Assessing hurricane exposure with R

Packages to facilitate environmental epidemiology

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Workshop overview

- Topics: ...
- Packages: ...

Required set-up (1)

- Install R [add link]
- Install RStudio [add link] (Recommended but not required)

Required set-up (2)

- Install `hurricaneexposuredata` (from our personal repo)

```
install.packages("drat") # Only run if you don't have `drat` ins
library("drat")

addRepo("geanders")
install.packages("hurricaneexposuredata")
```

Required set-up (2)

[Screenshot—R Journal article]

Required set-up (3)

- Install `hurricaneexposure` (from GitHub)

Required set-up (4)

- Install supplementary packages:
  - `tidyverse`
  - `sf`
  - `tigris`
  - `rnaturalearth` and `rnaturalearthdata`
  - `weathermetrics`
  - `noaastormevents`
  - `stormwindmodel`
  - `viridis`

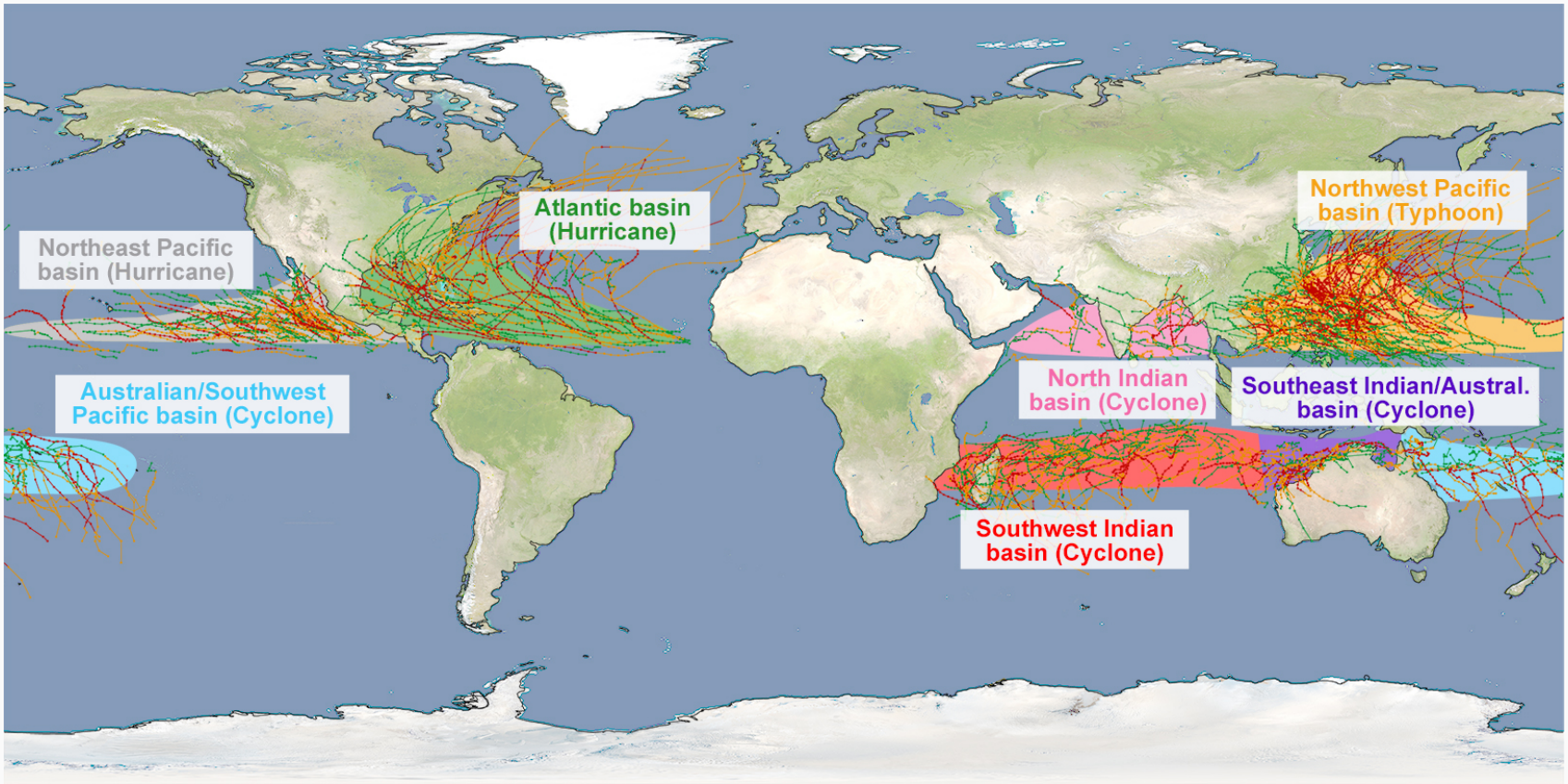
Load packages

To start, load only the two `hurricaneexposure` packages and the `tidyverse` package (for standard data science R tools).

```
library("hurricaneexposuredata")
library("hurricaneexposure")
library("tidyverse")
```

Basics on tropical cyclone data

Tropical cyclone basins



Source: Deutsche Wetterdienst

Tropical cyclone names

What's in a hurricane's name?

Atlantic tropical storm name lists, 2016-2021

2016	2017	2018	2019	2020	2021
Alex	Arlene	Alberto	Andrea	Arthur	Ana
Bonnie	Bret	Beryl	Barry	Bertha	Bill
Colin	Cindy	Chris	Chantal	Cristobal	Claudette
Danielle	Don	Debby	Dorian	Dolly	Danny
Earl	Emily	Ernesto	Erin	Edouard	Elsa
Fiona	Franklin	Florence	Fernand	Fay	Fred
Gaston	Gert	Gordon	Gabrielle	Gonzalo	Grace
Hermine	Harvey	Helene	Humberto	Hanna	Henri
Ian	Irma	Isaac	Imelda	Isaias	Ida
Julia	Jose	Joyce	Jerry	Josephine	Julian
Karl	Katia	Kirk	Karen	Kyle	Kate
Lisa	Lee	Leslie	Lorenzo	Laura	Larry
Matthew	Maria	Michael	Melissa	Marco	Mindy
Nicole	Nate	Nadine	Nestor	Nana	Nicholas
Otto	Ophelia	Oscar	Olga	Omar	Odette
Paula	Philippe	Patty	Pablo	Paulette	Peter
Richard	Rina	Rafael	Rebekah	Rene	Rose
Shary	Sean	Sara	Sebastien	Sally	Sam
Tobias	Tammy	Tony	Tanya	Teddy	Teresa
Virginie	Vince	Valerie	Van	Vicky	Victor
Walter	Whitney	William	Wendy	Wilfred	Wanda

Source: National Oceanic and Atmospheric Administration

CNBC

Source: CNBC / NOAA

Retiring names

Source: Lex18

“Best tracks” data

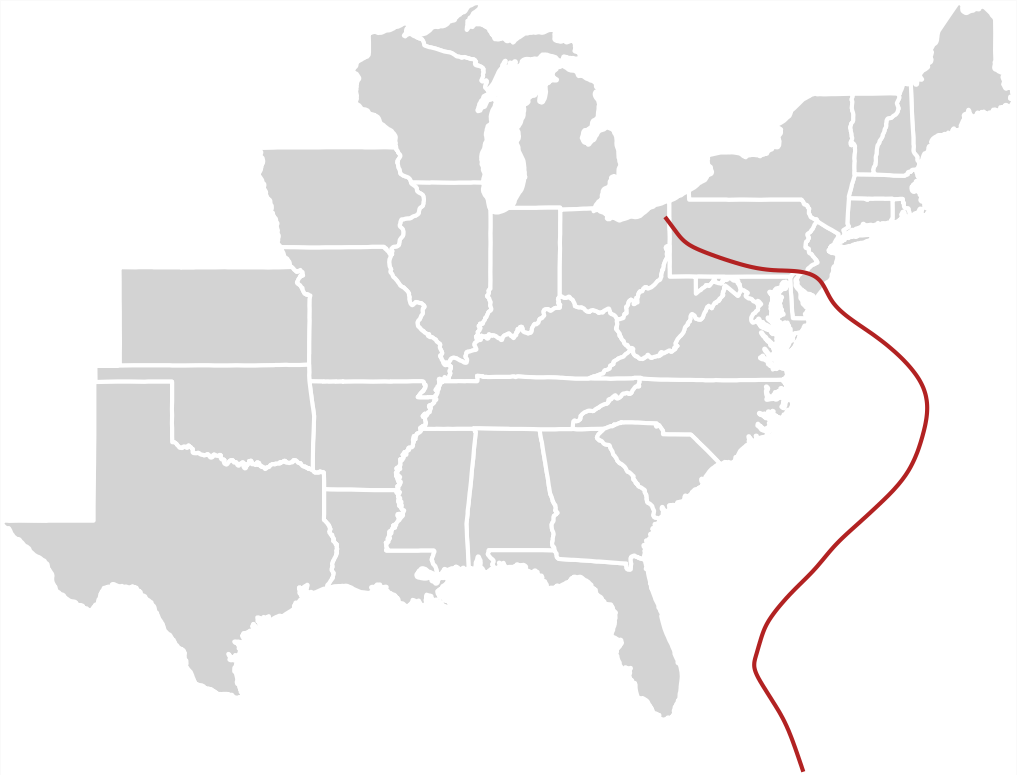
Interpolating tracks

[Plot from stormwindmodel vignette]

Mapping storm tracks

You can map a storm's track with the `map_tracks` function from `hurricaneexposure`. For example, map the track of Hurricane Sandy with:

```
map_tracks(storm = "Sandy-2012")
```



Mapping storm tracks

The output is a ggplot-class object, so you can add elements as with other ggplot-class objects:

```
map_tracks(storm = "Sandy-2012") +
   labs(title = "Central track of Hurricane Sandy, 2012",
        caption = "Based on HURDAT2 Best Tracks")
```

Mapping storm tracks

You can plot the tracks of multiple storms. For example, you can plot the tracks of all the tracked storms that came near the US in 2018 with:

```
map_tracks(storm = c("Alberto-2018", "Chris-2018", "Florence-201
                     "Gordon-2018", "Michael-2018"))
```

Storm track data

This function is using storm track data that we've included in the `hurricaneexposuredata` package, in a dataset called `hurr_tracks`:

```
data("hurr_tracks")
hurr_tracks %>% sample_n(3)
```

```
##       storm_id         date latitude longitude wind
## 1   Mitch-1998 199810300300   15.500  -85.7925   52
## 2 Michael-2018 201810140000   48.400  -33.1000   65
## 3   Cindy-2017 201706211500   27.535  -92.6802   47
```

Storm track data

You can work directly with this dataset. For example, you can use regular expressions to identify all the storms in the dataset within a certain year and the number of tracking data points for each in this data:

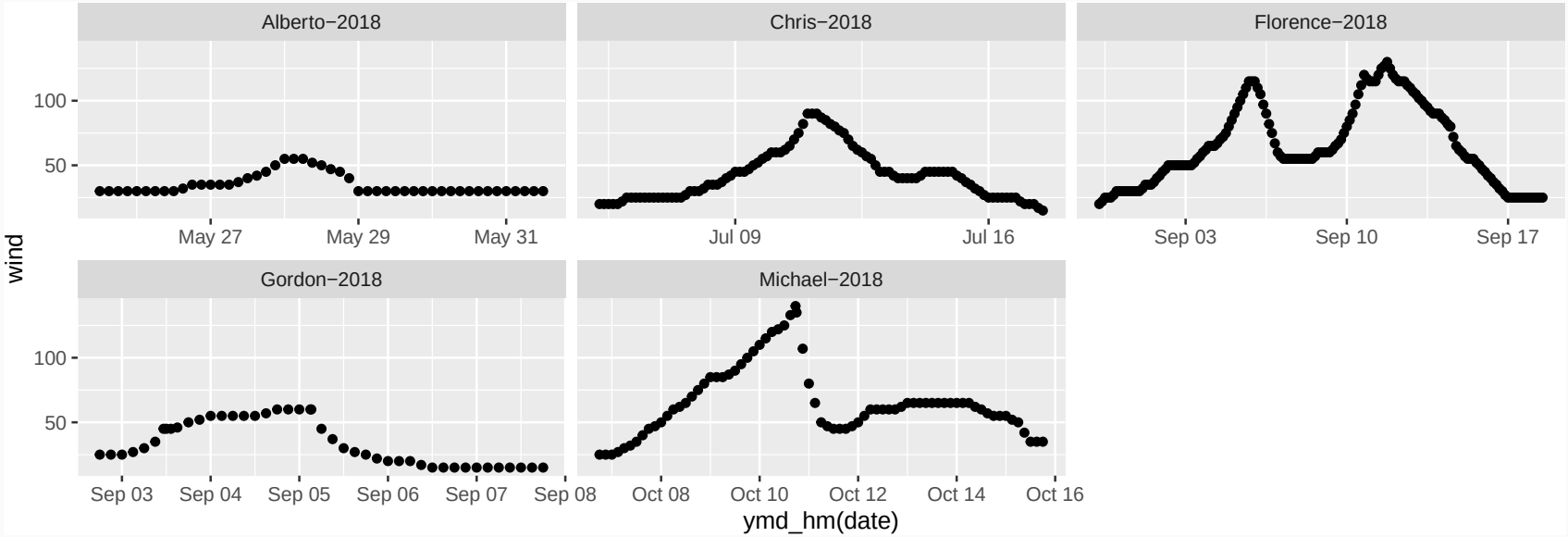
```
hurr_tracks %>%
   filter(str_detect(storm_id, "2018")) %>%
   group_by(storm_id) %>%
   summarize(n = n(), max_wind = max(wind),
             start_date = first(date))
```

```
## # A tibble: 5 x 4
##   storm_id           n max_wind start_date
##   <chr>          <int>    <dbl> <chr>
## 1 Alberto-2018      49       55 201805251200
## 2 Chris-2018        99       90 201807050600
## 3 Florence-2018    156      130 201808300600
## 4 Gordon-2018       44       60 201809021800
## 5 Michael-2018      74      140 201810061800
```

Storm track data

Similarly, you can explore patterns in the storm track measurements, like each storm's pattern of maximum sustained winds over time:

```
library("lubridate")
hurr_tracks %>%
    filter(str_detect(storm_id, "2018")) %>%
    ggplot(aes(x = ymd_hm(date), y = wind)) +
    geom_point() +
    facet_wrap(~ storm_id, scales = "free_x")
```



Other R sources for storm tracks

[IBTrACS?]

Your turn

- Map the tracks of Hurricane Harvey in 2012 using `map_tracks`.
- Map the tracks of Hurricane Harvey in 2012 and Tropical Storm Allison in 2011 using `map_tracks`
- Create these maps using the `sf` package, adding color for the maximum sustained wind of the storm at each time point

R tools for geospatial tools

`sf` framework for geospatial data

```
library("sf")
storms_2018 <- hurr_tracks %>%
   filter(str_detect(storm_id, "2018")) %>%
   st_as_sf(coords = c("longitude", "latitude"))
```

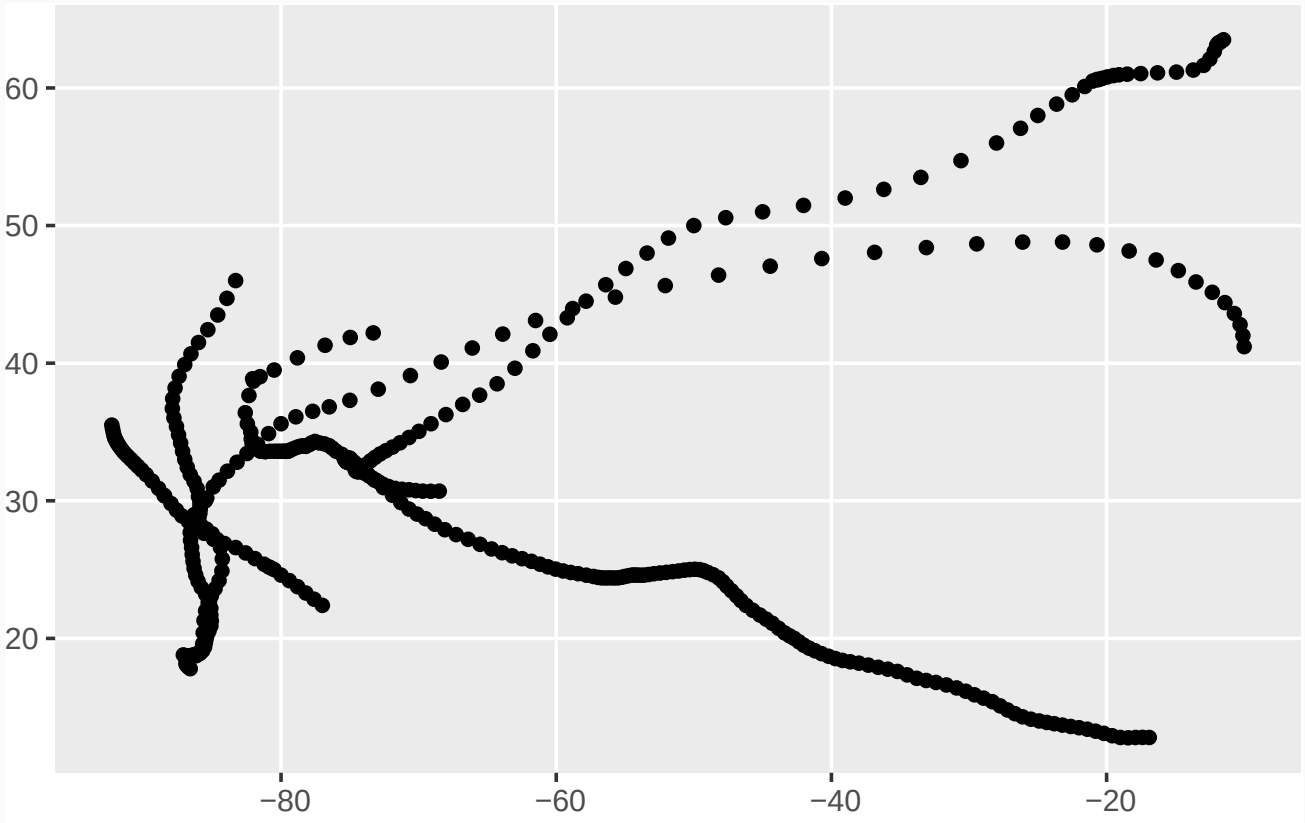
sf framework for geospatial data

```
storms_2018
```

```
## Simple feature collection with 422 features and 3 fields
## geometry type:  POINT
## dimension:      XY
## bbox:           xmin: -92.3 ymin: 12.7774 xmax: -10 ymax: 63.5
## epsg (SRID):    NA
## proj4string:    NA
## First 10 features:
##        storm_id         date wind                  geometry
## 1  Alberto-2018 201805251200   30       POINT (-87.1 18.8)
## 2  Alberto-2018 201805251500   30 POINT (-86.8099 18.7325)
## 3  Alberto-2018 201805251800   30       POINT (-86.5 18.7)
## 4  Alberto-2018 201805252100   30   POINT (-86.17 18.7401)
## 5  Alberto-2018 201805260000   30       POINT (-85.9 18.9)
## 6  Alberto-2018 201805260300   30 POINT (-85.7624 19.1374)
## 7  Alberto-2018 201805260600   30       POINT (-85.7 19.6)
## 8  Alberto-2018 201805260900   30  POINT (-85.6572 20.405)
## 9  Alberto-2018 201805261200   30       POINT (-85.6 21.3)
```

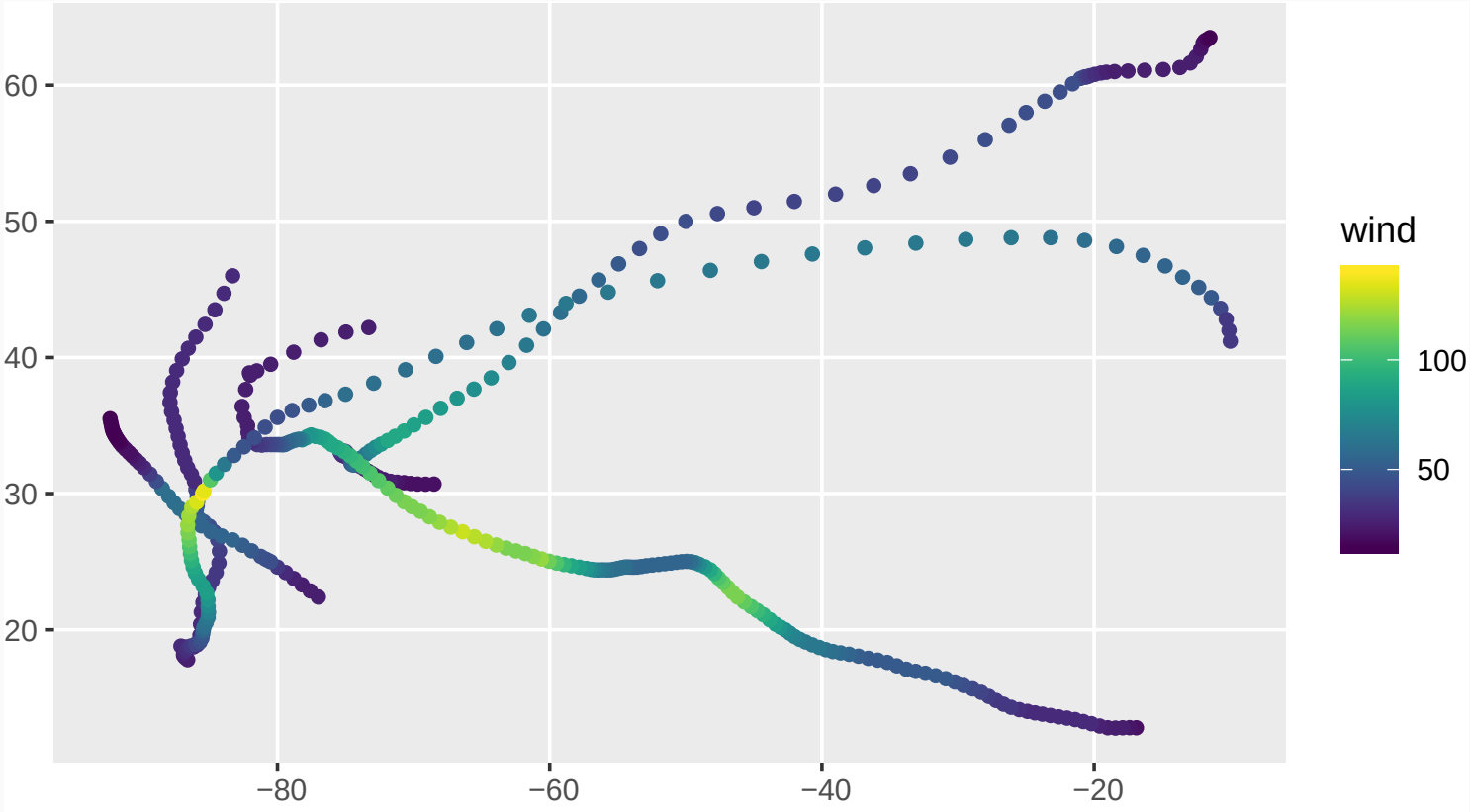
sf framework for geospatial data

```
ggplot() +
    geom_sf(data = storms_2018)
```



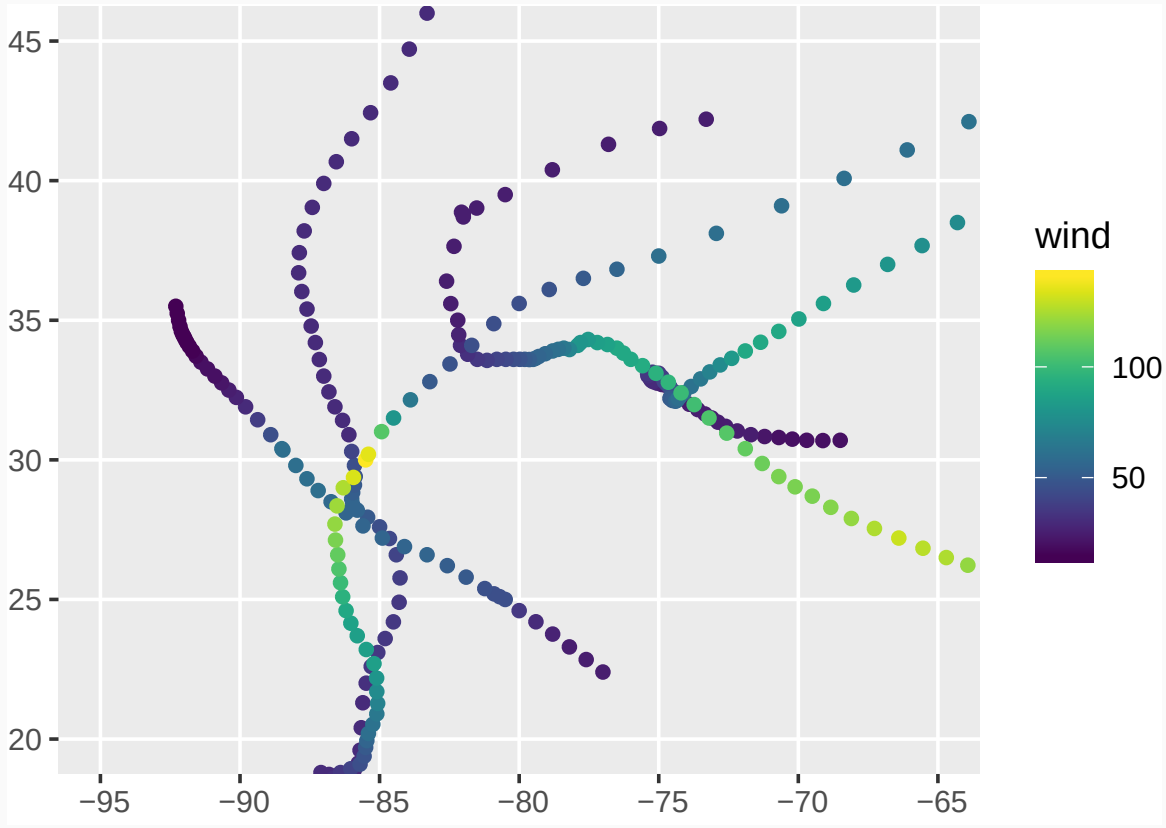
sf framework for geospatial data

```
library("viridis")
ggplot() +
    geom_sf(data = storms_2018,
            aes(color = wind)) +
    scale_color_viridis()
```



sf framework for geospatial data

```
ggplot() +
    geom_sf(data = storms_2018,
            aes(color = wind)) +
    scale_color_viridis() +
    xlim(c(-95, -65)) +
    ylim(c(20, 45))
```



tigris package

```
library("tigris")
fl_counties <- counties(state = "FL",
                        cb = FALSE, resolution = "20m",
                        class = "sf")
```

```
##
  |
  |
  |
  |
  |
  |=
  |
  |=
  |
  |==
  |
  |==
```

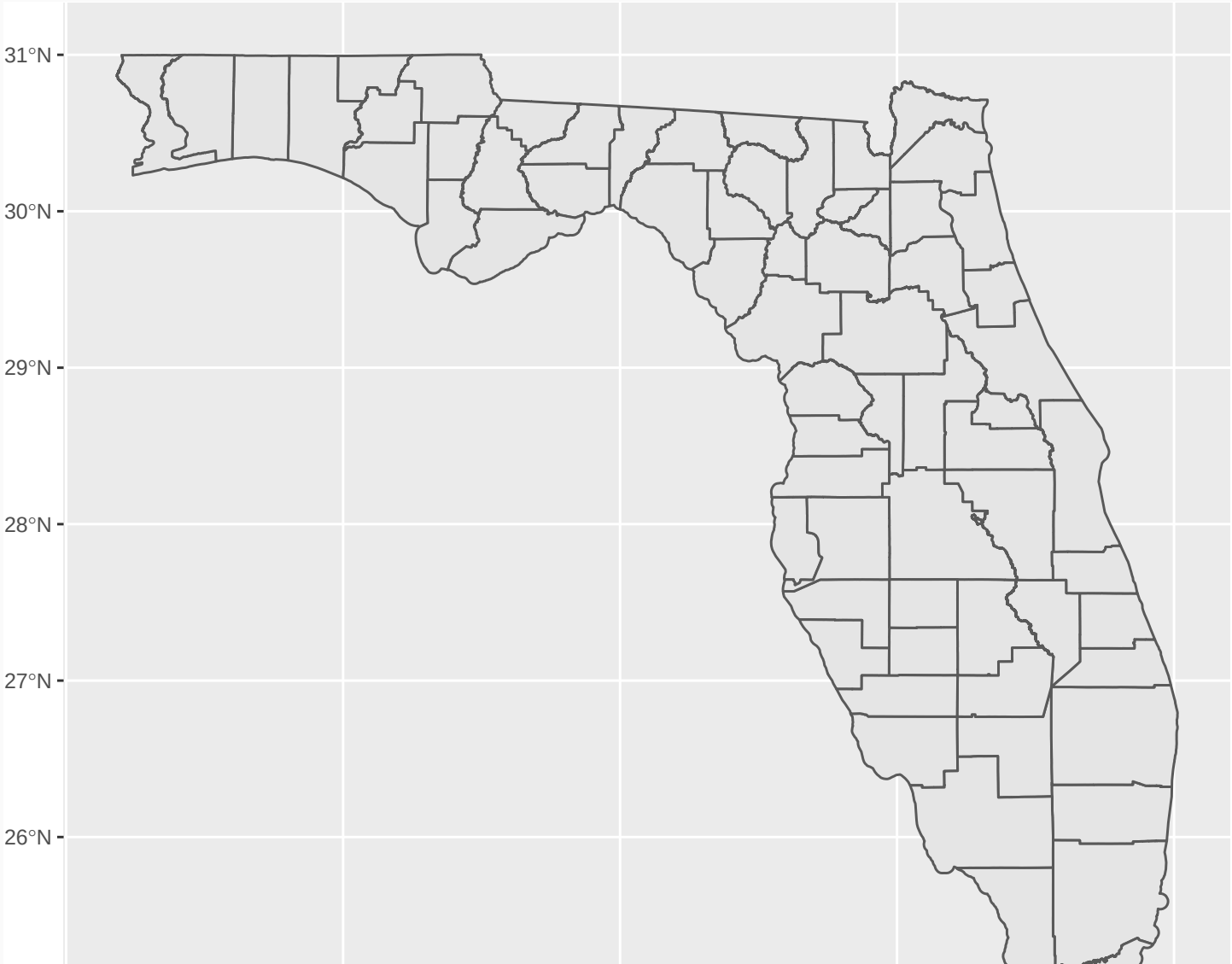
tigris package

```
fl_counties %>% slice(1:3)
```

```
## Simple feature collection with 3 features and 17 fields
## geometry type:  MULTIPOLYGON
## dimension:      XY
## bbox:           xmin: -86.3975 ymin: 28.43329 xmax: -82.05447
## epsg (SRID):    4269
## proj4string:    +proj=longlat +ellps=GRS80 +towgs84=0,0,0,0,0
##   STATEFP COUNTYFP COUNTYNS GEOID     NAME        NAMELSAD LS
## 1      12      053 00295751 12053 Hernando Hernando County
## 2      12      129 00306912 12129  Wakulla  Wakulla County
## 3      12      131 00295727 12131   Walton   Walton County
##   MTFCC CSAFP CBSAFP METDIVFP FUNCSTAT      ALAND    AWATER
## 1 G4020  <NA>  45300     <NA>        A 1224692722 300863005 +
## 2 G4020   533  45220     <NA>        A 1570625279 334901690 +
## 3 G4020  <NA>  18880     <NA>        A 2687686788 522848570 +
##       INTPTLON                       geometry
## 1 -082.4662272 MULTIPOLYGON (((-82.55258 2...
```

tigris package

```
ggplot() +
    geom_sf(data = fl_counties)
```



Putting things together

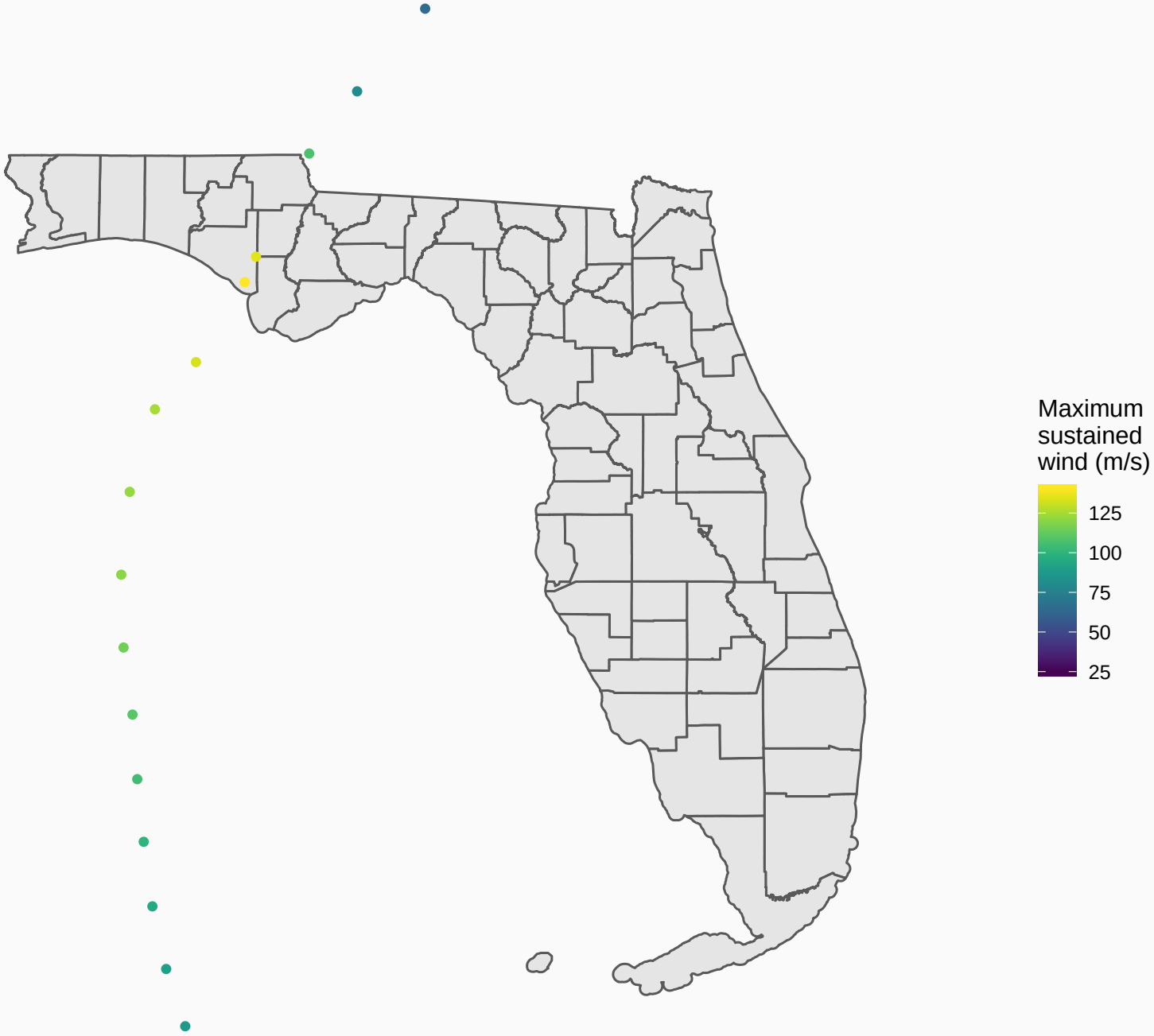
```
michael_2018 <- storms_2018 %>%
   st_set_crs(4269) %>%
   filter(storm_id == "Michael-2018")
michael_2018 %>% slice(1:3)
```

```
## Simple feature collection with 3 features and 3 fields
## geometry type:  POINT
## dimension:      XY
## bbox:           xmin: -86.9 ymin: 17.8 xmax: -86.6 ymax: 18.1
## epsg (SRID):    4269
## proj4string:    +proj=longlat +ellps=GRS80 +towgs84=0,0,0,0,0
##       storm_id         date wind                  geometry
## 1 Michael-2018 201810061800   25       POINT (-86.6 17.8)
## 2 Michael-2018 201810062100   25 POINT (-86.7824 17.9526)
## 3 Michael-2018 201810070000   25       POINT (-86.9 18.1)
```

Putting things together

```
ggplot() +
   geom_sf(data = fl_counties) +
   geom_sf(data = michael_2018,
           aes(color = wind)) +
   scale_color_viridis() +
   xlim(c(-88, -79)) +
   ylim(c(24, 32)) +
   theme_void() +
   labs(color = "Maximum\nsustained\nwind (m/s)")
```

Putting things together



rnaturalearth packages

Converting to `sf` object

[Convert hurricane tracks to `sf`]

Your turn

- Create a map of North America and the track of [storm]
- Create a map of Florida ZIP codes and the track of [storm]

How close have storms come to US counties?

Population mean centers

```
data("county_centers")
head(county_centers)
```

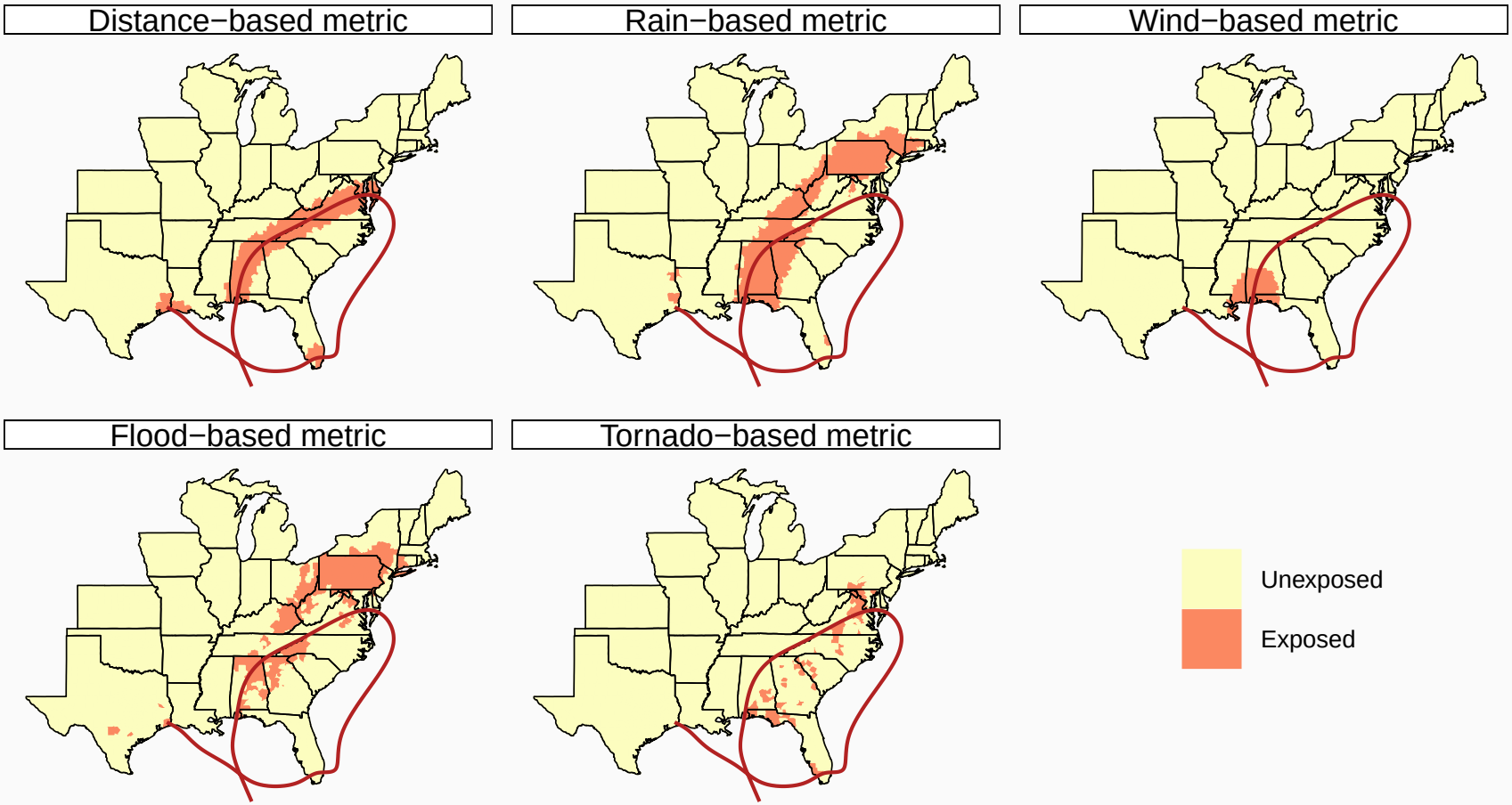
```
##    fips county_name state_name population latitude longitude
## 1 01001     Autauga    Alabama      54571 32.50039 -86.49416
## 2 01003     Baldwin    Alabama     182265 30.54892 -87.76238
## 3 01005     Barbour    Alabama      27457 31.84404 -85.31004
## 4 01007        Bibb    Alabama      22915 33.03092 -87.12766
## 5 01009      Blount    Alabama      57322 33.95524 -86.59149
## 6 01011     Bullock    Alabama      10914 32.11633 -85.70119
```

FIPs codes

Tropical cyclone hazards

Tropical cyclone hazards

Different patterns in hazards



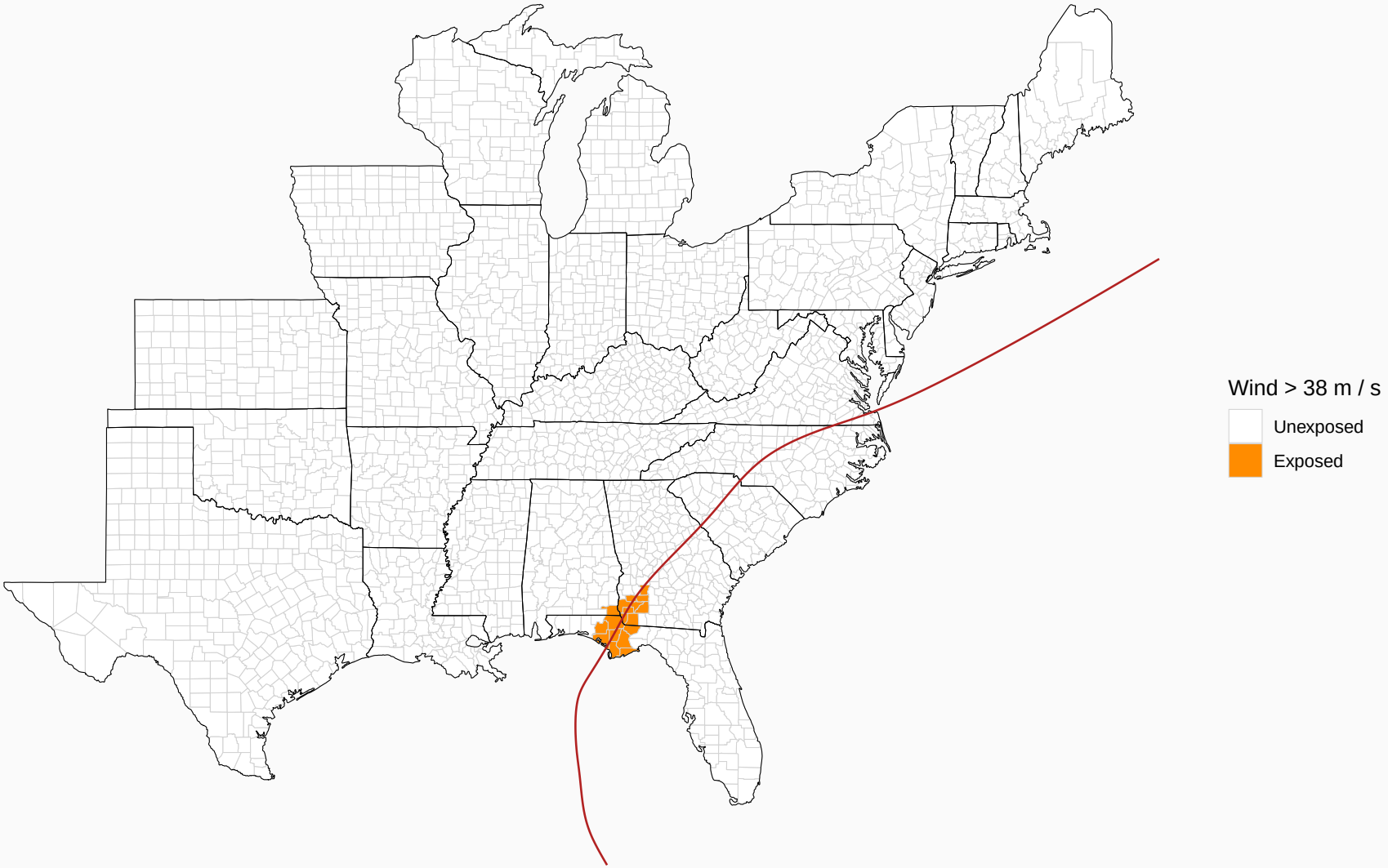
Wind exposures

Modeling storm wind field

Determining county peak sustained wind

All wind exposures for a storm

```
map_wind_exposure(storm = "Michael-2018", wind_limit = 38)
```



All wind exposures for a storm

[Dataframe]

All wind exposures for a county

```
fl_counties <- county_centers %>%
   filter(str_sub(fips, 1, 2) == "12") %>%
   purrr::pluck("fips")
fl_counties
```

```
##  [1] "12001" "12003" "12005" "12007" "12009" "12011" "12013"
##  [9] "12017" "12019" "12021" "12023" "12027" "12029" "12031"
## [17] "12035" "12037" "12039" "12041" "12043" "12045" "12047"
## [25] "12051" "12053" "12055" "12057" "12059" "12061" "12063"
## [33] "12067" "12069" "12071" "12073" "12075" "12077" "12079"
## [41] "12083" "12085" "12086" "12087" "12089" "12091" "12093"
## [49] "12097" "12099" "12101" "12103" "12105" "12107" "12109"
## [57] "12113" "12115" "12117" "12119" "12121" "12123" "12125"
## [65] "12129" "12131" "12133"
```

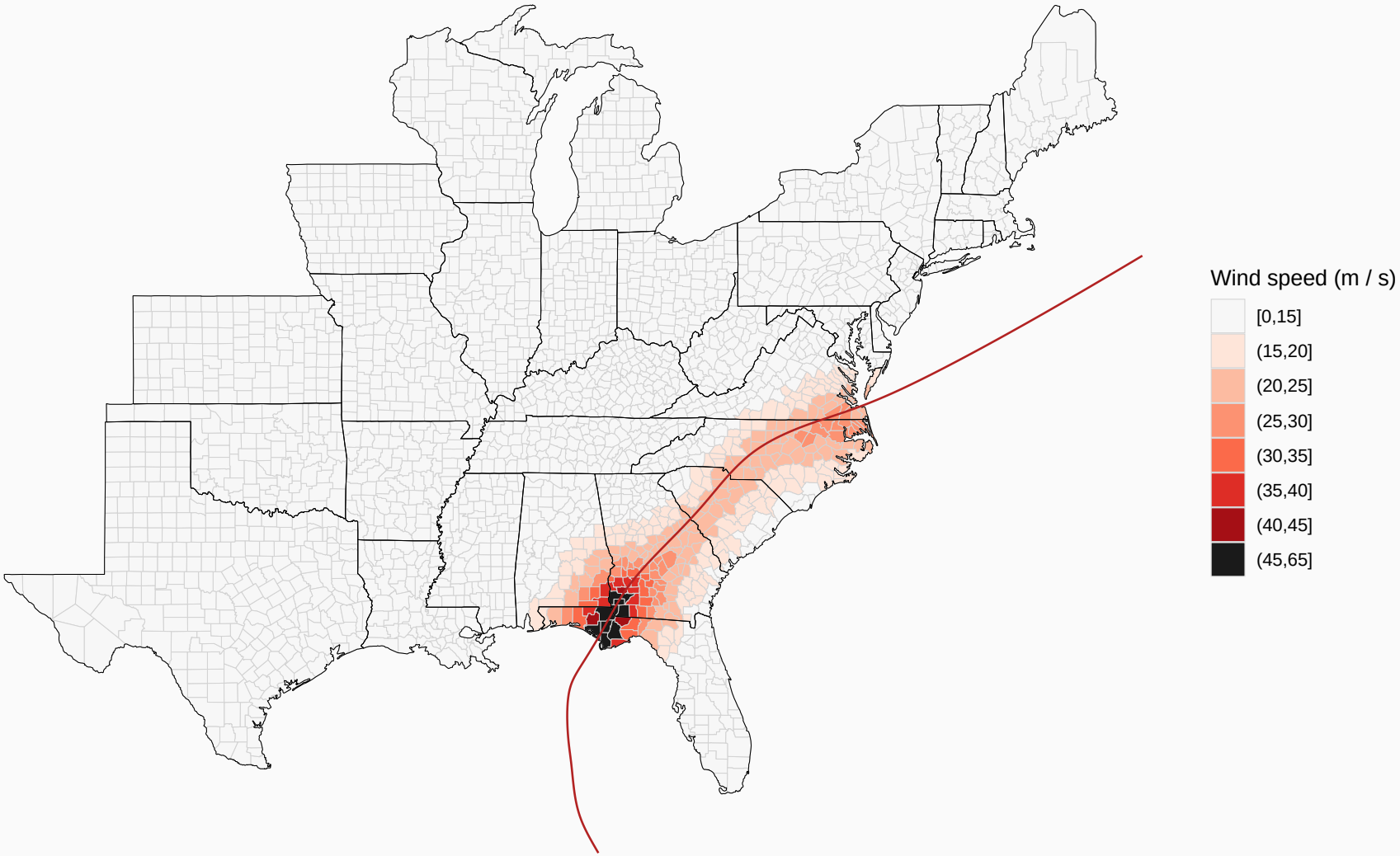
All wind exposures for a county

```
county_wind(counties = fl_counties, wind_limit = 38,
            start_year = 2016, end_year = 2018)
```

```
##         storm_id  fips vmax_sust vmax_gust sust_dur gust_dur
## 1     Irma-2017 12021  42.62840  63.51632      705     1200
## 2     Irma-2017 12071  39.36319  58.65116      735     1200
## 3     Irma-2017 12087  46.83800  69.78862     1230     1935
## 4  Michael-2018 12005  56.99529  84.92299      750     1140
## 5  Michael-2018 12013  59.94077  89.31175      690     1095
## 6  Michael-2018 12037  38.55300  57.44397      690     1140
## 7  Michael-2018 12039  44.17512  65.82092      645     1035
## 8  Michael-2018 12045  65.00964  96.86436      765     1155
## 9  Michael-2018 12063  54.44459  81.12244      645     1050
## 10 Michael-2018 12077  54.66943  81.45745      675     1110
## 11 Michael-2018 12133  43.86118  65.35316      660     1080
##    closest_time_utc storm_dist       local_time closest_date
## 1  2017-09-10 21:00   1.835589 2017-09-10 17:00   2017-09-10
## 2  2017-09-10 23:00  17.727964 2017-09-10 19:00   2017-09-10
## 3  2017-09-10 13:15  26.233467 2017-09-10 09:15   2017-09-10
```

All wind exposures for a county

```
map_counties(storm = "Michael-2018", metric = "wind")
```



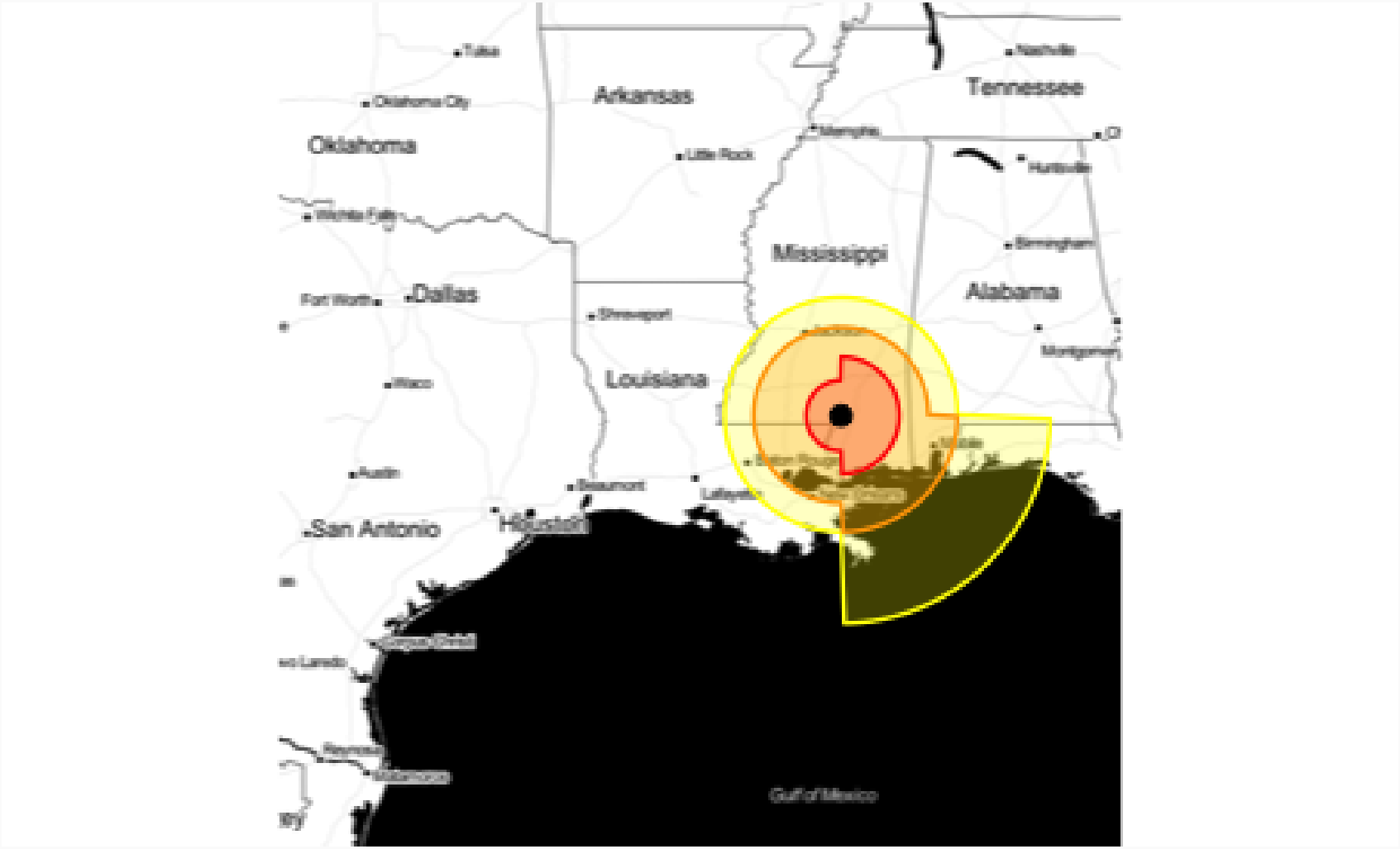
All wind exposures for a county

[Histogram of intensities]

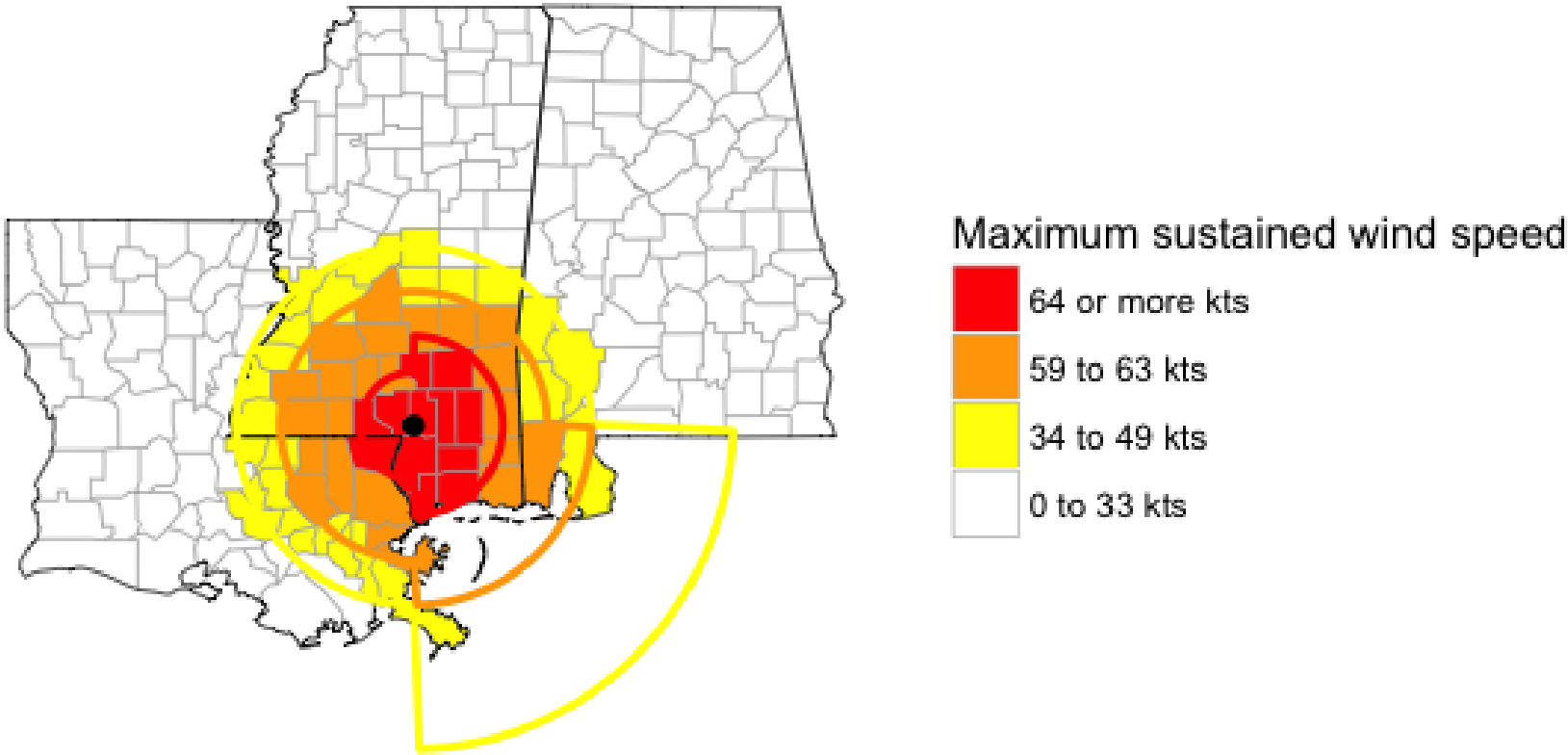
Joining wind exposure and outcomes

[Air delay example]

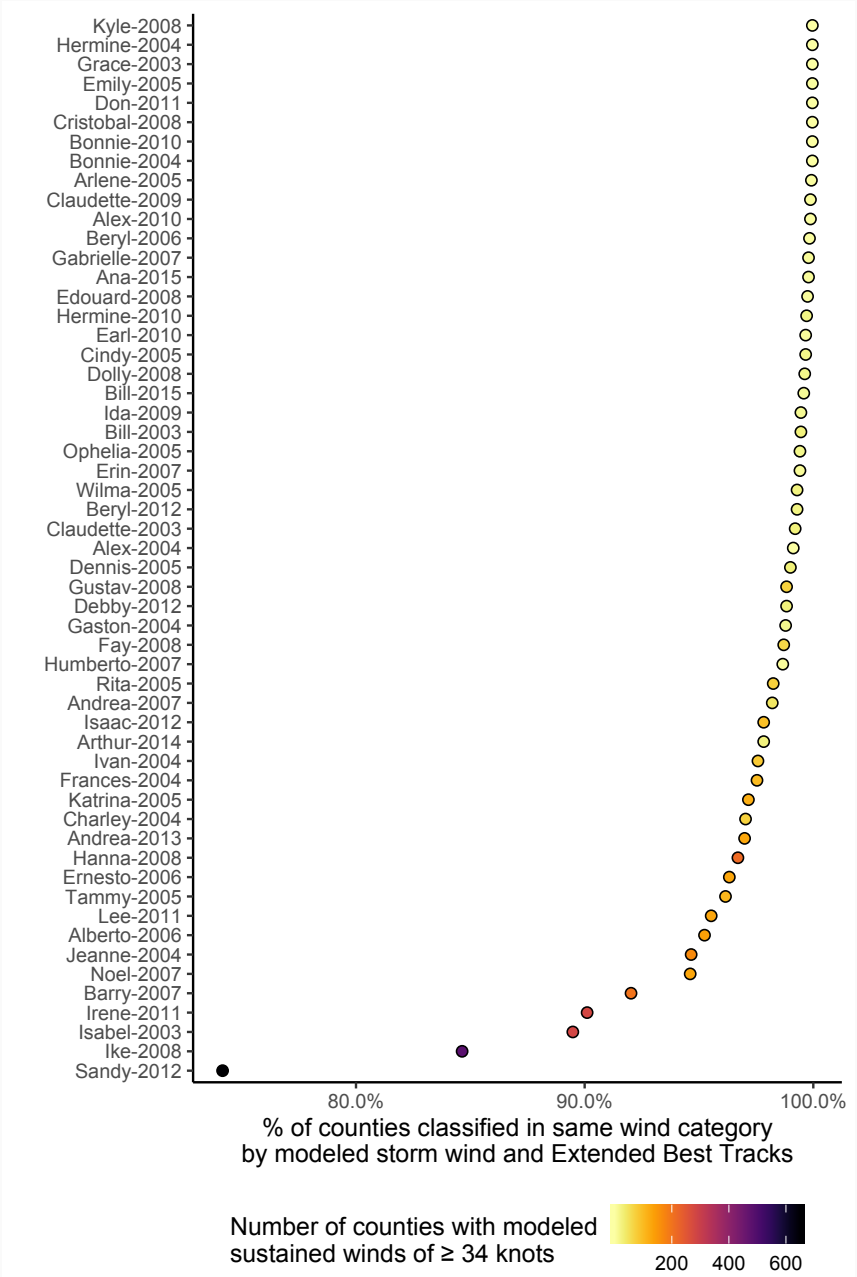
Other sources of wind exposure



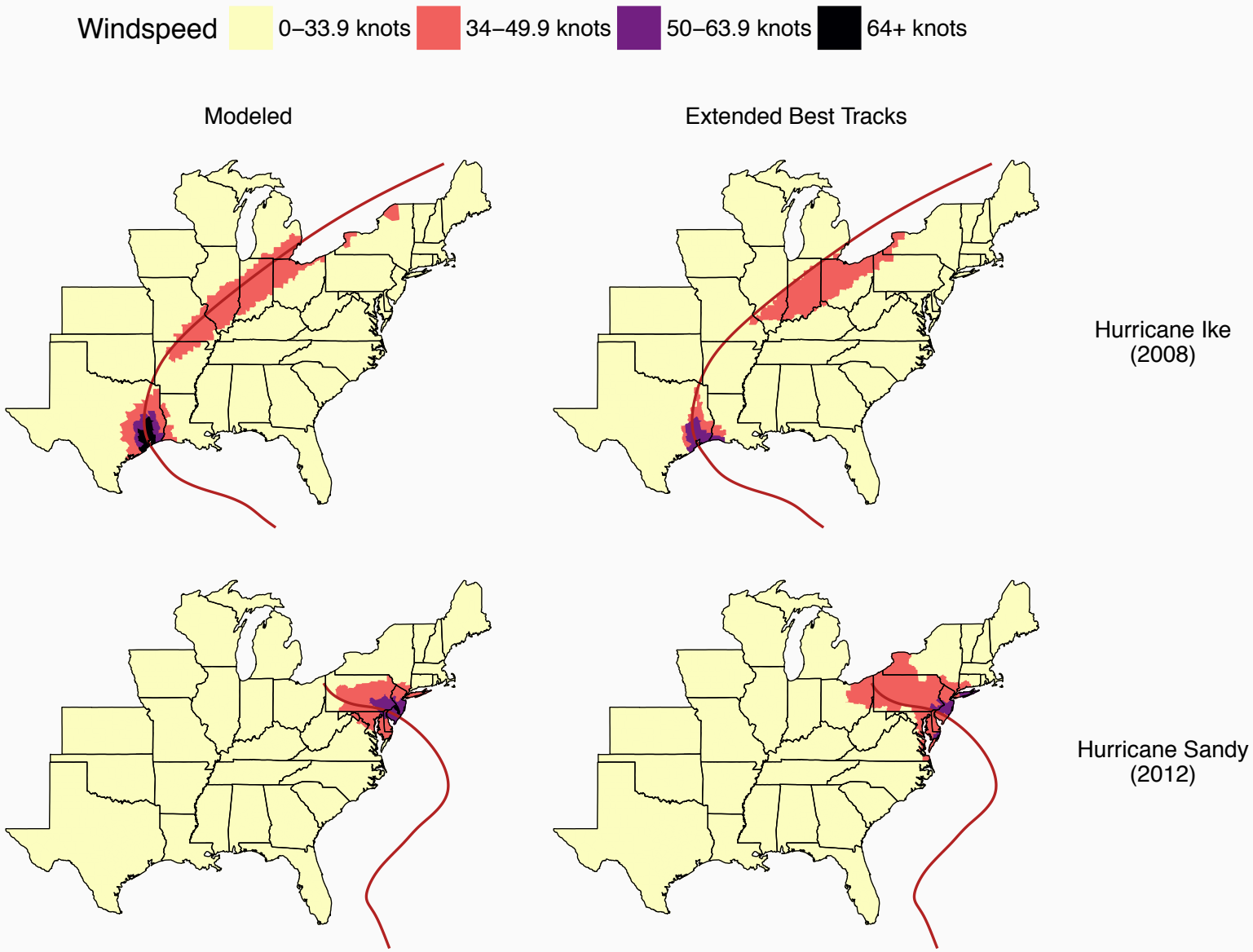
Other sources of wind exposure



Comparison of wind data



Comparison of wind data



Using wind radii–based metrics

[Code for using wind radii]

Other wind metrics

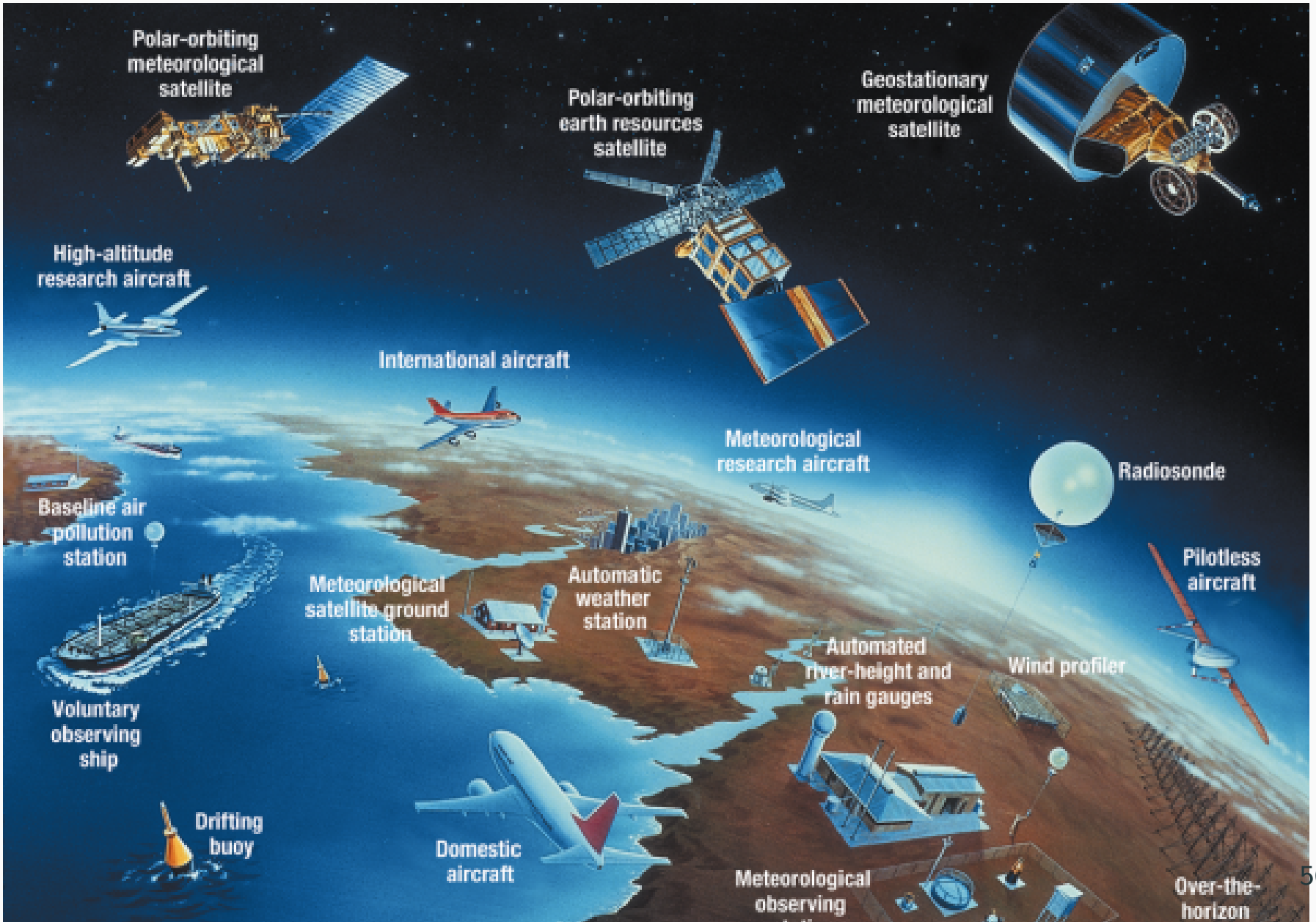
- Gust wind speed
- Duration of high wind

Your turn

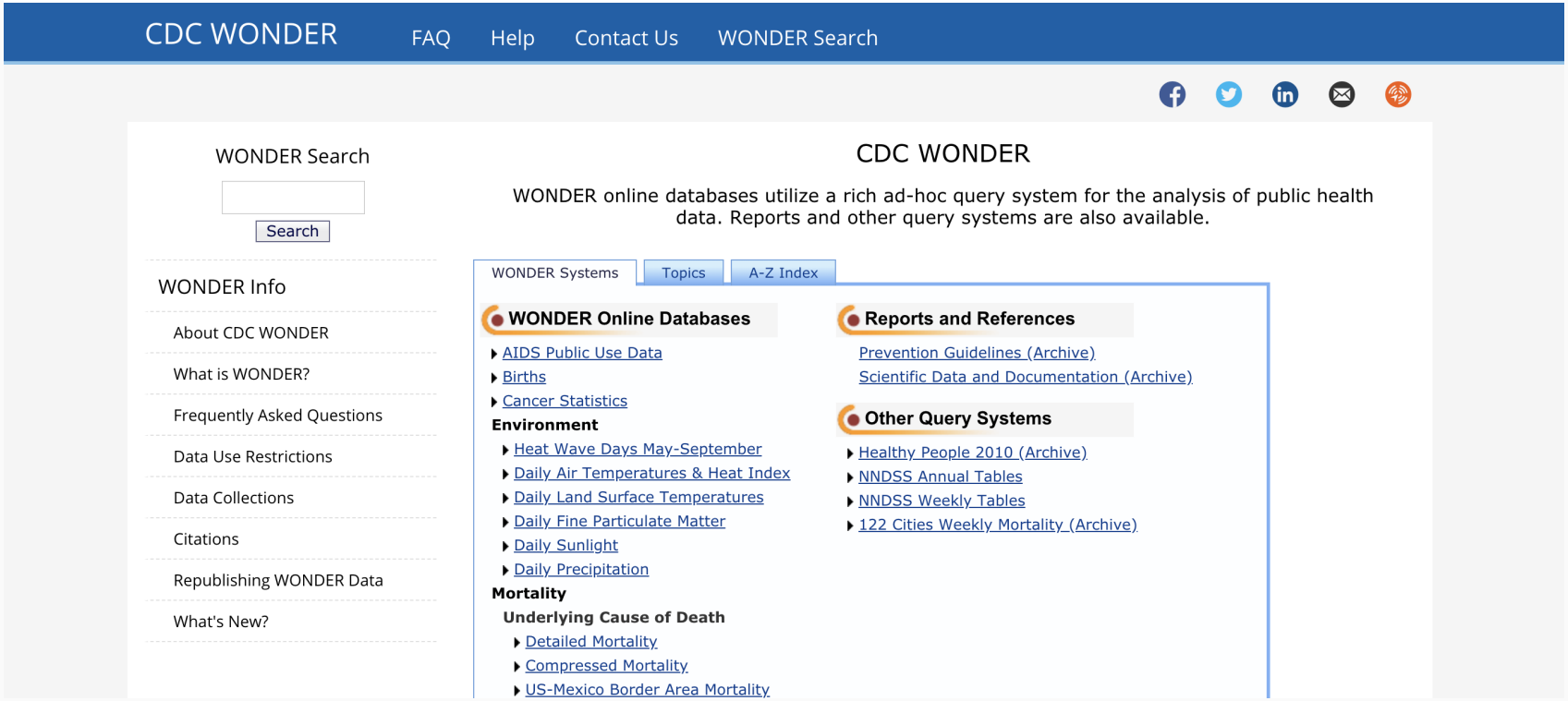
- Determine all the storms that brought winds of [x] m / s or higher to the following counties: x, y, z.
- Which brought the most intense wind to county x? Create a map showing the peak sustained wind that storm brought to each eastern US county.
- Create the same map, but use the wind radii–based wind exposure values rather than the modeled wind values.
- Create a scatterplot comparing modeled wind estimates versus wind radii–based estimates for all storms that brought winds of [x] m / s or higher to county x (based on modeled wind estimates).

Rain exposures

Re-analysis weather data



CDC WONDER database



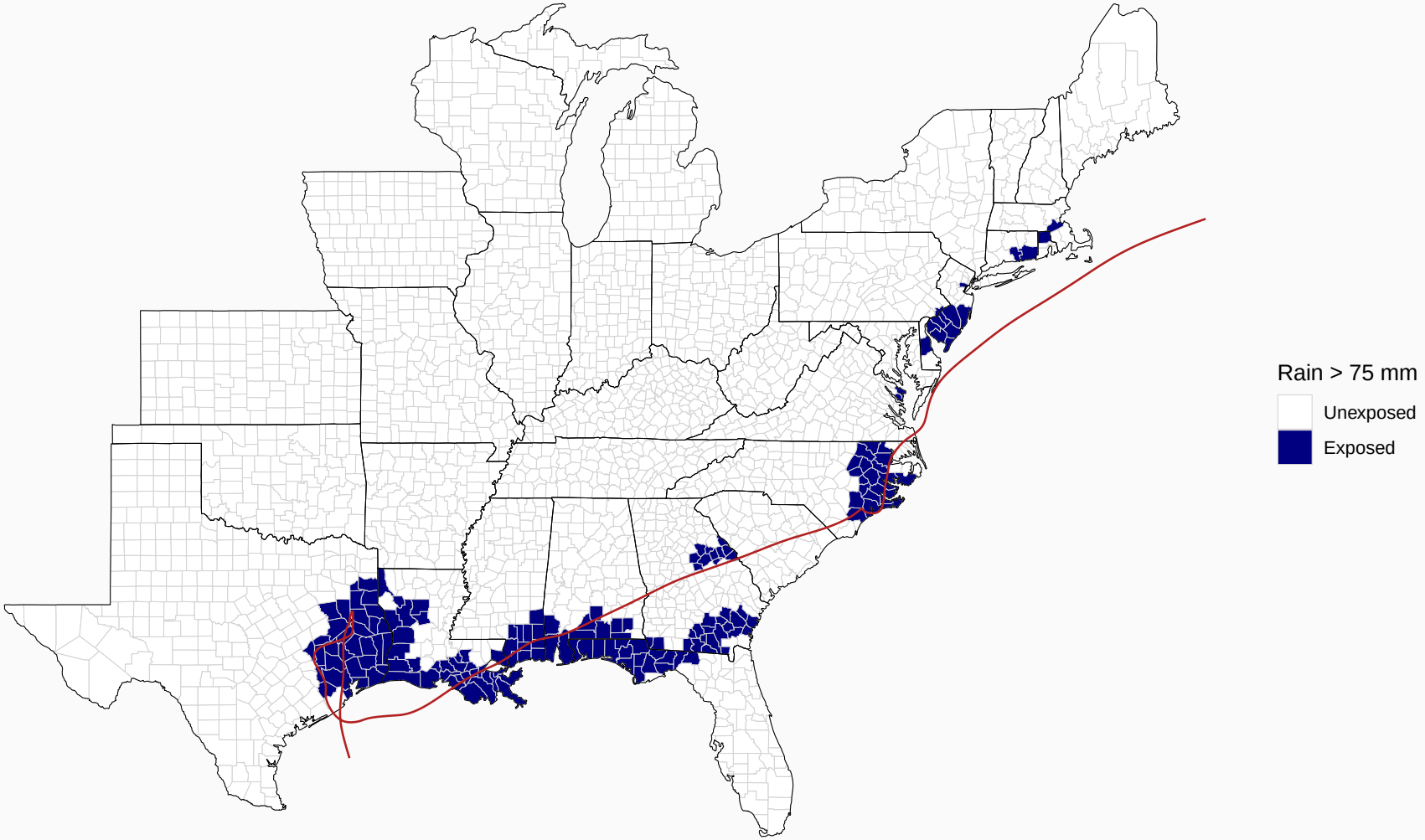
Source: US Centers for Disease Control and Prevention

Matching with storm tracks

Cumulative rainfall

All rain exposures for a storm

```
map_rain_exposure(storm = "Allison-2001", rain_limit = 75,
                  dist_limit = 250)
```



All rain exposures for a storm

```
all_fips <- county_centers %>% pull("fips")
county_rain(counties = all_fips,
            rain_limit = 150, dist_limit = 250,
            start_year = 2001, end_year = 2001) %>%
   filter(storm_id == "Allison-2001")
```

```
##        storm_id  fips closest_date  storm_dist tot_precip
## 1 Allison-2001 22057   2001-06-11  34.6818251      152.4 2001
## 2 Allison-2001 48005   2001-06-07  17.0465190      170.4 2001
## 3 Allison-2001 48185   2001-06-08  18.9167371      179.9 2001
## 4 Allison-2001 48241   2001-06-07 101.3829776      171.0 2001
## 5 Allison-2001 48455   2001-06-07   0.2772971      169.8 2001
## 6 Allison-2001 48457   2001-06-07  71.5347264      182.0 2001
## 7 Allison-2001 48471   2001-06-07  19.5921732      154.2 2001
##   closest_time_utc
## 1 2001-06-11 05:00
## 2 2001-06-07 13:30
## 3 2001-06-08 10:45
```

All rain exposures for a county

```
tx_counties <- county_centers %>%
   filter(str_sub(fips, 1, 2) == "48") %>%
   pull("fips")
tx_counties %>% head()
```

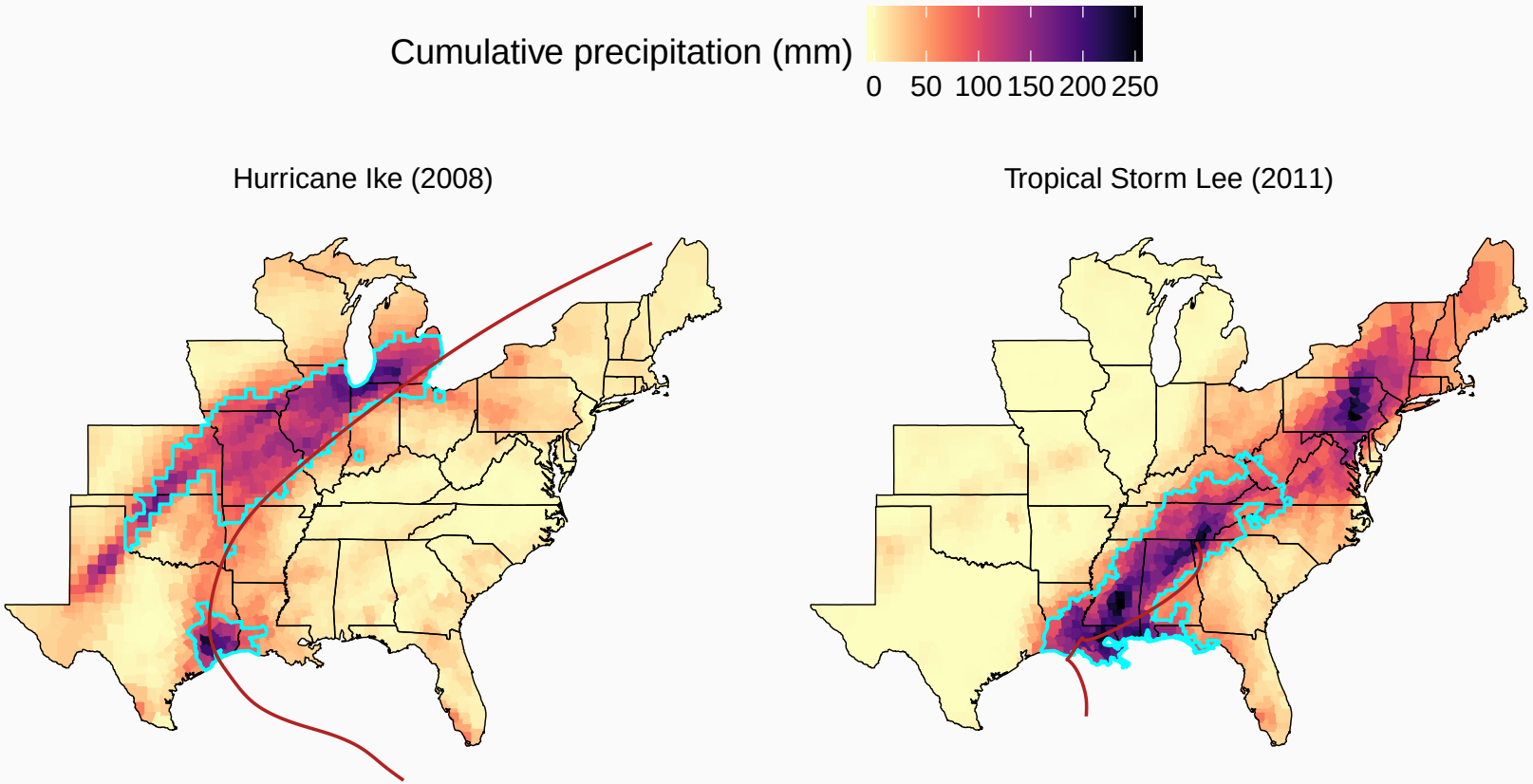
```
## [1] "48001" "48003" "48005" "48007" "48009" "48011"
```

All rain exposures for a county

```
county_rain(counties = tx_counties, rain_limit = 175,
            dist_limit = 250,
            start_year = 2009, end_year = 2011)
```

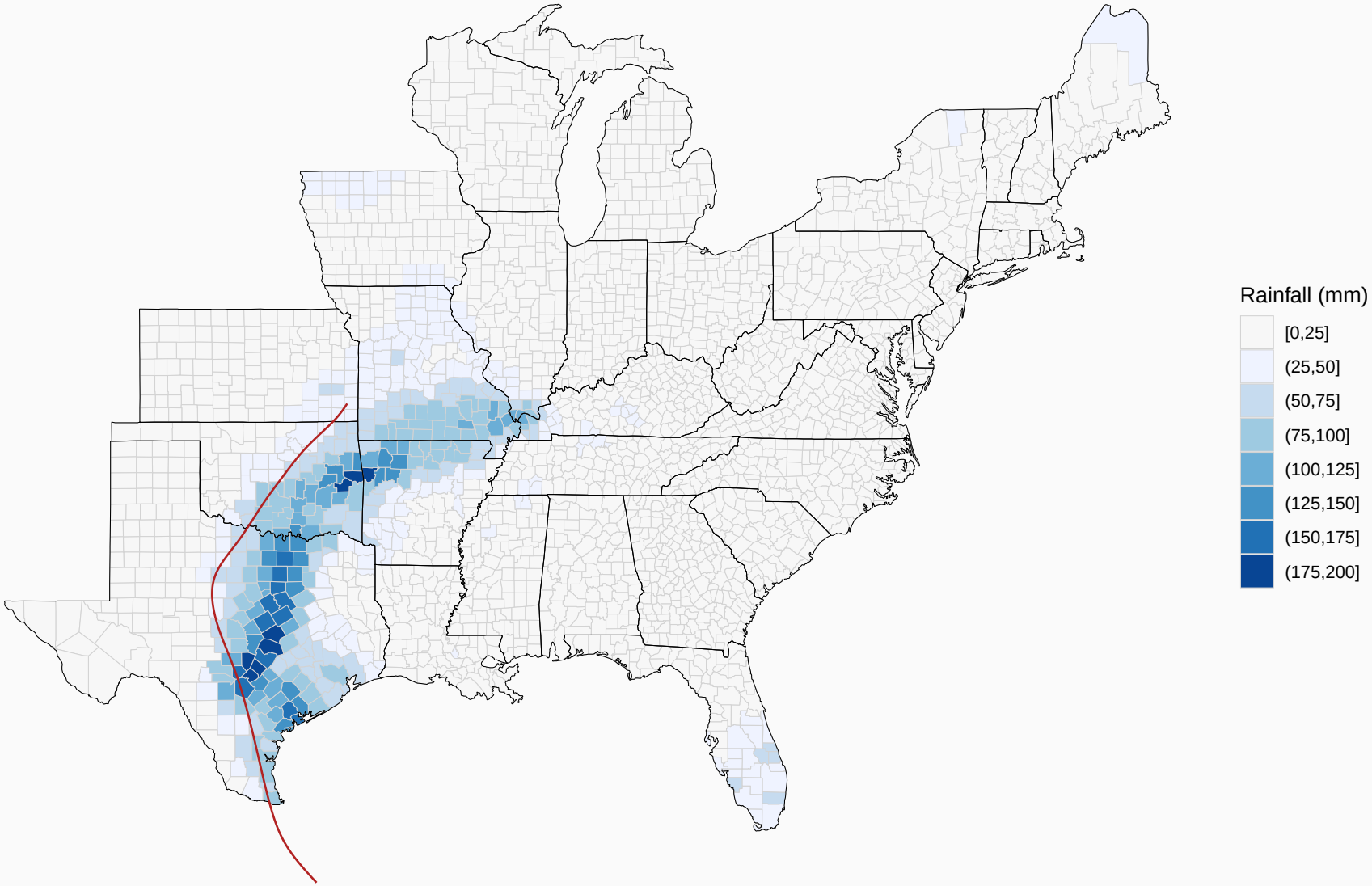
```
##        storm_id  fips closest_date storm_dist tot_precip       local
## 1:    Alex-2010 48215   2010-06-30  230.15397      183.3 2010-06-30
## 2: Hermine-2010 48027   2010-09-07  154.26915      181.4 2010-09-07
## 3: Hermine-2010 48031   2010-09-07   47.00182      175.5 2010-09-07
## 4: Hermine-2010 48091   2010-09-07   47.27736      187.8 2010-09-07
## 5: Hermine-2010 48209   2010-09-07   81.80723      186.1 2010-09-07
## 6: Hermine-2010 48491   2010-09-07  122.60846      187.4 2010-09-07
##    closest_time_utc
## 1: 2010-07-01 01:00
## 2: 2010-09-07 23:45
## 3: 2010-09-07 21:00
## 4: 2010-09-07 19:00
## 5: 2010-09-07 19:30
## 6: 2010-09-07 21:30
```

Distance constraint



All rain exposures for a county

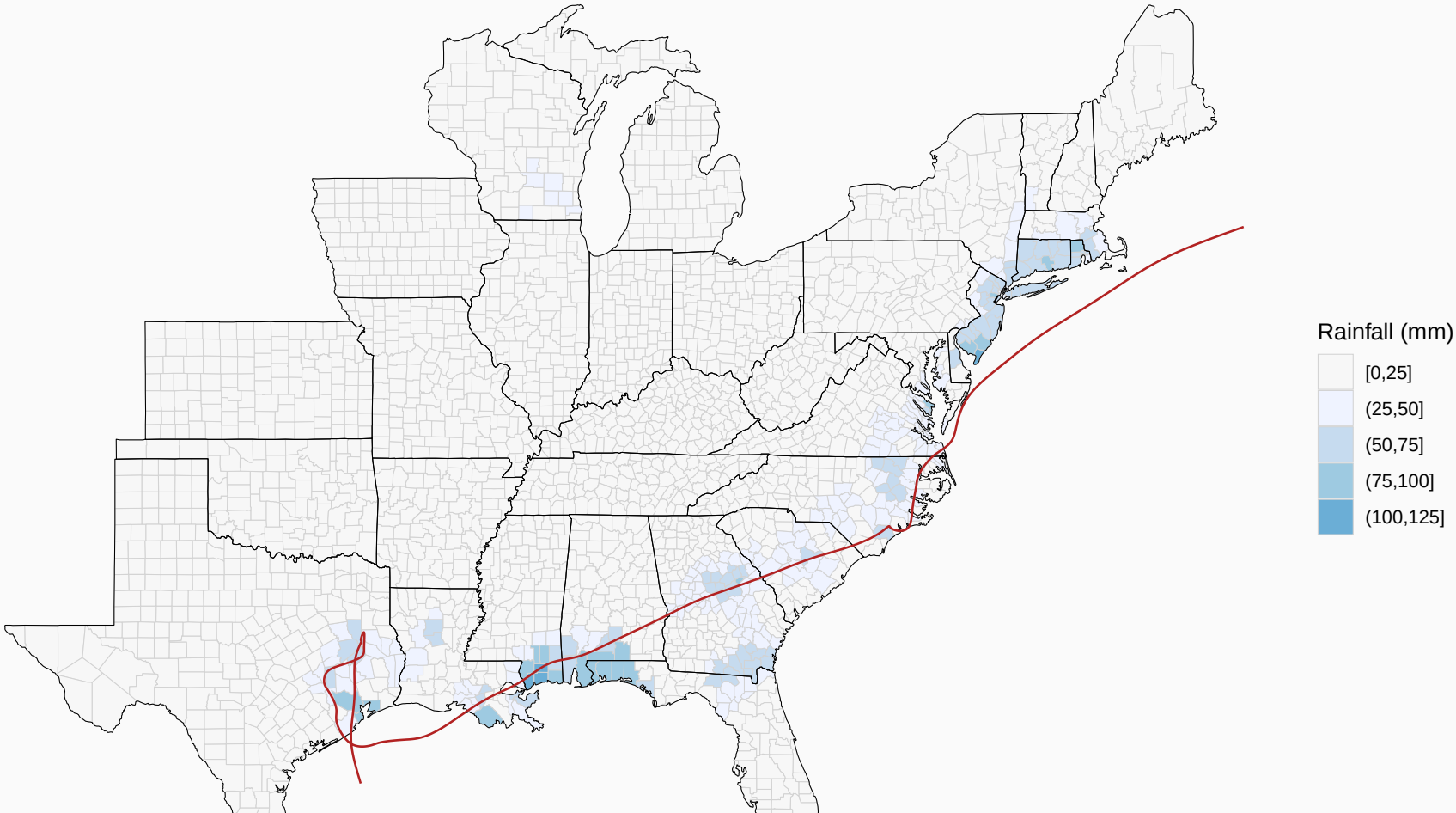
```
map_counties(storm = "Hermine-2010", metric = "rainfall")
```



Choice of days to include

Use only the storm day for the cumulative precipitation for Tropical Storm Allison.

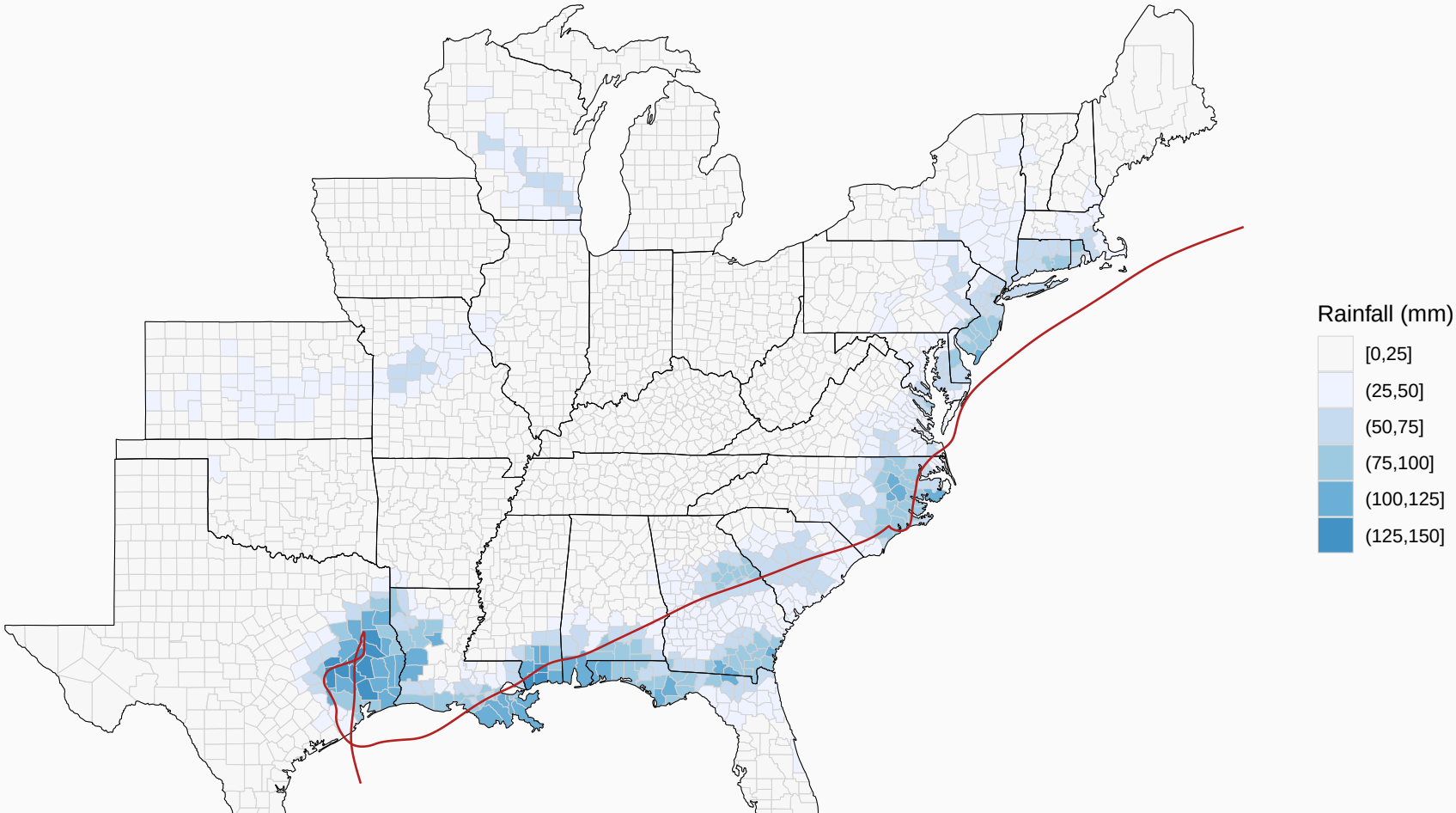
```
map_counties(storm = "Allison-2001", metric = "rainfall",
             days_included = 0)
```



Choice of days to include

Use a three-day window for the cumulative precipitation for Tropical Storm Allison.

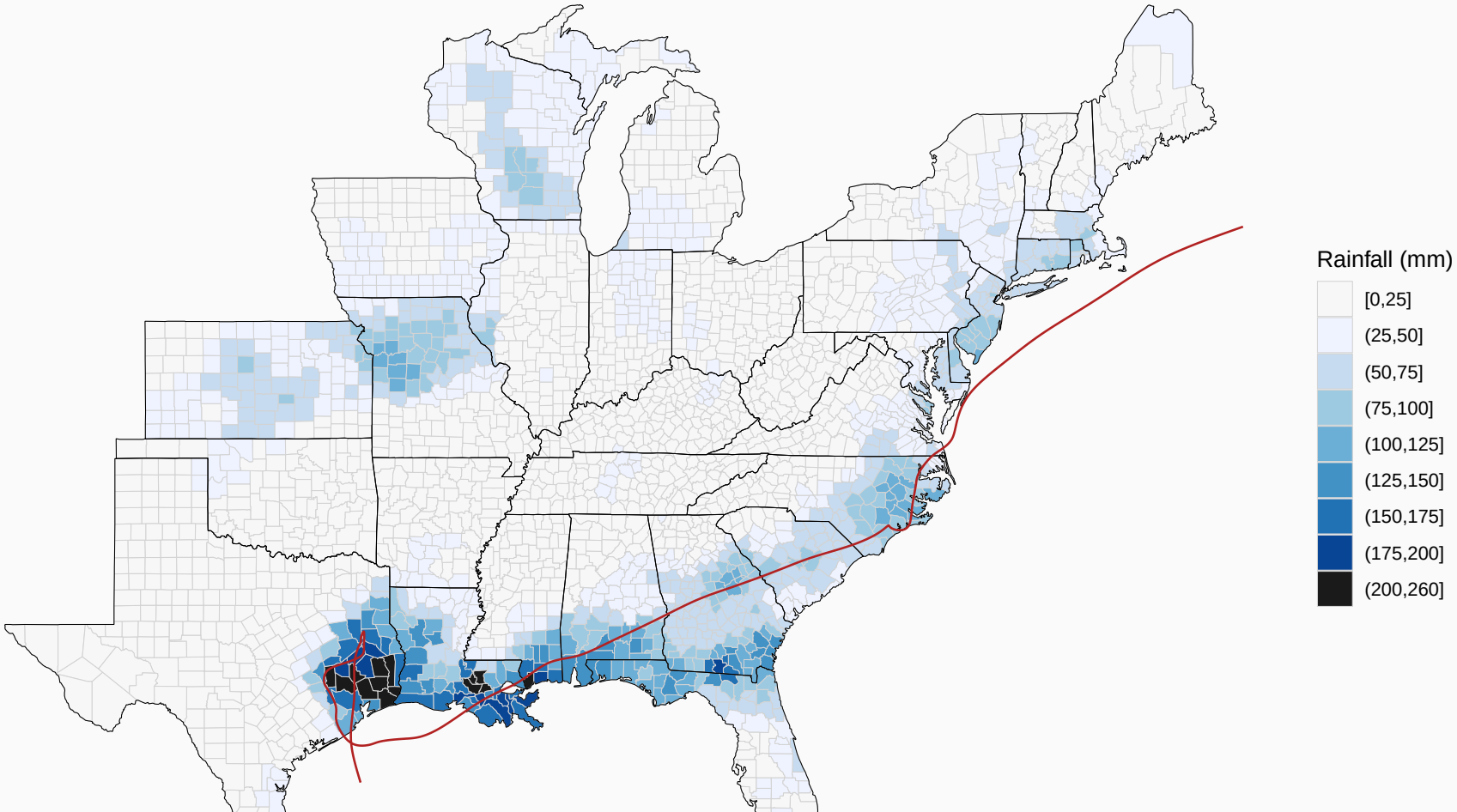
```
map_counties(storm = "Allison-2001", metric = "rainfall",
             days_included = -1:1)
```



Choice of days to include

Use a six-day window for the cumulative precipitation for Tropical Storm Allison.

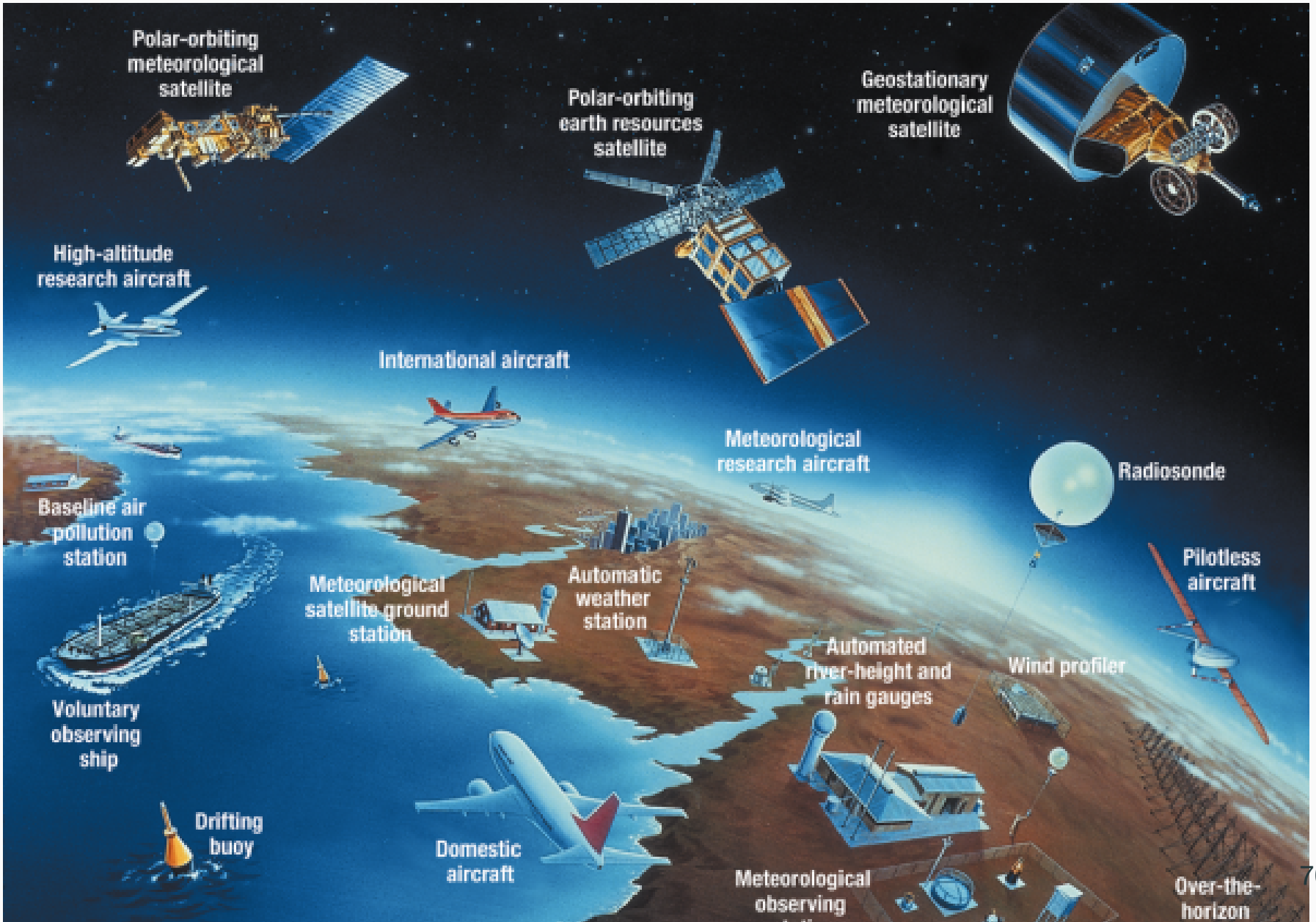
```
map_counties(storm = "Allison-2001", metric = "rainfall",
             days_included = -3:3)
```



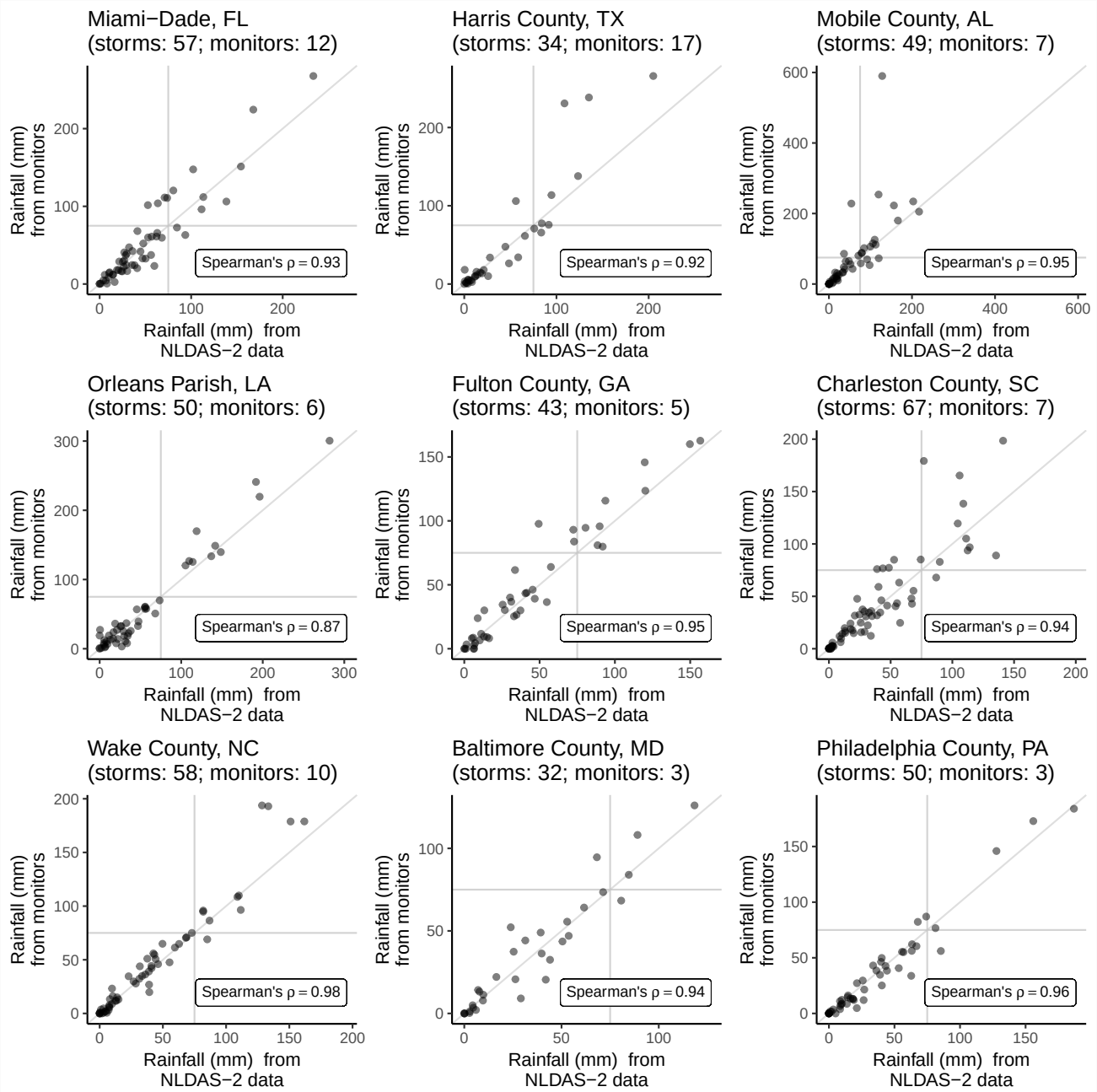
All rain exposures for a county

[Histogram of intensities]

Alternative precipitation data



Comparison with ground-based monitors



Your turn

- Map the precipitation associated with [storm] for the day of the storm.
- Map the cumulative precipitation associated with [storm] from one day before to one day after the storm.
- Map the cumulative precipitation associated with [storm] from three days before to three days after (i.e., a one week window around the storm day).

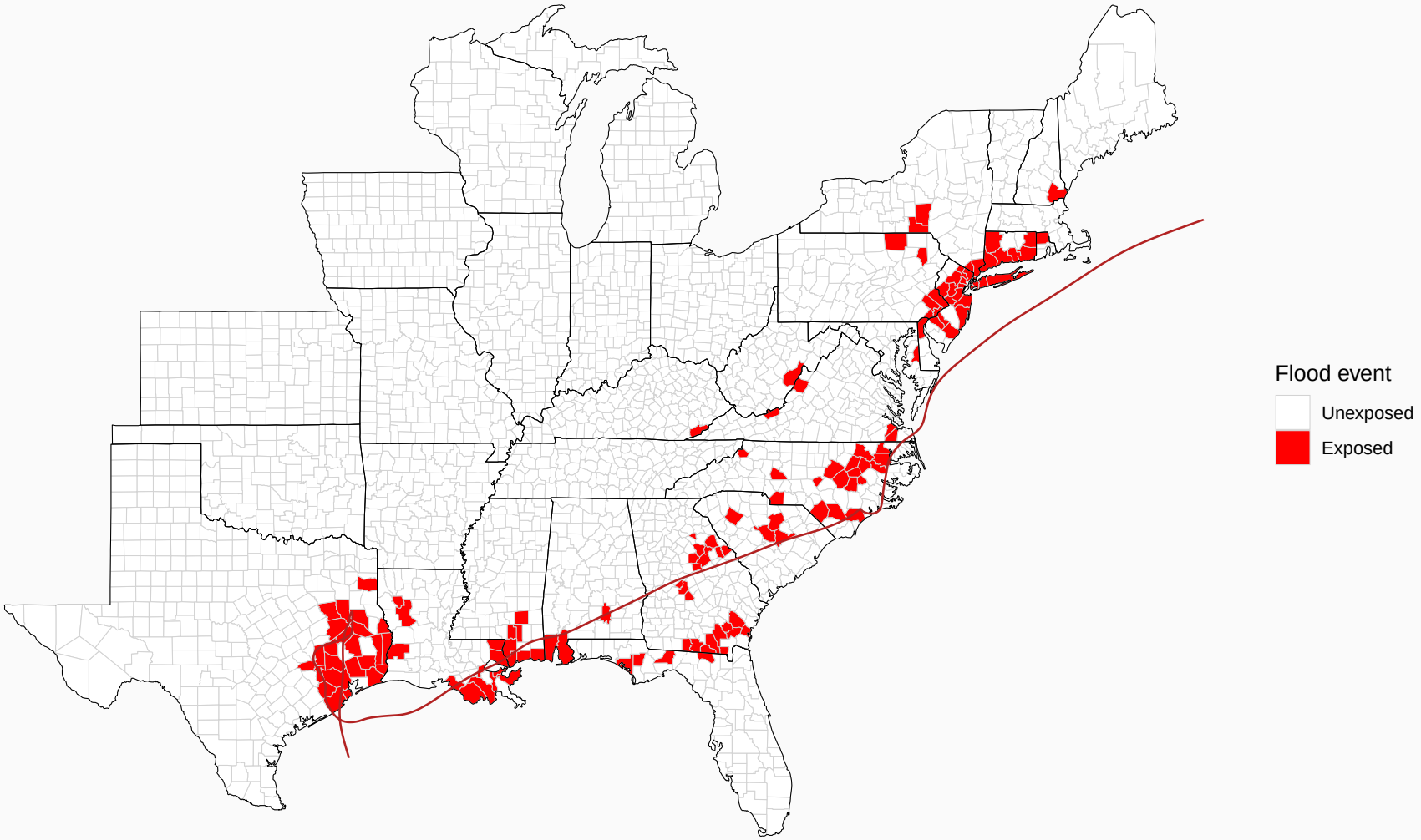
Flood and tornado exposures

NOAA Storm Events database

Matching event listings with storm tracks

Mapping flood events for a storm

```
map_event_exposure(storm_id = "Allison-2001", event_type = "floo
```

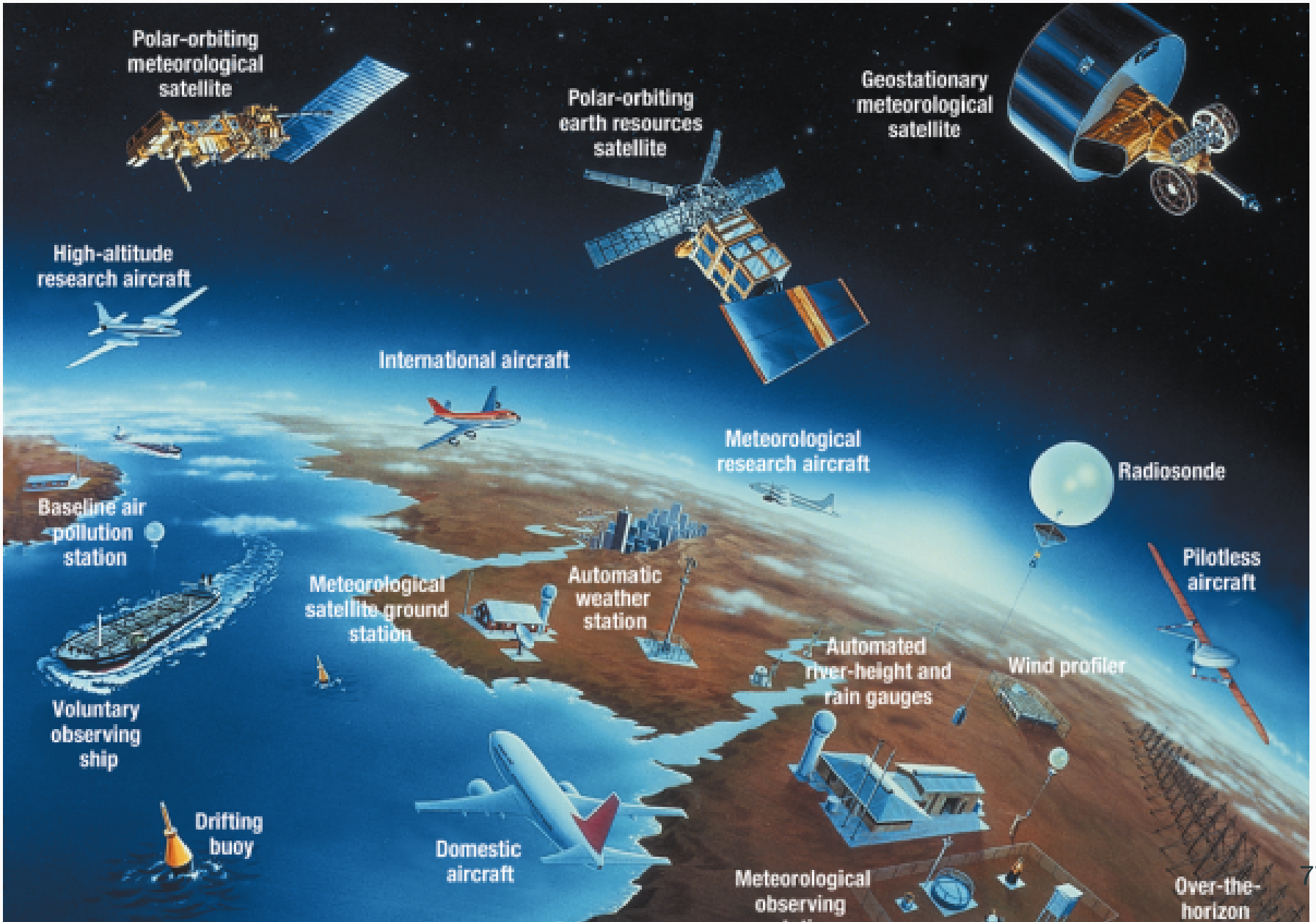


Identifying counties with flood events for a storm

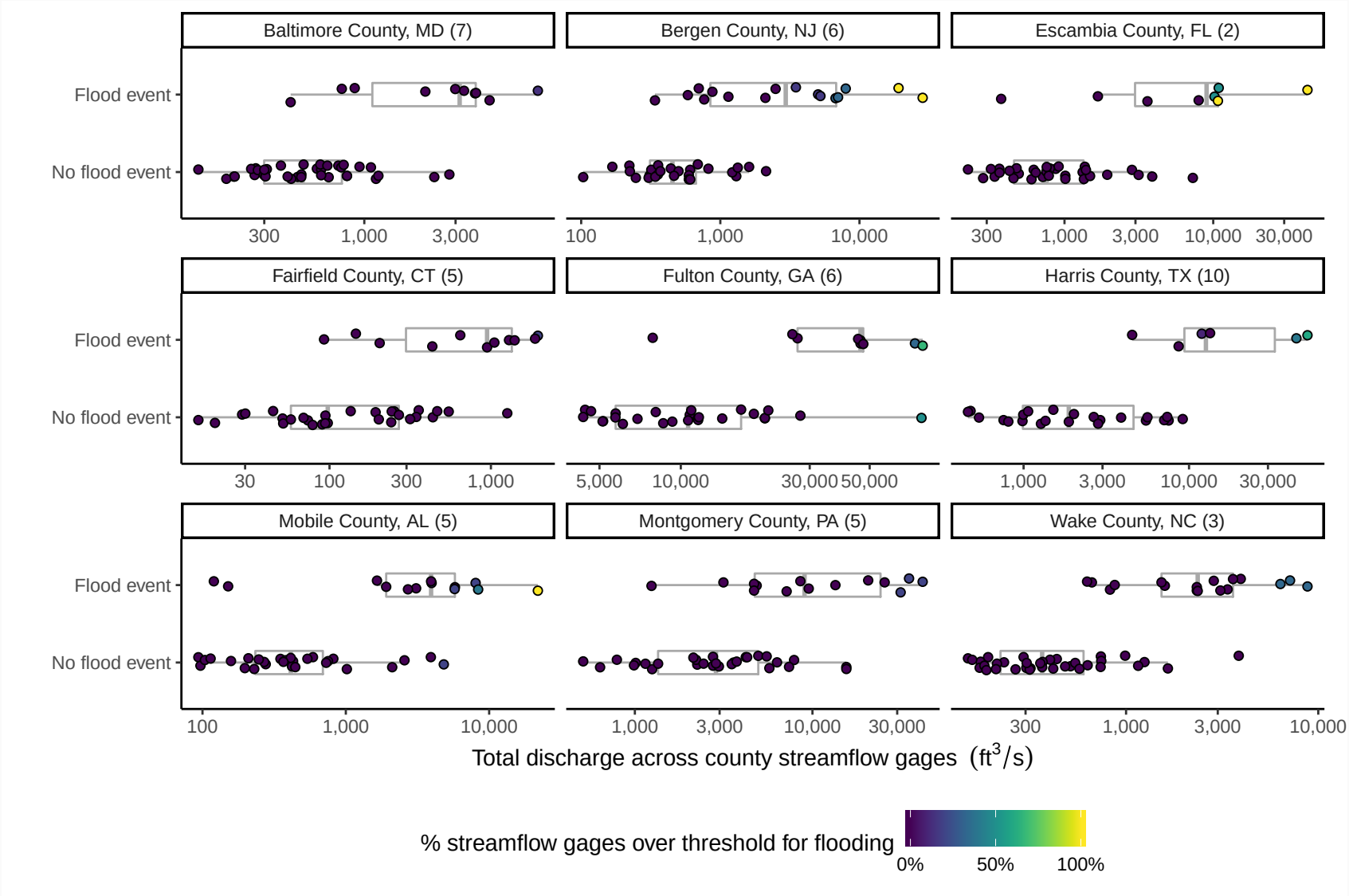
```
county_events(counties = tx_counties, event_type = "flood",
              start_year = 2001, end_year = 2001) %>%
  filter(storm_id == "Allison_2001")
```

```
## [1] fips              storm_id          closest_time_utc storm_
## [5] local_time        closest_date
## <0 rows> (or 0-length row.names)
```

Other sources of flood data



Comparison with streamgage data



Your turn

- Which county had the most tropical cyclone tornado exposures between 1988 and 2015?
- Which state had the most county tropical cyclone tornado exposures between 1988 and 2015?
- Which storm brought the most tornado exposures to this state? Map county tornado exposures during this storm.

Other helpful packages

`weathermetrics` package

`stormwindmodel` package

noaastormevents package

`futureheatwaves` package

[R Journal article on working with climate data]