Investigating the Relationship Between Rainfall and Crop Production in India

Anastacia Wienecke

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Introduction

India is an agrarian country - just over half of its working population is involved in agriculture, and nearly one fifth of the country's GDP comes from this sector [1,2]. India ranks second in the world for production of rice, wheat, sugarcane, peanuts, cotton, fruits, and vegetables. It ranks first for milk, legumes, and jute [3]. The Indian economy is the world's third largest, worth $2.1 trillion [3].

With climate change, the yearly monsoon rains, which the agricultural industry is so dependent upon, have intensified, shortened, and become more sporadic [4]. This study will investigate how farming practices have responded to this change. These results will shed light on the future of India's crop output, help determine which states and territories have been hardest hit, which states and territories are most at risk, and inform decisions on environmental policy. To achieve this end, I will analyze two datasets, both downloaded from kaggle.com.

The first dataset is titled "Rainfall Data from 1901 to 2017 for India" and consists of monthly rainfall measurements for all 28 Indian states and 8 Union territories. This land area spans 1.3 million square miles (for reference, the land area of the United States is 3.6 million square miles) [5]. These data were compiled by kaggle user Sai Saran using information available from data.gov.in. All measurements are in millimeters and collected by the Indian Meteorological Department, Ministry of Earth Sciences. These measurements span 116 years, giving a wide historical perspective, but not preceding the Industrial Revolution of the 18th century (which would have been quite interesting). I will begin with an initial exploratory analysis of the data. The goal is to visualize which areas experience the most and the least rainfall. Per quarter-century, I will plot the annual rainfall per state, and analyze any changes over time. I will monitor any trends in the way rainfall has changed geographically, which can prove useful for predicting trends of the future. The Finance Minister of India, Pranab Mukherjee, calls India's monsoon season "the real finance minister" [6].

The second dataset is titled "Crop Production in India" and was uploaded to kaggle by user Abhinand. It spans the years 1997 to 2014 and contains information for all 28 Indian states, breaking them down into districts. Per district, the dataset lists: the season (Kharif - the fall harvest, Rabi - the spring harvest, or the whole year), the crop (eg. rice, banana, sugarcane, coconut), the farmed area, and the total crop production. The units of farmed area and crop production are unspecified, but based on published statistics from various online sources, I will attempt to identify these units. I propose that over time, as rainfall patterns change, farmers become forced to adapt and plant different crops. The land area covered by certain crops will probably change too, as will their production levels.

To tie together crop and rainfall data, I will ask: When the rainfall is low, do the drought-tolerant crops become the most sown? Essentially, is there a detectable relationship between rainfall and crop production? For which crops? I predict to see a change in production based on extreme rainfall variability, and I would even expect to see this change propagate into succeeding years as farmers become concerned about the growing unpredictability of monsoons. These results will summarize the effects of one component of climate change on agricultural yield.

Methods and Results

Exploratory Analysis of Rainfall Data

I begin by reading in rainfall data. Since 1901, the names and boundaries of many Indian states and territories have changed, especially after the end of the British imperial period in 1947. To account for this, I manually grouped and renamed states and territories where applicable.

```r
### Read in rainfall data (annual per Indian state from 1901-2017)
rains <- read.csv("data/india_rains.csv") %>%
         select(-Name,-Jan.Feb,-Mar.May,-June.September,-Oct.Dec)

### Standardize state labels
rains.state <- unique(rains$SUBDIVISION)
rains <- rains %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Andaman & Nicobar Islands",
                                     "Andaman and Nicobar Islands")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Coastal Andhra Pradesh"|
                                      SUBDIVISION=="Rayalseema",
                                     "Andhra Pradesh")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Assam & Meghalaya",
                                      "Assam and Meghalaya")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Haryana Delhi & Chandigarh",
                                      "Chandigarh and Haryana")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Konkan & Goa"|
                                      SUBDIVISION=="Madhya Maharashtra"|
                                      SUBDIVISION=="Vidarbha"|
                                      SUBDIVISION=="Matathwada",
                                      "Goa and Maharashtra")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Gujarat Region"|
                                      SUBDIVISION=="Saurashtra & Kutch",
                                      "Gujarat")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Jammu & Kashmir",
                                      "Jammu and Kashmir")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Coastal Karnataka"|
                                      SUBDIVISION=="North Interior Karnataka"|
                                      SUBDIVISION=="South Interior Karnataka",
                                      "Karnataka")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="West Madhya Pradesh"|
                                      SUBDIVISION=="East Madhya Pradesh",
                                      "Madhya Pradesh")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                      SUBDIVISION=="Naga Mani Mizo Tripura",
                                      "Nagaland, Manipur, Mizoram, Tripura")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
```

```
                                        SUBDIVISION=="Orissa",
                                        "Odisha")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                        SUBDIVISION=="West Rajasthan"|
                                        SUBDIVISION=="East Rajasthan",
                                        "Rajasthan")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                        SUBDIVISION=="Sub Himalayan West Bengal & Sikkim"|
                                        SUBDIVISION=="Gangetic West Bengal",
                                        "Sikkim and West Bengal")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                        SUBDIVISION=="Sub Himalayan West Bengal & Sikkim"|
                                        SUBDIVISION=="Gangetic West Bengal",
                                        "Sikkim and West Bengal")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                        SUBDIVISION=="East Uttar Pradesh"|
                                        SUBDIVISION=="West Uttar Pradesh",
                                        "Uttar Pradesh")) %>%
         filter(!SUBDIVISION %in% c('Lakshadweep'))

### Re-group according to new labels
rains <- rains %>%
         group_by(SUBDIVISION, YEAR) %>%
         dplyr::summarize(JAN=median(JAN), FEB=median(FEB), MAR=median(MAR),
                          APR=median(APR), MAY=median(MAY), JUN=median(JUN),
                          JUL=median(JUL), AUG=median(AUG), SEP=median(SEP),
                          OCT=median(OCT), NOV=median(NOV), DEC=median(DEC),
                          ANNUAL=median(ANNUAL),
                          Latitude=median(Latitude),
                          Longitude=median(Longitude))

### Compute median and variance in annual rainfall per state
meds <- rains %>%
        group_by(SUBDIVISION) %>%
        summarise_at(vars(ANNUAL), list(median=median, variance=var))
meds$stdev <- sqrt(meds$variance)
meds$stdev.norm <- meds$stdev / meds$median
meds.order <- meds$SUBDIVISION[order(meds$median, decreasing = TRUE)]
```

Next, I read in land area for each state and territory. These values come from the Office of the Registrar General of India, Ministry of Home Affairs. It was compiled as part of their 2011 Census and the units are square-kilometers.

```
### Read in area data
areas <- read.csv("data/india_areas.csv")
colnames(areas) <- c('SUBDIVISION', 'area')

### Standardize state labels
areas <- areas %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                        SUBDIVISION=="A.& N.Islands",
                                       "Andaman and Nicobar Islands")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
```

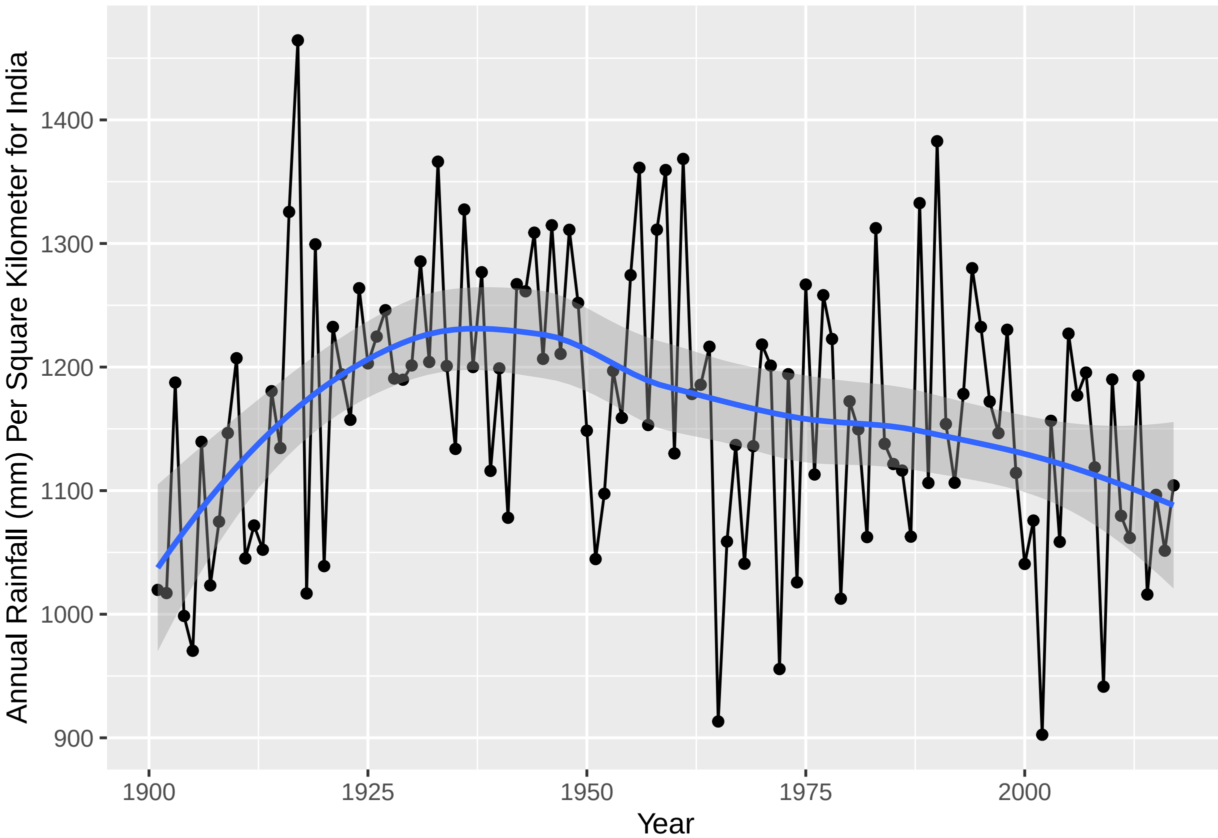
```r
                                     SUBDIVISION=="Assam"|
                                     SUBDIVISION=="Meghalaya",
                                     "Assam and Meghalaya")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                     SUBDIVISION=="Haryana"|
                                     SUBDIVISION=="Delhi"|
                                     SUBDIVISION=="Chandigarh",
                                     "Chandigarh and Haryana")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                     SUBDIVISION=="Goa"|
                                     SUBDIVISION=="Maharashtra",
                                     "Goa and Maharashtra")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                     SUBDIVISION=="Jammu & Kashmir",
                                     "Jammu and Kashmir")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                     SUBDIVISION=="Nagaland"|
                                     SUBDIVISION=="Manipur"|
                                     SUBDIVISION=="Mizoram"|
                                     SUBDIVISION=="Tripura",
                                     "Nagaland, Manipur, Mizoram, Tripura")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                     SUBDIVISION=="Orissa",
                                     "Odisha")) %>%
         mutate(SUBDIVISION = replace(SUBDIVISION,
                                     SUBDIVISION=="Sikkim"|
                                     SUBDIVISION=="West Bengal",
                                     "Sikkim and West Bengal")) %>%
         filter(!SUBDIVISION %in% c('Lakshadweep', 'D.& N.Haveli', 'Daman & Diu', 'Lakshadweep' ))

### Combine relevant area measurements
areas <- areas %>%
         group_by(SUBDIVISION) %>%
         dplyr::summarize(area=sum(area))

### Add column of areas to rains dataframe
rains <- rains %>%
           distinct() %>%
           left_join(areas, by="SUBDIVISION")
```

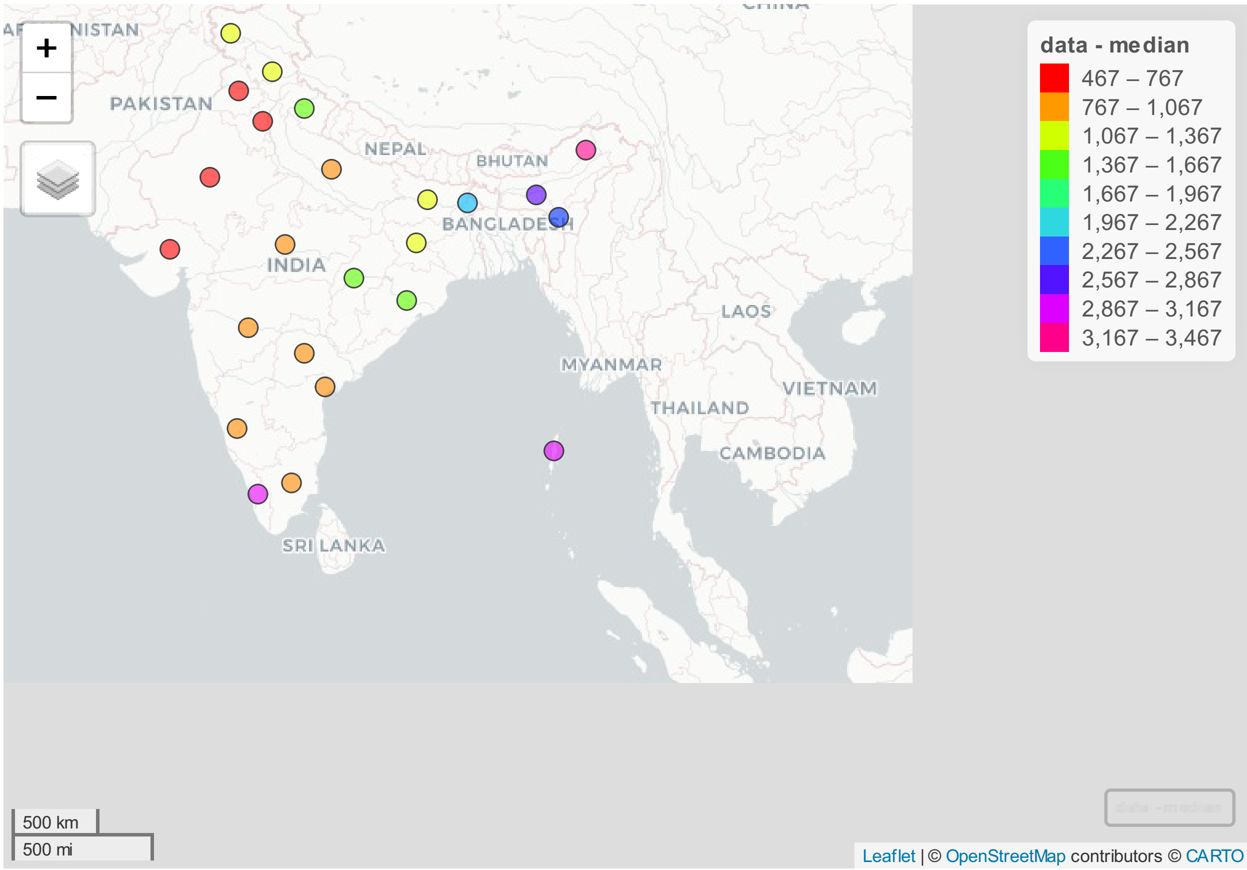
To begin the exploratory analysis as broadly as possible, I had planned to plot year vs. annual rainfall across the entire country. However, because I have rainfall data per subdivision only, I had to take a different approach. I will compute an estimate of the annual rainfall country-wide. To begin, I find that the smallest region area-wise is the Andaman and Nicobar Islands (ANI), with an area of 8249 square kilometers. Then I:

1. Find how many ANI land areas fit inside each state and territory, rounding to the nearest integer.
2. Multiply a subdivision's annual rainfall by the value from part 1.
3. By year, sum corresponding values from part 2, divide by the total number of ANI land areas that fit inside of India.



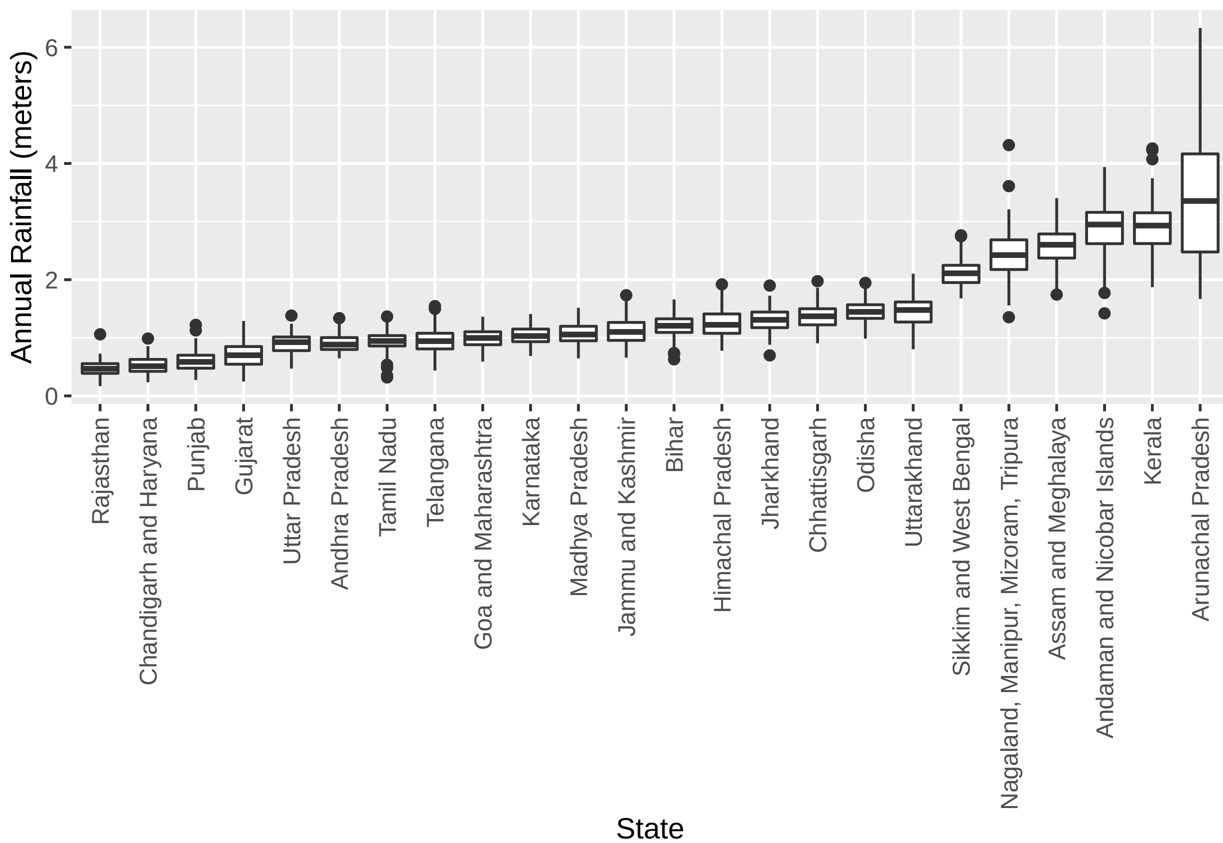
As we see from the plot above, the loess smoothing curve shows a quick increase and then a gradual decrease in rainfall country-wide. This decrease began at about the year 1937. In general, the annual rainfall is near 1150mm, which agrees with online sources [7].

To continue, The first question we might like to know more about is: What does the median annual rainfall from 1901-2017 look like per state?



In the above widget, if the "Esri.WorldImagery" option is selected from the layer menu, we see that the mountainous and central regions receive the least amount of rain, while the coastal areas and islands receive substantial rain. The far east of India is also quite wet, probably because it is far enough away from the mountains that the rain shadow no longer exerts an effect. One follow up question is: what does the variability in annual rainfall for each state and territory look like between 1901 and 2017?

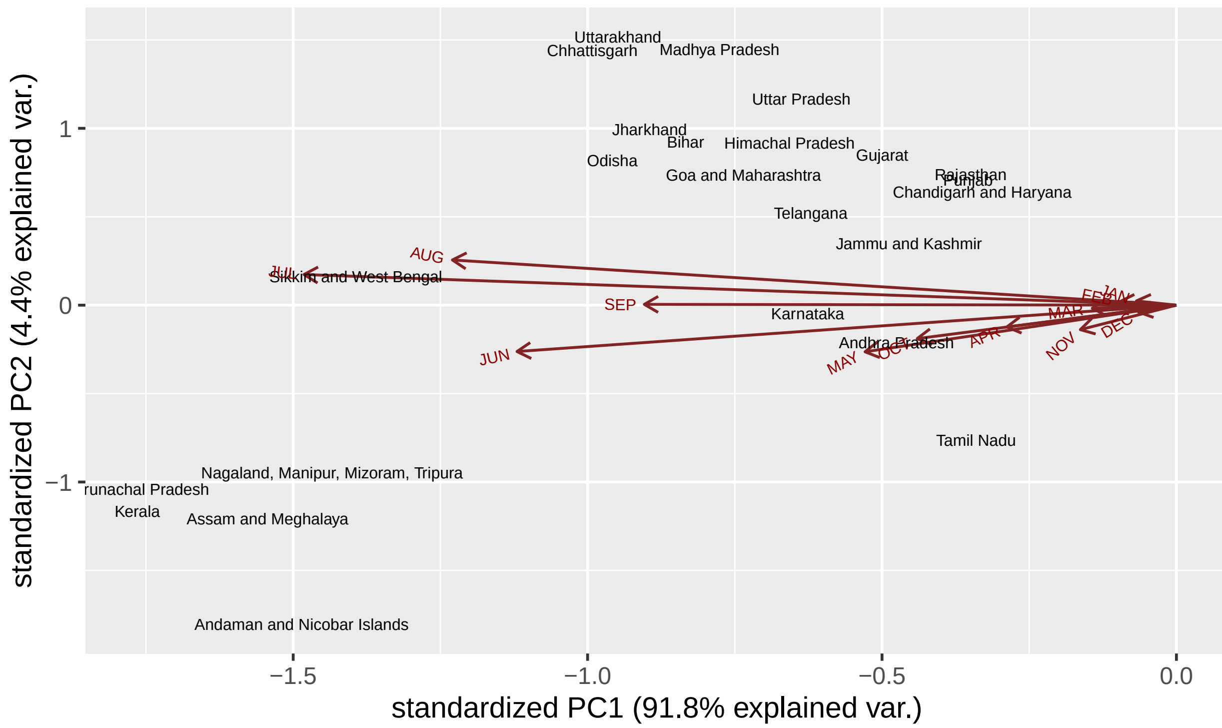
```
### Create a boxplot of annual rainfall per state
ggplot(rains, aes(x=reorder(SUBDIVISION,ANNUAL), y=ANNUAL/1000)) +
              scale_x_discrete(guide = guide_axis(angle = 90)) +
              labs(x = "State", y = "Annual Rainfall (meters)") +
              geom_boxplot()
```



It appears that the states with the most rainfall also experience the most variability in rainfall. I will explore this further below. Outlier datapoints do not seem to be an issue here.

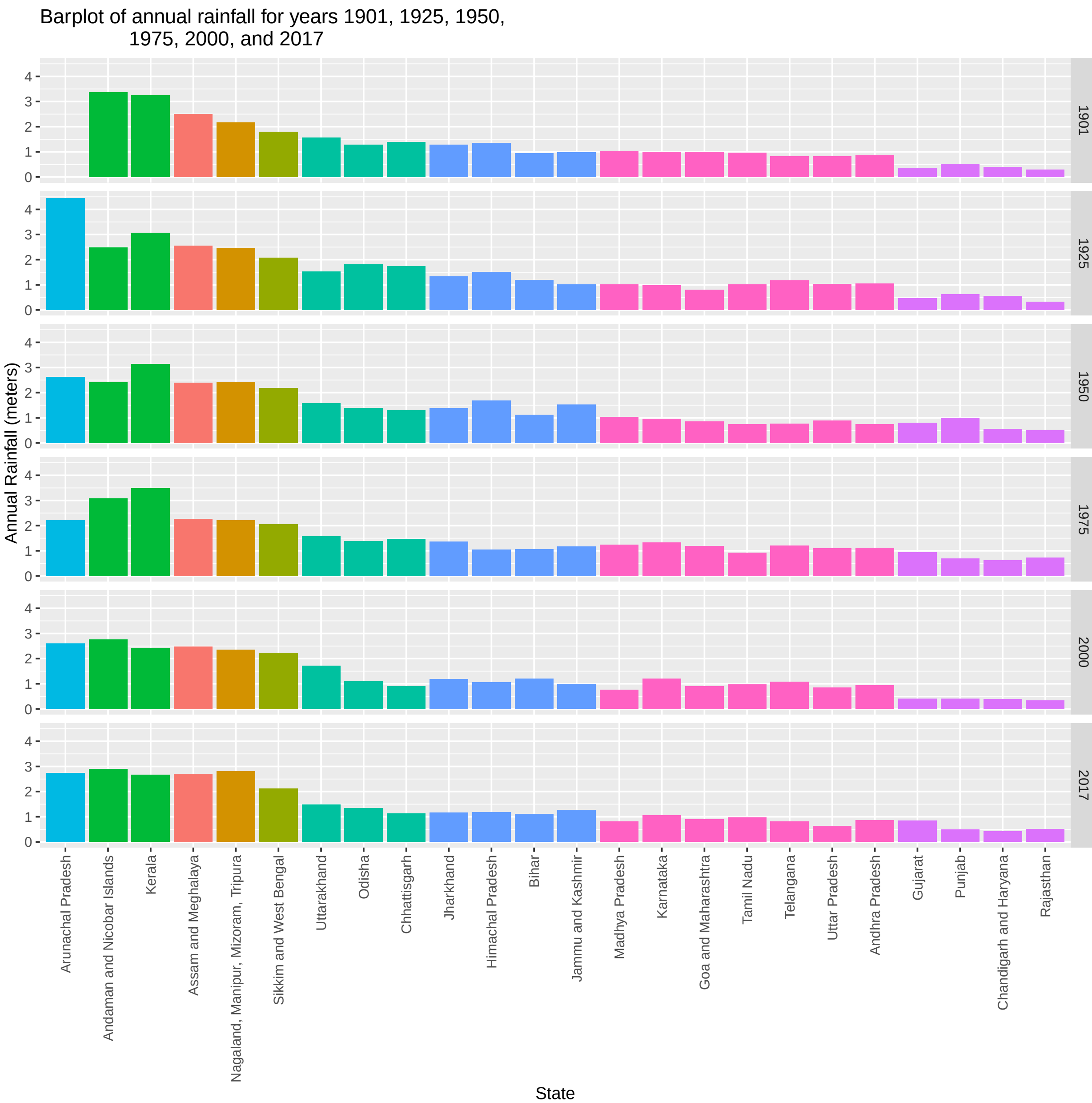
To understand which states are most similar in terms of their monthly median rainfall between 1901-2017, I ran a principle component analysis (PCA). States that cluster close together are most similar in their rainfall amounts and patterns, while states that are far apart in the PCA plot, are more dissimilar.

```
### Run a PCA on monthly median rainfalls
monthly.med <- aggregate(rains[,3:14], list(rains$SUBDIVISION), median) %>%
               column_to_rownames(var="Group.1")
monthly.pca <- prcomp(monthly.med, center = F,scale = F)
ggbiplot(monthly.pca, labels=rownames(monthly.med), varname.size=2, labels.size=2)+ coord_equal(ratio =
```

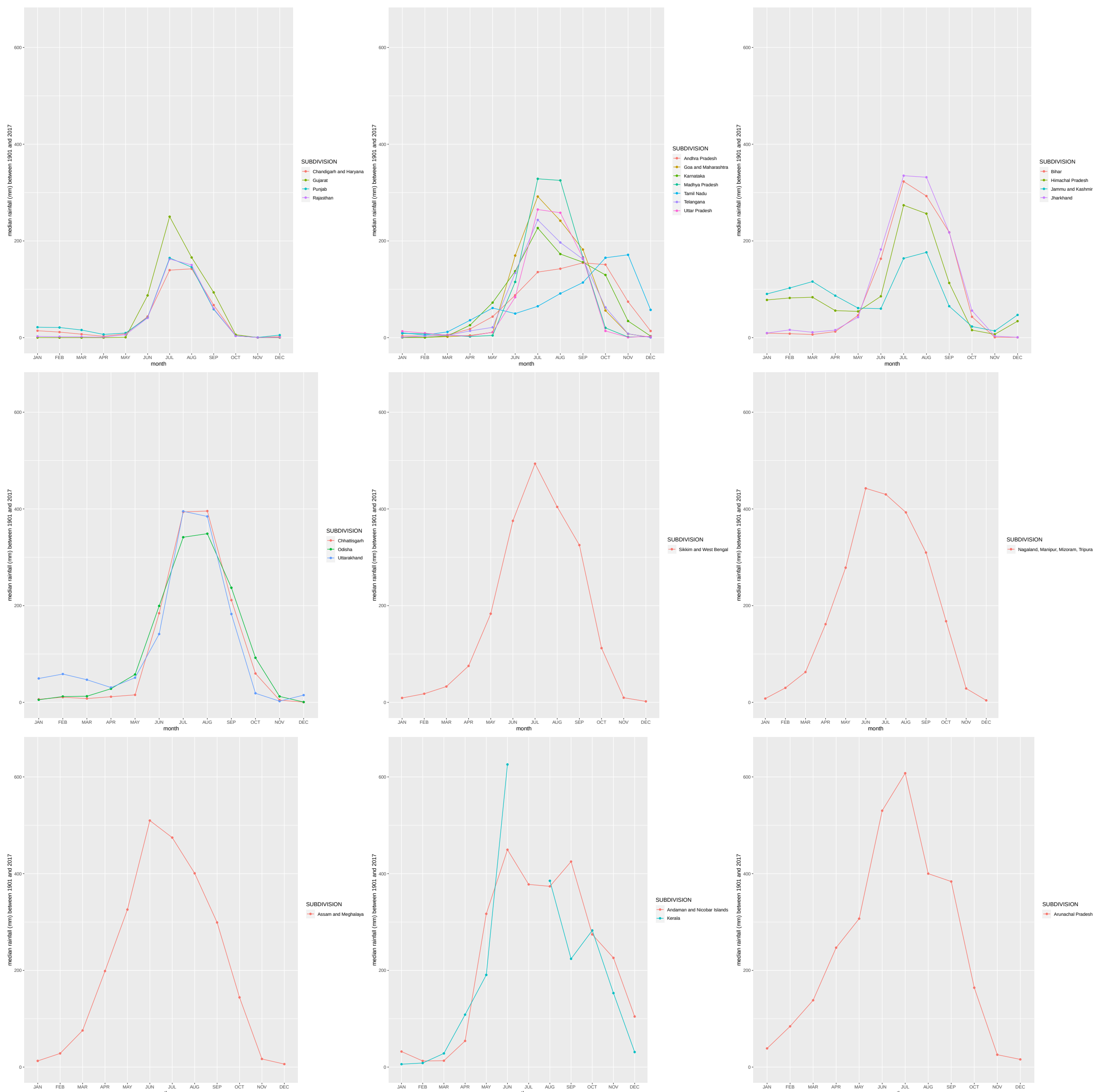


We see from the principal components that the most rainfall variability between states occurs in the months of June to September. These four months explain the differences in rainfall between states best. As such, we could more-or-less predict the state ID based on knowledge of summer rainfall. Similar to the map of India above, here we see clustering of states based on geographic location.

To investigate trends in quarter-century rainfall, below I plot annual rainfall per state in 1901, 1925, 1950, 1975, 2000, and 2017. There are no apparent linear differences through time.



Looking back to the map of India above, we might like to group states based on median annual rainfall over the span of 1901-2017. In these groupings, we might like to see each state's median monthly rainfall over 1901-2017.

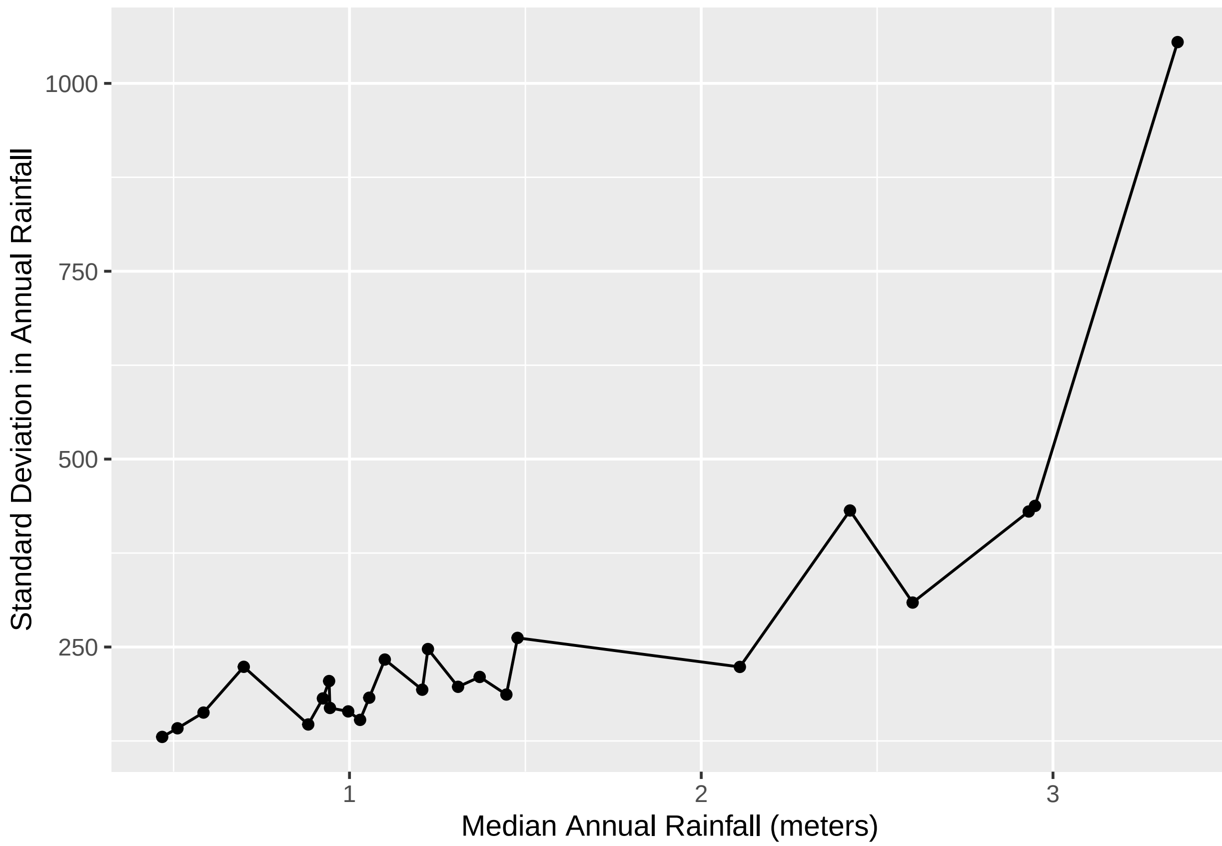


From the above set of plots, we see that rainfall always peaks in the summer. We also see that states with similar amounts of annual rainfall have very similar monthly patterns of rainfall. This result is expected given the previous plots.

The plots above hint that a greater annual rainfall is linked to a higher variability in rainfall. Let's explore this more systematically. For instance, across all states, is there a relationship between the median annual rainfall and the standard deviation in annual rainfall between 1901 and 2017?

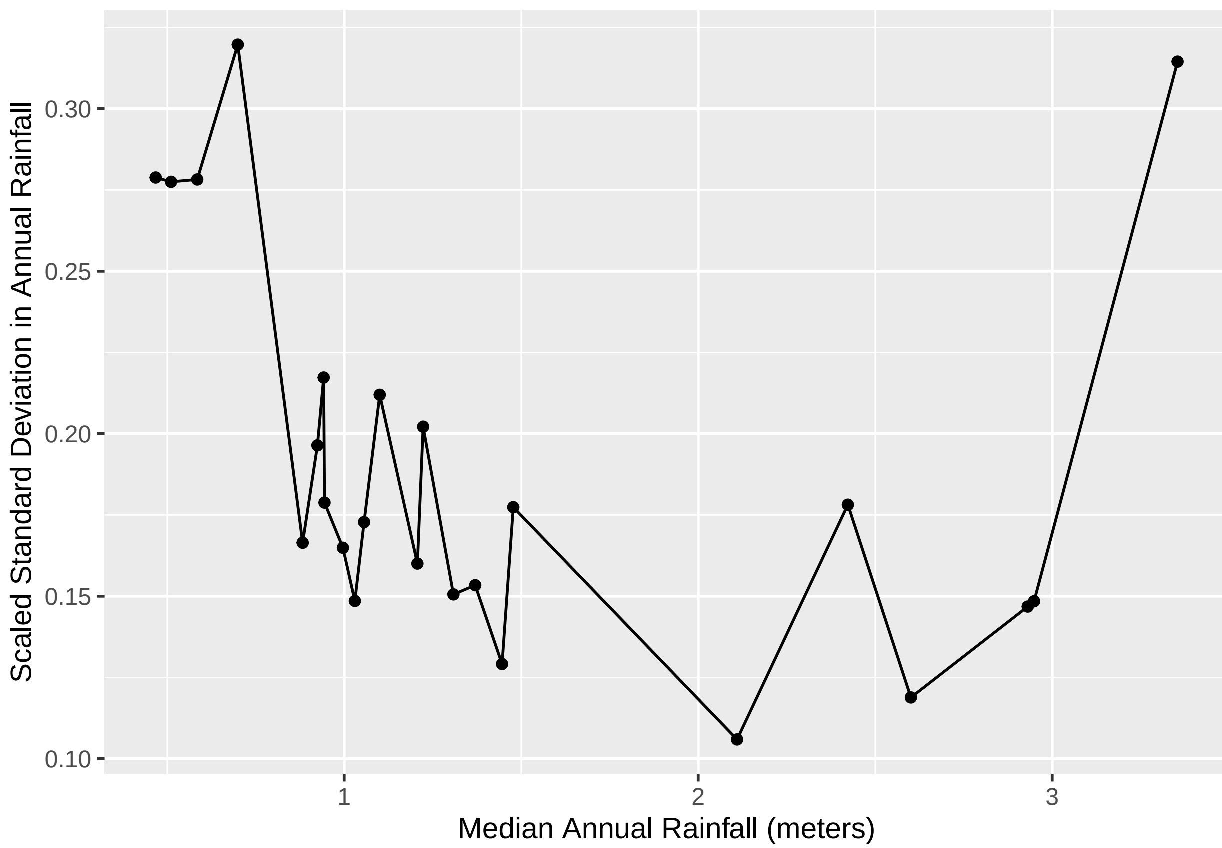
```
### Comparison of median annual rainfall and the standard deviation in annual rainfall
# Non-normalized
nnorms <- ggplot(data=meds, aes(x=median/1000, y=stdev)) +
                 geom_line() +
                 geom_point() +
                 labs(x = "Median Annual Rainfall (meters)",
                      y = "Standard Deviation in Annual Rainfall")
```

```
#ggsave("figures/lineplot_median_stdev_rainfall.png", nnorms)
nnorms
```



Perhaps the relationship we see is muddied by the magnitude of the data. For instance, an equal-sized variation in rainfall in drier states is much more impactful than in wetter states. Let's normalize the standard deviation by the median and replot.

```
### Comparison of median annual rainfall and the standard deviation in annual rainfall
# Normalized
norms <- ggplot(data=meds, aes(x=median/1000, y=stdev.norm)) +
                geom_line() +
                geom_point() +
                labs(x = "Median Annual Rainfall (meters)",
                     y = "Scaled Standard Deviation in Annual Rainfall")
#ggsave("figures/lineplot_median_norm_stdev_rainfall.png", norms)
norms
```



Here we see that states at the high and low extremes of rainfall experience the most relative variation in rainfall. States receiving a moderate amount of rainfall are the most consistent year after year.

Exploratory Analysis of Crop Production Data

I first read in crop production data. I make sure that the state and territory naming conventions match those from the rainfall data, re-grouping as necessary. Note: while the rainfall data spans the years 1901-2017, this crop data spans a much shorter timeline of 1997-2015.

```
### Read in crops data (annual per Indian state from 1997 to 2015)
crops <- read.csv("data/india_crops.csv")

### Standardize state labels
### These state names are most accurate according to "knowindia.india.gov.in"
crops.state <- unique(crops$State_Name)
crops <- crops %>%
         mutate(State_Name = replace(State_Name,
                                     State_Name=="Assam"|State_Name=='Meghalaya',
                                     "Assam and Meghalaya")) %>%
         mutate(State_Name = replace(State_Name,
                                     State_Name=="Chandigarh"|State_Name=='Haryana',
                                     "Chandigarh and Haryana")) %>%
         mutate(State_Name = replace(State_Name,
                                     State_Name=="Goa"|State_Name=='Maharashtra',
                                     "Goa and Maharashtra")) %>%
```

```
        mutate(State_Name = replace(State_Name,
                                    State_Name=="Manipur"|State_Name=='Mizoram'|
                                    State_Name=='Nagaland'|State_Name=='Tripura',
                                    "Nagaland, Manipur, Mizoram, Tripura")) %>%
        mutate(State_Name = replace(State_Name,
                                    State_Name=="Sikkim"|State_Name=='West Bengal',
                                    "Sikkim and West Bengal")) %>%
        mutate(State_Name = replace(State_Name,
                                    State_Name=="Jammu and Kashmir ",
                                    "Jammu and Kashmir")) %>%
        mutate(State_Name = replace(State_Name,
                                    State_Name=="Telangana ",
                                    "Telangana")) %>%
        filter(!State_Name %in% c('Dadra and Nagar Haveli','Puducherry')) %>%
        select(State_Name, Crop_Year, Crop, Area, Production)

### Re-group according to new labels
crops <- crops %>%
        group_by(State_Name, Crop_Year, Crop) %>%
        dplyr::summarize(Area=sum(Area), Production=sum(Production))
```

```
## `summarise()` has grouped output by 'State_Name', 'Crop_Year'. You can override
## using the `.groups` argument.
```

To begin, I determine which crops appear most frequently in the dataset.

```
### Which crops appear most frequently?
crop.counts <- crops$Crop %>% table() %>% stack() %>% rev()
crop.counts <- crop.counts[order(crop.counts$values, decreasing=T), ]
head(crop.counts,15)
```

```
##                   ind values
## 99               Rice    378
## 110         Sugarcane    364
## 60              Maize    357
## 123             Wheat    347
## 106           Sesamum    336
## 96  Rapeseed &Mustard    321
## 44          Groundnut    320
## 42               Gram    317
## 4           Arhar/Tur    311
## 64  Moong(Green Gram)    307
## 120              Urad    303
## 91             Potato    295
## 7               Bajra    284
## 34        Cotton(lint)    281
## 49              Jowar    266
```

```
freq.hi <- crop.counts$ind[1:50]
```

Now I see which crops are the most heavily produced over time. As mentioned in the introduction, the units of production data are unavailable.

```r
### Get total crop area and production for each state per year
crops.area.wide <- crops[,c('State_Name','Crop_Year','Crop', 'Area')] %>%
                       pivot_wider(names_from = Crop, values_from = Area) %>%
                       replace(is.na(.), 0)
crops.prod.wide <- crops[,c('State_Name','Crop_Year','Crop', 'Production')] %>%
                       pivot_wider(names_from = Crop, values_from = Production) %>%
                       replace(is.na(.), 0)

### Which crops are most heavily produced over time?
prod.sort <- crops.prod.wide[3:126] %>%
             colSums() %>%
             sort(decreasing=T) %>%
             data.frame()
colnames(prod.sort) <- c('sum_production')
head(prod.sort,15)
```

```
##                sum_production
## Coconut          129548704257
## Sugarcane          5425760880
## Rice               1533026391
## Wheat              1332712669
## Potato              423154240
## Cotton(lint)        271827923
## Maize               261312791
## Jute                181549528
## Banana              137518903
## Soyabean            127588703
## Bajra               111392882
## Jowar               111025768
## Groundnut           107544871
## Tapioca             100319263
## Gram                 97084355
```

```r
prod.hi <- rownames(prod.sort)[1:50]
```

Based on the result that coconut is the most produced crop, I imagine that the units of crop production must be weight or volume, not counts. One online source reports that 130 million tonnes of rice were produced in the year 2021-2022. This data says that the average rice production between 1997-2015 was roughly 85 million units [8]. Going forward, I will assign units of tonnes to this data.

Let's see which crops cover the most area.

```r
### Which crops cover the most area over time?
area.sort <- crops.area.wide[3:126] %>%
             colSums() %>%
             sort(decreasing=T) %>%
             data.frame()
colnames(area.sort) <- c('sum_area')
head(area.sort,15)
```

```
##                      sum_area
## Rice                746509102
## Wheat               470704537
```

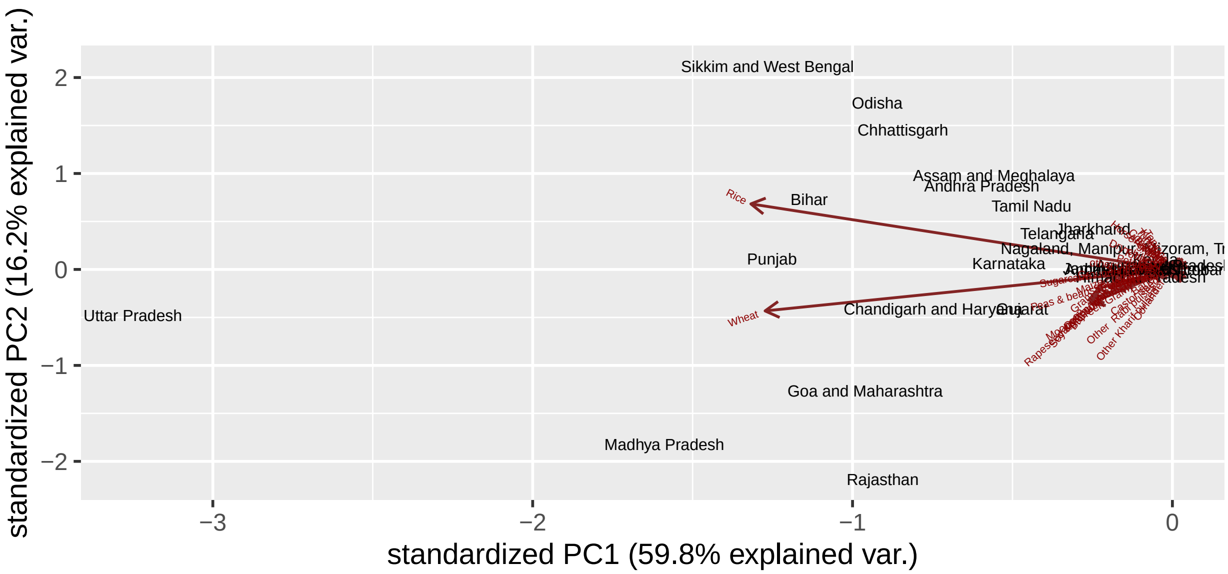
```
## Cotton(lint)      156564190
## Bajra             141139450
## Jowar             137707497
## Soyabean          135450782
## Maize             121745571
## Gram              118205187
## Groundnut         102723591
## Rapeseed &Mustard  86580384
## Sugarcane          76625521
## Arhar/Tur          57769524
## Oilseeds total     55366581
## Moong(Green Gram)  48548213
## Urad               47541084
```

```
area.hi <- rownames(area.sort)[1:50]
```

We see that rice has covered the most area over time. On average, 41.5 million units of rice covered India per year. One online source reports that 45 million hectares were covered in rice in the crop year 2021 [9]. I conclude that hectares must be the unit of measurement for crop production in this data.

To see which states and territories are most similar in their crop production, let's run a PCA.

```
### Run a PCA on median crop production
common.crops <- intersect(freq.hi, intersect(area.hi, prod.hi))
monthly.med <- aggregate(crops.area.wide[,common.crops], list(crops.area.wide$State_Name), median) %>%
               column_to_rownames(var="Group.1")
monthly.pca <- prcomp(monthly.med, center = F,scale = F)
ggbiplot(monthly.pca, labels=rownames(monthly.med), varname.size=1.5, labels.size=2)+ coord_equal(ratio
```



From these results, we see that the driest states are the ones furthest from the cluster at the origin. Rice and wheat are the main crops whose production appreciably differs between states and leads to the clustering. Rice and wheat are also some of the thristiest crops so this result is in line with what could be expected.

Combining Rainfall and Crop Production

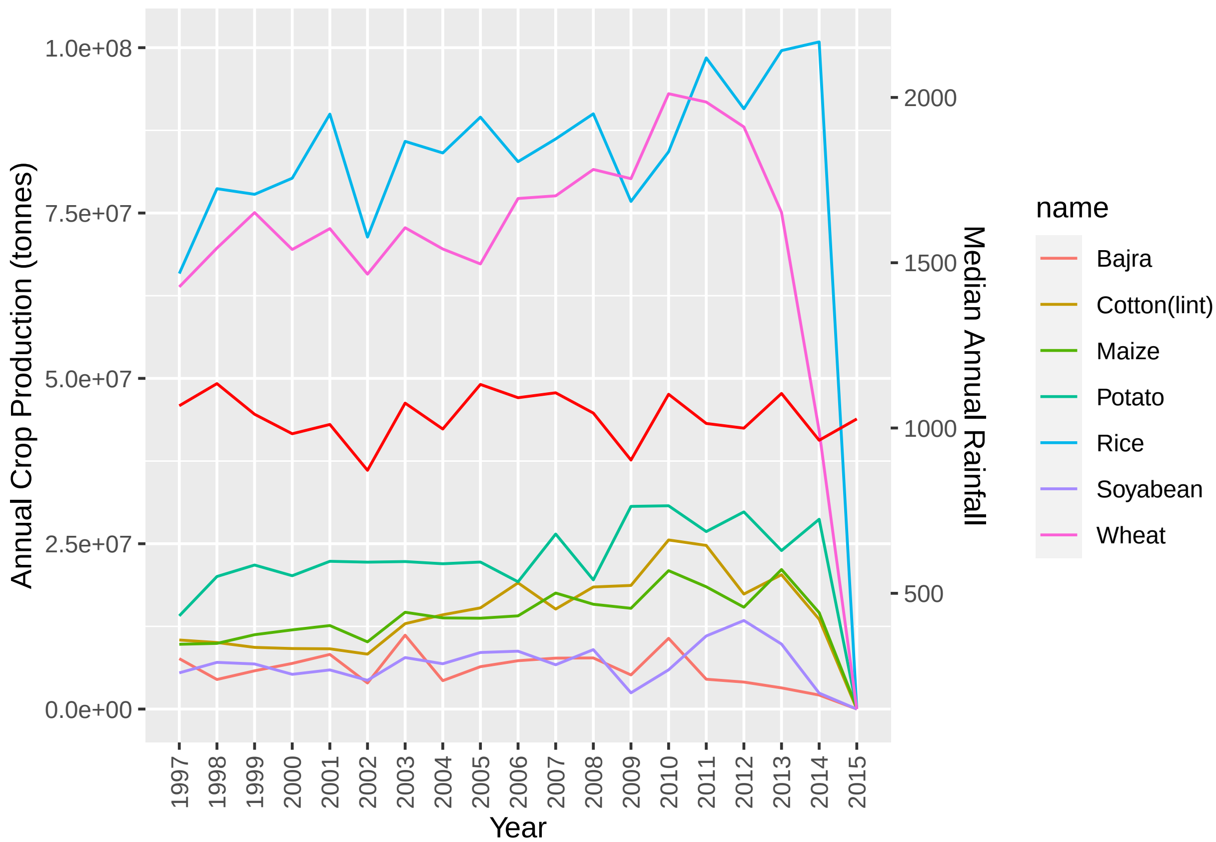
Let's create a plot of year vs. annual crop production and vs. median annual rainfall country-wide. I will focus on crops that are most highly produced, most widespread over India, and showing at least some variation in production over the years. Crops that fit this criteria are bajra, cotton, maize, potato, rice, soyabean, and wheat. In red is rain data.

```
### Focus on Rice and Wheat, two very thirsty crops
mycrops <- common.crops[rev(order(prod.sort[common.crops,]))][2:11]
focus.crops <- c('State_Name','Crop_Year', mycrops)
focus.area <- crops.area.wide[,focus.crops]
focus.prod <- crops.prod.wide[,focus.crops]
focus.prod.Y <- ddply(focus.prod, "Crop_Year", numcolwise(sum))

rains.Y <- rains.all.india %>% subset(YEAR %in% focus.prod.Y$Crop_Year)
focus.prod.Y$Rain <- rains.Y$ANNUAL.rain*20

ggplot(focus.prod.Y %>%
         select(-Sugarcane, -Jute, -Banana, -Rain) %>%
         pivot_longer(!Crop_Year), aes(x = Crop_Year, y = value, color = name)) +
  geom_line() +
```

```
geom_line(data=focus.prod.Y, aes(x=Crop_Year, y=Rain*2000), color = "red") +
scale_x_continuous(breaks=seq(1997, 2015), guide = guide_axis(angle = 90)) +
scale_y_continuous(
 name = "Annual Crop Production (tonnes)",
 sec.axis = sec_axis(~ . * 1/5e4+150, name="Median Annual Rainfall")) +
xlab('Year') +
theme(panel.grid.minor.x = element_blank())
```



The sharp decrease in crop production in 2015 occurs because the crop data was published partway through 2015.

Discussion

The plot in section "Combining Rainfall and Crop Production" is the most telling. In red is the line representing my best estimate of the annual rainfall across the country. We see general patterns of crop production following rainfall - dips in rainfall generally (but not always!) correspond to dips in crop output. Drought years are 2002, 2009, and 2014. I will summarize a few observations.

- In 2009, relatively little rice was produced due to drought. When rainfall rebounded in 2010 however, rice production still lagged. Only in 2011 was rice output back to normal, indicating a lag period after severe drought. This was not observed with any other crop. Interestingly, in 2014, drought did not cause low rice.
- 2009 was the first drought that did not affect wheat. Perhaps better farming practices avoided a weak wheat crop.

- Potatoes appear to be relatively robust to drought. In 2002, potato was the only unaffected crop. In 2009, potato production was at an all time high. While potatoes are not known to be the most drought-tolerant, they do require less irrigation than rice and wheat.

As other studies have mentioned, changing the crops sown as rainfall patterns change will allow farmers to make the most use of their land. While trends in rainfall are quite difficult to predict, a gradual shift to less thirsty crops will prove beneficial to the agriculture industry.

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