Week 3
Relationships & Comparisons

Data Visualization for Social Scientists

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Road map for today

- Today:
  - Dual y-axes in ggplot()
  - Combining plots with `patchwork`
  - Correlations, scatterplot matrices, and correlograms
  - Regression, predictions, and marginal effectsd plot them with `ggplot2`
- By next week, please...
  - Problem set #3

Legal dual y-axes

- Safe when both axes measure same underlying quantity
  - Ex: counts vs %, Fahrenheit vs Celsius, pounds vs kilograms
- In ggplot2: use `sec.axis` inside `scale_y_continuous()`

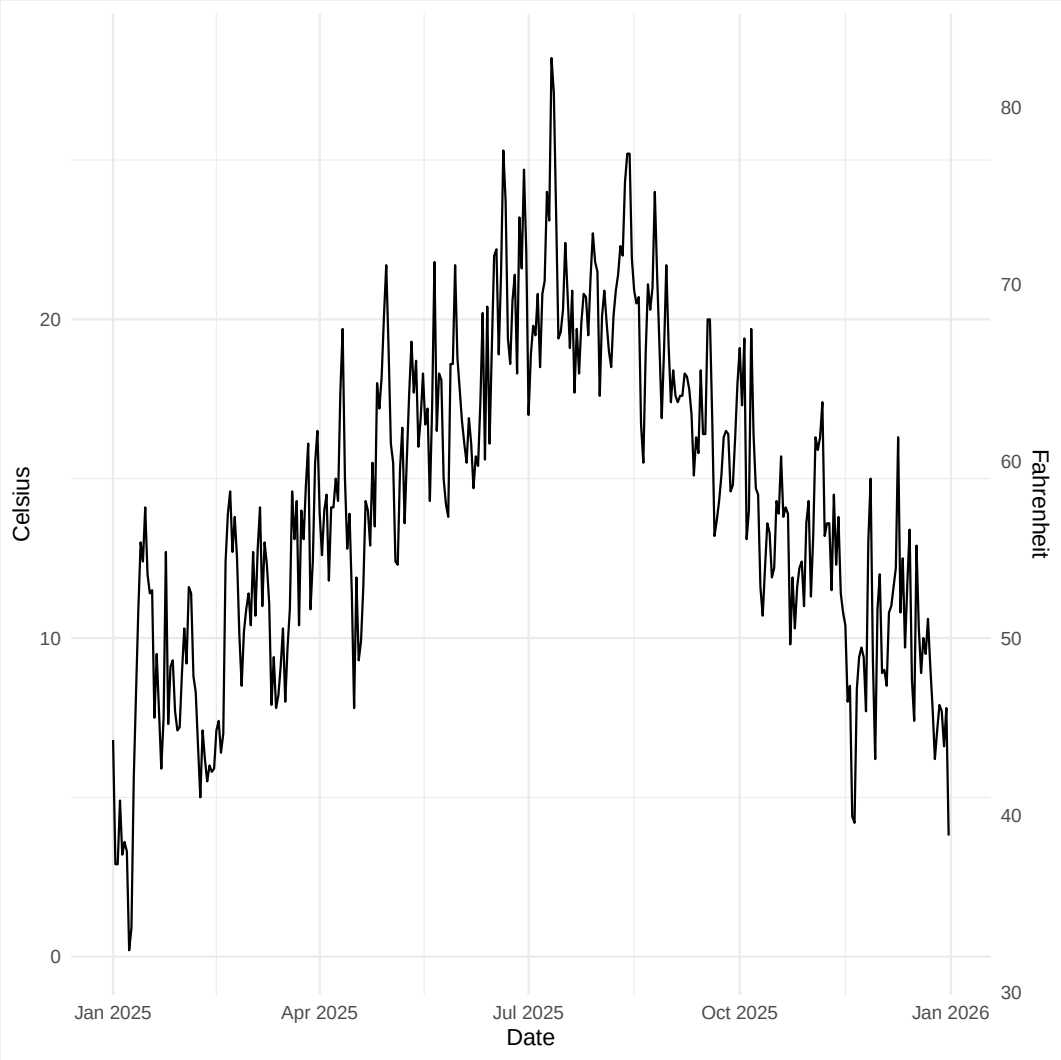
Ex: Dual y-axes: Fahrenheit & Celsius

- Historical weather for Dublin: Met Éireann
- Variables include temperature, humidity, wind speed, precipitation, etcvspace*.25cm
- C to F conversion: $F = (C) \times \frac{9}{5}) + 32$

Ex: Max temp by day in 2025 for Dublin

```
# we'll only look at 2025
DUB_weather <- DUB_weather[30317:
    nrow(DUB_weather),]
CORK_weather <- CORK_weather[23012:
    nrow(CORK_weather),]
IRE_weather <- rbind(subset(DUB_
    weather, select=-c(g_rad)),
    CORK_weather)
# need to alter date variable to
    not be character
IRE_weather$date <- dmy(DUB_weather
    $date)
```

```
ggplot(IRE_weather[IRE_weather$
    station=="Dublin",], aes(x =
    date, y = maxtp)) +
  geom_line() +
  scale_y_continuous(sec.axis = sec
    _axis(trans = ~ (. * 9/5) +
    32, name = "Fahrenheit")) +
  labs(x = "Date", y = "Celsius") +
  theme_minimal()
```



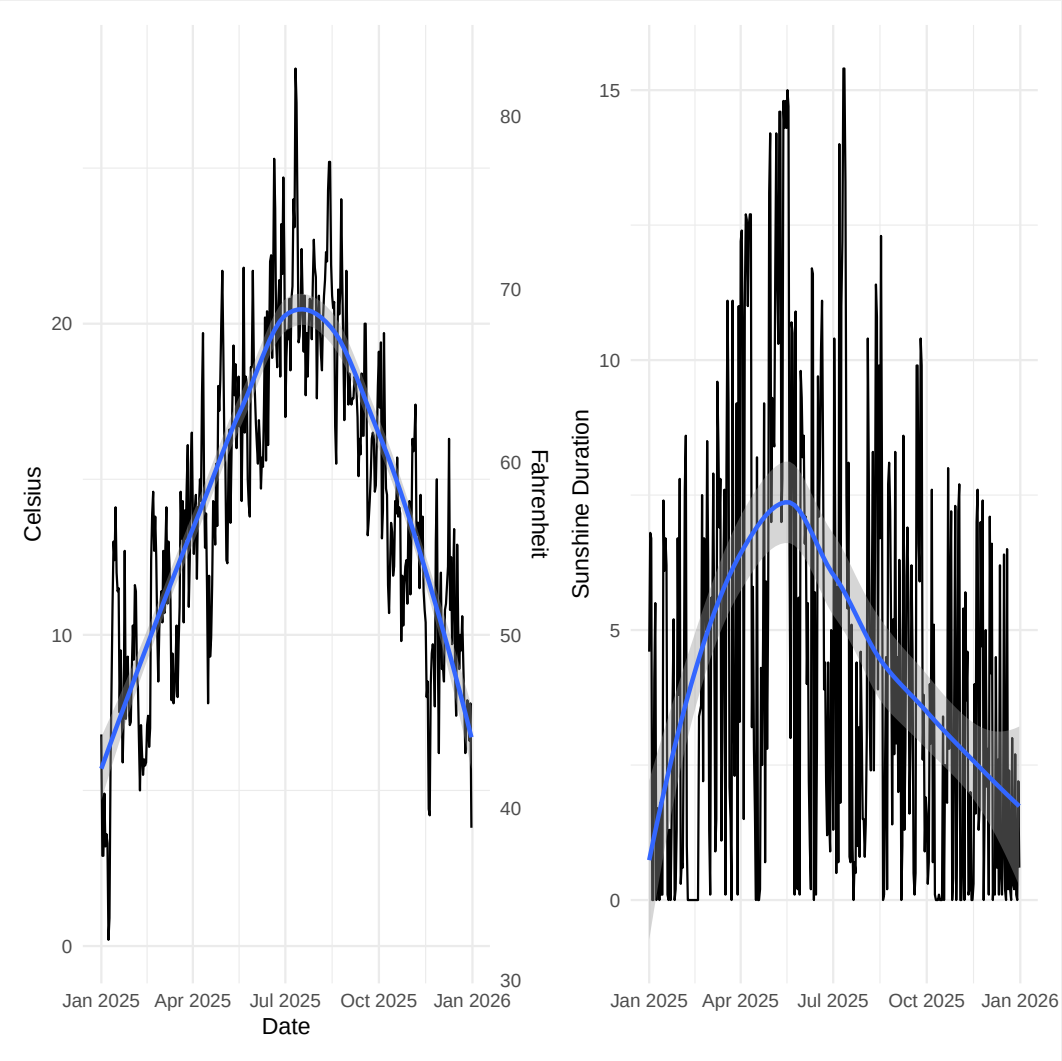
Combining plots with patchwork

- Alternative to dual axes: separate, aligned plots
- `patchwork` combines ggplots
  - To use `patchwork`, we need to (1) save our plots as objects and (2) add them together with +
- Supports layouts, relative heights, and more

Ex: Relationship of temp & sunshine duration

```r
sun_plot <- ggplot(IRE_weather[IRE_
    weather$station=="Dublin",],
    aes(x = date, y = sun)) +
  geom_line() +
  geom_smooth() +
  labs(x = NULL, y = "Sunshine
    Duration") +
  theme_minimal()
```

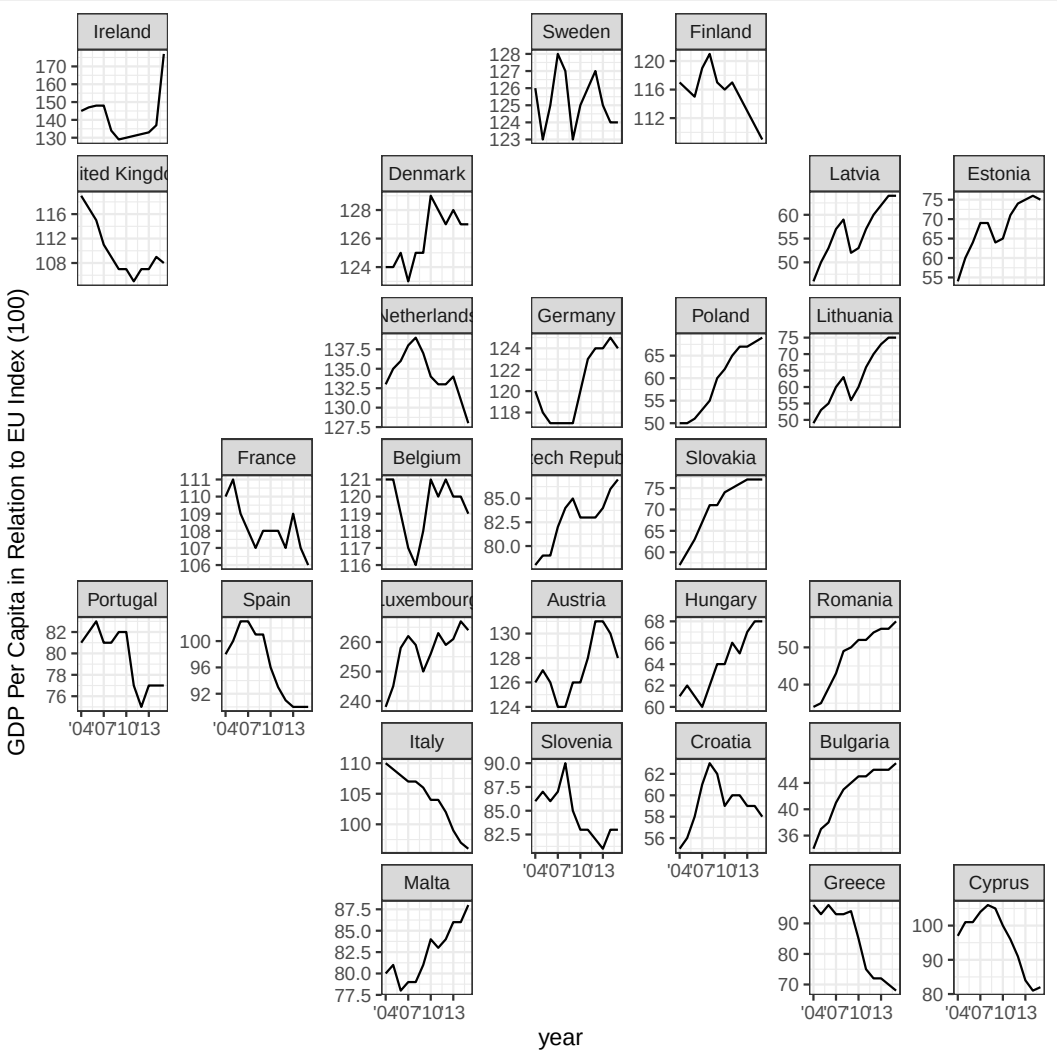
```r
# library(patchwork)
temp_plot + sun_plot
```



Comparing time series

- Many-group (i.e., country, city) line charts can become difficult to read
- Strategies:
  - Highlight a few focal groups
  - Use small multiples (facets)
  - Use map-based facet layouts with `geofacet`
    - `geofacet` arranges country facets in map-like grids
    - Preserves some geographic structure while showing small multiples
    - Useful for regional or global comparisons

Geofacet example

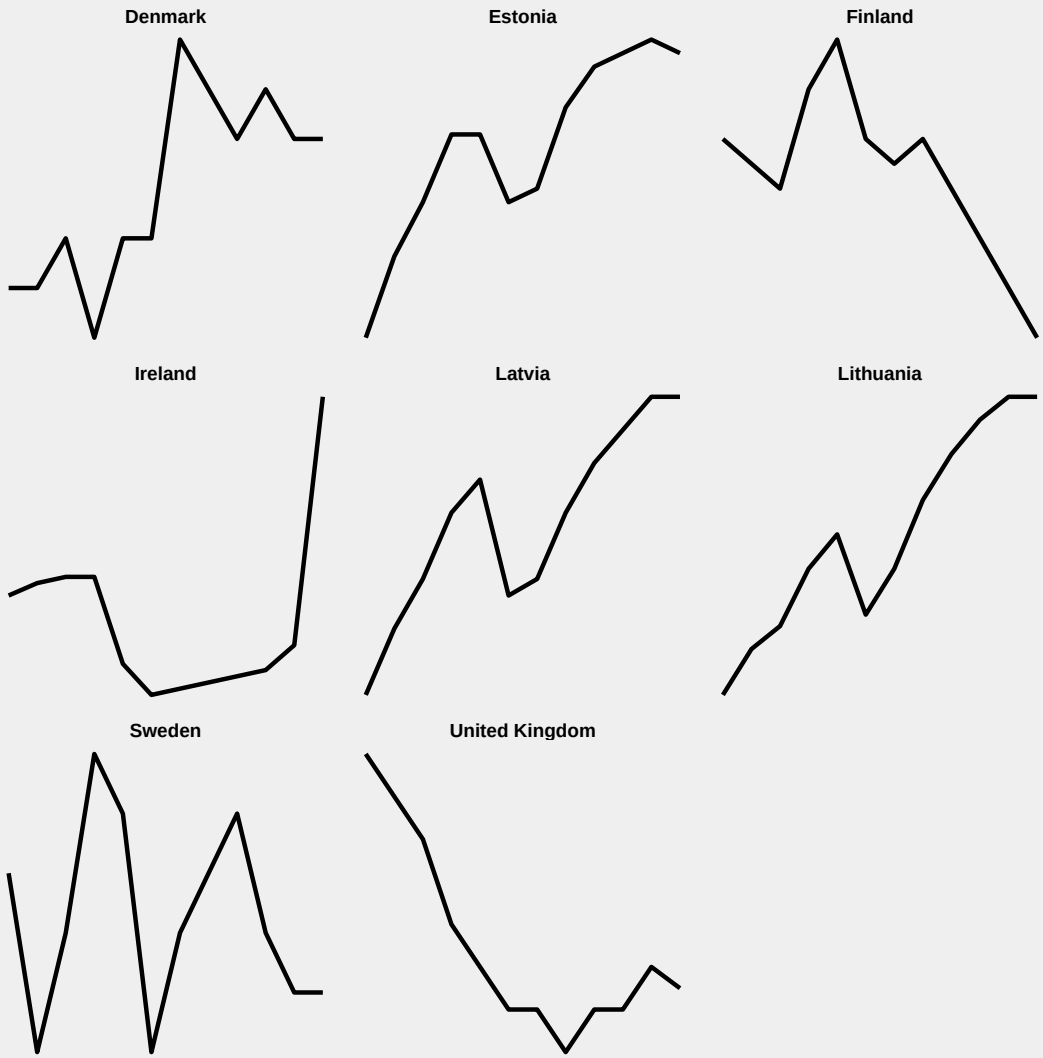



```
1  # library("geofacet")
2  ggplot(eu_gdp, aes(year, gdp_pc)) +
3    geom_line() +
4    facet_geo(~ name, grid = "eu_
         grid1", scales = "free_y") +
5    scale_x_continuous(labels =
         function(x) pasteo("'", substr
         (x, 3, 4))) +
6    ylab("GDP Per Capita in Relation
         to EU Index (100)") +
7    theme_bw()
```

Ex: Small multiples - EU GDP in Northern Europe

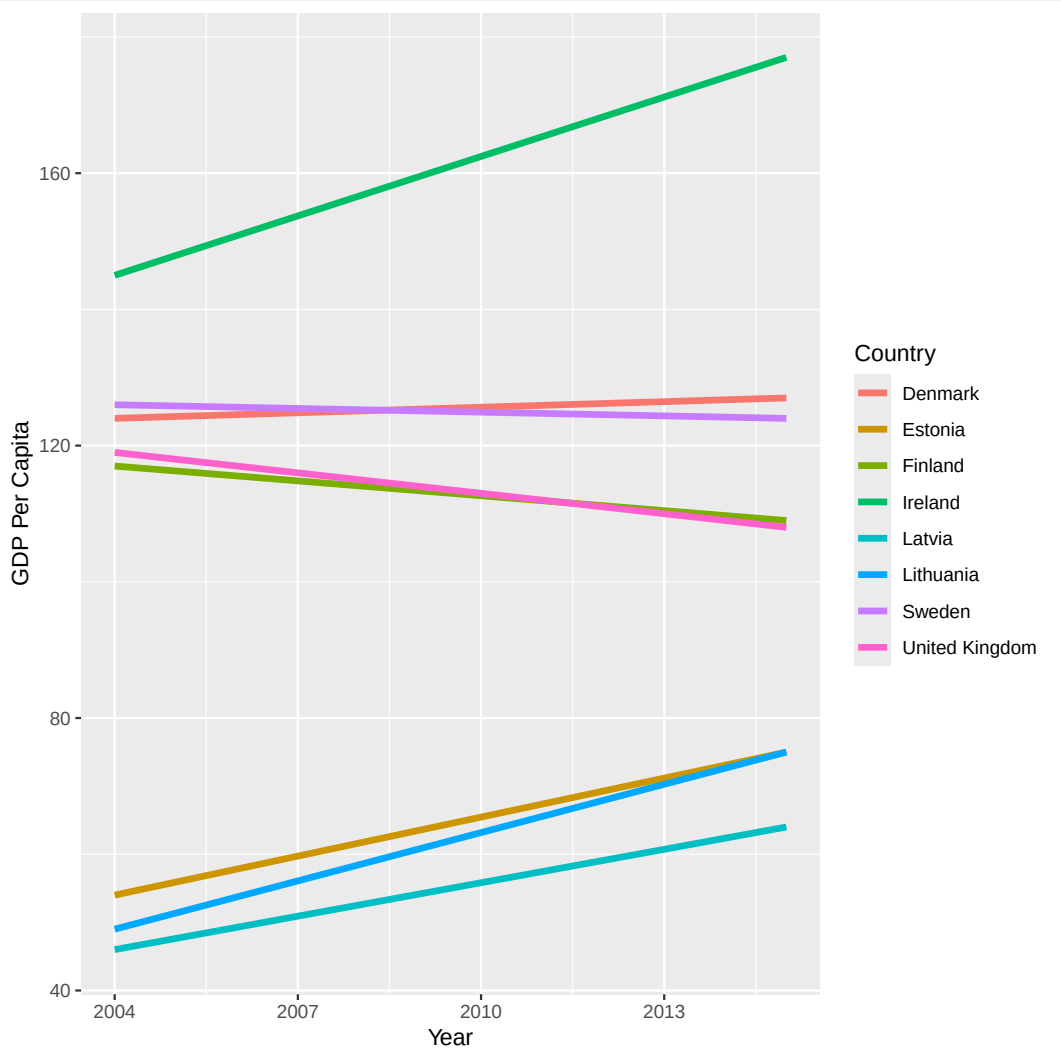
```r
# create "Northern Europe"
    indicator based on UN
    geoscheme
eu_gdp$north_europe <- ifelse(eu_
    gdp$name %in% c("Denmark", "
    Estonia", "Finland", "Ireland"
    , "Latvia", "Lithuania", "
    Norway", "Sweden", "United
    Kingdom"), 1, 0)
```

```r
ggplot(data = eu_gdp |> filter(
    north_europe == 1), aes(x =
    year, y = gdp_pc)) +
  geom_line(linewidth = 1) +
  facet_wrap(vars(name), scales = "
    free_y", nrow = 3) +
  theme_void() +
  theme(strip.text = element_text(
    face = "bold"))
```



Slopegraphs

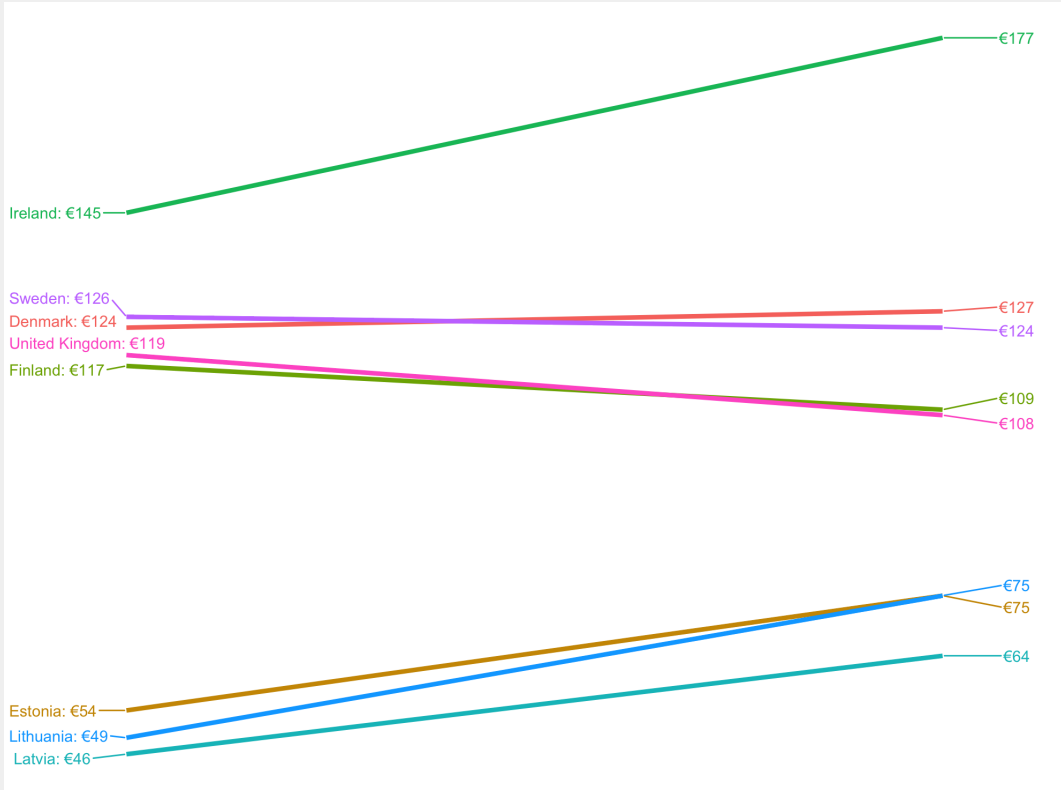
Show only change in GDP per capita between two time periods




```
north_europe_gdp <- eu_gdp |>
      filter(north_europe == 1) |>
      filter(year %in% c(2004, 2015)
      ) |>
  mutate(label_first = ifelse(year
      == 2004, pasteo(name, ": ",
      label_dollar(prefix = "   ")(
      round(gdp_pc))), NA),
         label_last = ifelse(year
      == 2015, label_dollar(prefix =
       "   ")(round(gdp_pc, 0)), NA)
      )
ggplot(north_europe_gdp, aes(x =
      year, y = gdp_pc, group = name
      , color = name)) +
  geom_line(linewidth = 1.5) +
  labs(y="GDP Per Capita", x="Year"
      , color="Country")
```

Labeling selected points with ggrepel

```
1 ggplot(north_europe_gdp, aes(x =
      year, y = gdp_pc, group = name
      , color = name)) +
2   geom_line(linewidth = 1.5) +
3   geom_text_repel(aes(label = label
      _first), direction = "y",
      nudge_x = -1, seed = 1234) +
4   geom_text_repel(aes(label = label
      _last), direction = "y", nudge
      _x = 1, seed = 1234) +
5   guides(color = "none") +
6   theme_void()
```



Design considerations

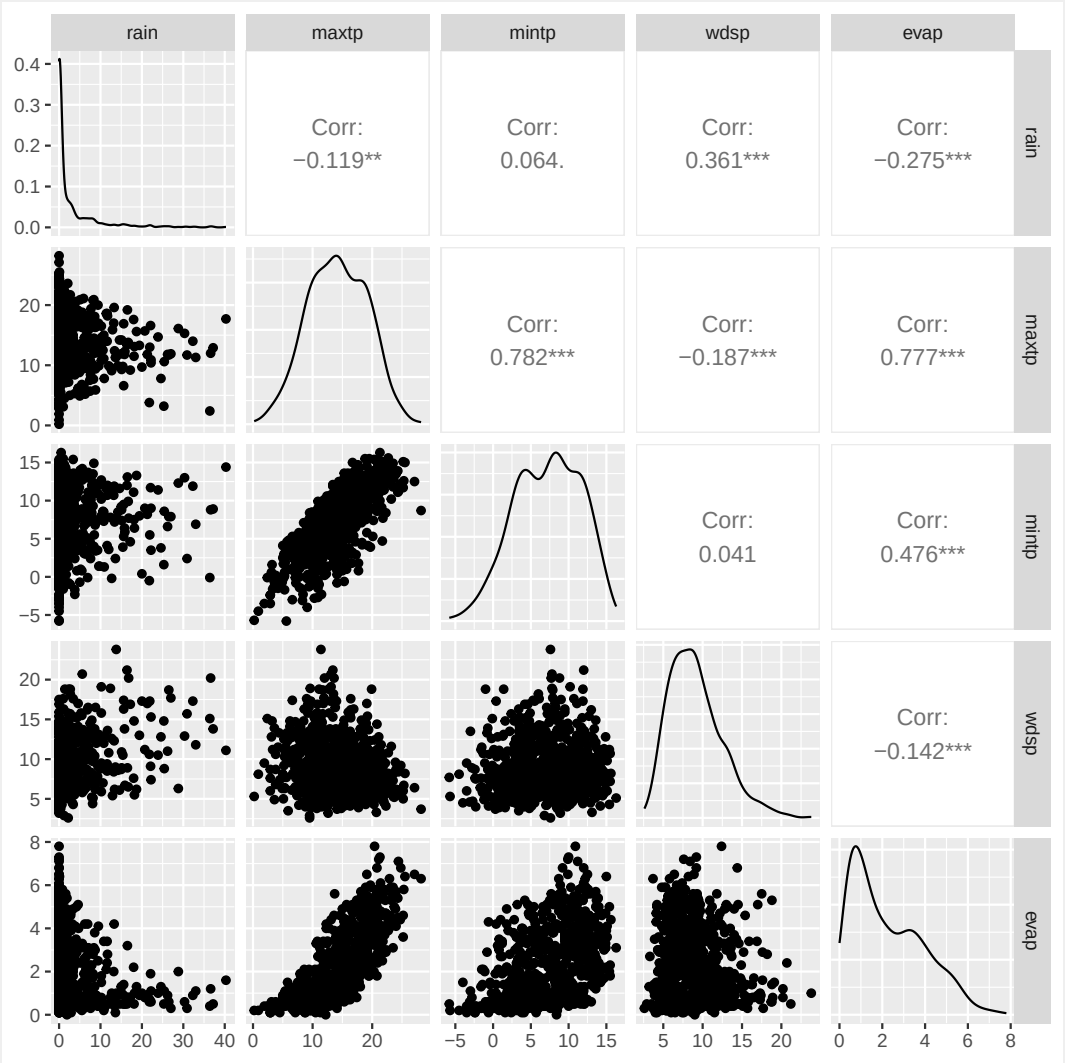
- Use sorting and consistent scales to clarify comparisons
- Prefer small multiples over overloaded single panels
- Highlight only a few key labels; avoid label clutter
- Use log scales when data span orders of magnitude

Exploring correlations

- Use `GGally::ggpairs()` for scatterplot matrices
- Visualize relationships among several variables at once
- Good for exploration; often too dense for publication

Scatterplot matrix with ggpairs

```
# library(GGally)
weather_cor <- IRE_weather |> select(rain, maxtp, mintp, wdsp, evap)
```



Correlation patterns

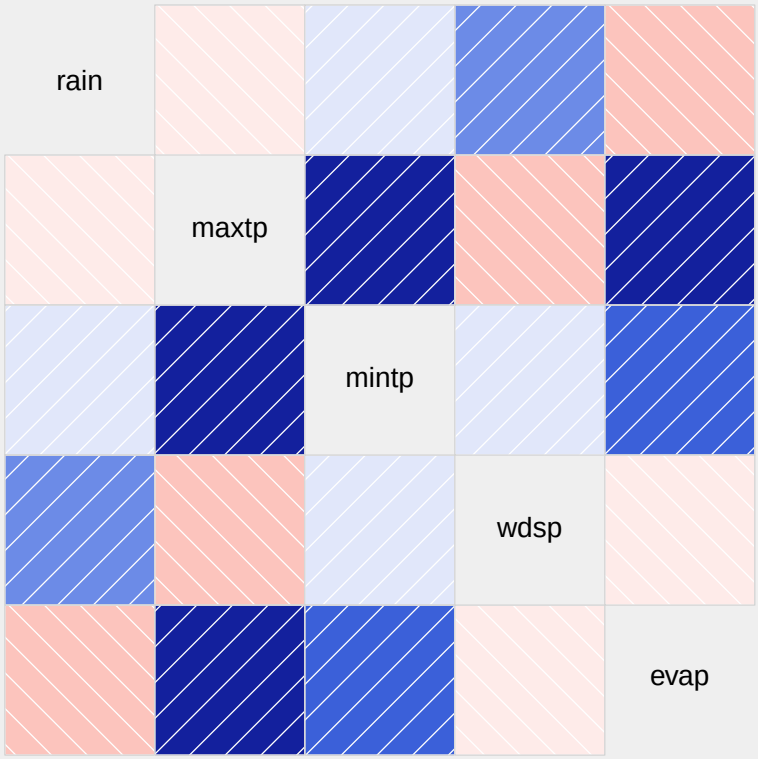
- High vs low temperature: very strong positive correlation ($r \approx 0.78$)
- High temp vs evaporation: very strong positive correlation ($r \approx 0.77$)
- Wind speed vs rain: moderate positive correlation
- Wind speed vs temperature: minor negative correlation
- Little or no correlation for some variable pairs (e.g., wind speed vs min temp)

Correlograms

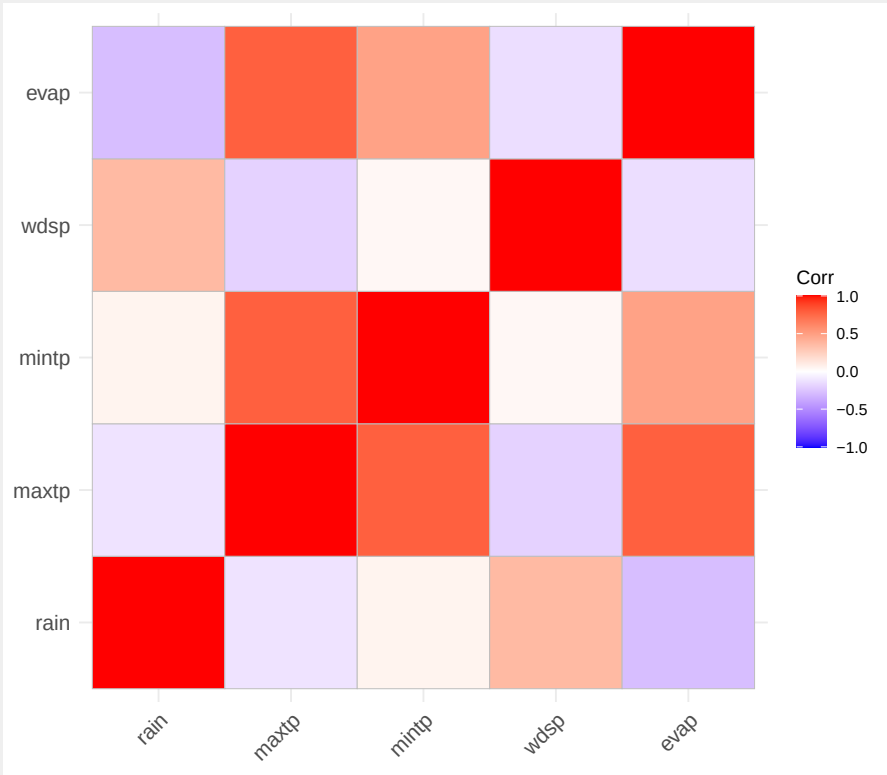
- Heatmaps of correlation coefficients
- More suitable for publication than full scatterplot matrices
- Depending on package, need to compute a correlation matrix and tidy it

Ex: Correlogram with weather

```
# library(corrgram)
corrgram(weather_cor)
```




```
# library(ggcorrplot)
ggcorrplot(cor(weather_cor))
```



Simple regression: idea

- Outcome: Daily high temperature
- Predictor: Rain

```
# run our "simple" regression w/ max temp as outcome
model_simple <- lm(maxtp ~ rain, data = IRE_weather)
# library(broom)
tidy(model_simple, conf.int = TRUE)
```

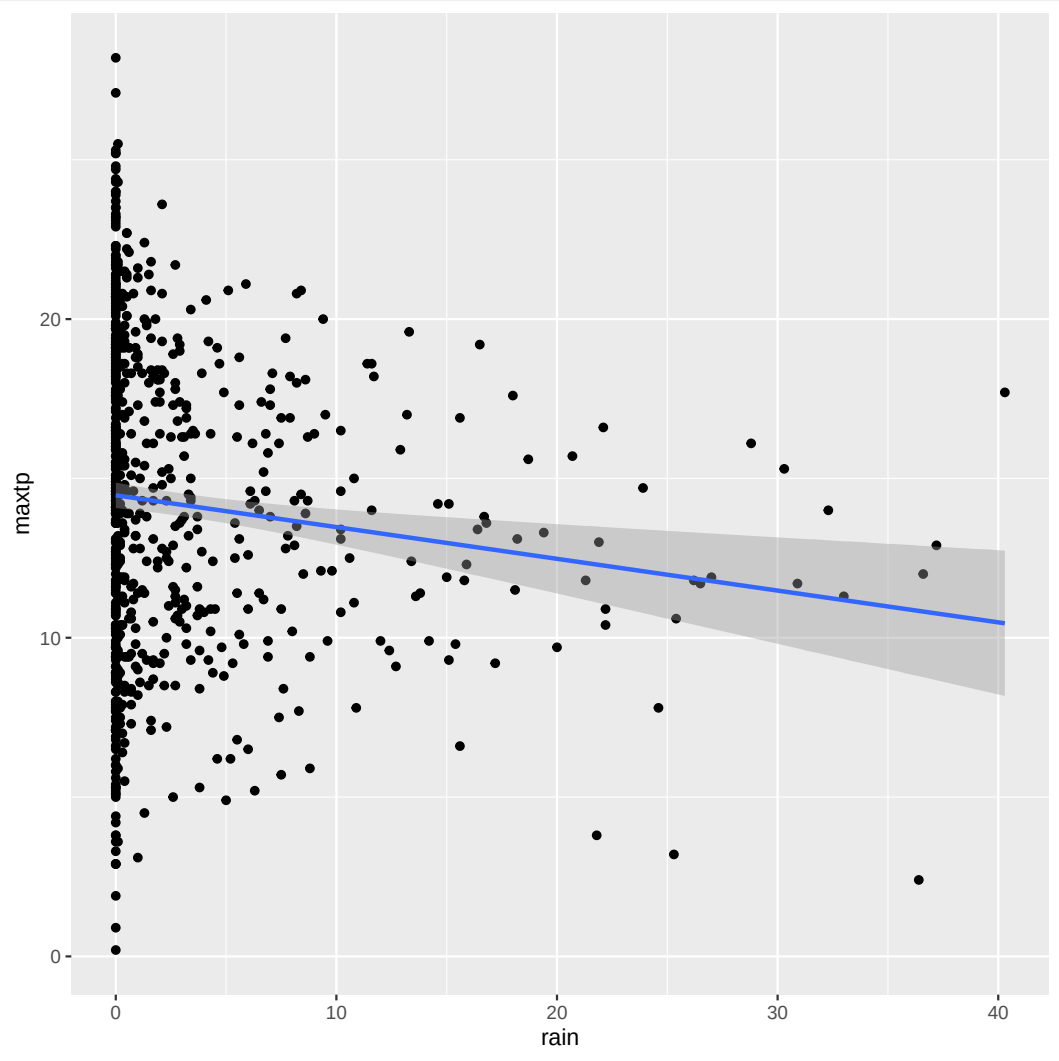
```
# A tibble: 2 × 7
term        estimate std.error statistic p.value conf.low conf.high
<chr>          <dbl>     <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
1 (Intercept)  14.5       0.204      70.9  0          14.1     14.9
2 rain         -0.0997    0.0307     -3.24 0.00124   -0.160   -0.0393
```

We can interpret these coefficients like so:

- Intercept: Average temperature when there's no rain is 14.5°C
- β_{rain}: ↑ 1mm of rain is associated with a 0.0997° decrease in max temp, on average

Visualizing simple regression

```
ggplot(IRE_weather,
       aes(x = rain, y = maxtp)) +
  geom_point() +
  geom_smooth(method = "lm")
```



Multiple regression

- Add predictors: humidity, moon phase, rain probability, wind speed, pressure, cloud cover
- Hard to visualize directly in original space
- Use coefficient plots and predicted values

Multiple regression

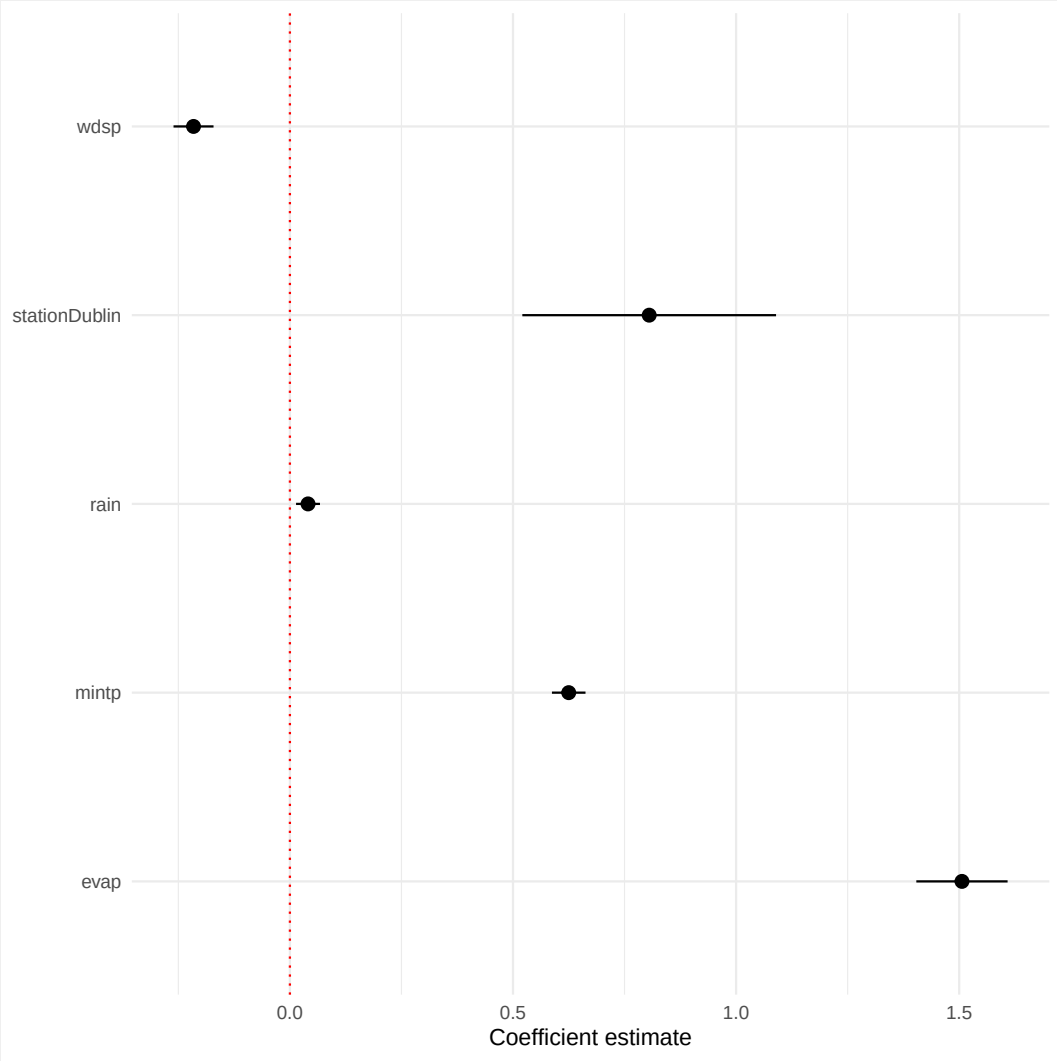
```r
# run our "complex" regression w/ max temp as outcome
model_complex <- lm(maxtp ~ rain + mintp + wdsp + evap + station,
                    data = IRE_weather)
tidy(model_complex, conf.int = TRUE)
```

```
# A tibble: 6 × 7
term          estimate std.error statistic   p.value conf.low conf.high
<chr>            <dbl>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>
1 (Intercept)     7.70      0.267      28.8  3.38e-122   7.17      8.22
2 rain            0.0406    0.0136      2.98 3.00e-  3   0.0138    0.0674
3 mintp           0.625     0.0192     32.6  2.87e-144   0.587     0.663
4 wdsp           -0.216     0.0228     -9.46 4.16e- 20  -0.261    -0.171
5 evap            1.51      0.0521     28.9  8.80e-123   1.40      1.61
6 stationDublin   0.805     0.145       5.56 3.79e-  8   0.521     1.09
```

- β_{rain}: On average, $\uparrow$ 1mm of rain is associated with a 0.0406°C increase in max temp, holding all else constant
- β_{Dublin}: On average, Dublin has a 0.805°C higher max temp than Cork, holding all else constant

Coefficient plot

```
1 ggplot(tidy(model_complex, conf.int
      = TRUE) |> filter(term != "(
    Intercept)"),
2       aes(x = estimate, y = term))
      +
3   geom_vline(xintercept = 0, color
    = "red", linetype = "dotted")
    +
4   geom_pointrange(aes(xmin = conf.
    low, xmax = conf.high)) +
5   labs(x = "Coefficient estimate",
    y = NULL) +
6   theme_minimal()
```



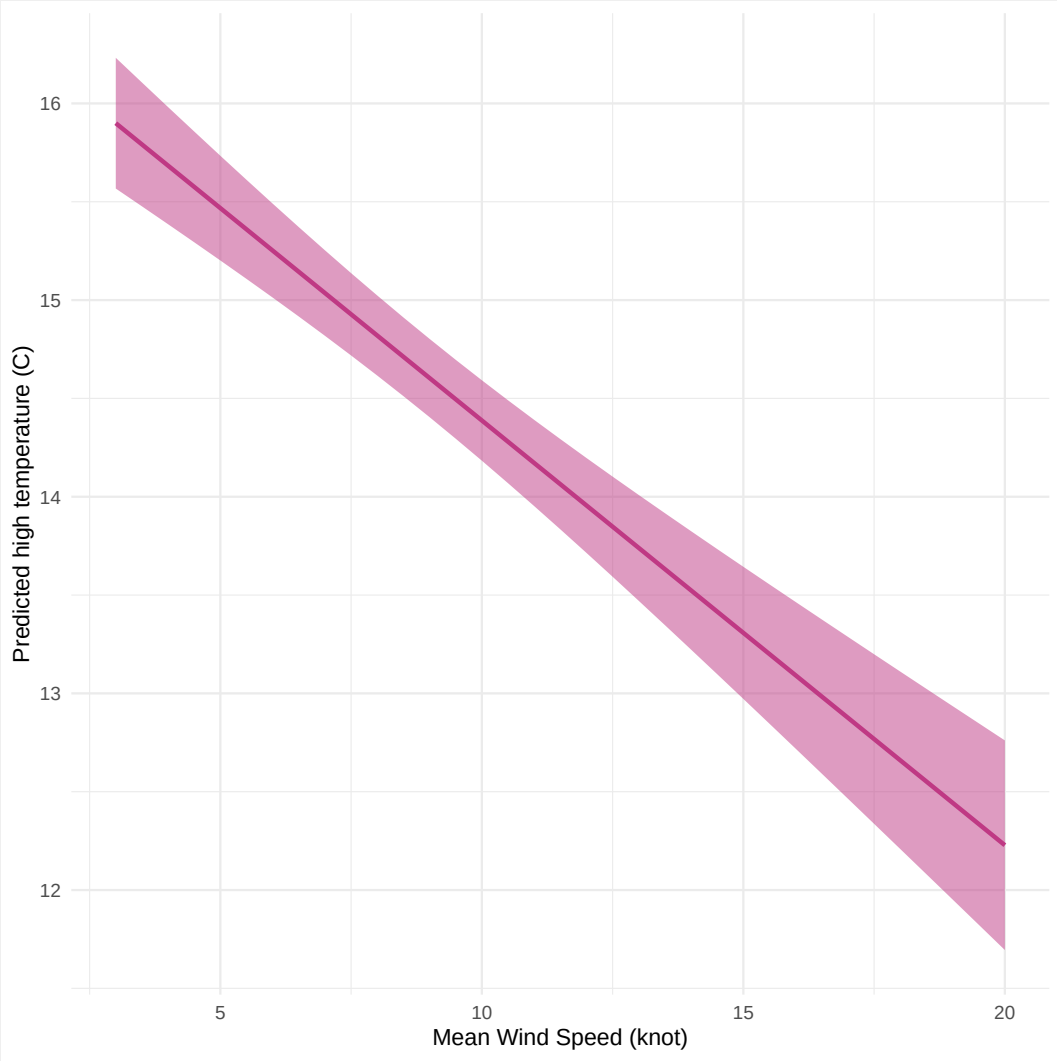
Using marginaleffects

- `predictions()` for predicted values with CIs
- `slopes()` for marginal effects (slopes)
- `datagrid()` constructs scenarios, holding other variables at typical values

MARGINALEFFECTS - WIND

```r
# library(marginaleffects)
# Calculate predictions across a range of windSpeed
predicted_values_easy <- predictions(model_complex,
  newdata = datagrid(wdsp = seq(3, 20, 0.5))
)
```

```r
ggplot(predicted_values_easy, aes(x = wdsp, y = estimate)) +
  geom_ribbon(aes(ymin = conf.low, ymax = conf.high),
              fill = "#BF3984", alpha = 0.5) +
  geom_line(linewidth = 1, color = "#BF3984") +
  labs(x = "Mean Wind Speed (knot)", y = "Predicted high temperature (C)") +
```



Nonlinear and interaction model

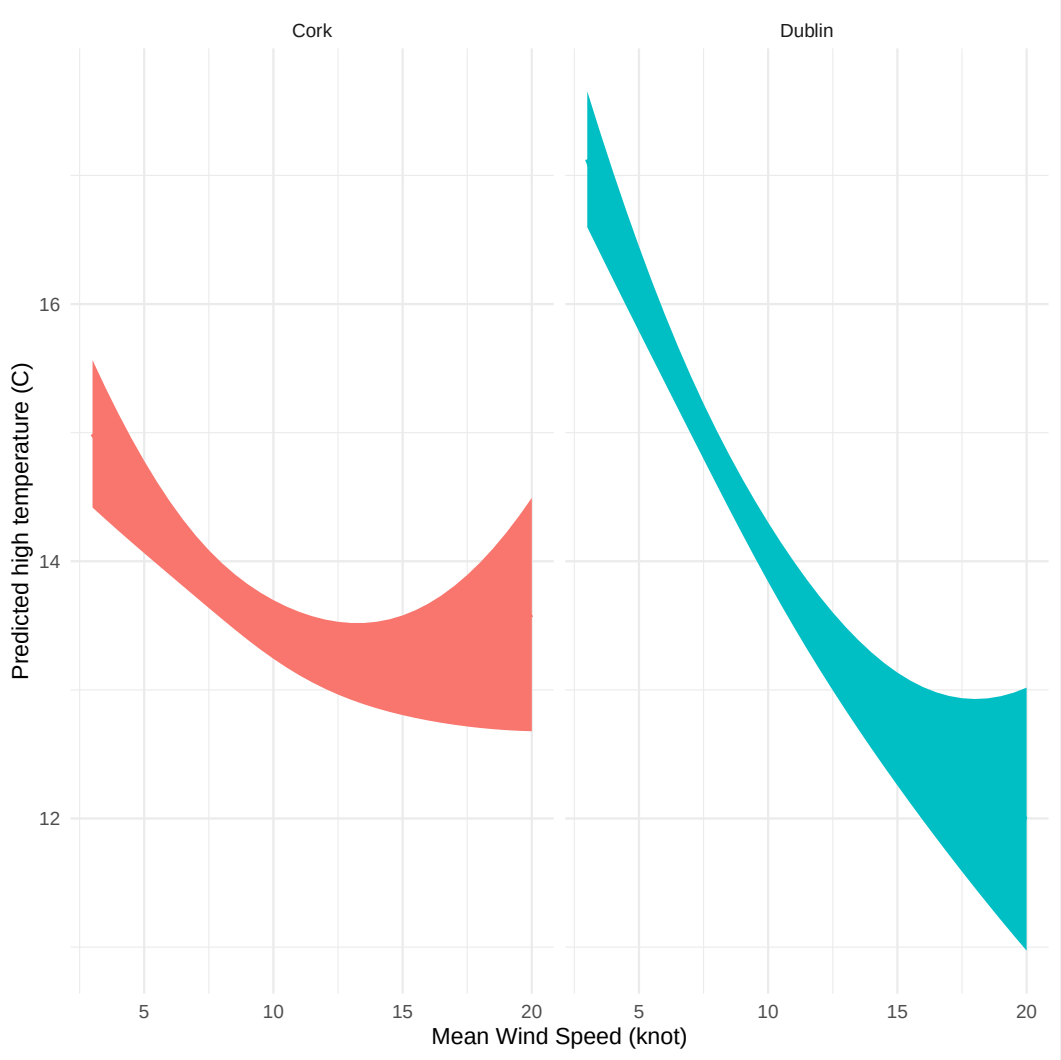
You could:

- Add quadratic term for wind speed
- Add interaction: wind speed $\times$ station

```
model_wild <- lm(maxtp ~ rain + mintp + wdsp + evap + station + I(wdsp^2) + wdsp:station,
       data = IRE_weather)

predicted_values_wild <- predictions(
  model_wild,
  newdata = datagrid(
    wdsp = seq(3, 20, 0.5),
    station = c("Cork", "Dublin")))
```

MARGINALEFFECTS - INTERACTIONS




```
ggplot(predicted_values_wild, aes(x = wdsp, y = estimate)) +
  geom_ribbon(aes(ymin = conf.low, ymax = conf.high, fill = station)) +
  geom_line(aes(color = station), linewidth = 1) +
  labs(x = "Mean Wind Speed (knot)", y = "Predicted high temperature (C)") +
  theme_minimal() +
  guides(fill = "none", color = "none") +
  facet_wrap(vars(station), nrow = 1)
```

Wrap up

- Dual y-axes are safe when measuring the same quantity in different units
- `patchwork` simplifies multi-plot layouts
- Correlograms give compact views of many correlations
- `broom` + `marginaleffects` streamline predictions and marginal effects

Class business

- Read required (and suggested) online materials
- Fork `GitHub` repository
- Problem set #2 is up on GitHub