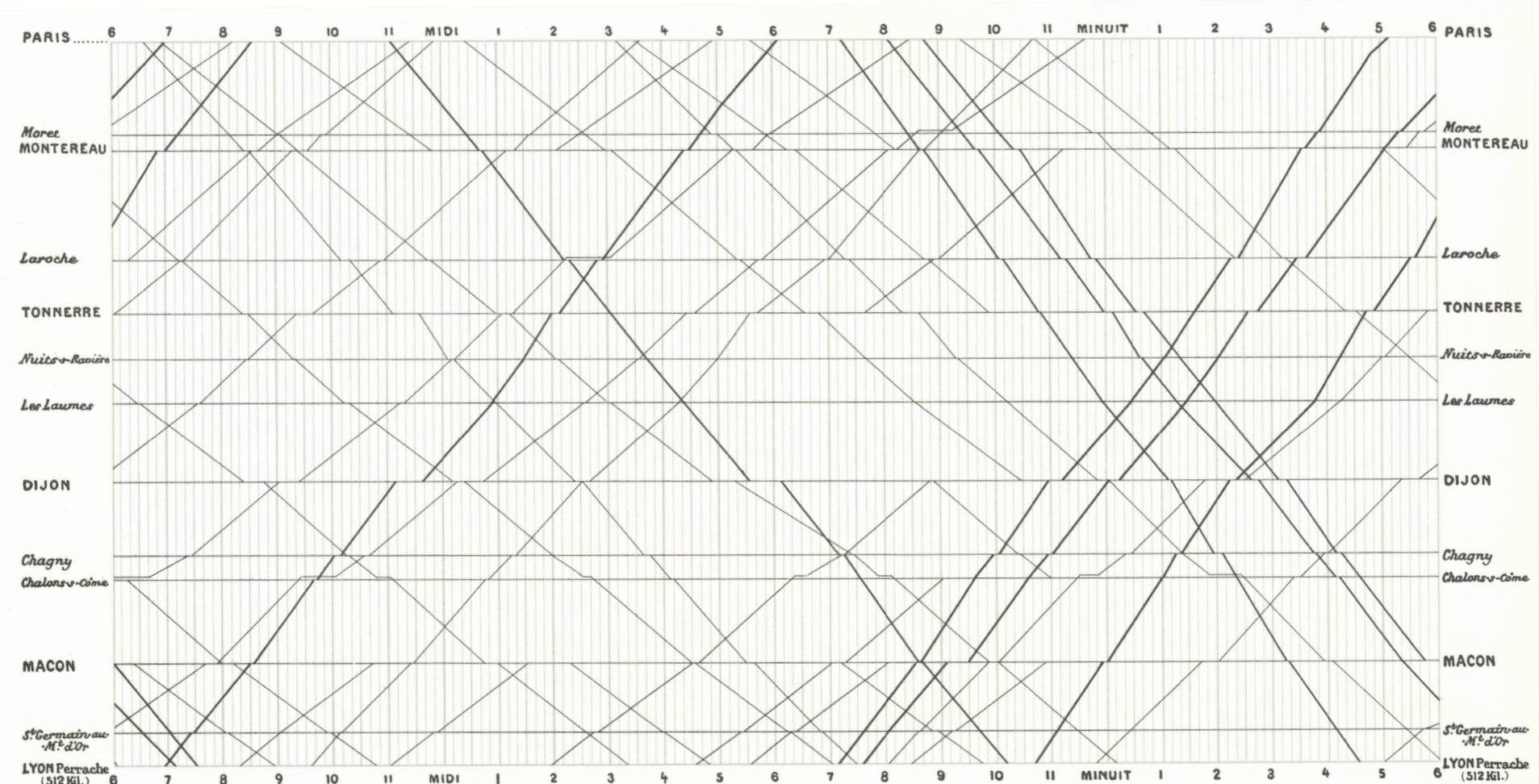
Data visualisation and the Grammar of Graphics

- Visualising data is to convert values into visual elements that make up a graphic.
- We "map" data values onto quantifiable features of the resulting graphic - the aesthetics.
- Variation along each “dimension” in the data is mapped onto one aesthetic.



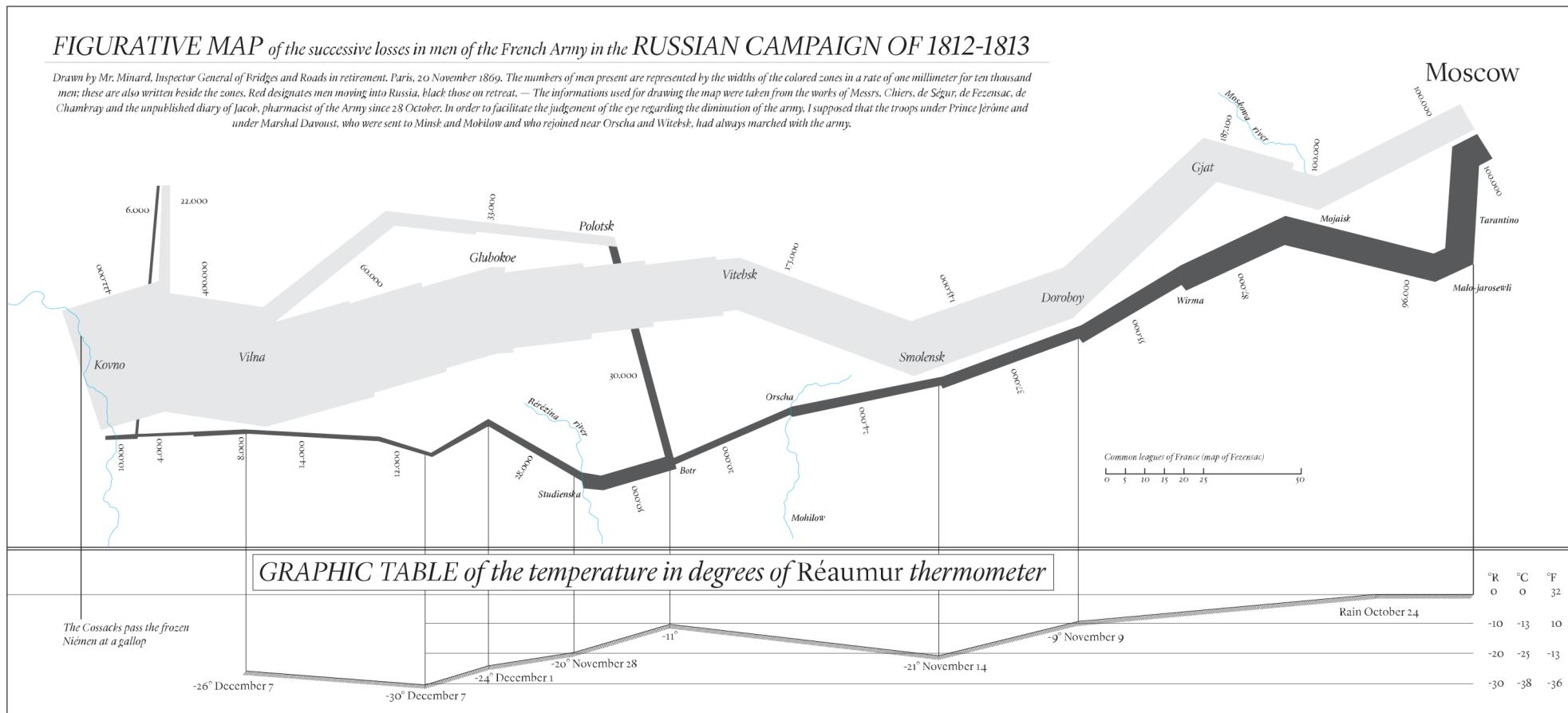
Visualising time

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S
CD
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E. J. Marey, 1885
<https://badriadhikari.github.io/data-viz-workshop-2021/minards/>

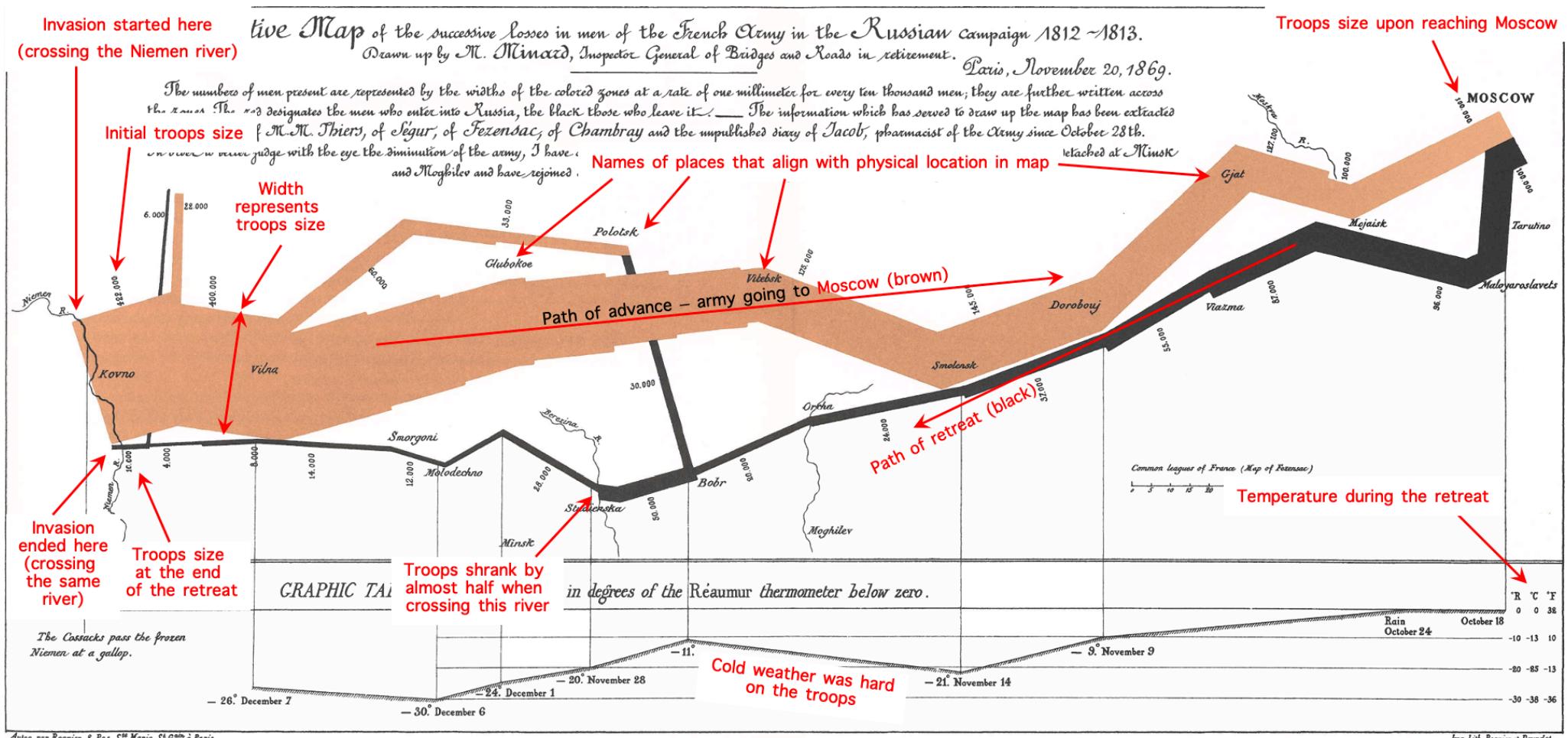
Quantitative information in geographical space



Charles-Joseph Minard, 1869
<https://badriadhikari.github.io/data-viz-workshop-2021/minards/>

Quantitative information in geographical space

AC
S
D
I

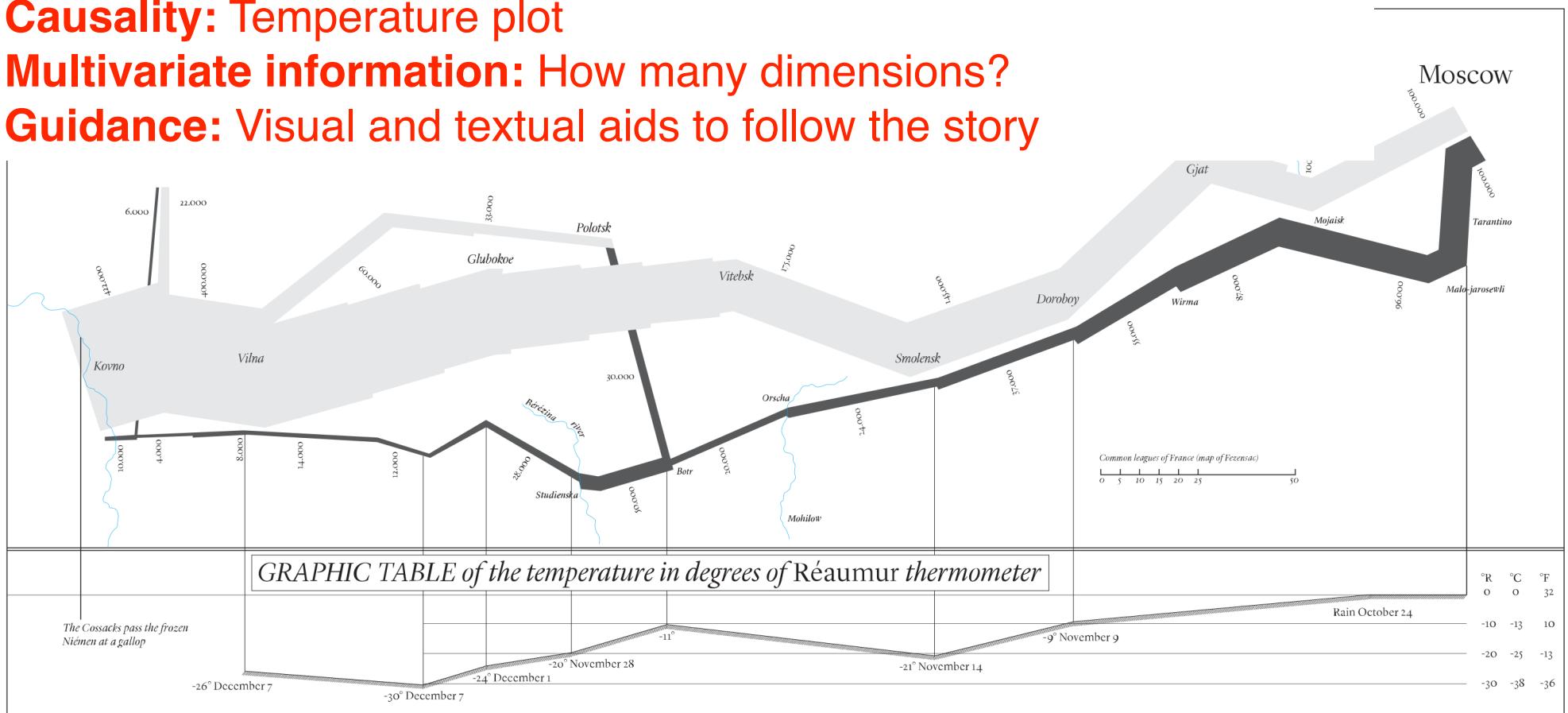


Minard, 1869

<https://badriadhikari.github.io/data-viz-workshop-2021/minards/>

Quantitative information in geographical space

- **Contrast:** Colors of advance and retreat. Width of lines back-to-back
- **Causality:** Temperature plot
- **Multivariate information:** How many dimensions?
- **Guidance:** Visual and textual aids to follow the story



Charles-Joseph Minard, 1869

<https://badriadhikari.github.io/data-viz-workshop-2021/minards/>

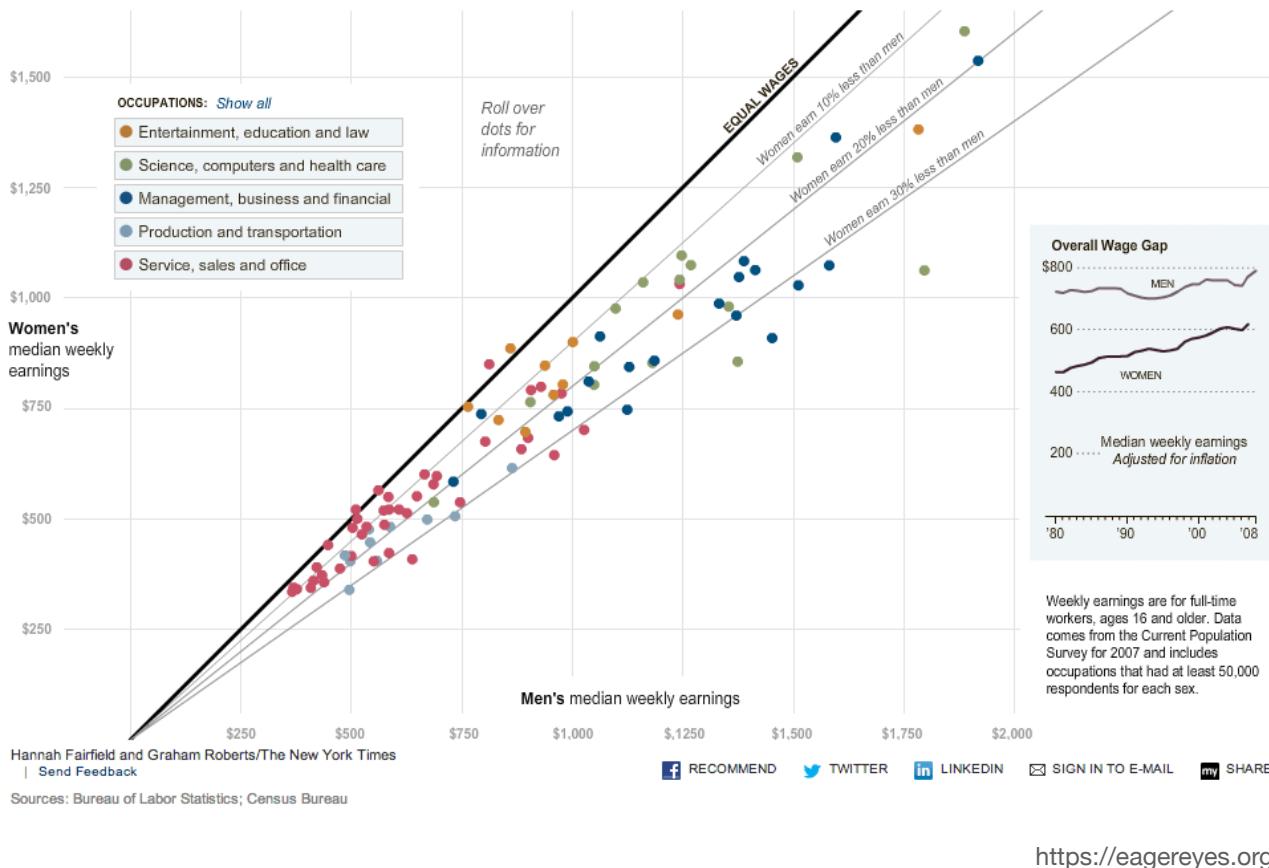
Scatterplots

ACG
ID

Published: May 18, 2010

Why Is Her Paycheck Smaller?

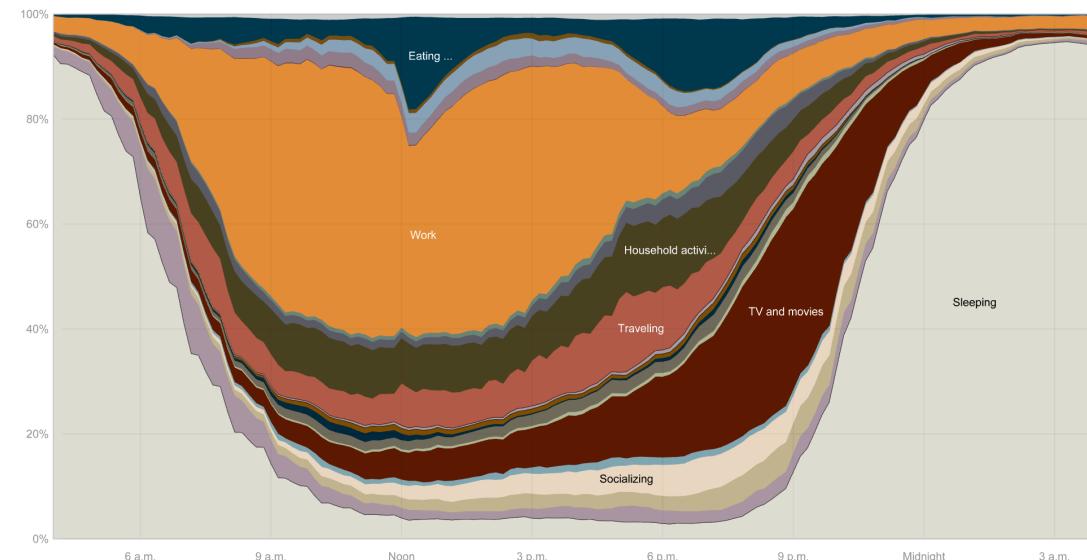
Nearly every occupation has the gap — the seemingly unbridgeable chasm between the size of the paycheck brought home by a woman and the larger one earned by a man doing the same job. Economists cite a few reasons: discrimination as well as personal choices within occupations are two major factors, and part of the gap can be attributed to men having more years of experience and logging more hours.



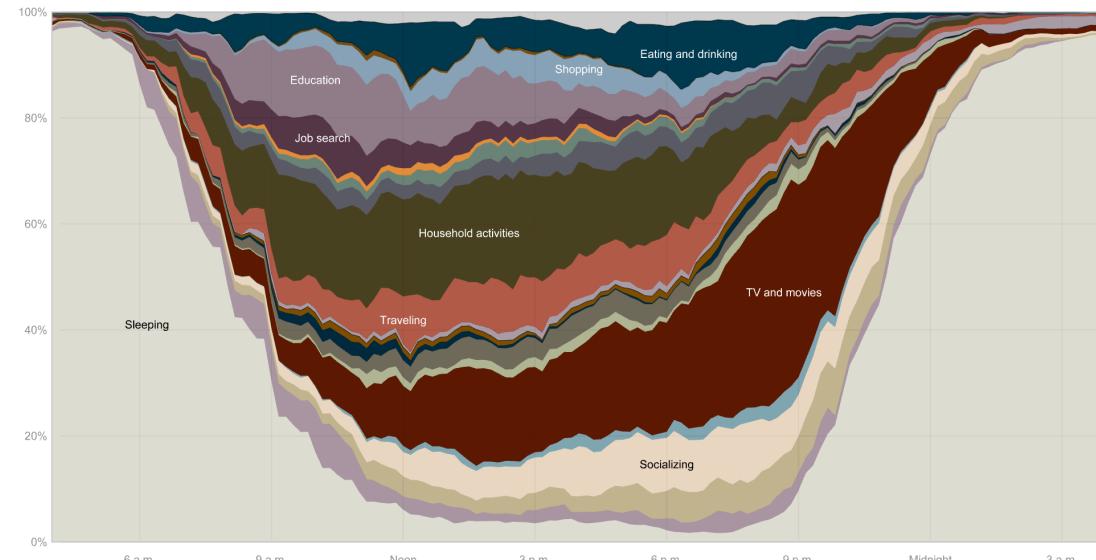
Hannah Fairfield and Graham Roberts
New York Times, 2010
<https://eagereyes.org/journalism/the-explanatory-power-of-data-points>

Proportions over time

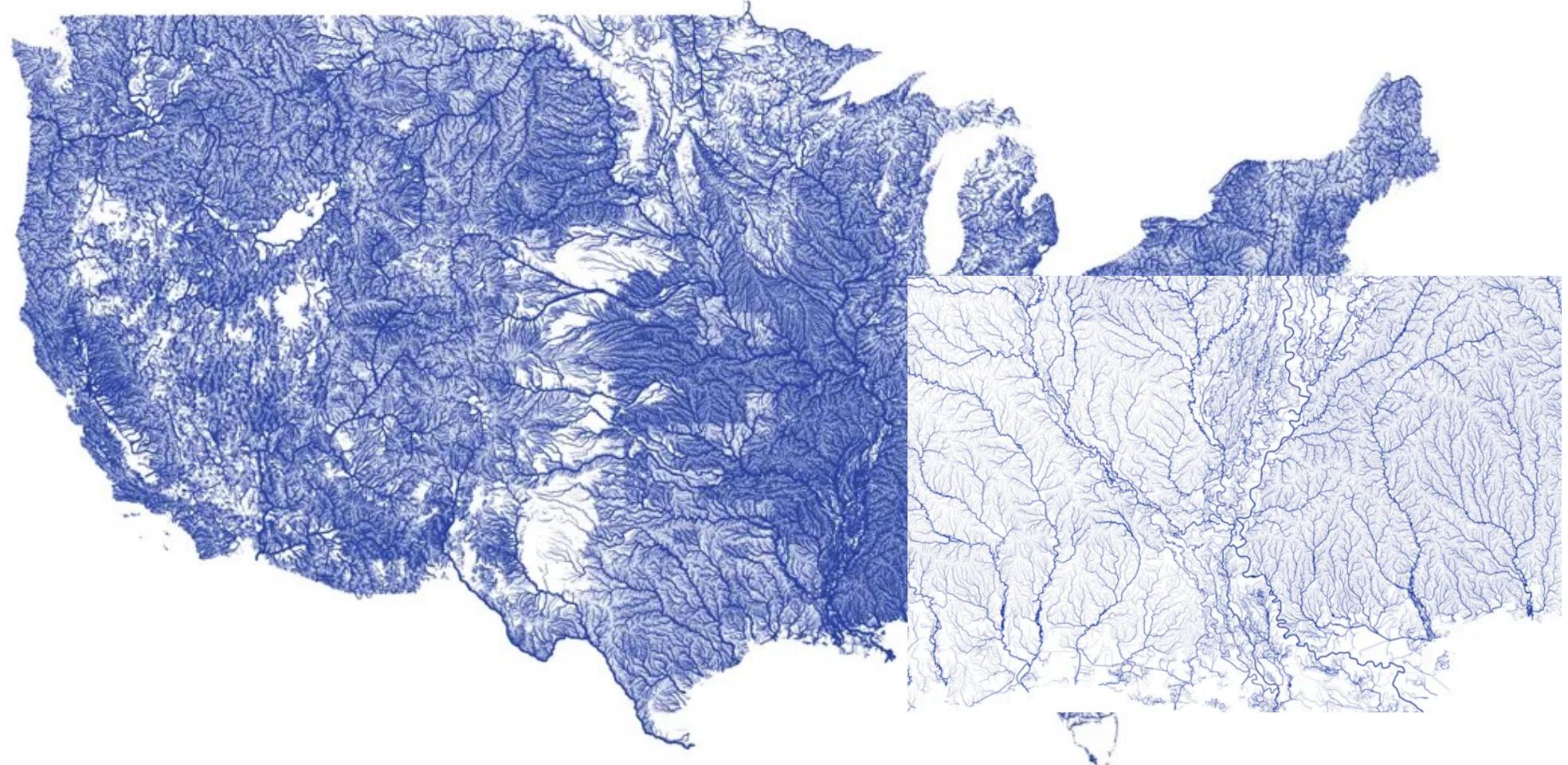
Employed



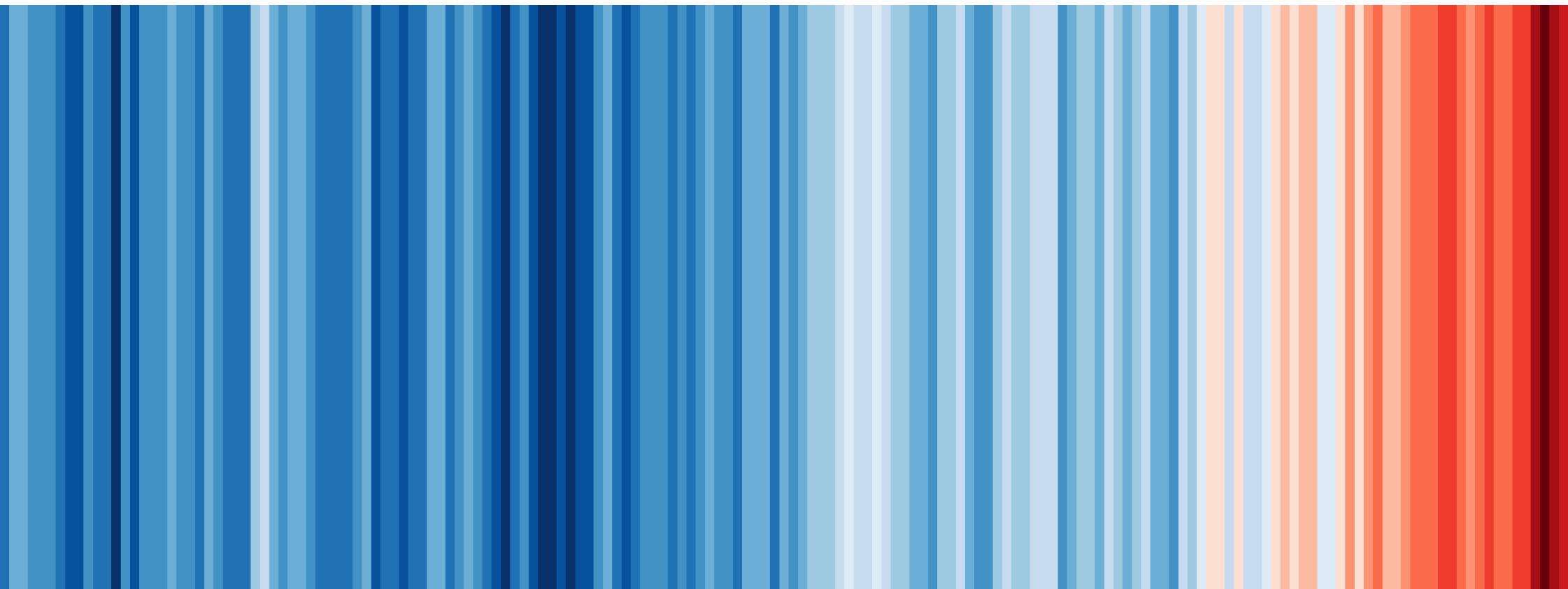
Unemployed

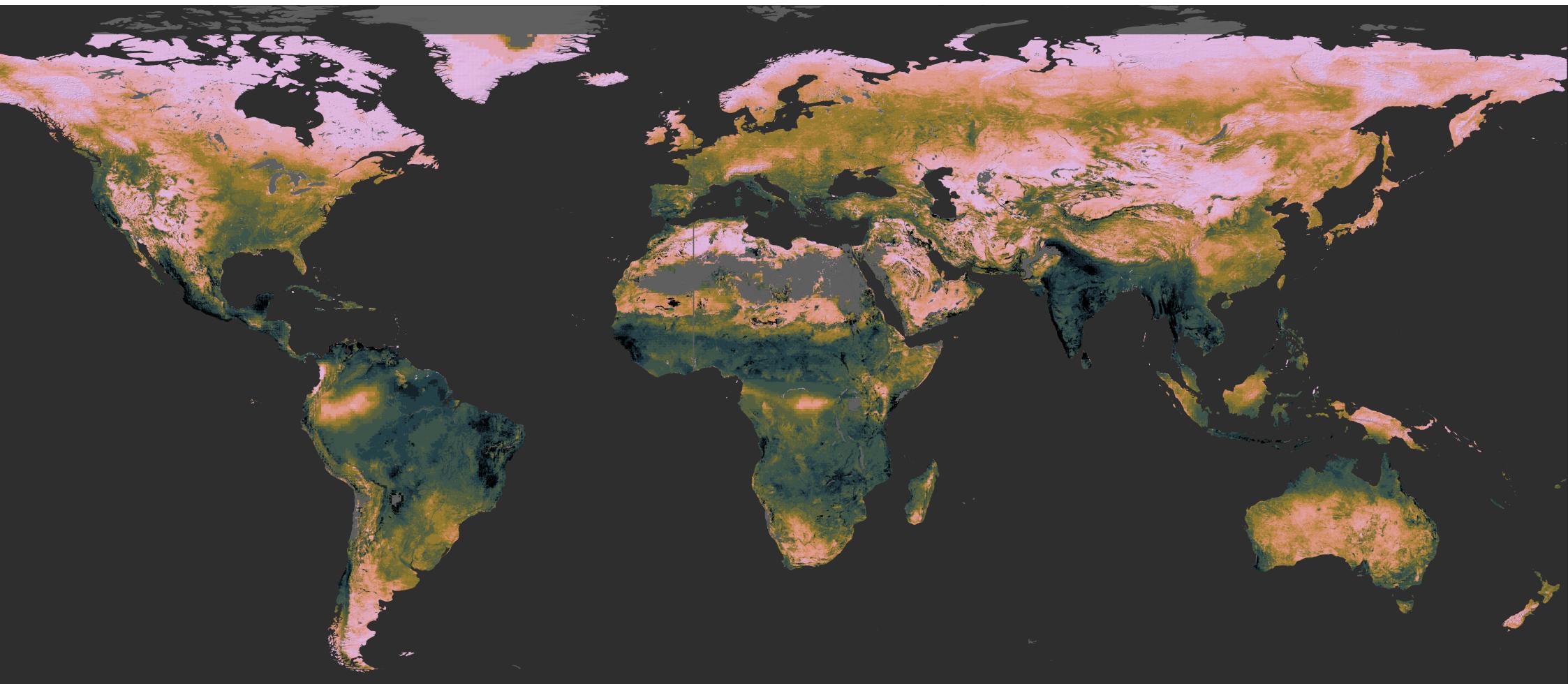


Amanda Cox, *New York Times*
<https://gestalten.com/blogs/journal/visualizing-a-new-new-york-times>

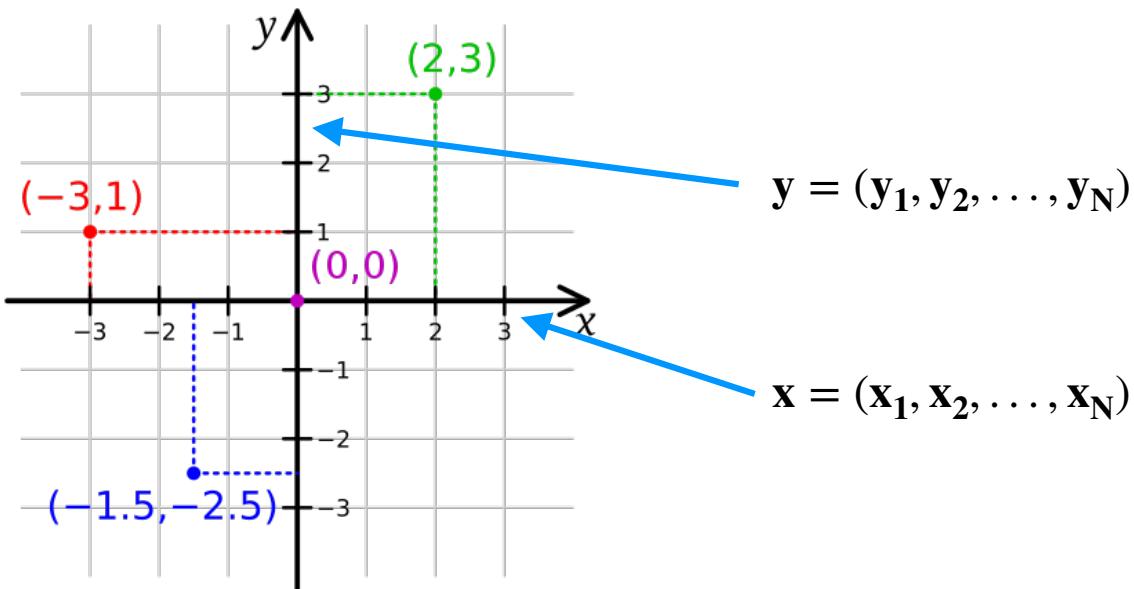


Nelson Minar,
<https://www.wired.com/2013/06/infographic-this-detailed-map-shows-every-river-in-the-united-states/?viewall=true>





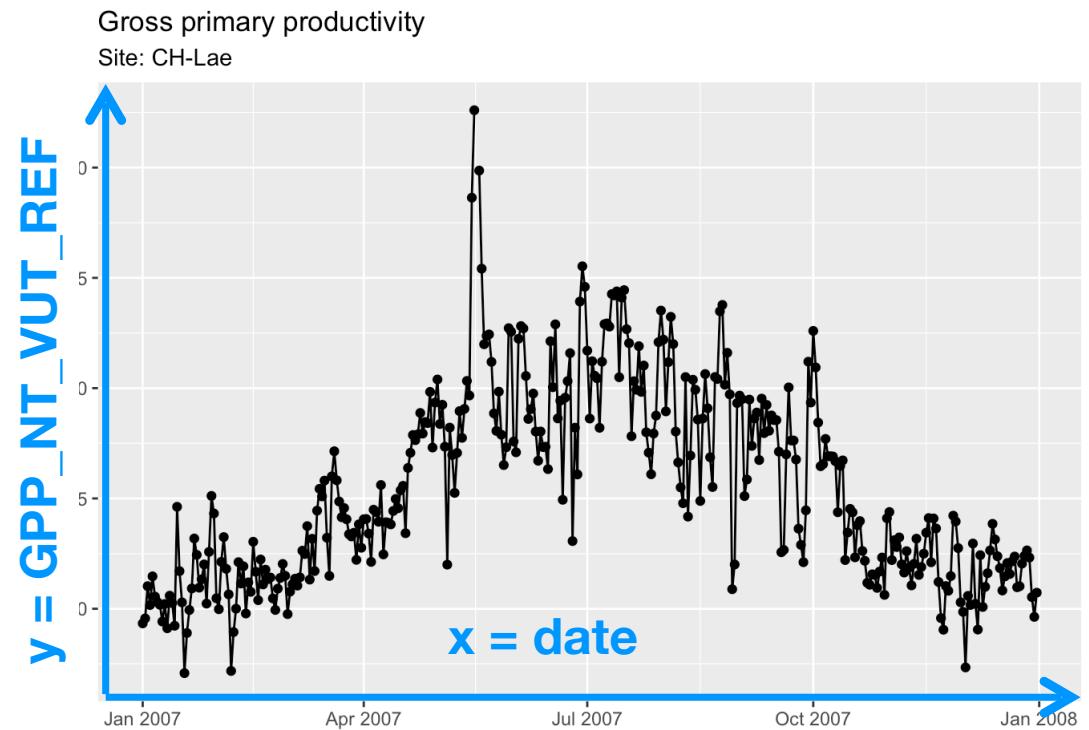
Cartesian coordinate system



- We "map" data values onto quantifiable features of the resulting graphic - the aesthetics.

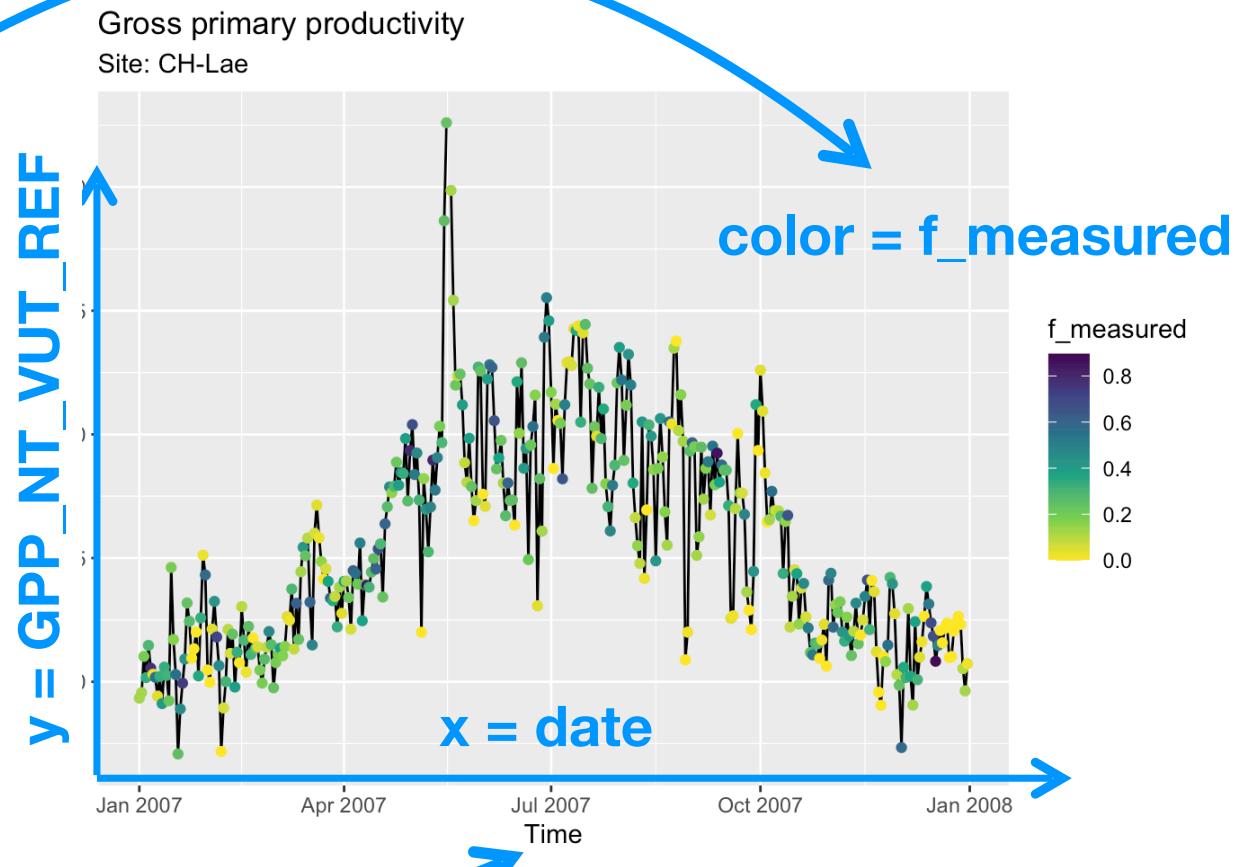
Mapping to two aesthetics

```
> df
# A tibble: 3,912 x 3
  date      GPP_NT_VUT_REF f_measured
  <date>        <dbl>      <dbl>
1 2004-03-31     1.62    0.333
2 2004-04-01     5.03    0.396
3 2004-04-02     3.73    0.312
4 2004-04-03     3.87    0.5
5 2004-04-04     6.06    0.333
6 2004-04-05     4.46    0.396
7 2004-04-06    10.5    0.0417
8 2004-04-07     7.09    0.312
9 2004-04-08     6.90    0.208
10 2004-04-09    4.66    0.667
# ... with 3,902 more rows
```



Mapping to three aesthetics

```
> df
# A tibble: 3,912 x 3
  date      GPP_NT_VUT_REF f_measured
  <date>        <dbl>      <dbl>
1 2004-03-31     1.62    0.333
2 2004-04-01     5.03    0.396
3 2004-04-02     3.73    0.312
4 2004-04-03     3.87    0.5
5 2004-04-04     6.06    0.333
6 2004-04-05     4.46    0.396
7 2004-04-06    10.5    0.0417
8 2004-04-07     7.09    0.312
9 2004-04-08     6.90    0.208
10 2004-04-09    4.66    0.667
# ... with 3,902 more rows
```



A data frame

Aesthetics mapping

```
ddf %>%
  ggplot(aes(x = date, y = GPP_NT_VUT_REF)) +
  geom_line() +
  geom_point()
```

(A second visualisation element)

Visualisation element. Function interprets 'x' and 'y'.

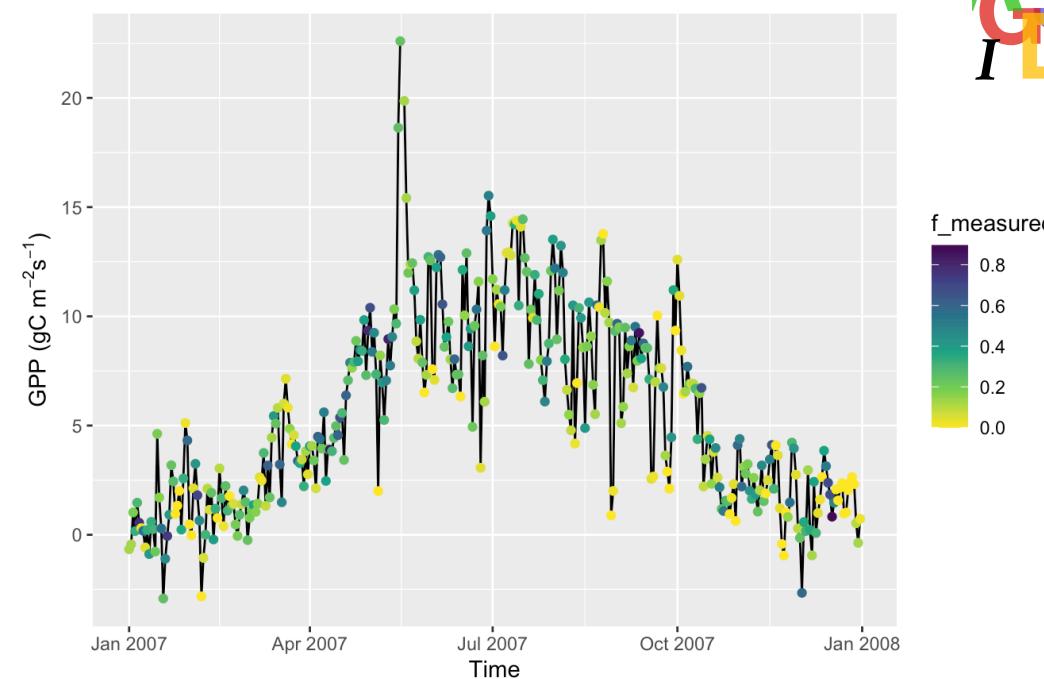
ggplot2

```
> df
```

```
# A tibble: 3,912 x 3
  date      GPP_NT_VUT_REF f_measured
  <date>          <dbl>      <dbl>
1 2004-03-31      1.62     0.333
2 2004-04-01      5.03     0.396
3 2004-04-02      3.73     0.312
4 2004-04-03      3.87     0.5
5 2004-04-04      6.06     0.333
6 2004-04-05      4.46     0.396
7 2004-04-06     10.5     0.0417
8 2004-04-07      7.09     0.312
9 2004-04-08      6.90     0.208
10 2004-04-09     4.66     0.667
# ... with 3,902 more rows
```

Gross primary productivity

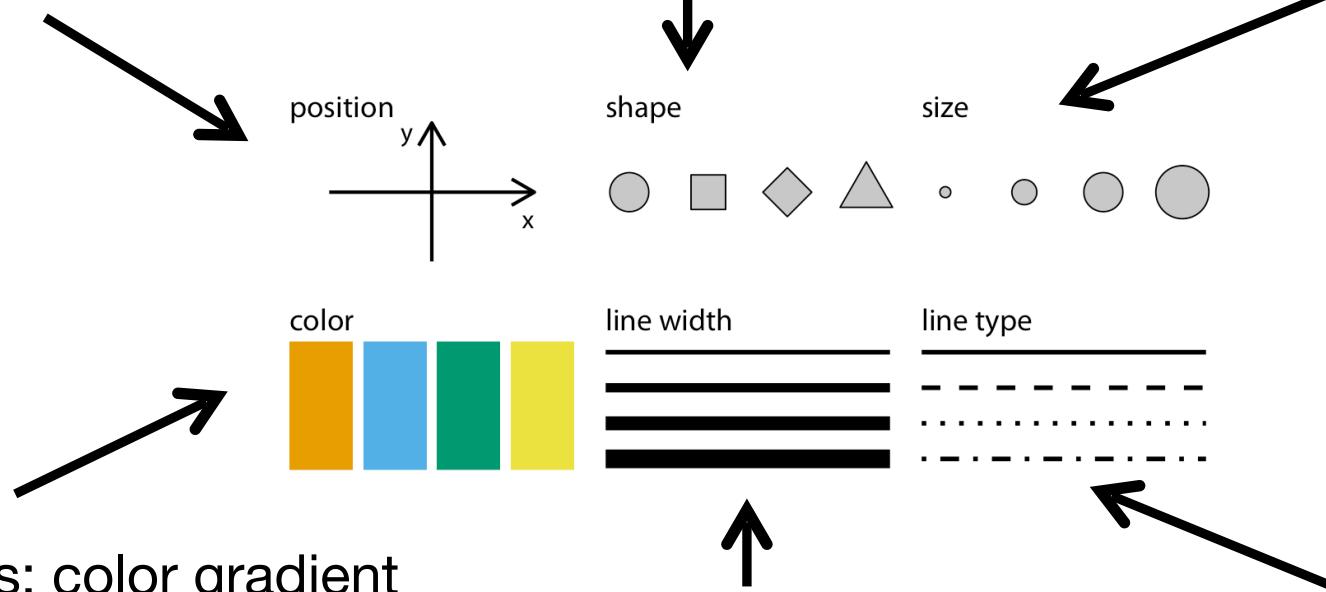
Site: CH-Lae



```
ddf %>%
  ggplot(aes(x = date, y = GPP_NT_VUT_REF, color = f_measured)) +
  geom_line() +
  geom_point() +
  scale_color_viridis_c()
```

Aesthetics for continuous and categorical data

Continuous
but...

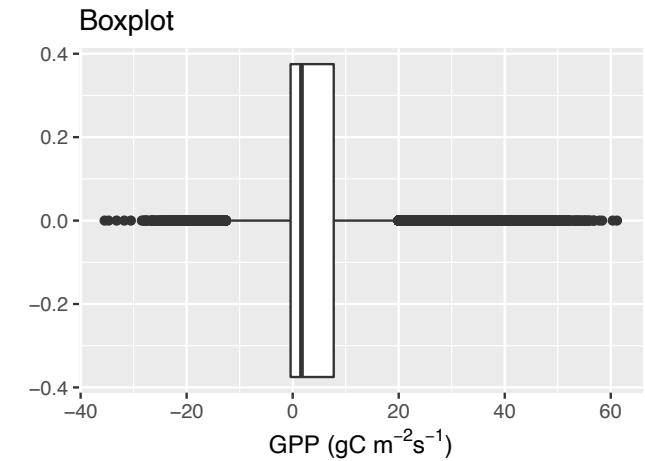
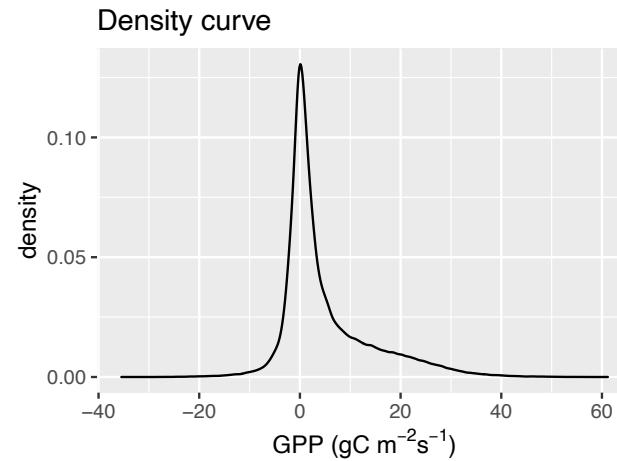
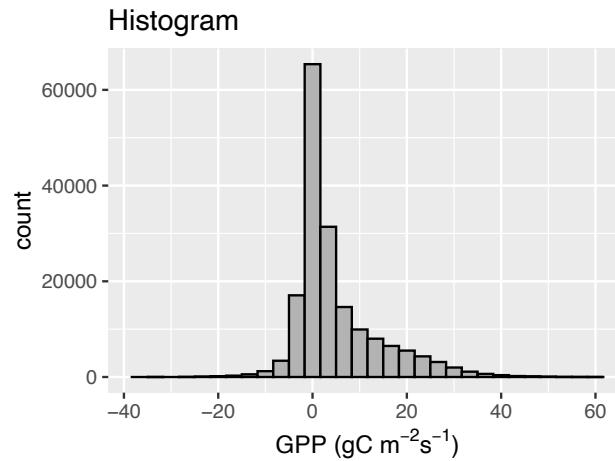


Continuous: color gradient
Categorical: color set

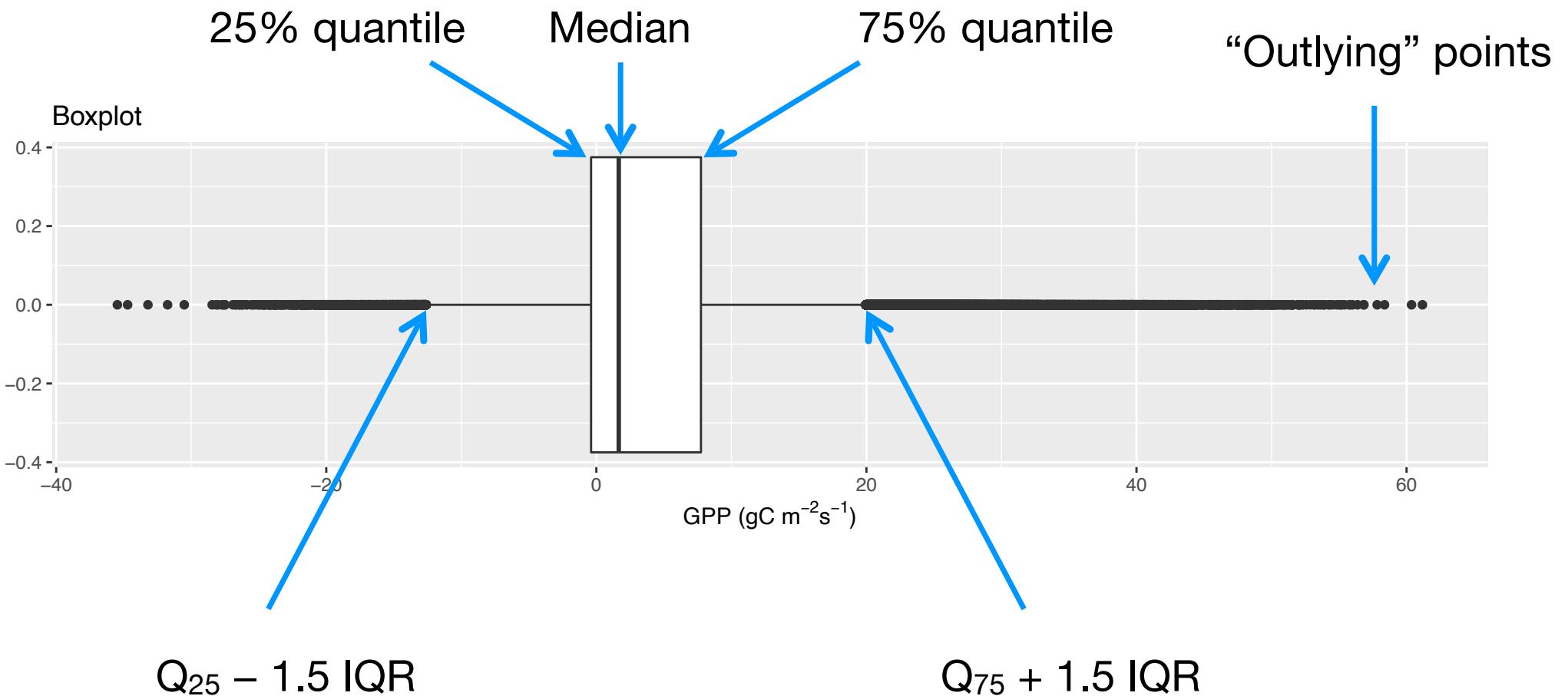
Continuous

Different “geoms” for different aspects of the data

Distributions



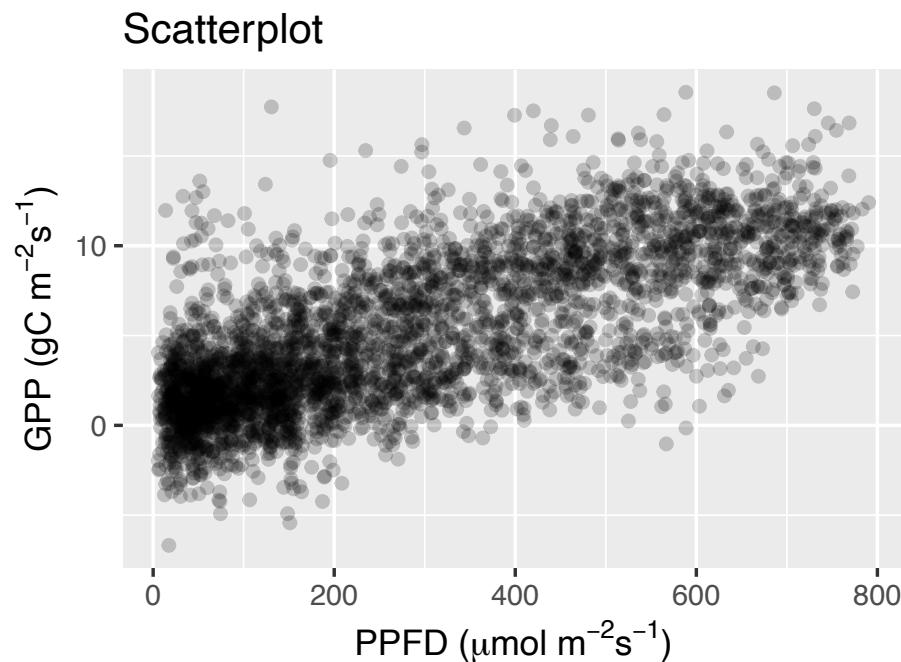
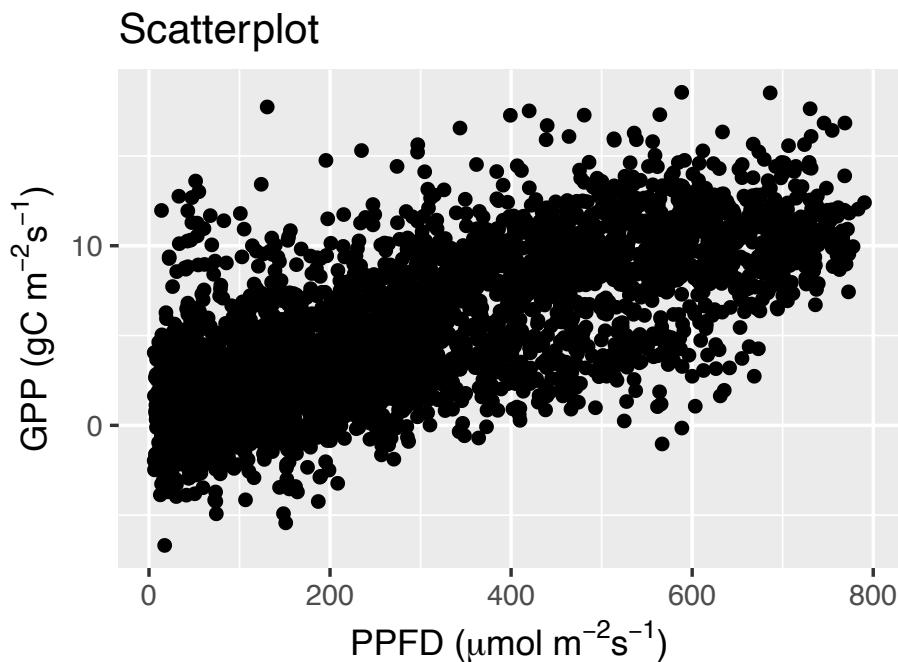
Boxplot



Different “geoms” for different aspects of the data

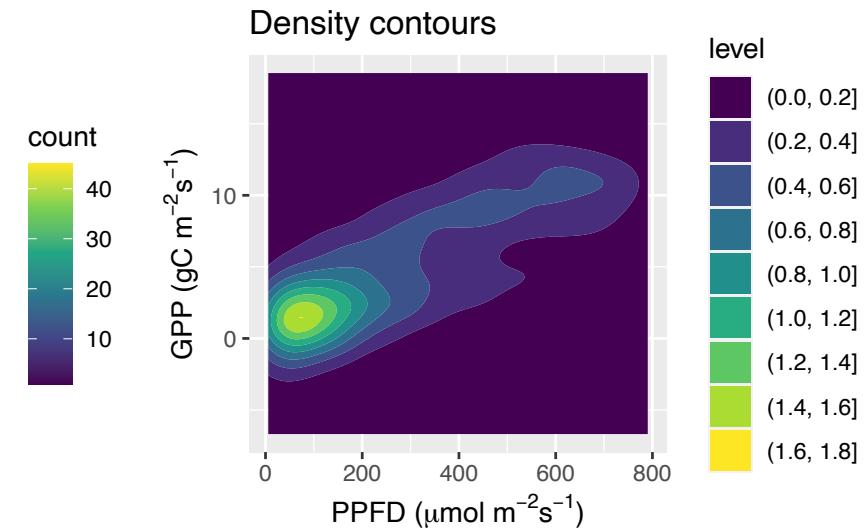
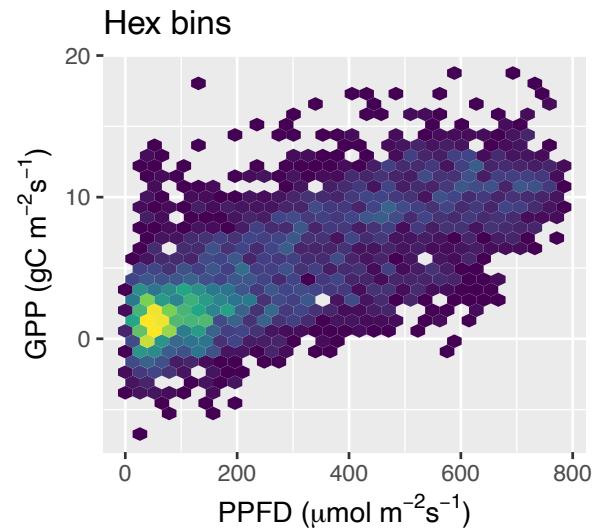
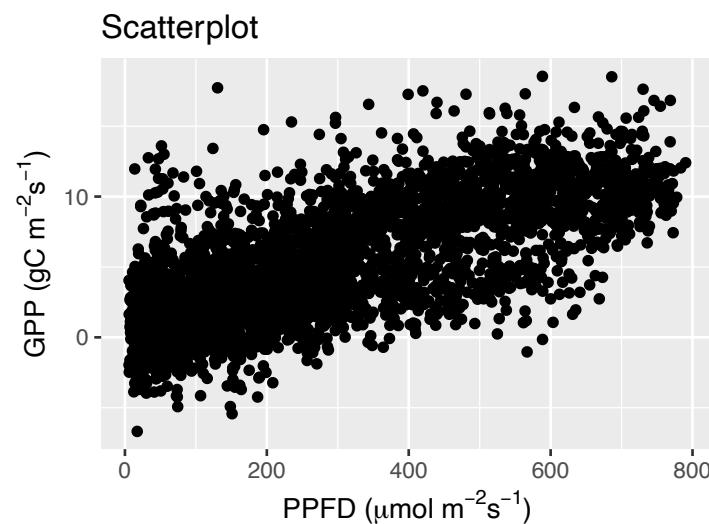
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Relationships



Different “geoms” for different aspects of the data

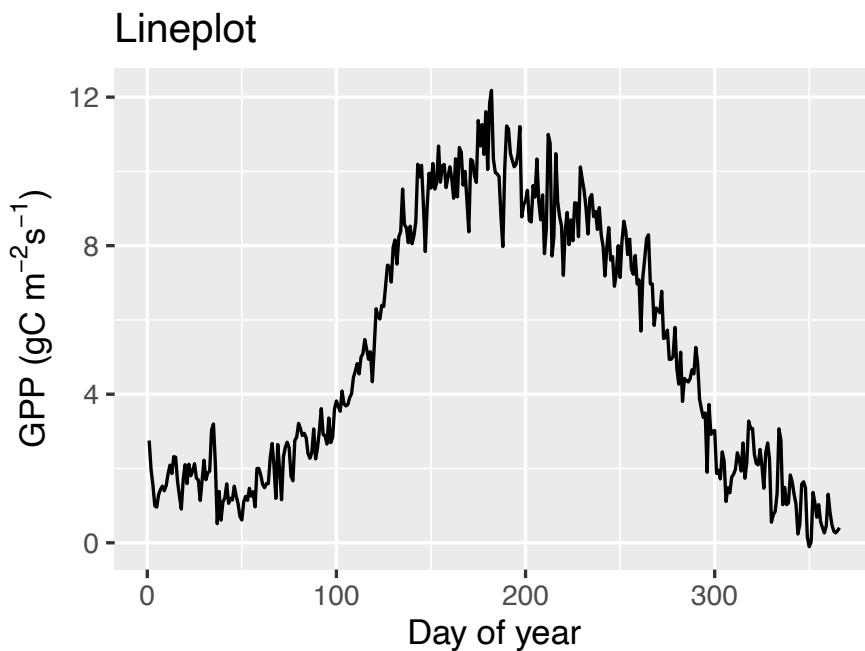
Relationships



Different “geoms” for different aspects of the data

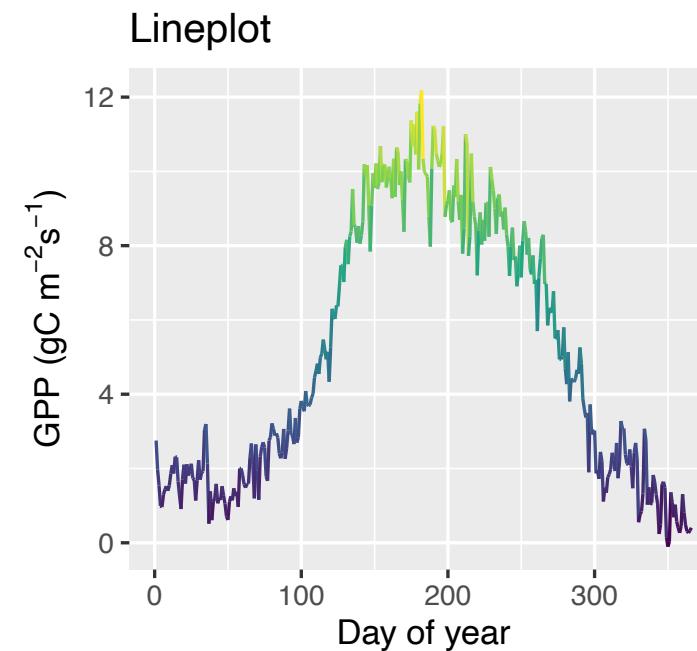
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Time series



Avoid:

- Same dimension to multiple aesthetics

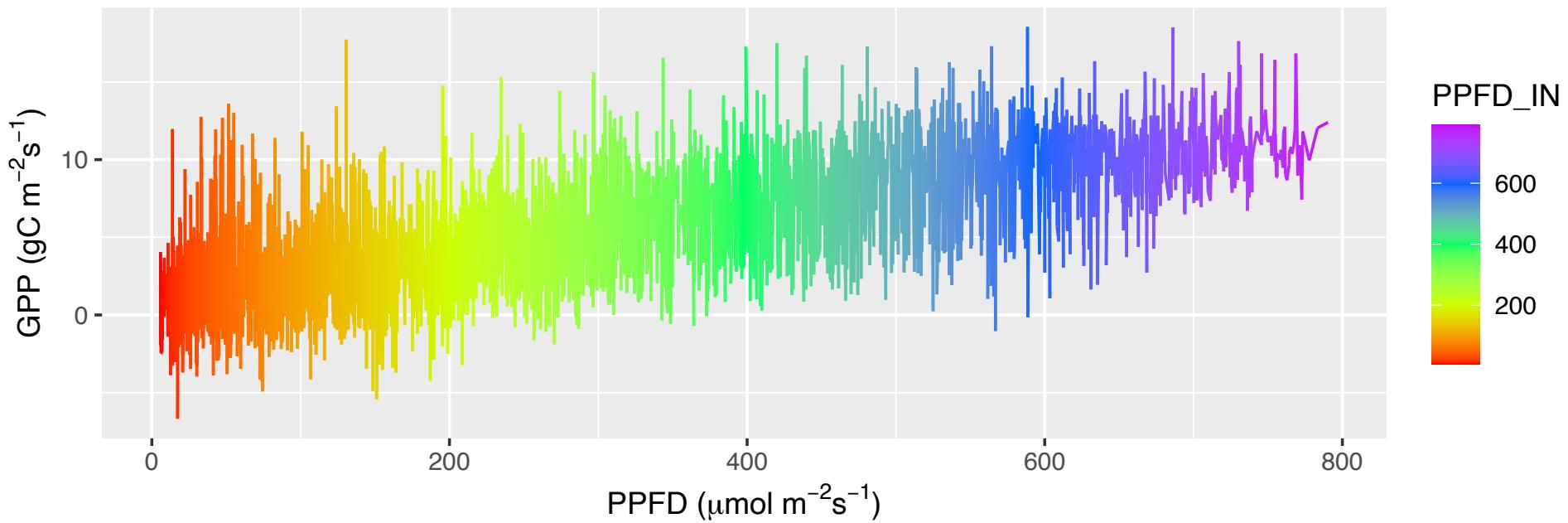


Different “geoms” for different aspects of the data

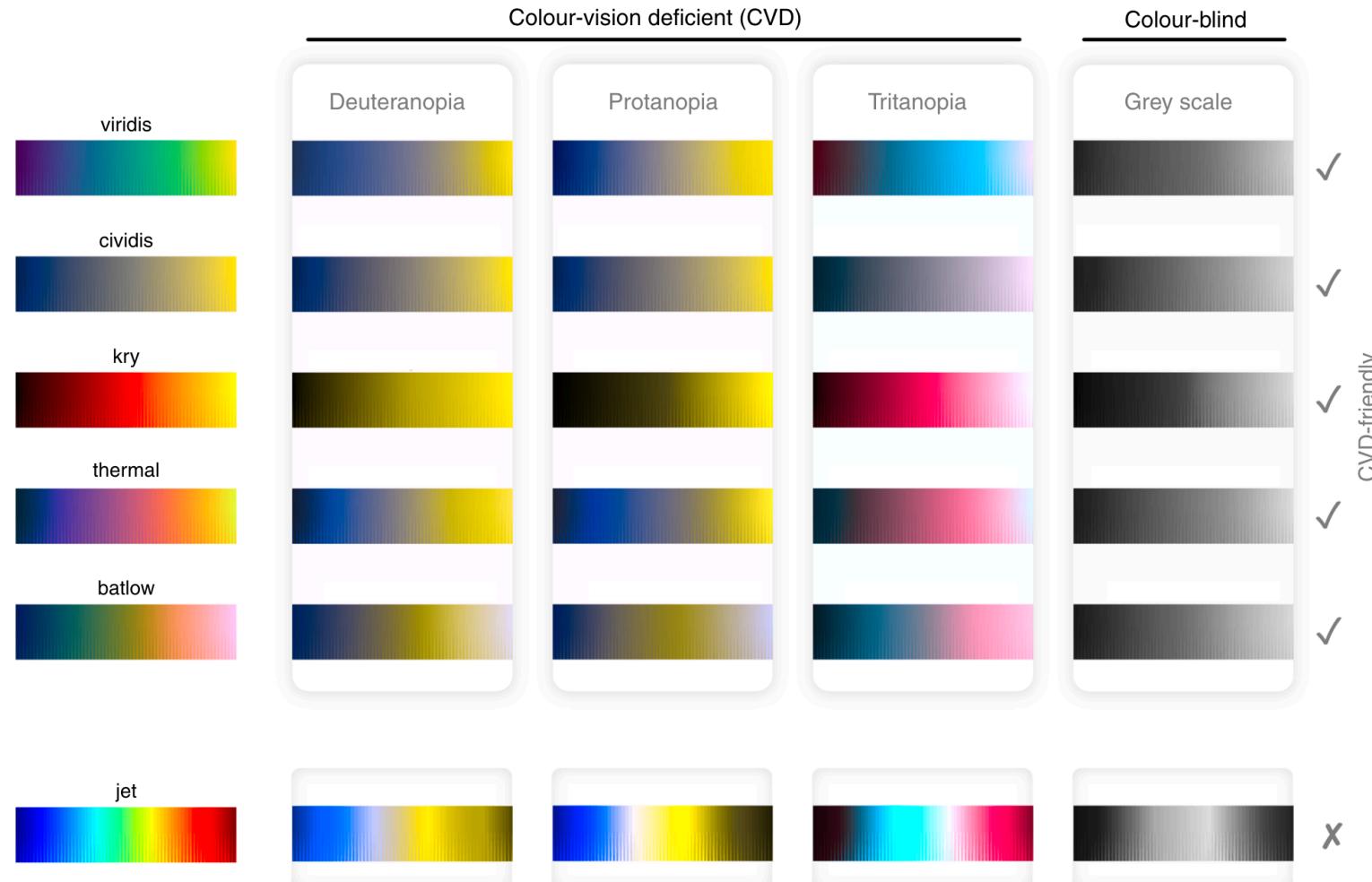
Avoid:

- Non-monotonic color scale for numeric values
- Color scale not adjusted to color vision deficiency

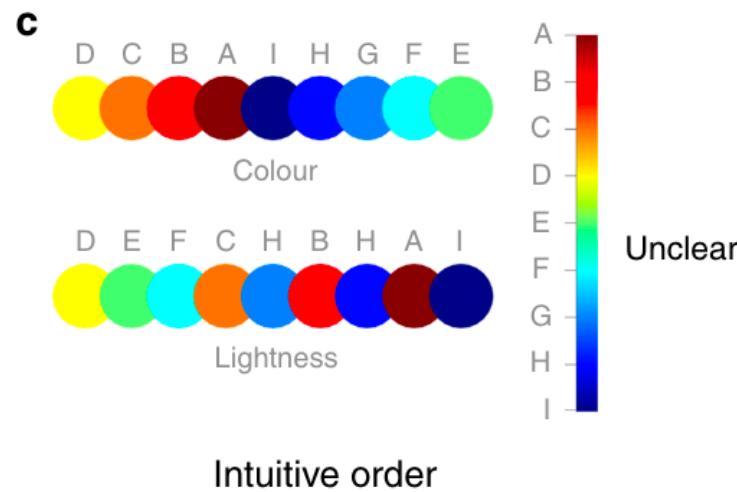
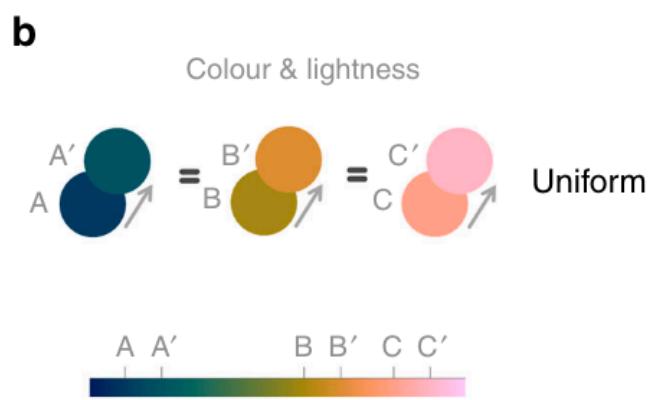
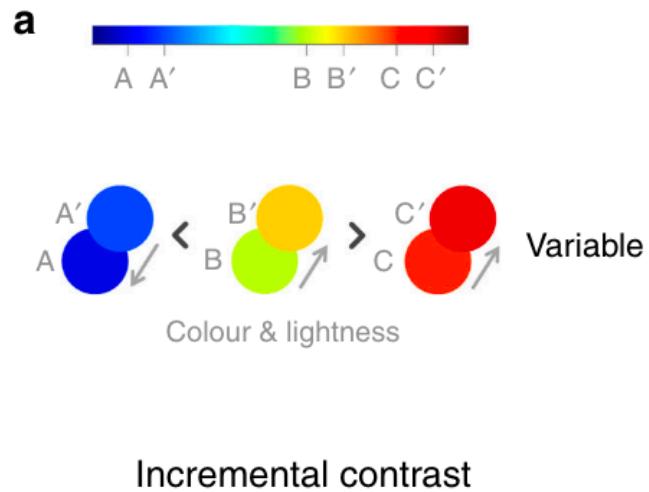
Lineplot



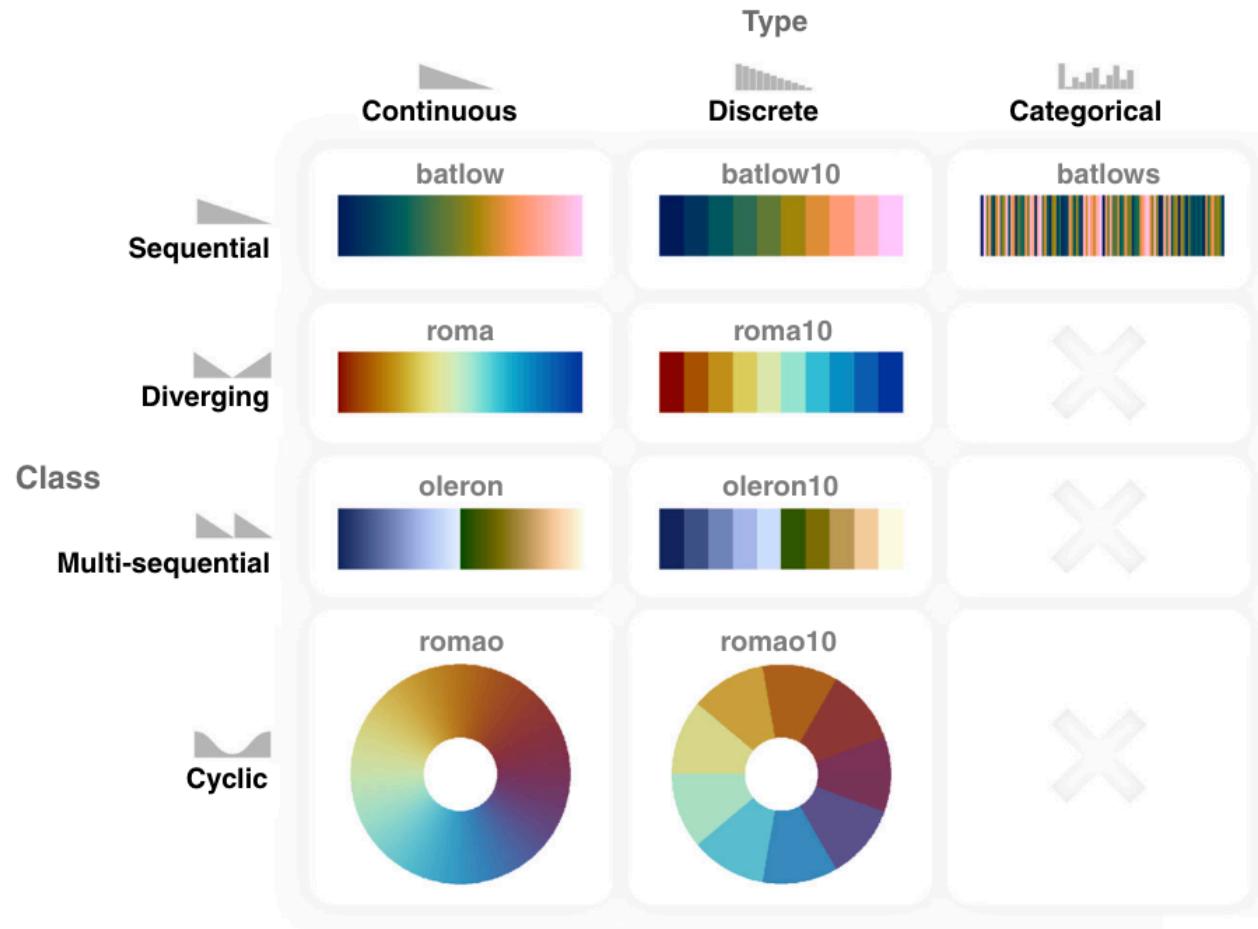
Color scales and color vision deficiencies



Color scales and lightness gradients



Color scales for different purposes



Color scales in R

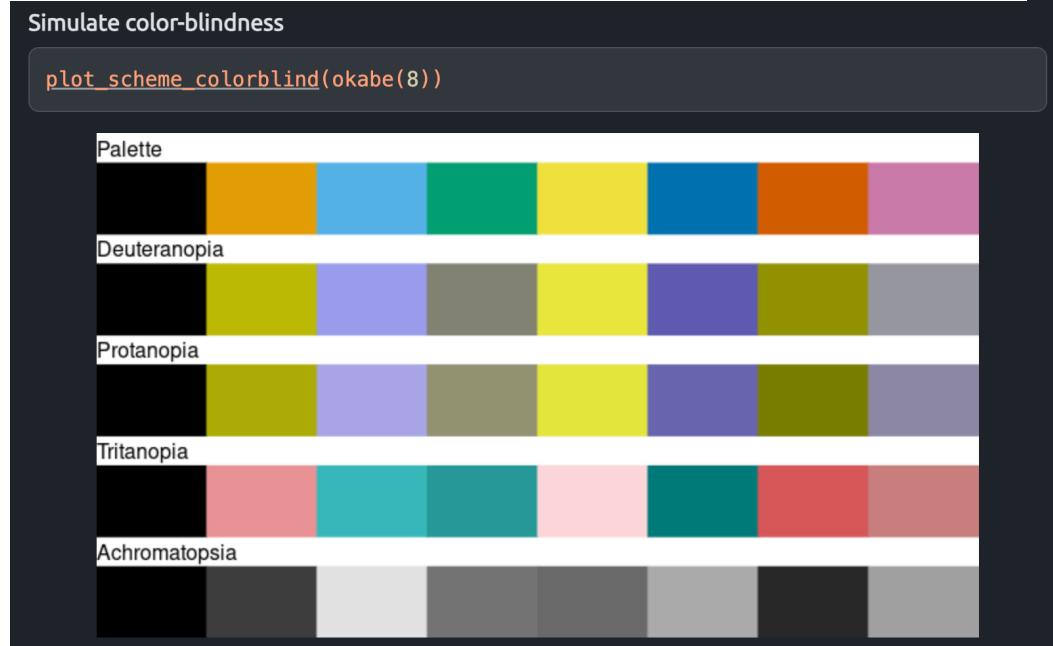
khroma 1.16.0 Reference Articles ▾ Changelog

khroma

CRAN 1.16.0 CRAN OK downloads 1710/month

repo status Active

DOI 10.5281/zenodo.1472077



Diagnostic tools

Test how well the colors are identifiable

```
## Okabe & Ito's color scheme  
okabe <- color("okabe_ito")
```

```
set.seed(12345)  
plot_map(okabe(8))
```

