In [1]:
```python
# Import related libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
plt.style.use('ggplot')
pd.set_option('display.max_rows', 100)
pd.set_option('display.max_columns', 50)
import warnings
warnings.filterwarnings("ignore")
```

Data Review

In [263]:
```python
# Import the dataset
df = pd.read_csv('C:/Users/AS/Downloads/data/US_Accidents_June20.csv')
```

In [3]:
```python
# df.head()
```

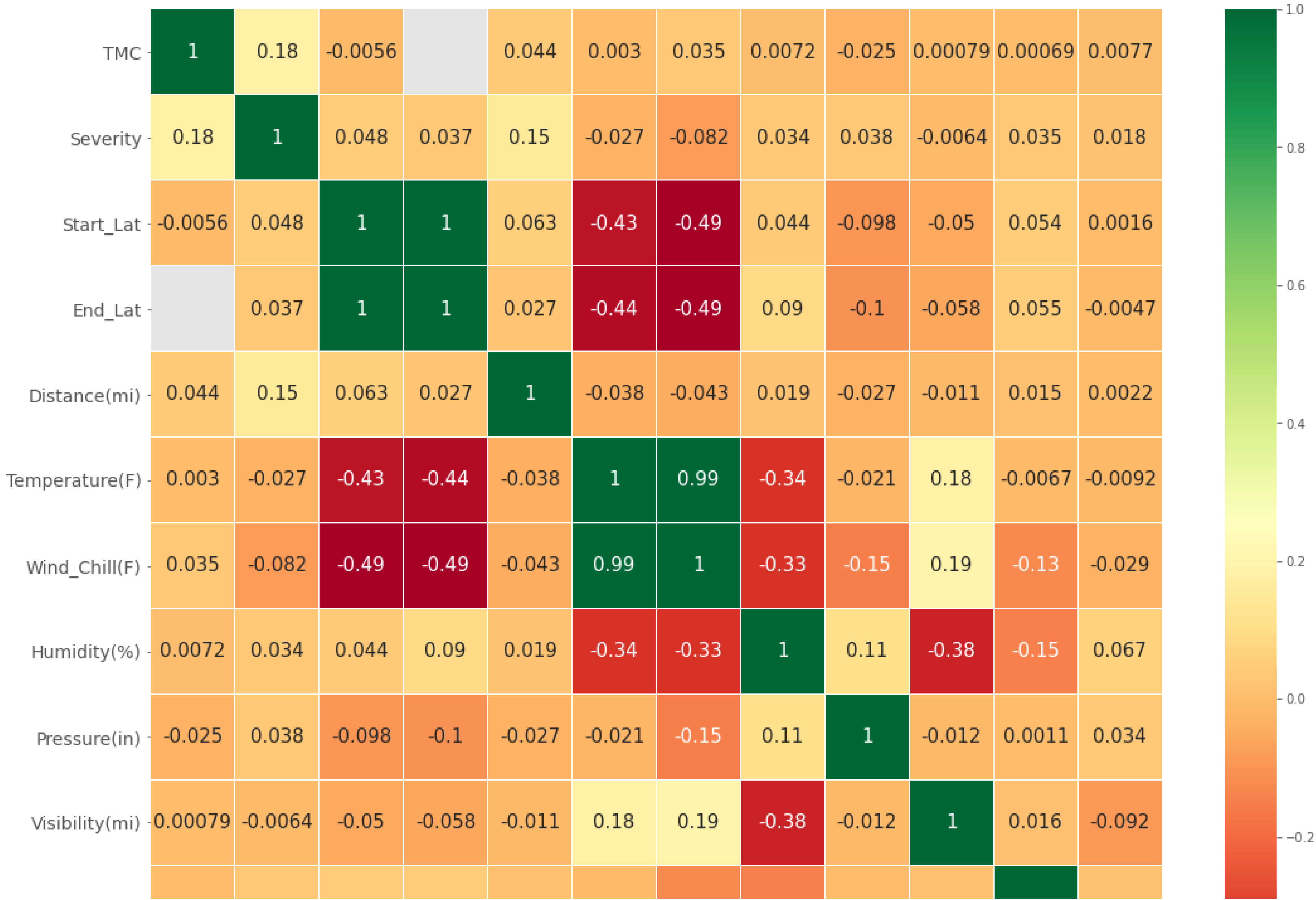
In [4]:
```python
# df.info()
```

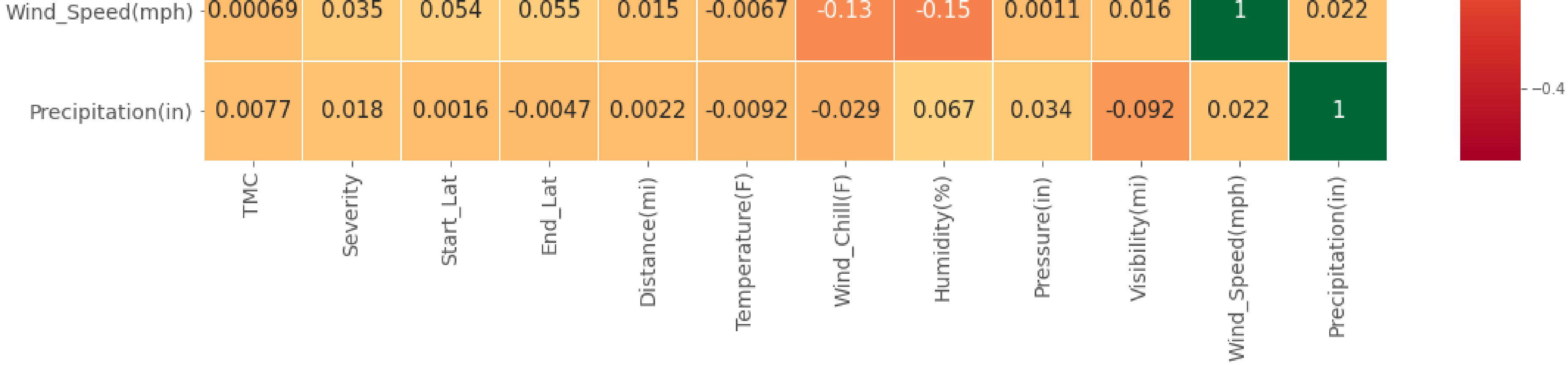
In [5]:
```python
# print('Features: \n', df.columns.tolist())
# print('\nMissing values: \n', df.isnull().values.sum())
# print('\nUnique values: \n', df.nunique())
```

Data Visualization

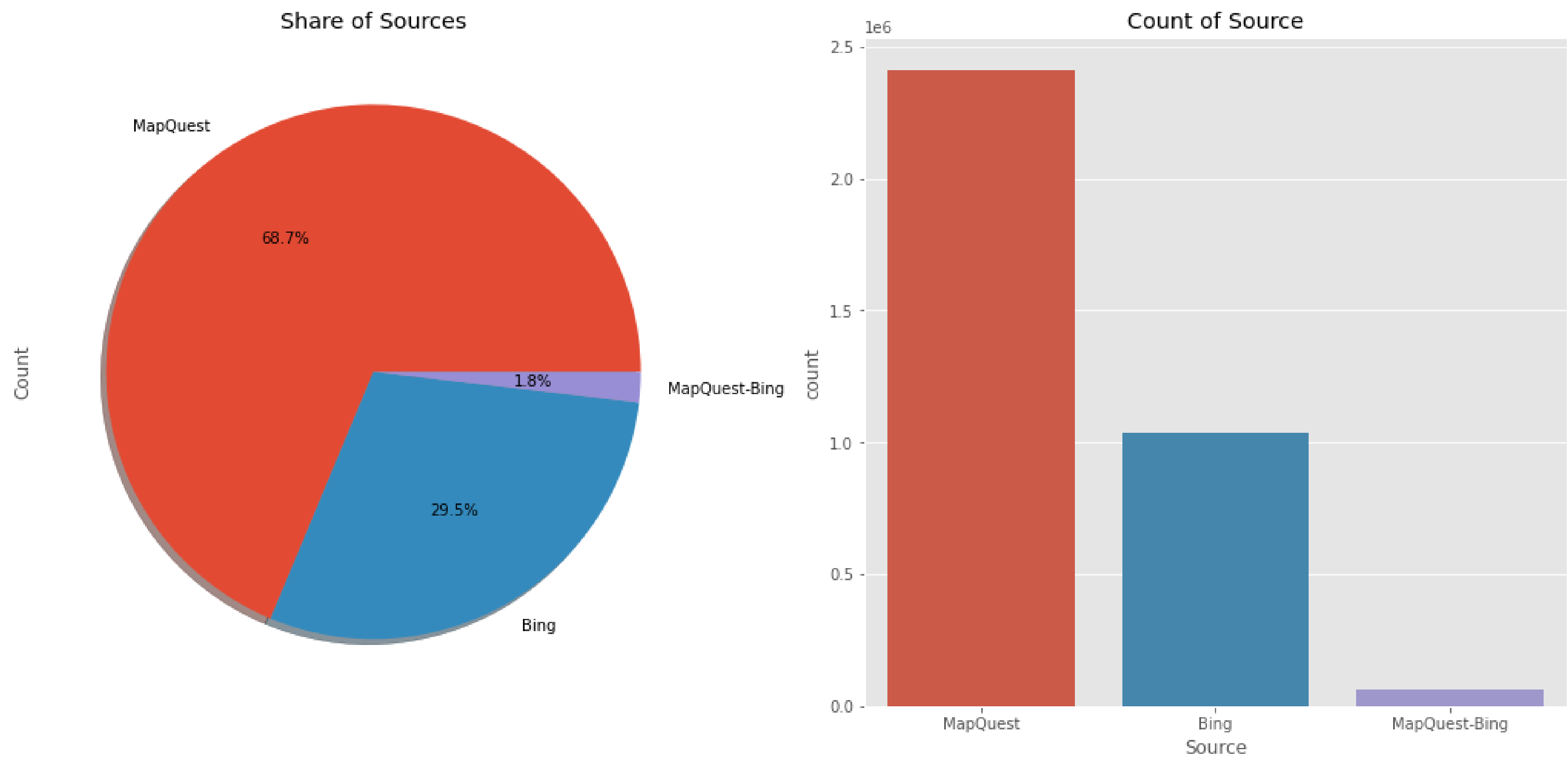
In [6]:

```python
# Correlation
fig = sns.heatmap(
    df[['Severity','Start_Lat','End_Lat','Distance(mi)','Temperature(F)','Wind_Chill(F)',
        'Humidity(%)','Pressure(in)','Visibility(mi)','Wind_Speed(mph)','Precipitation(in)']].corr(),
    annot = True, cmap = 'RdYlGn', linewidths = 0.2, annot_kws = {'size':15})
fig = plt.gcf()
fig.set_size_inches(18,15)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.show()
```

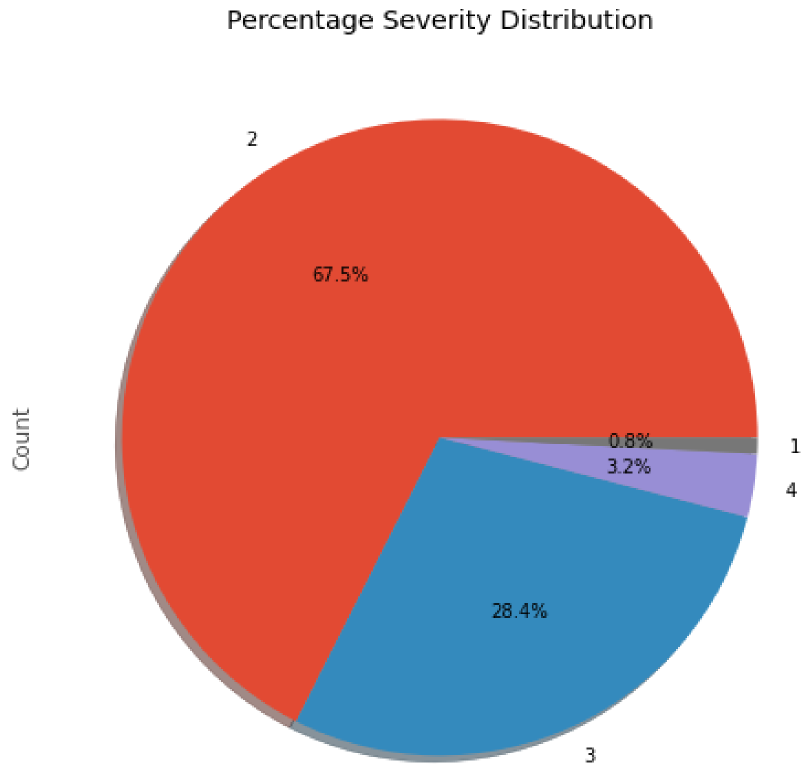


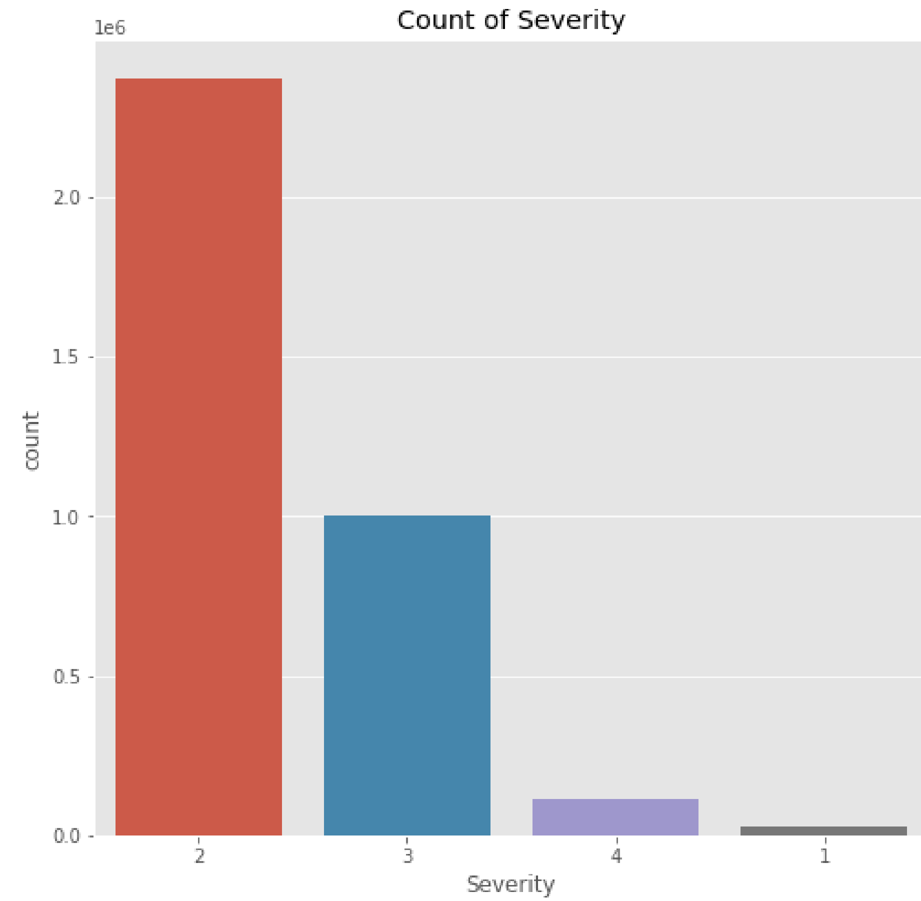

Wind_Speed(mph)
0.00069
0.035
0.054
0.055
0.015
-0.0067
-0.13
-0.15
0.0011
0.016
1
0.022
Precipitation(in)
0.0077
0.018
0.0016
-0.0047
0.0022
-0.0092
-0.029
0.067
0.034
-0.092
0.022
1
TMC
Severity
Start_Lat
End_Lat
Distance(mi)
Temperature(F)
Wind_Chill(F)
Humidity(%)
Pressure(in)
Visibility(mi)
Wind_Speed(mph)
Precipitation(in)
−0.4

In [7]:
```
# Source of Data
f, ax = plt.subplots(1, 2, figsize=(18,8))
df['Source'].value_counts().plot.pie(autopct = '%1.1f%%', ax = ax[0], shadow = True)
ax[0].set_title('Share of Sources')
ax[0].set_ylabel('Count')
sns.countplot('Source', data = df, ax = ax[1], order = df['Source'].value_counts().index)
ax[1].set_title('Count of Source')
plt.show()
```

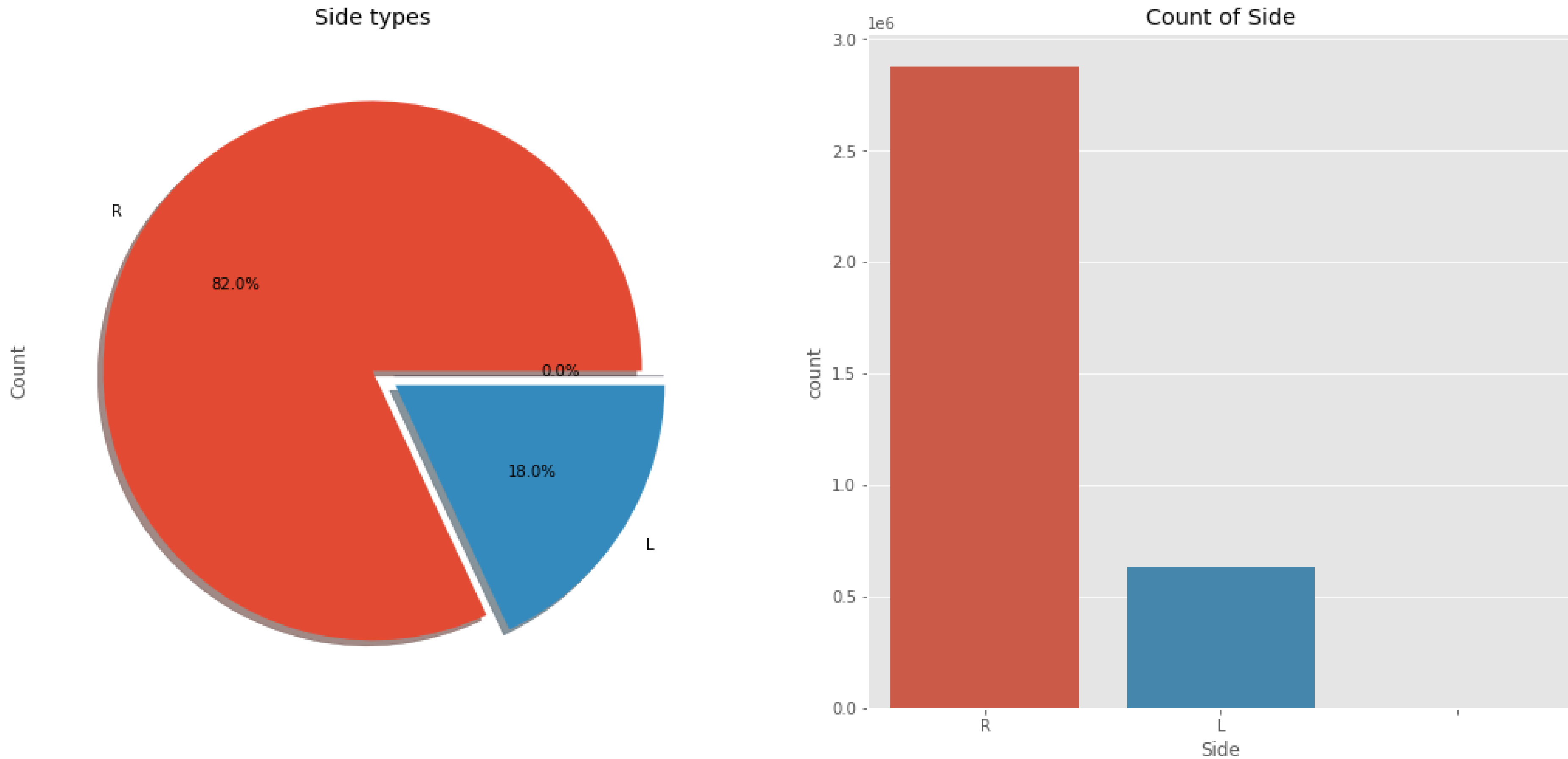


In [8]:
```
# Severity
f, ax = plt.subplots(1, 2, figsize=(18,8))
df['Severity'].value_counts().plot.pie(autopct = '%1.1f%%', ax = ax[0], shadow = True)
ax[0].set_title('Percentage Severity Distribution')
ax[0].set_ylabel('Count')
sns.countplot('Severity', data = df, ax = ax[1], order = df['Severity'].value_counts().index)
ax[1].set_title('Count of Severity')
plt.show()
```



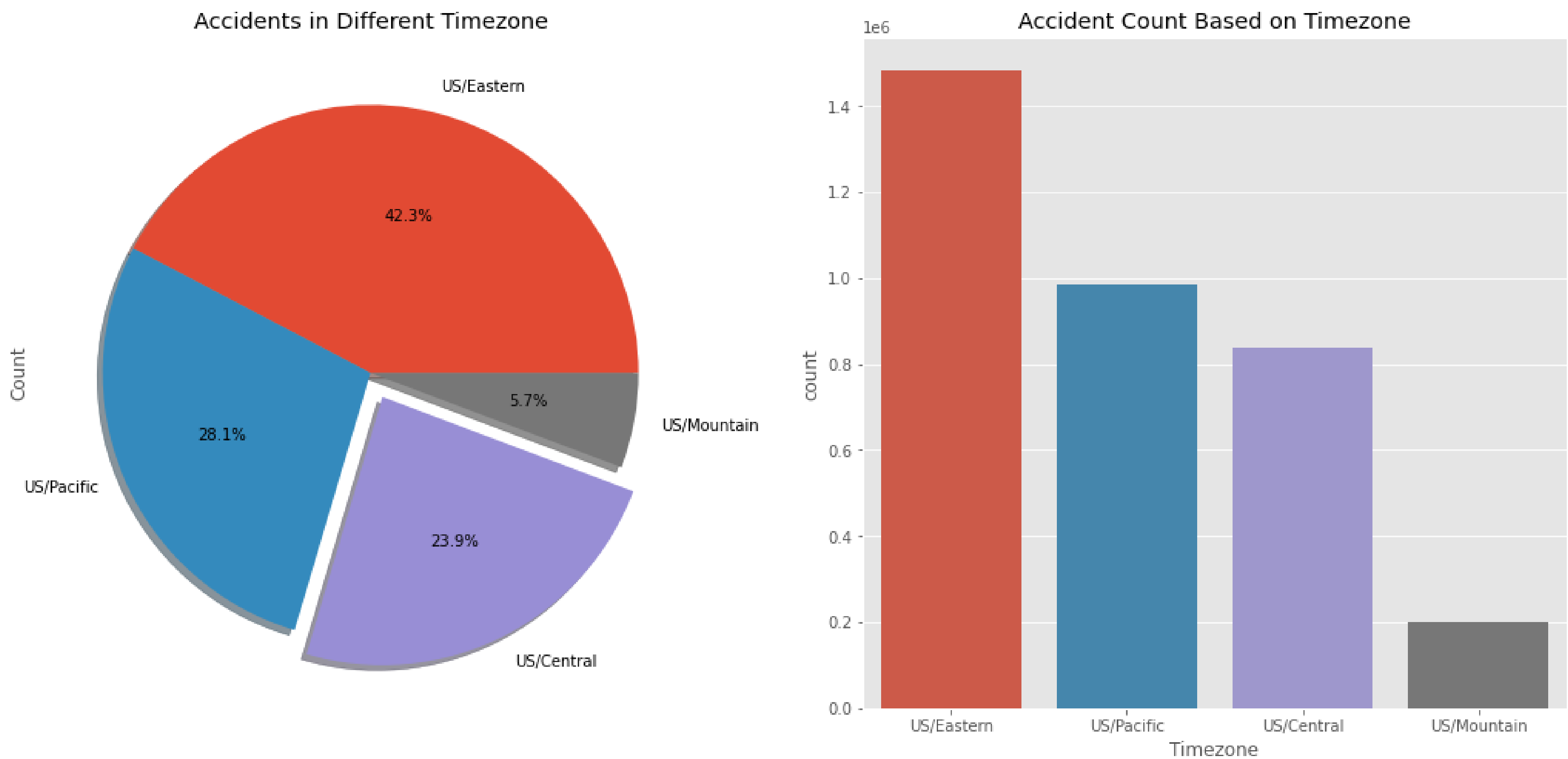


In [9]:
```
# Side: There are three things mentioned in side (Right Left and third one is a blank space)
f, ax = plt.subplots(1, 2, figsize=(18,8))
df['Side'].value_counts().plot.pie(explode=[0, 0.1, 0.1], autopct = '%1.1f%%', ax = ax[0], shadow = True)
ax[0].set_title('Side types')
ax[0].set_ylabel('Count')
sns.countplot('Side', data = df, ax = ax[1], order = df['Side'].value_counts().index)
ax[1].set_title('Count of Side')
plt.show()
```



In [10]:

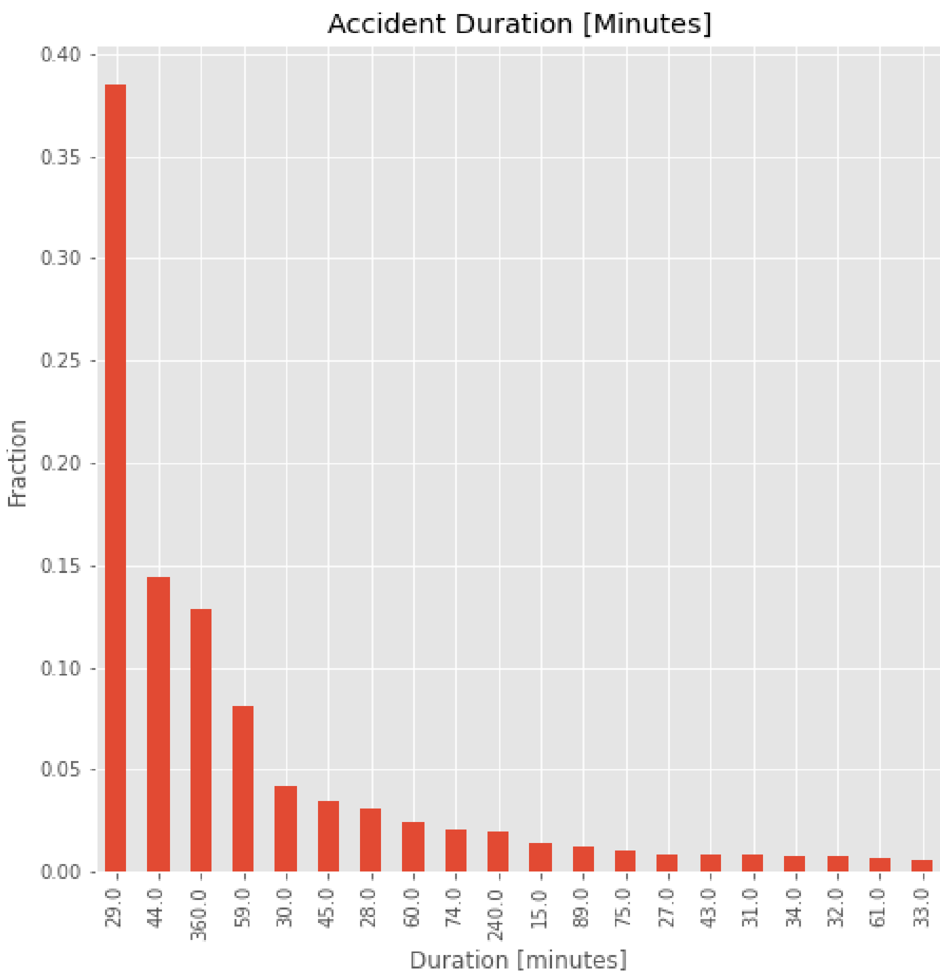
```
# USA has four time zones Pacific, Mountain, Central and Eastern as we move from West to the east of the country
f,ax=plt.subplots(1,2,figsize=(18,8))
df['Timezone'].value_counts().plot.pie(explode=[0,0,0.1,0],autopct='%1.1f%%',ax=ax[0],shadow=True)
ax[0].set_title('Accidents in Different Timezone')
ax[0].set_ylabel('Count')
sns.countplot('Timezone',data=df,ax=ax[1],order=df['Timezone'].value_counts().index)
ax[1].set_title('Accident Count Based on Timezone')
plt.show()
```



In [264]:
```
# Time taken to clear the traffice
df['Start_Time'] = pd.to_datetime(df.Start_Time, format='%Y-%m-%d %H:%M:%S')
df['End_Time'] = pd.to_datetime(df.End_Time, format='%Y-%m-%d %H:%M:%S')
df['diff'] = (df['End_Time']-df['Start_Time'])
```

In [12]:
```
top20 = df['diff'].astype('timedelta64[m]').value_counts().nlargest(20)
print('top 20 accident durations correspond to {:.1f}% of the data'.format(top20.sum()*100/len(df['diff'])))
(top20/top20.sum()).plot.bar(figsize=(8,8))
plt.title('Accident Duration [Minutes]')
plt.xlabel('Duration [minutes]')
plt.ylabel('Fraction');
```

```
top 20 accident durations correspond to 81.8% of the data
```



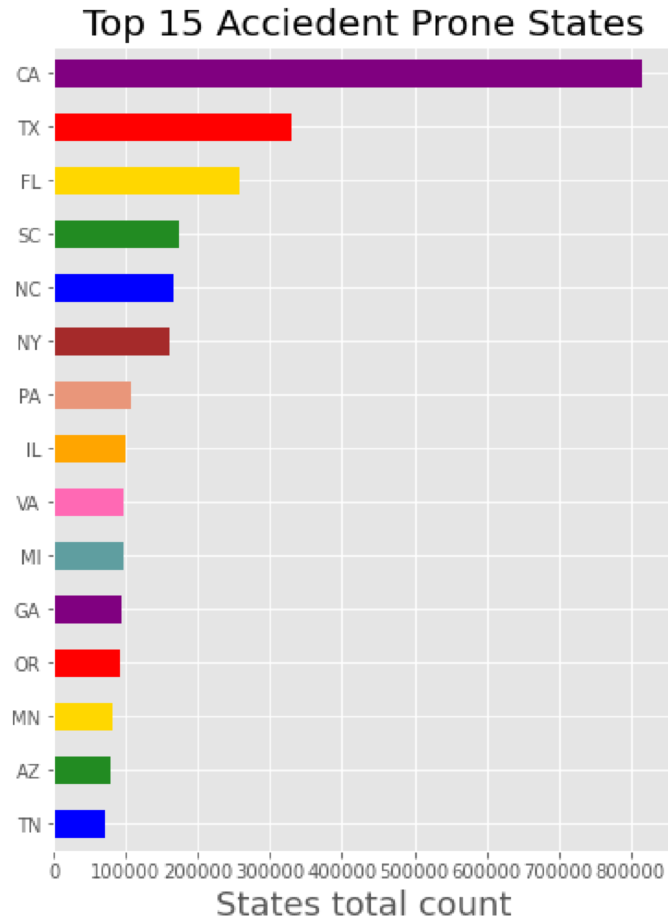
From the above curve we can see that most of the accidents take less than an hours time to get resolved. But more than 15% of the accidents are taking 360 minutes to resolve.

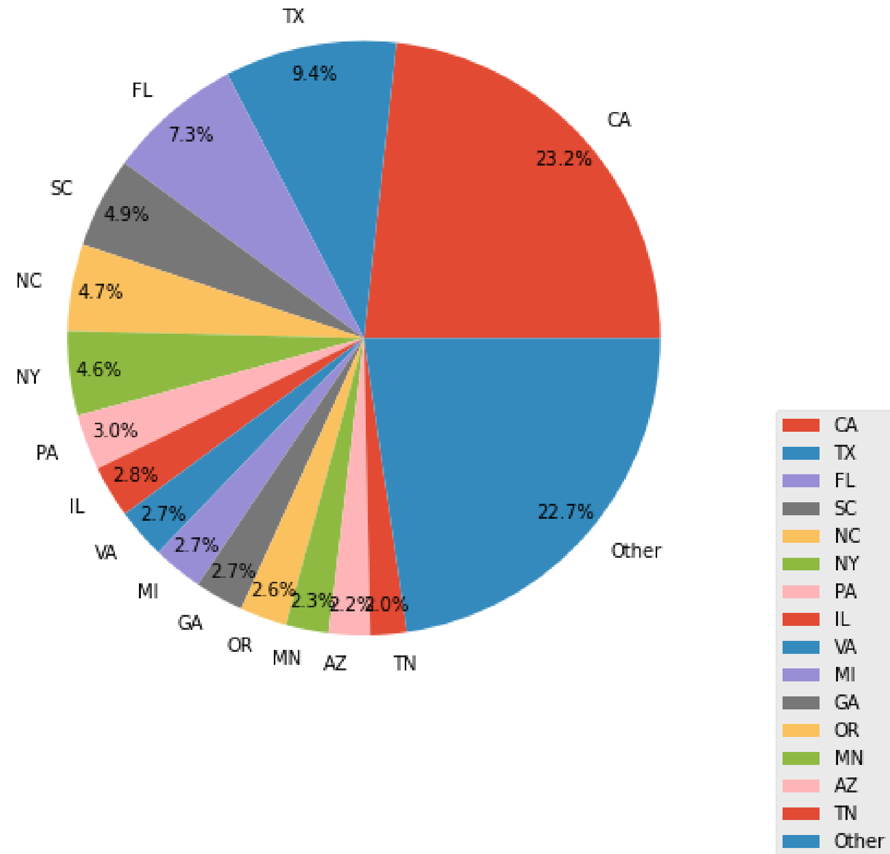
In [13]:

```
# create df for state accidents
import plotly.graph_objects as go
state_count_acc = pd.value_counts(df['State'])

fig = go.Figure(data = go.Choropleth(
    locations = state_count_acc.index,
    z = state_count_acc.values.astype(float),
    locationmode = 'USA-states',
    colorscale = 'Reds',
    colorbar_title = "Count Accidents",
))

fig.update_layout(
    title_text = '2016 - 2020 US Traffic Accident Dataset by State',
    geo_scope='usa',
)
fig.show()
```

In [14]:
```
# Acceident in different states
fig,ax = plt.subplots(1, 2, figsize = (15, 8))
clr = ("blue", "forestgreen", "gold", "red", "purple",'cadetblue','hotpink','orange','darksalmon','brown')
df.State.value_counts().sort_values(ascending = False)[:15].sort_values().plot(kind = 'barh', ax = ax[0], color = clr)
ax[0].set_title("Top 15 Acciedent Prone States", size = 20)
ax[0].set_xlabel('States total count', size = 18)

count = df['State'].value_counts()
groups = list(df['State'].value_counts().index)[:15]
counts = list(count[:15])
counts.append(count.agg(sum) - count[:15].agg(sum))
groups.append('Other')
type_dict = pd.DataFrame({"group": groups, "counts": counts})
qx = type_dict.plot(kind = 'pie', y = 'counts', labels = groups, autopct = '%1.1f%%',
                    pctdistance = 0.9, radius = 1.2, ax = ax[1])
plt.legend(loc = 0, bbox_to_anchor = (1.15, 0.4))
plt.subplots_adjust(wspace = 0.5, hspace = 0)
plt.ioff()
plt.ylabel('')
```

Out[14]:
```
Text(0, 0.5, '')
```

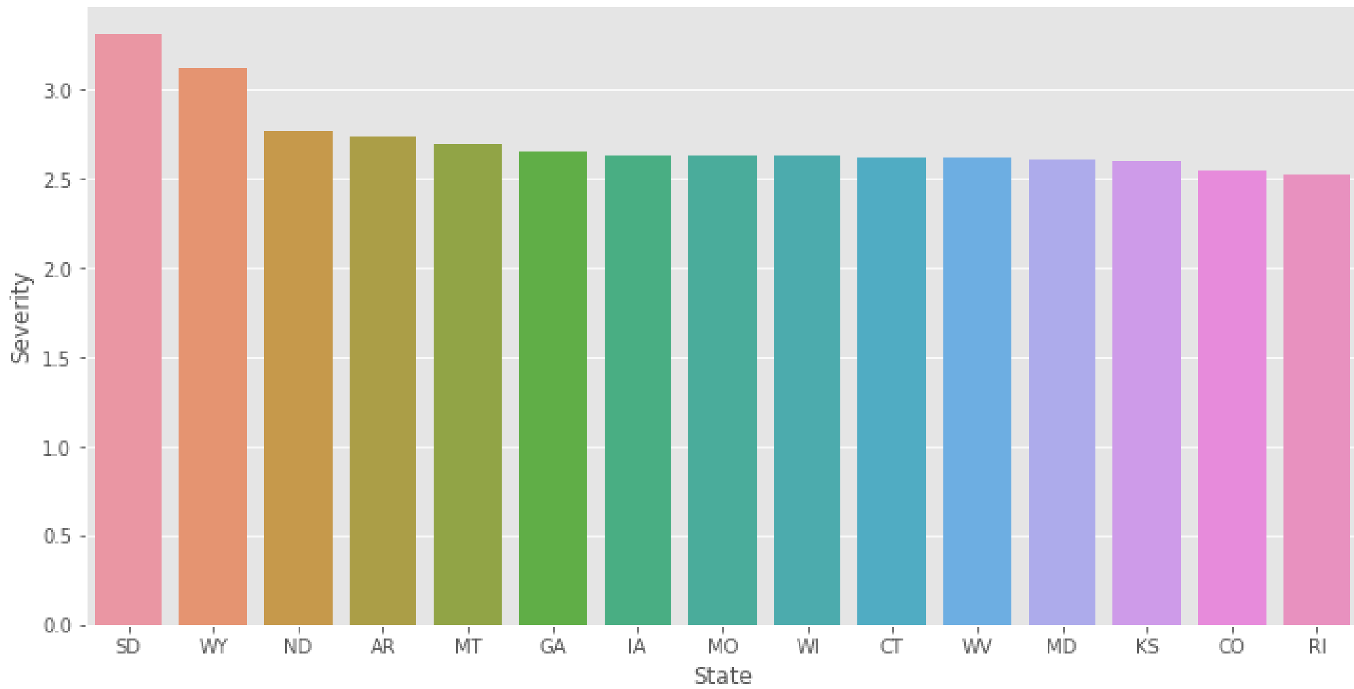




We can see that more accidents are happening in state of California(CA), Texas(TX) and Florida(FL)

In [15]:
```python
# Severity accidents
df_sever = df.sample(n=10000)

fig = go.Figure(
    data = go.Scattergeo(
        locationmode = 'USA-states',
        lon = df_sever['Start_Lng'],
        lat = df_sever['Start_Lat'],
        text = df_sever['City'],
        mode = 'markers',
        marker = dict(
            size = 8,
            opacity = 0.5,
            reversescale = False,
            autocolorscale = False,
            symbol = 'circle',
            line = dict(
                width = 1,
                color = 'rgba(102, 102, 102)'),
            colorscale = 'Reds',
            color = df_sever['Severity'],
            colorbar_title = "Severity"
        )
    )
)

fig.update_layout(
        title = 'Severity of accidents',
        geo = dict(
            scope='usa',
            projection_type='albers usa',
            showland = True,
            landcolor = "rgb(250, 250, 250)",
            subunitcolor = "rgb(217, 217, 217)",
            countrycolor = "rgb(217, 217, 217)",
            countrywidth = 0.7,
            subunitwidth = 0.7
        ),
    )
fig.show()
```

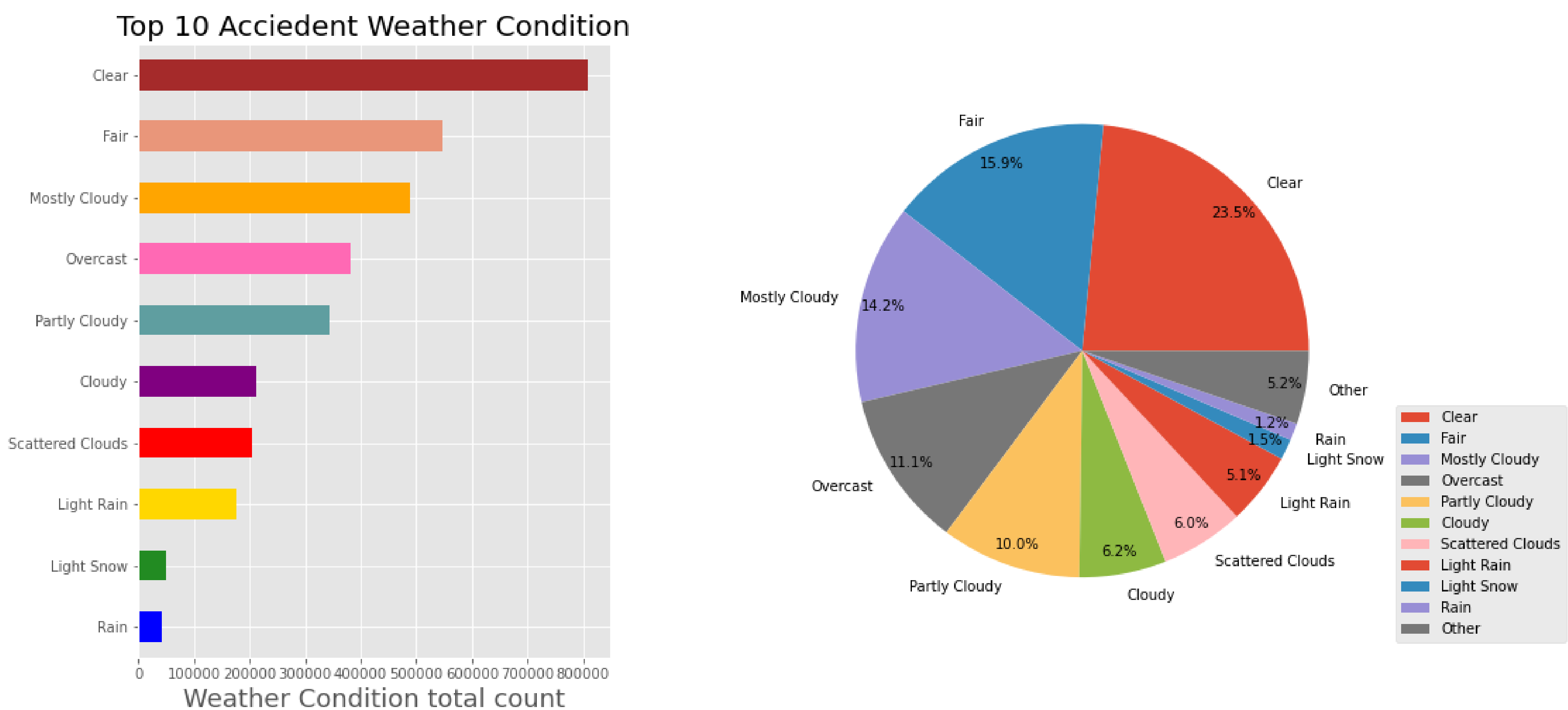
In [16]:
```
# Severity in different states
df_top_Severity_State = df.groupby('State').agg({'Severity': 'mean'}).sort_values('Severity', ascending = False).reset_index()

plt.figure(figsize=(12,6))
sns.barplot(y = "Severity", x = "State", data = df_top_Severity_State.head(15))
plt.ioff()
```



In [17]:

```
# Weather confition for the accidents
fig,ax = plt.subplots(1, 2, figsize = (15, 8))
clr = ("blue", "forestgreen", "gold", "red", "purple",'cadetblue','hotpink','orange','darksalmon','brown')
df.Weather_Condition.value_counts().sort_values(ascending = False)[:10].sort_values().plot(kind = 'barh', ax = ax[0], color = clr
ax[0].set_title("Top 10 Acciedent Weather Condition", size = 20)
ax[0].set_xlabel('Weather Condition total count', size = 18)

count = df['Weather_Condition'].value_counts()
groups = list(df['Weather_Condition'].value_counts().index)[:10]
counts = list(count[:10])
counts.append(count.agg(sum) - count[:10].agg(sum))
groups.append('Other')
type_dict = pd.DataFrame({"group": groups, "counts": counts})
qx = type_dict.plot(kind = 'pie', y = 'counts', labels = groups, autopct = '%1.1f%%',
                    pctdistance = 0.9, radius = 1.2, ax = ax[1])
plt.legend(loc = 0, bbox_to_anchor = (1.15, 0.4))
plt.subplots_adjust(wspace = 0.5, hspace = 0)
plt.ioff()
plt.ylabel('')
```

Out[17]: Text(0, 0.5, '')



Most accidents occure when the weather is clear. Maybe people drive faster and inattention when the weather is clear, and more carefully when the weather is bad.

In [18]:
```
# Where are Accidents occuring
bool_cols = [col for col in df.columns if df[col].dtype == np.dtype('bool')] # find the bool type columns
booldf = df[bool_cols]
more_than_one = booldf[booldf.sum(axis = 1) > 1] # find combination with more than 1 fact
print('There are {} more than one fact metadata rows, which are {:.1f}% of the data'.format(len(more_than_one),100*len(more_than_
```

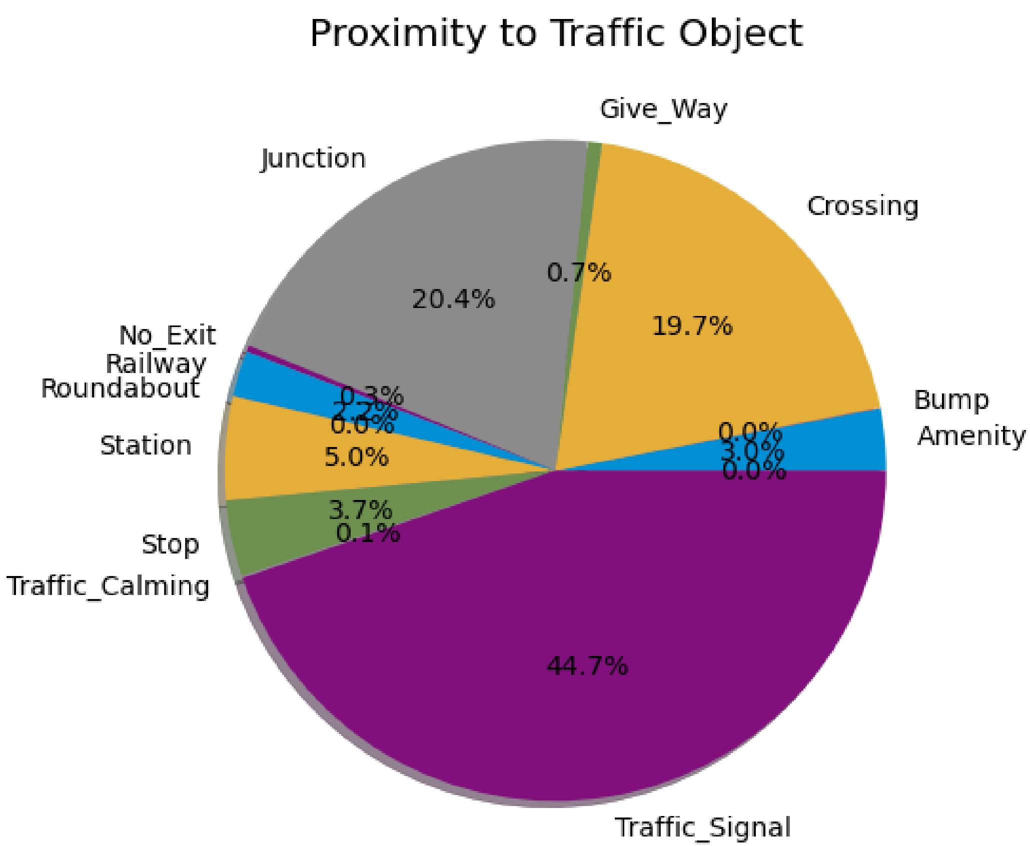
```
There are 284711 more than one fact metadata rows, which are 8.1% of the data
```

In [19]:
```
bools = booldf.sum(axis = 0)
bools
```

Out[19]:
```
Amenity             42082
Bump                  606
Crossing           274526
Give_Way             9564
Junction           284449
No_Exit              4384
Railway             31175
Roundabout            184
Station             70321
Stop                51976
Traffic_Calming      1401
Traffic_Signal     623623
Turning_Loop            0
dtype: int64
```

In [20]:
```python
plt.figure(figsize=(9,8))
plt.style.use('fivethirtyeight')
bools.plot.pie(autopct='%1.1f%%', shadow = True)
plt.ylabel('')
plt.title('Proximity to Traffic Object')
```

Out[20]: `Text(0.5, 1.0, 'Proximity to Traffic Object')`

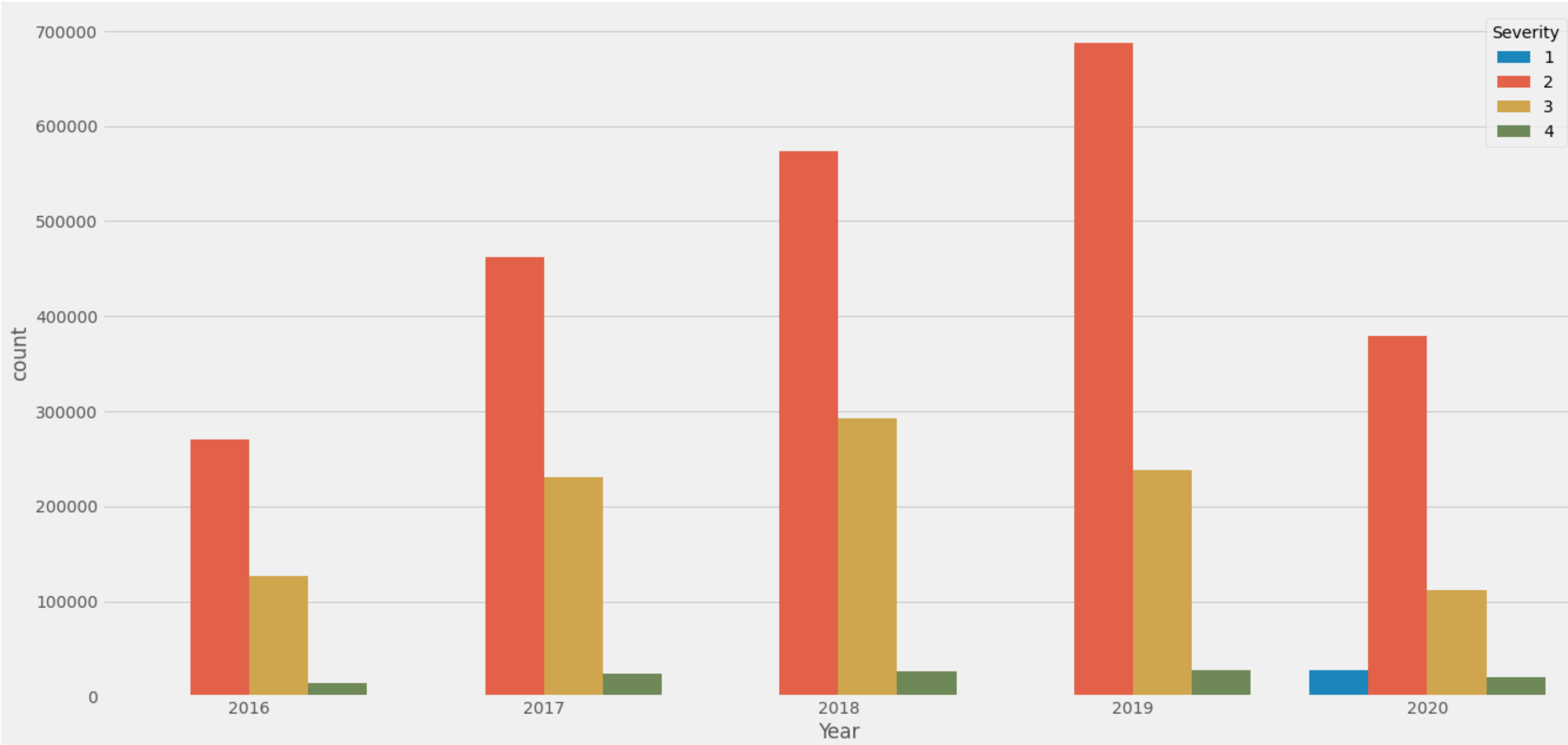


We can see that more accidents are happening near traffic signal,junction, and crossings

In [21]:
```python
# Extract year, month, day, hour and weekday
df['Year'] = df['Start_Time'].dt.year
df['Month'] = df['Start_Time'].dt.month
df['Day'] = df['Start_Time'].dt.day
df['Hour'] = df['Start_Time'].dt.hour
df['Weekday'] = df['Start_Time'].dt.strftime('%a')
```

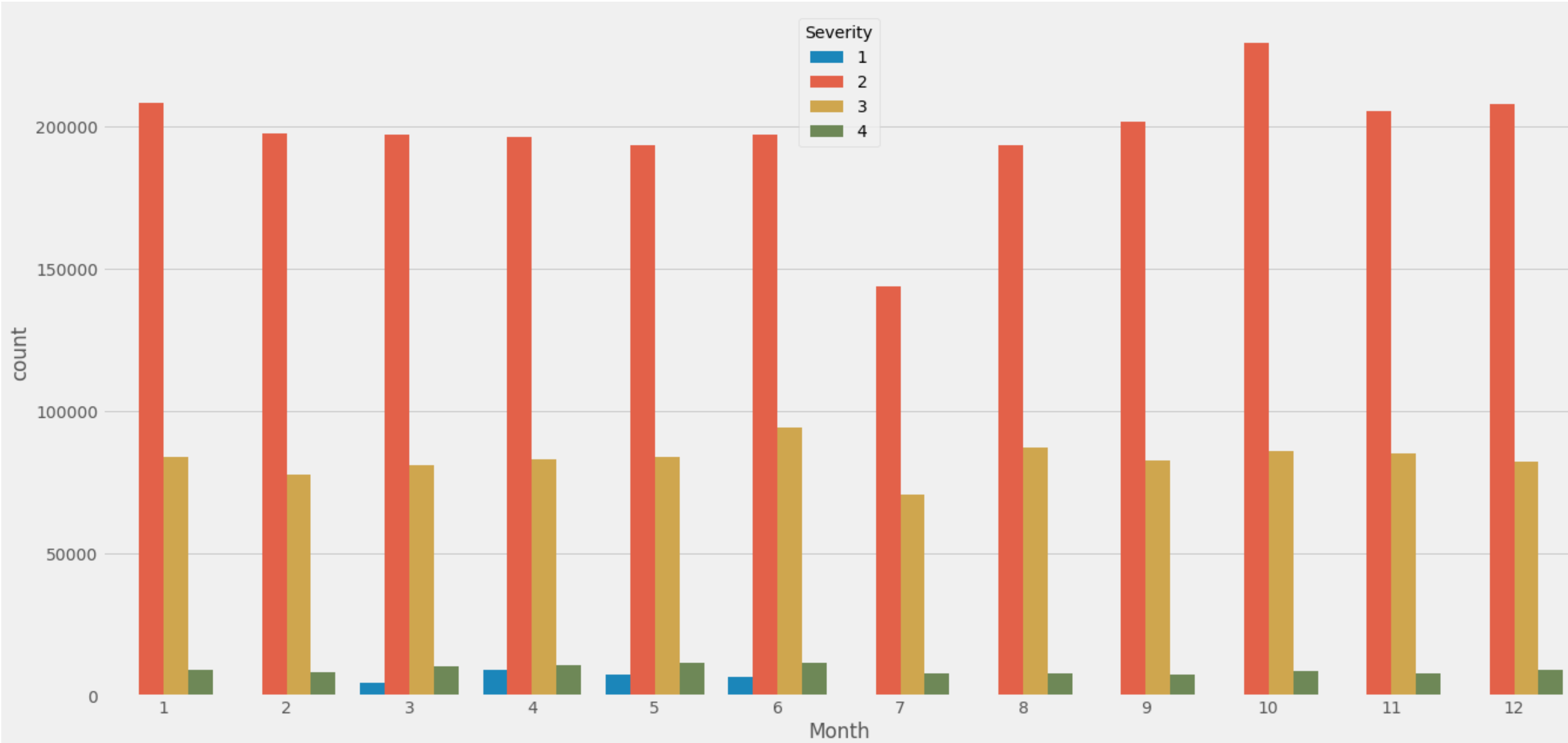
In [22]:
```
plt.figure(figsize = (20, 10))
sns.countplot(x = "Year", hue = "Severity", data = df)
```

Out[22]: <AxesSubplot:xlabel='Year', ylabel='count'>



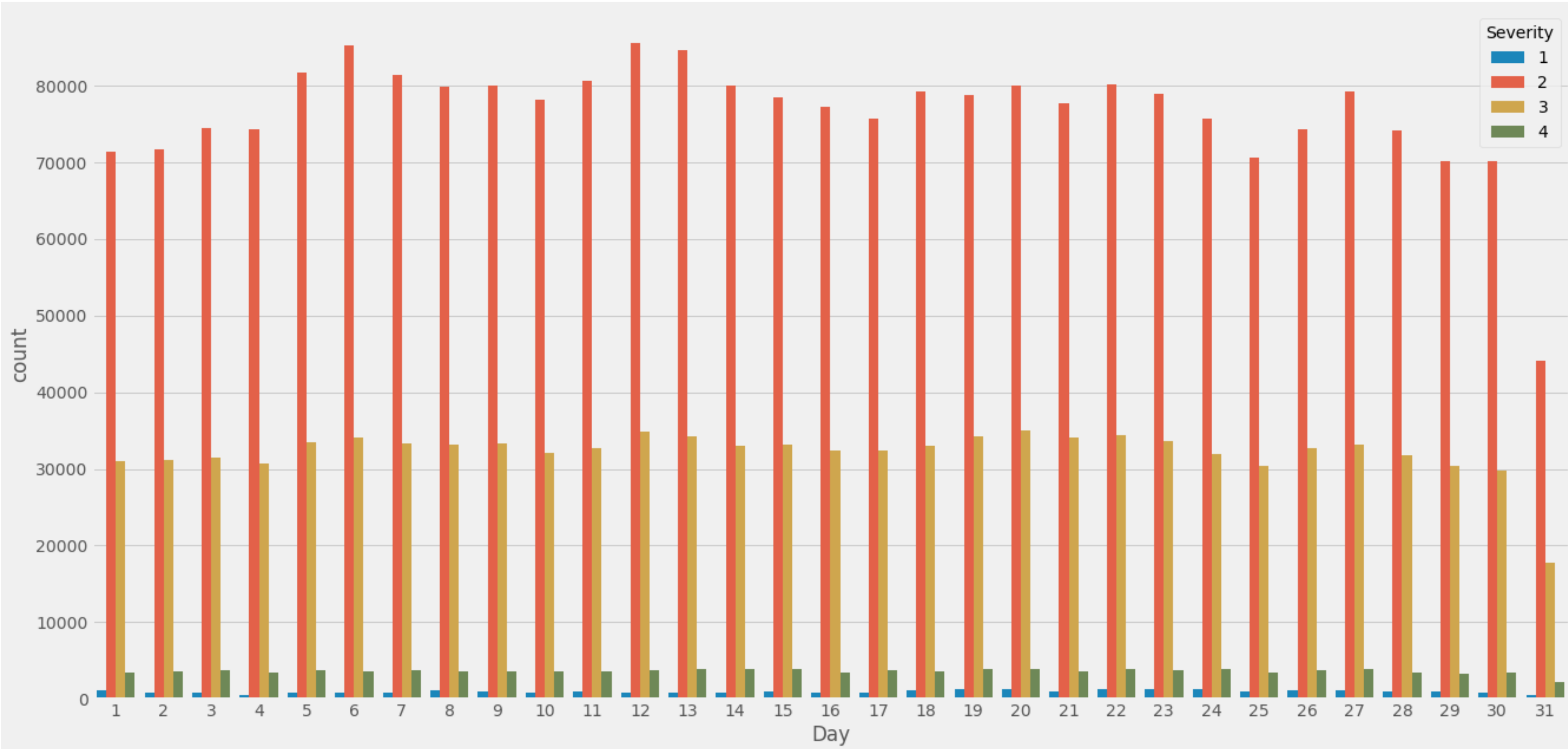
In [23]:
```python
plt.figure(figsize = (20, 10))
sns.countplot(x = "Month", hue = "Severity", data = df)
```

Out[23]: <AxesSubplot:xlabel='Month', ylabel='count'>



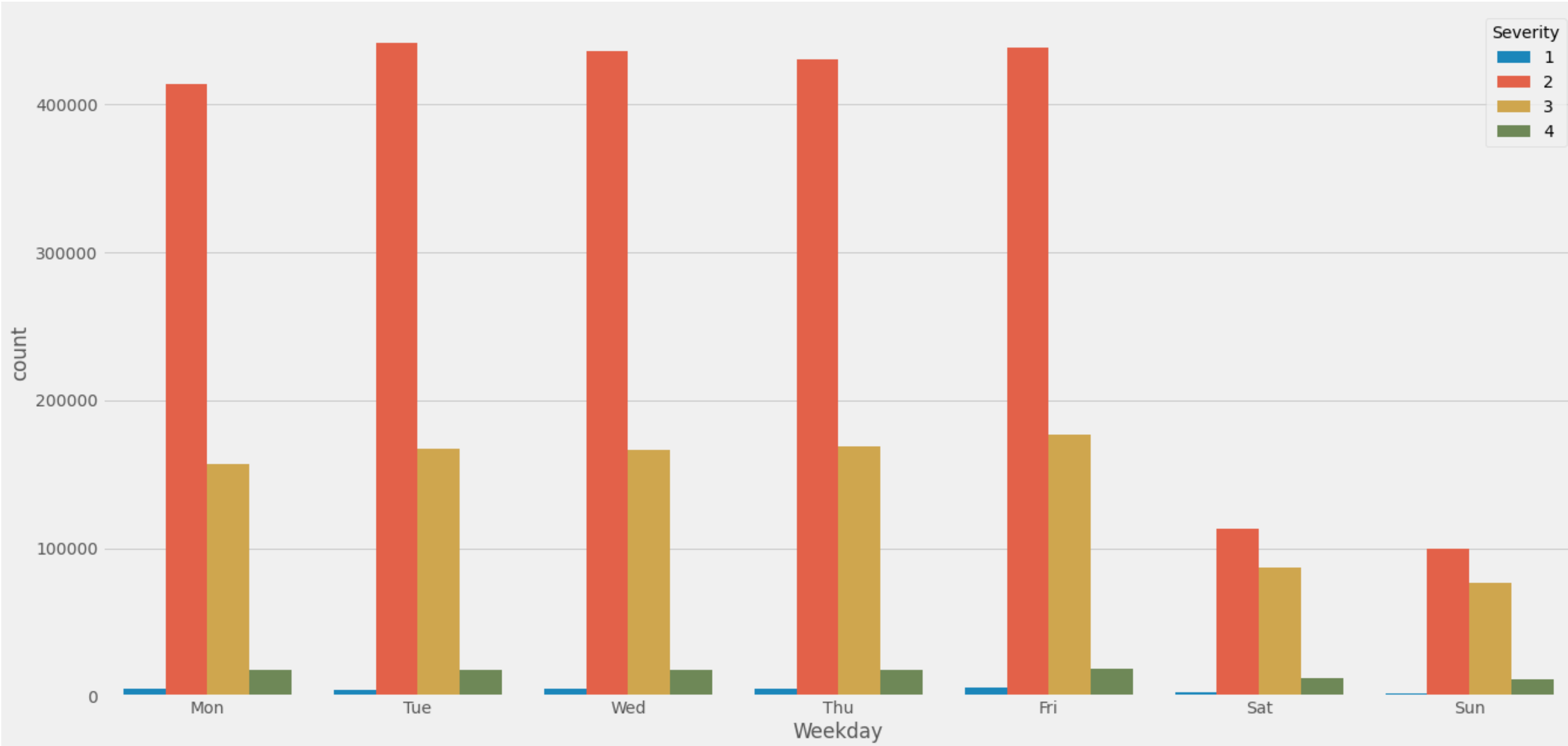
In [24]:
```python
plt.figure(figsize=(20, 10))
sns.countplot(x = "Day", hue = "Severity", data = df)
```

Out[24]: <AxesSubplot:xlabel='Day', ylabel='count'>



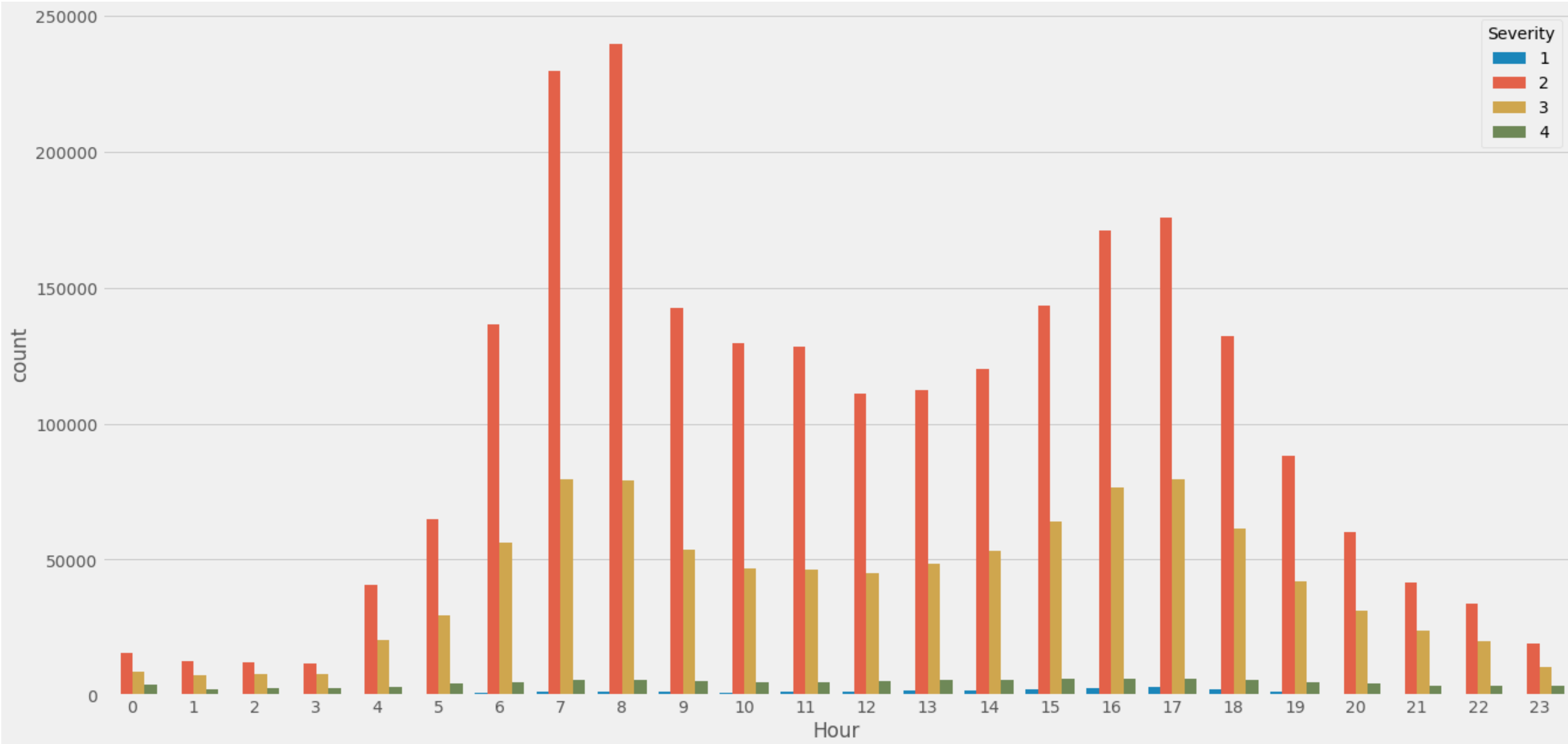
In [25]:
```python
plt.figure(figsize=(20, 10))
sns.countplot(x = "Weekday", hue = "Severity", data = df)
```

Out[25]: <AxesSubplot:xlabel='Weekday', ylabel='count'>



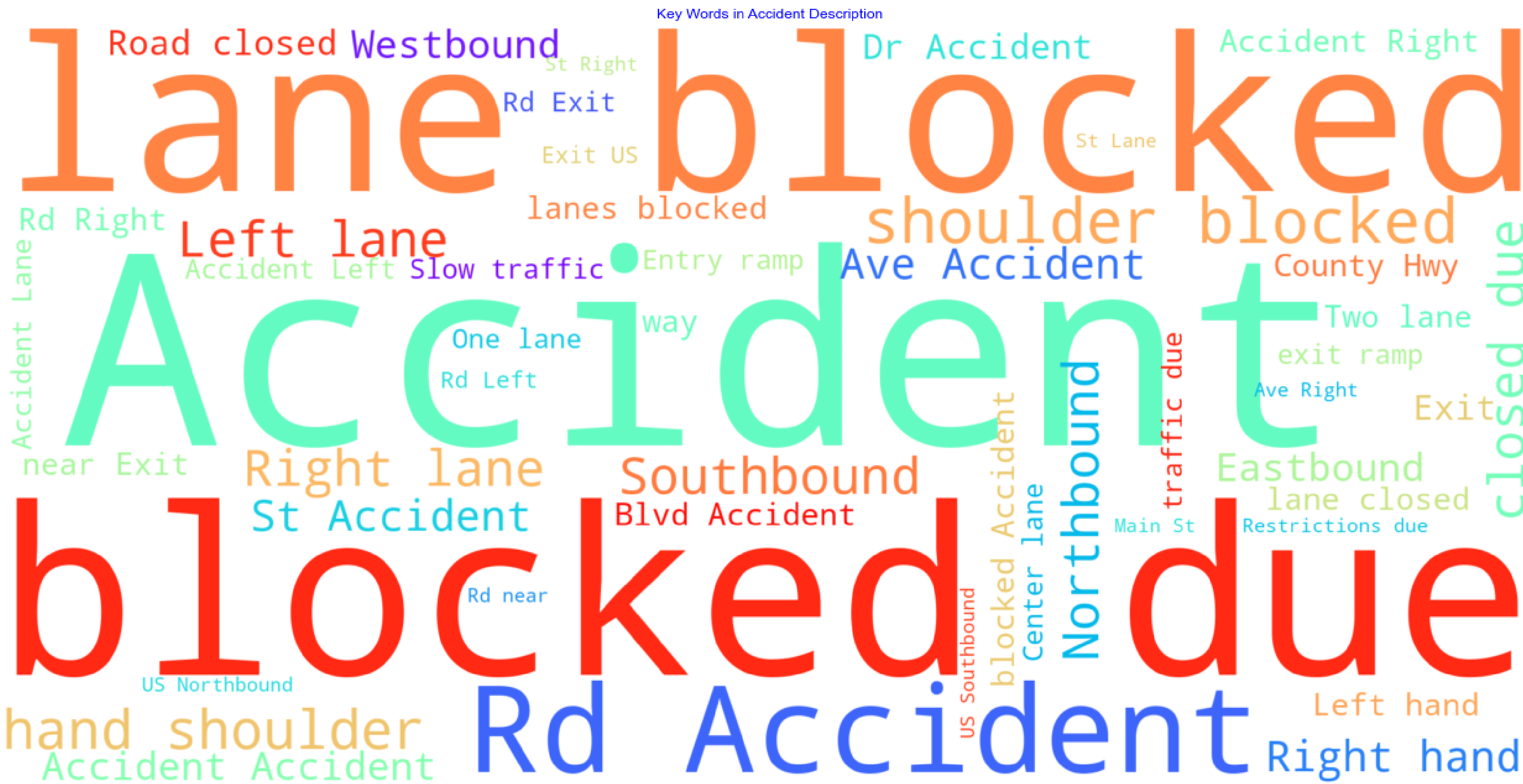
In [26]:
```
plt.figure(figsize=(20, 10))
sns.countplot(x = "Hour", hue = "Severity", data = df)
```

Out[26]: <AxesSubplot:xlabel='Hour', ylabel='count'>



In [27]:

```python
# Key Words in Description
from wordcloud import WordCloud
plt.style.use('seaborn')
wrds1 = df["Description"].str.split("(").str[0].value_counts().keys()

wc1 = WordCloud(scale = 5, max_words = 50, colormap = "rainbow", mode = "RGBA", background_color = "white").generate(" ".join(wrd
plt.figure(figsize = (20, 15))
plt.imshow(wc1,interpolation = "bilinear")
plt.axis("off")
plt.title("Key Words in Accident Description", color = 'b')
plt.show()
```



Data Clearning

In [28]:
```
# copy the dataframe before start cleaning the data
df_tmp = df.copy()
```

Clean the outliers of the time_duration

In [29]:
```python
# Check if there is any negative time_duration values
df_tmp.loc[df_tmp['diff']/np.timedelta64(1, 'm') <= 0]
```

Out[29]:

	ID	Source	TMC	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End_Lng	Distance(mi)	Description	Number	
69719	A-69721	MapQuest	201.0	3	2016-11-06 01:38:13	2016-11-06 01:37:57	34.032963	-118.435738	NaN	NaN	0.010	Accident on I-10 Eastbound at Exits 3A 3B I-405.	NaN	
69720	A-69722	MapQuest	241.0	2	2016-11-06 01:38:45	2016-11-06 01:38:23	34.053040	-118.228264	NaN	NaN	0.010	Lane blocked due to accident on US-101 Northbo...	NaN	
69721	A-69723	MapQuest	201.0	3	2016-11-06 01:35:47	2016-11-06 01:35:31	33.804443	-118.207527	NaN	NaN	0.010	Accident on I-710 Northbound at Exits 3A 3B Wi...	NaN	
69722	A-69724	MapQuest	201.0	2	2016-11-06 01:32:24	2016-11-06 01:31:50	34.134960	-117.597748	NaN	NaN	1.230	Hov lane blocked due to accident on CA-210 Eas...	NaN	
69723	A-69725	MapQuest	201.0	2	2016-11-06 01:33:05	2016-11-06 01:32:33	34.070320	-117.208679	NaN	NaN	0.010	Accident on Lugonia Ave at Alabama St.	1298.0	A
309387	A-309390	MapQuest	201.0	2	2016-11-06 01:51:04	2016-11-06 01:20:49	47.608002	-122.296280	NaN	NaN	0.010	Accident on Martin Luther King Jr Way at Cherr...	2733.0	E
309388	A-309391	MapQuest	201.0	2	2016-11-06 01:51:49	2016-11-06 01:21:35	47.530354	-122.270004	NaN	NaN	0.010	Accident on Rainier Ave at Elmgrove St.	8099.0	F
860988	A-861014	MapQuest	201.0	2	2019-11-03 01:25:16	2019-11-03 01:12:56	42.793083	-78.818367	NaN	NaN	6.210	Accident on I-90 Eastbound from Exit 57 NY-75 ...	NaN	
861024	A-861050	MapQuest	201.0	2	2019-11-03 01:47:49	2019-11-03 01:17:08	43.091412	-75.747284	NaN	NaN	0.000	Accident on I-90 Eastbound at Exit 34 NY-13 Pe...	NaN	
861041	A-861067	MapQuest	201.0	2	2019-11-03 01:34:54	2019-11-03 01:34:31	41.043110	-73.835861	NaN	NaN	0.000	Accident on I-87 Northbound at Exit 7A Saw Mil...	NaN	

	ID	Source	TMC	Severity	Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	End_Lng	Distance(mi)	Description	Number
861475	A-861501	MapQuest	201.0	3	2019-11-03 01:20:44	2019-11-03 01:06:33	45.635433	-122.663467	NaN	NaN	0.000	Center lane closed due to accident on I-5 Nort...	1814.0
861494	A-861520	MapQuest	201.0	3	2019-11-03 01:44:47	2019-11-03 01:44:26	37.561687	-122.036362	NaN	NaN	0.000	Accident on I-880 Northbound at Decoto Rd.	NaN
861495	A-861521	MapQuest	201.0	2	2019-11-03 01:43:50	2019-11-03 01:13:31	37.730671	-121.747063	NaN	NaN	0.000	Accident on Raymond Rd at Dagnino Rd.	4357.0
1497823	A-1497855	MapQuest	201.0	3	2018-11-04 01:30:41	2018-11-04 01:00:17	34.172119	-118.467529	NaN	NaN	0.000	#4 lane blocked due to accident on I-405 North...	NaN
1497824	A-1497856	MapQuest	201.0	3	2018-11-04 01:40:28	2018-11-04 01:09:39	34.067585	-117.201378	NaN	NaN	0.000	#1 lane blocked due to accident on I-210 Eastb...	987.0
2234574	A-2234614	MapQuest	201.0	2	2017-11-05 01:56:55	2017-11-05 01:26:32	47.121880	-122.434883	NaN	NaN	0.000	Right lane blocked due to accident on WA-7 Pac...	100.0
2234659	A-2234699	MapQuest	241.0	3	2017-11-05 01:32:24	2017-11-05 01:02:02	34.045719	-117.310364	NaN	NaN	0.000	One lane blocked due to accident on I-215 Sout...	NaN
2234660	A-2234700	MapQuest	201.0	2	2017-11-05 01:55:55	2017-11-05 01:25:05	33.923199	-117.857597	NaN	NaN	0.000	Accident on Lambert Rd at Sunflower St.	292.0
3104499	A-3104659	Bing	NaN	2	2019-11-03 01:57:00	2019-11-03 01:22:55	43.024010	-71.195290	43.024880	-71.190330	0.258	At Old Manchester Rd/Exit 4 - Accident.	NaN
3104975	A-3105135	Bing	NaN	2	2019-11-03 01:13:00	2019-11-03 01:05:47	34.041208	-118.064316	34.041208	-118.064316	0.000	At CA-19/Rosemead Blvd - Accident.	NaN
3104978	A-3105138	Bing	NaN	2	2019-11-03 01:22:00	2019-11-03 01:14:47	36.326633	-119.279029	36.326633	-119.279029	0.000	At Ben Maddox Way - Accident.	NaN
3232740	A-3232900	Bing	NaN	2	2018-11-04 01:51:53	2018-11-04 01:21:22	40.705504	-111.888270	40.703211	-111.888260	0.158	At Bank Ave - Accident. Two lanes blocked.	NaN

22 rows × 55 columns

In [30]:

```
# Drop the rows with above
df_tmp['diff'] = df_tmp['diff']/np.timedelta64(1, 'm')
df_tmp = df_tmp[df_tmp['diff'] > 0]
```

In [31]:
```
# review the status of missing values for each column
num = df_tmp.isna().sum()
num
```

Out[31]:
```
ID                          0
Source                      0
TMC                   1034795
Severity                    0
Start_Time                  0
End_Time                    0
Start_Lat                   0
Start_Lng                   0
End_Lat               2478800
End_Lng               2478800
Distance(mi)                0
Description                 1
Number                2262850
Street                      0
Side                        0
City                      112
County                      0
State                       0
Zipcode                  1069
Country                     0
Timezone                 3880
Airport_Code             6758
Weather_Timestamp       43323
Temperature(F)          65732
Wind_Chill(F)         1868237
Humidity(%)             69687
Pressure(in)            55882
Visibility(mi)          75856
Wind_Direction          58874
Wind_Speed(mph)        454602
Precipitation(in)     2025863
Weather_Condition       76138
Amenity                     0
Bump                        0
Crossing                    0
Give_Way                    0
Junction                    0
No_Exit                     0
Railway                     0
Roundabout                  0
Station                     0
Stop                        0
Traffic_Calming             0
Traffic_Signal              0
Turning_Loop                0
```

```
Sunrise_Sunset             115
Civil_Twilight             115
Nautical_Twilight          115
Astronomical_Twilight      115
diff                         0
Year                         0
Month                        0
Day                          0
Hour                         0
Weekday                      0
dtype: int64
```

In [32]:
```
# replace na in Precipitation(in) with 0
df_tmp['Precipitation(in)'] = df_tmp['Precipitation(in)'].fillna(0)
```

Clean the outliers in 'Distance(mi)', 'Temperature(F)', 'Pressure(in)', 'Visibility(mi)', and 'Wind_Speed(mph)'

In [33]:
```
# check how much outliers these columns has
outlier_list = ['Distance(mi)', 'Temperature(F)', 'Pressure(in)', 'Visibility(mi)', 'Wind_Speed(mph)', 'Precipitation(in)']

for item in outlier_list:

#     iqr = df_tmp[item].quantile(0.75) - df_tmp[item].quantile(0.25)
#     q_abnormal_L = df_tmp[item] < df_tmp[item].quantile(0.25) - 1.5 * iqr
#     q_abnormal_U = df_tmp[item] > df_tmp[item].quantile(0.75) + 1.5 * iqr
#     print(item + ' has ' + str(q_abnormal_L.sum() + q_abnormal_U.sum()) + ' outliers')

    df_tmp[item + '_zscore'] = (df_tmp[item] - df_tmp[item].mean())/df_tmp[item].std()
    z_abnormal = abs(df_tmp[item + '_zscore']) > 3
    print(item + ' has ' + str(z_abnormal.sum()) + ' outliers')
```

```
Distance(mi) has 37756 outliers
Temperature(F) has 13420 outliers
Pressure(in) has 84587 outliers
Visibility(mi) has 32400 outliers
Wind_Speed(mph) has 21468 outliers
Precipitation(in) has 7417 outliers
```

In [34]:
```
for item in outlier_list:

#     iqr = df_tmp[item].quantile(0.75) - df_tmp[item].quantile(0.25)
#     lower = df_tmp[item].quantile(0.25) - 1.5 * iqr
#     upper = df_tmp[item].quantile(0.75) + 1.5 * iqr
#     df_tmp = df_tmp[df_tmp[item] >= lower]
#     df_tmp = df_tmp[df_tmp[item] <= upper]

    median = df_tmp[item].median()
    std = df_tmp[item].std()
    df_tmp = df_tmp[(df_tmp[item] - median).abs() <= std * 3]
```

In [35]:
```
df_tmp[outlier_list].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2782632 entries, 2 to 3513616
Data columns (total 6 columns):
Distance(mi)         float64
Temperature(F)       float64
Pressure(in)         float64
Visibility(mi)       float64
Wind_Speed(mph)      float64
Precipitation(in)    float64
dtypes: float64(6)
memory usage: 148.6 MB
```

Deal with missing values

In [36]:
```
# Set the list of features to include in Machine Learning
feature_lst=['Severity','Start_Time','Start_Lng','Start_Lat','Distance(mi)','Side','City','County','State','Timezone',
             'Temperature(F)','Humidity(%)','Pressure(in)','Visibility(mi)','Wind_Direction','Wind_Speed(mph)',
             'Precipitation(in)','Weather_Condition','Amenity','Bump','Crossing','Give_Way','Junction','No_Exit','Railway',
             'Roundabout','Station','Stop','Traffic_Calming','Traffic_Signal','Turning_Loop','Sunrise_Sunset','Hour','Weekday']
```

In [37]:
```
# Select the dataset to include only the selected features
df_sel = df_tmp[feature_lst].copy()
# df_sel.info()
```

In [38]:
```
# drop the rows with missing values
df_sel.dropna(subset = df_sel.columns[df_sel.isnull().mean()!=0], how = 'any', axis = 0, inplace = True)
# df_sel.shape
```

```
In [39]: # convert all bool columns to int type data (0,1)
         df_sel[bool_cols] = df_sel[bool_cols].astype(int)
```

```
In [40]: df_sel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2774942 entries, 2 to 3513616
Data columns (total 34 columns):
Severity             int64
Start_Time           datetime64[ns]
Start_Lng            float64
Start_Lat            float64
Distance(mi)         float64
Side                 object
City                 object
County               object
State                object
Timezone             object
Temperature(F)       float64
Humidity(%)          float64
Pressure(in)         float64
Visibility(mi)       float64
Wind_Direction       object
Wind_Speed(mph)      float64
Precipitation(in)    float64
Weather_Condition    object
Amenity              int32
Bump                 int32
Crossing             int32
Give_Way             int32
Junction             int32
No_Exit              int32
Railway              int32
Roundabout           int32
Station              int32
Stop                 int32
Traffic_Calming      int32
Traffic_Signal       int32
Turning_Loop         int32
Sunrise_Sunset       object
Hour                 int64
Weekday              object
dtypes: datetime64[ns](1), float64(9), int32(13), int64(2), object(9)
memory usage: 603.4+ MB
```

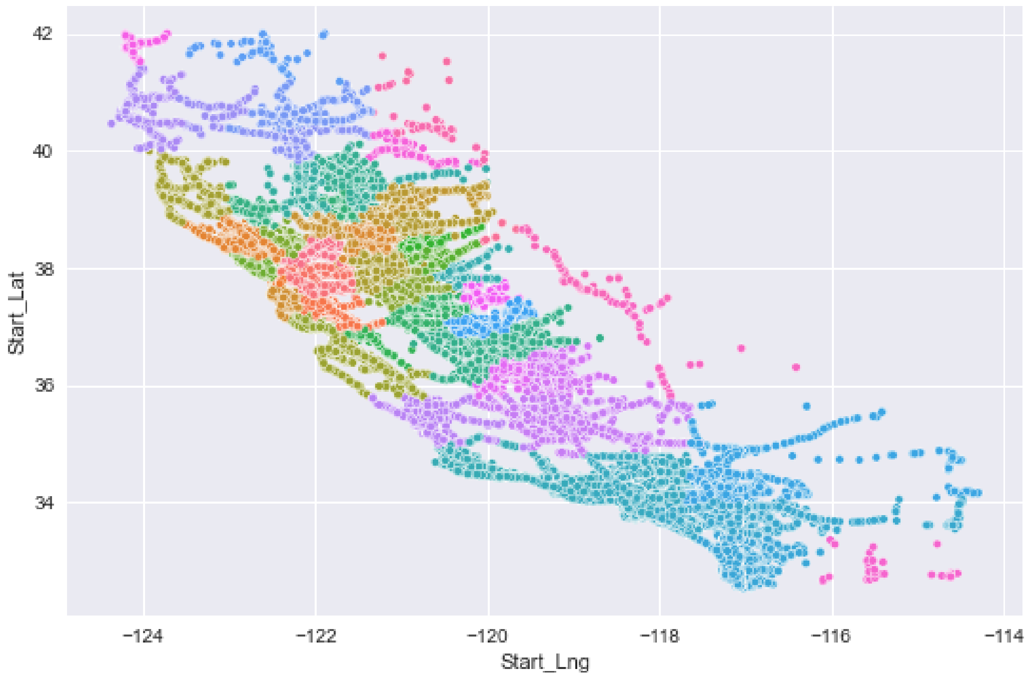
Select the sample data for analysing (state of interest, and the City of interest)

Due to the limitation of personal laptop, the whole US dataset is too big to handle

In [201]:
```
# Select the state of South Carolina, which has the most accident records
df_state = df_sel.loc[df_sel.State == 'CA'].copy()
df_state.drop('State', axis = 1, inplace = True)
df_state.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 650415 entries, 728 to 3513616
Data columns (total 33 columns):
Severity             650415 non-null int64
Start_Time           650415 non-null datetime64[ns]
Start_Lng            650415 non-null float64
Start_Lat            650415 non-null float64
Distance(mi)         650415 non-null float64
Side                 650415 non-null object
City                 650415 non-null object
County               650415 non-null object
Timezone             650415 non-null object
Temperature(F)       650415 non-null float64
Humidity(%)          650415 non-null float64
Pressure(in)         650415 non-null float64
Visibility(mi)       650415 non-null float64
Wind_Direction       650415 non-null object
Wind_Speed(mph)      650415 non-null float64
Precipitation(in)    650415 non-null float64
Weather_Condition    650415 non-null object
Amenity              650415 non-null int32
Bump                 650415 non-null int32
Crossing             650415 non-null int32
Give_Way             650415 non-null int32
Junction             650415 non-null int32
No_Exit              650415 non-null int32
Railway              650415 non-null int32
Roundabout           650415 non-null int32
Station              650415 non-null int32
Stop                 650415 non-null int32
Traffic_Calming      650415 non-null int32
Traffic_Signal       650415 non-null int32
Turning_Loop         650415 non-null int32
Sunrise_Sunset       650415 non-null object
Hour                 650415 non-null int64
Weekday              650415 non-null object
dtypes: datetime64[ns](1), float64(9), int32(13), int64(2), object(8)
memory usage: 136.5+ MB
```

In [42]:
```
# Map of accidents, color code by county
sns.scatterplot(x = 'Start_Lng', y = 'Start_Lat', data = df_state, hue = 'County', legend = False, s = 20)
plt.show()
```



In [202]:
```
# find the city with most accident cases
city = df_state.City.value_counts().sort_values(ascending = False)[:10]
city
```

Out[202]:
```
Los Angeles      56120
Sacramento       28805
San Diego        22663
San Jose         17454
Oakland          12811
Riverside        10925
Long Beach        9953
San Francisco     8810
Anaheim           8496
San Bernardino    7701
Name: City, dtype: int64
```

In [44]:
```
# Select Los Angeies as the target city for modeling
df_city = df_state.loc[df_state.City == 'Los Angeles'].copy()
df_city.drop('City', axis = 1, inplace = True)
# df_city.info()
```

In [45]:
```
df_city['Severity'].value_counts(normalize = True) * 100
```

Out[45]:
```
2    66.760513
3    32.435852
4     0.789380
1     0.014255
Name: Severity, dtype: float64
```

Which means our prediction accuracy should at least above 64%. Because if a model predicts all the case's Severity to "1", it will get an accuracy at 63.97%

Deal with categorical data: pd.get_dummies()

In [46]:
```
# Generate dummies for categorical data
df_city.drop('Start_Time', axis = 1, inplace = True)
df_city_dummy = pd.get_dummies(df_city, drop_first = True)
# df_city_dummy.info()
```

Predict the accident severity with various supervised machine learning algorithms

Import the machine learning libraries

In [18]:
```python
# Import LogisticRegression
from sklearn.linear_model import LogisticRegression

# Import KNeighborsClassifier from sklearn.neighbors
from sklearn.neighbors import KNeighborsClassifier

# Import DecisionTreeClassifier from sklearn.tree
from sklearn.tree import DecisionTreeClassifier

# Import RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve, auc
```

Data preparation: train_test_split

In [48]:
```python
# Set the target for the prediction
target='Severity'

# set X and y
y = df_city_dummy[target]
X = df_city_dummy.drop(target, axis = 1)

# Split the data set into training and testing data sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 21, stratify = y)
```

In [49]:
```python
# List of classification algorithms
algo_lst = ['Logistic Regression', 'K-Nearest Neighbors', 'Decision Trees', 'Random Forest']

# Initialize an empty list for the accuracy for each algorithm
accuracy_lst = []
```

Algorithm A. Logistic regression

In [50]:
```
# Logistic regression
lr = LogisticRegression(random_state = 0)
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)

# Get the accuracy score
acc = accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

print("[Logistic regression algorithm] accuracy_score: {:.3f}.".format(acc))
```

```
[Logistic regression algorithm] accuracy_score: 0.704.
```

Algorithm B. The K-Nearest Neighbors (KNN) algorithm

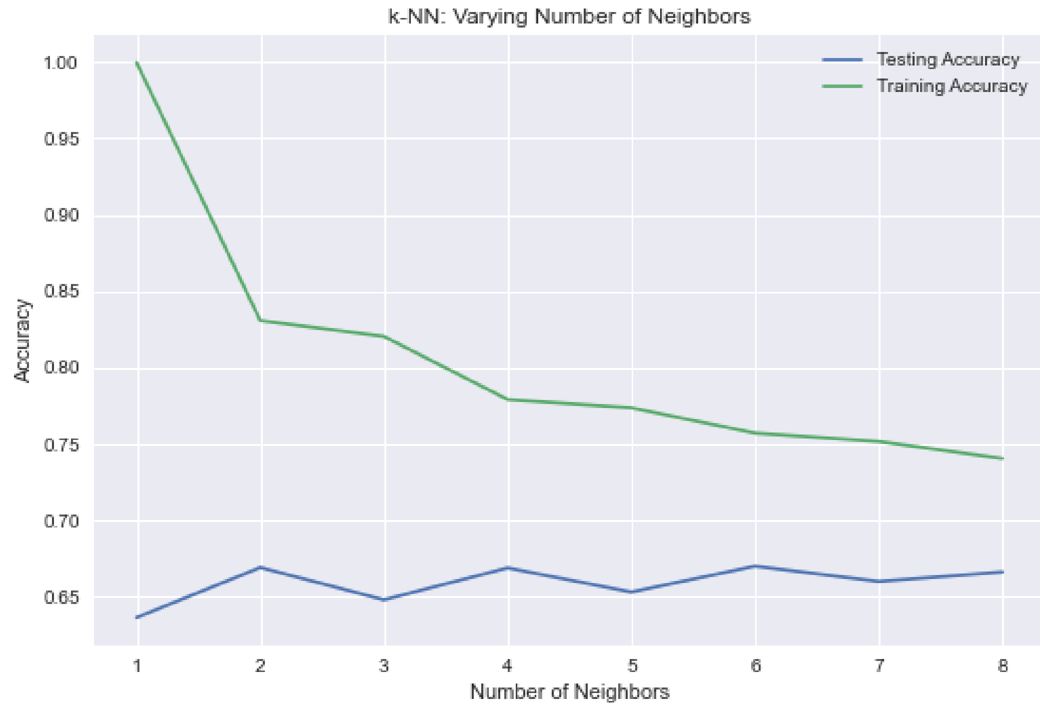
In [51]:
```
# Create a k-NN classifier with 6 neighbors
knn = KNeighborsClassifier(n_neighbors = 4)

# Fit the classifier to the data
knn.fit(X_train, y_train)

# Predict the labels for the training data X
y_pred = knn.predict(X_test)

# Get the accuracy score
acc = accuracy_score(y_test, y_pred)

# Append to the accuracy list
accuracy_lst.append(acc)

print('[K-Nearest Neighbors (KNN)] knn.score: {:.3f}.'.format(knn.score(X_test, y_test)))
print('[K-Nearest Neighbors (KNN)] accuracy_score: {:.3f}.'.format(acc))
```

```
[K-Nearest Neighbors (KNN)] knn.score: 0.669.
[K-Nearest Neighbors (KNN)] accuracy_score: 0.669.
```

Optmize the number of neighors: plot the accuracy versus number of neighbors

In [52]:

```
# Setup arrays to store train and test accuracies
neighbors = np.arange(1, 9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

# Loop over different values of k
for i, n_neighbor in enumerate(neighbors):

    # Setup a k-NN Classifier with n_neighbor
    knn = KNeighborsClassifier(n_neighbors = n_neighbor)

    # Fit the classifier to the training data
    knn.fit(X_train, y_train)

    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)

    #Compute accuracy on the testing set
    test_accuracy[i] = knn.score(X_test, y_test)

# Generate plot
plt.title('k-NN: Varying Number of Neighbors')
plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy')
plt.plot(neighbors, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show()
```



Algorithm C. Decision Tree

In [53]:
```
# Instantiate dt_entropy, set 'entropy' as the information criterion
dt_entropy = DecisionTreeClassifier(max_depth = 10, criterion = 'entropy', random_state = 1)

# Fit dt_entropy to the training set
dt_entropy.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred = dt_entropy.predict(X_test)

# Evaluate accuracy_entropy
accuracy_entropy = accuracy_score(y_test, y_pred)

# Print accuracy_entropy
print('[Decision Tree -- entropy] accuracy_score: {:.3f}.'.format(accuracy_entropy))

# Instantiate dt_gini, set 'gini' as the information criterion
dt_gini = DecisionTreeClassifier(max_depth = 10, criterion = 'gini', random_state = 1)

# Fit dt_entropy to the training set
dt_gini.fit(X_train, y_train)

# Use dt_entropy to predict test set labels
y_pred= dt_gini.predict(X_test)

# Evaluate accuracy_entropy
accuracy_gini = accuracy_score(y_test, y_pred)

# Append to the accuracy list
acc = accuracy_gini
accuracy_lst.append(acc)

# Print accuracy_gini
print('[Decision Tree -- gini] accuracy_score: {:.3f}.'.format(accuracy_gini))
```

```
[Decision Tree -- entropy] accuracy_score: 0.818.
[Decision Tree -- gini] accuracy_score: 0.809.
```

Algorithm D. Random Forest

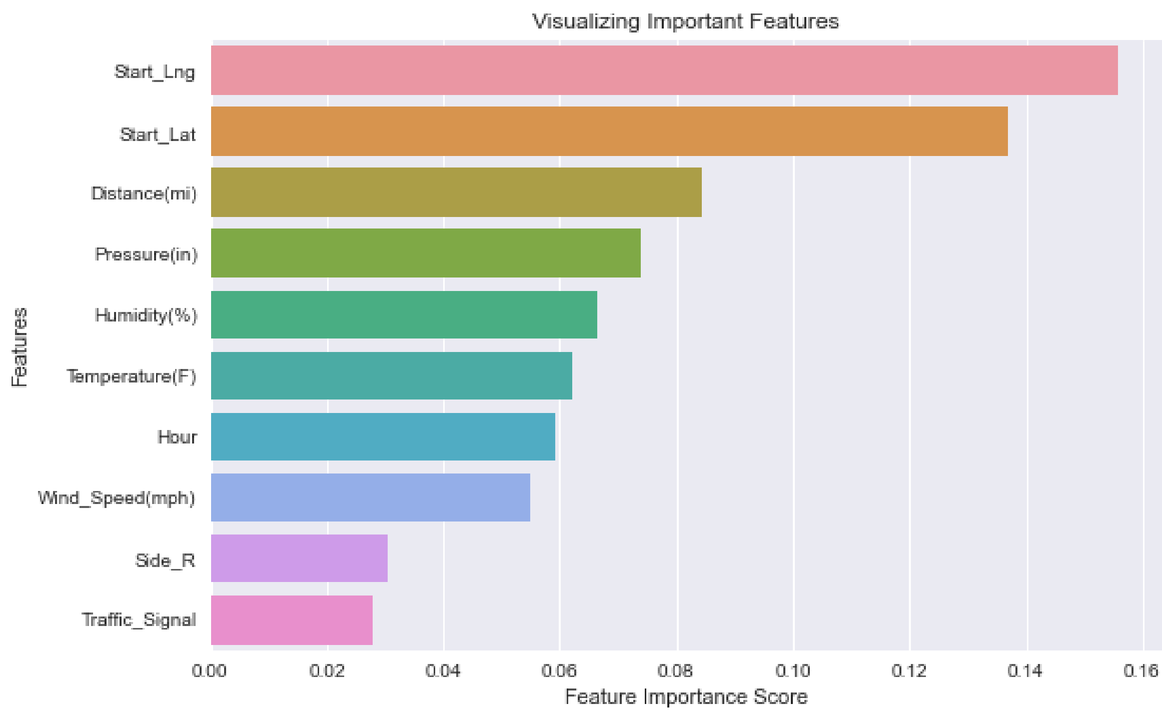
In [54]:
```
#Create a Gaussian Classifier
clf = RandomForestClassifier(n_estimators = 100)

#Train the model
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

# Model Accuracy, how often is the classifier correct?
print("[Randon forest algorithm] accuracy_score: {:.3f}.".format(acc))
```

```
[Randon forest algorithm] accuracy_score: 0.809.
```

Find the most important features

In [55]:
```
feature_imp = pd.Series(clf.feature_importances_, index = X.columns).sort_values(ascending = False)

# Creating a bar plot, displaying only the top k features
k = 10
sns.barplot(x = feature_imp[:10], y = feature_imp.index[:k])

# Add labels to your graph
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.legend()
plt.show()
```

```
No handles with labels found to put in legend.
```



In [56]:
```
# List top k important features
k = 20
feature_imp.sort_values(ascending = False)[:k]
```

Out[56]:
```
Start_Lng                   0.155800
Start_Lat                   0.136912
Distance(mi)                0.084278
Pressure(in)                0.073940
Humidity(%)                 0.066338
Temperature(F)              0.061989
Hour                        0.059239
Wind_Speed(mph)             0.055023
Side_R                      0.030569
Traffic_Signal              0.027936
Weather_Condition_Fair      0.022207
Visibility(mi)              0.017734
Weather_Condition_Clear     0.016928
Junction                    0.012951
Sunrise_Sunset_Night        0.011065
Weekday_Sat                 0.009557
Weekday_Wed                 0.008803
Weekday_Sun                 0.008688
Weekday_Tue                 0.008631
Weekday_Thu                 0.008388
dtype: float64
```

In [57]:
```
# Create a selector object that will use the random forest classifier to identify features which importance > 0.04
sfm = SelectFromModel(clf, threshold = 0.04)

# Train the selector
sfm.fit(X_train, y_train)

feat_labels = X.columns

# Print the names of the most important features
for feature_list_index in sfm.get_support(indices = True):
    print(feat_labels[feature_list_index])
```

```
Start_Lng
Start_Lat
Distance(mi)
Temperature(F)
Humidity(%)
Pressure(in)
Wind_Speed(mph)
Hour
```

In [58]:
```
# Transform the data to create a new dataset containing only the most important features
X_important_train = sfm.transform(X_train)
X_important_test = sfm.transform(X_test)

# Create a new random forest classifier for the most important features
clf_important = RandomForestClassifier(n_estimators = 500, random_state = 0, n_jobs = -1)

# Train the new classifier on the new dataset containing the most important features
clf_important.fit(X_important_train, y_train)
```

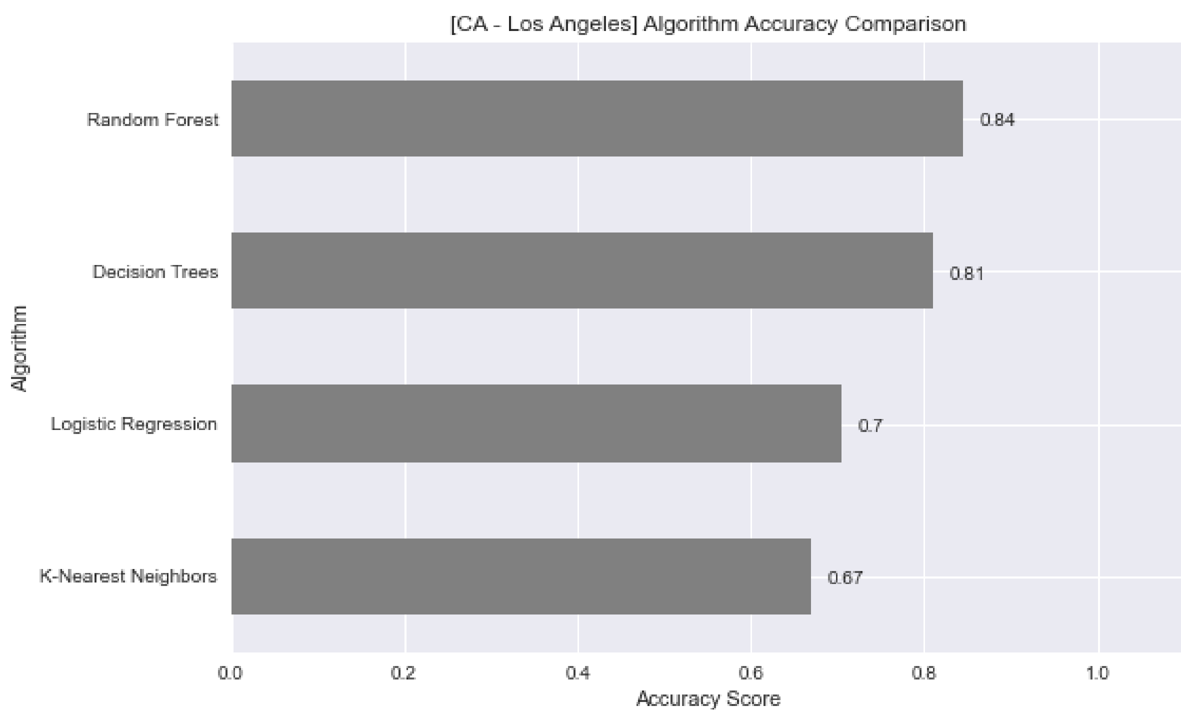
Out[58]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=-1, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

In [59]:
```
# Apply The Full Featured Classifier To The Test Data
y_pred = clf.predict(X_test)

# View The Accuracy Of Our Full Feature Model
print('[Randon forest algorithm -- Full feature] accuracy_score: {:.3f}.'.format(accuracy_score(y_test, y_pred)))

# Apply The Full Featured Classifier To The Test Data
y_important_pred = clf_important.predict(X_important_test)

# View The Accuracy Of Our Limited Feature Model
print('[Randon forest algorithm -- Limited feature] accuracy_score: {:.3f}.'.format(accuracy_score(y_test, y_important_pred)))

# Get the accuracy score
acc = accuracy_score(y_test, y_important_pred)

# Append to the accuracy list
accuracy_lst.append(acc)
```

```
[Randon forest algorithm -- Full feature] accuracy_score: 0.832.
[Randon forest algorithm -- Limited feature] accuracy_score: 0.844.
```

Accuracy Score VS. Algorithm

In [60]:
```
# Generate a list of ticks for y-axis
y_ticks = np.arange(len(algo_lst))

# Combine the list of algorithms and list of accuracy scores into a dataframe, sort the value based on accuracy score
df_acc = pd.DataFrame(list(zip(algo_lst, accuracy_lst)), columns = ['Algorithm', 'Accuracy_Score']).sort_values(by = ['Accuracy_S

# Make a plot
ax = df_acc.plot.barh('Algorithm', 'Accuracy_Score', align = 'center', legend = False, color = '0.5')

# Add the data label on to the plot
for i in ax.patches:
    # get_width pulls left or right; get_y pushes up or down
    ax.text(i.get_width() + 0.02, i.get_y() + 0.2, str(round(i.get_width(), 2)), fontsize = 10)

# Set the limit, lables, ticks and title
plt.xlim(0, 1.1)
plt.xlabel('Accuracy Score')
plt.yticks(y_ticks, df_acc['Algorithm'], rotation = 0)
plt.title('[CA - Los Angeles] Algorithm Accuracy Comparison')
plt.show()
```



In [182]:
```python
state_info = df_forecast.State.unique()
print(sorted(state_info))
```

```
['AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'IA', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA', 'MD', 'ME', 'MI',
'MN', 'MO', 'MS', 'MT', 'NC', 'ND', 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'RI', 'SC', 'SD', 'TN', 'TX', 'U
T', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY']
```

Accident Prediction

In [2]:
```python
# df_sel.to_csv('C:/Users/AS/Downloads/data/US_Accidents_forecast.csv', index = False, index_label = None)
import datetime
from sklearn import preprocessing
from sklearn.linear_model import LinearRegression
import itertools
```

In [3]:
```python
df_forecast = pd.read_csv('C:/Users/AS/Downloads/data/US_Accidents_forecast.csv')
# df_forecast.head()
```

In [4]:
```python
# Set the list of features to include in Machine Learning
feature_lst_2=['Start_Time','Severity','Start_Lng','Start_Lat','Distance(mi)','Side','State','Temperature(F)','Humidity(%)',
               'Pressure(in)','Visibility(mi)','Wind_Speed(mph)','Weather_Condition','Traffic_Signal','Hour','Weekday']
```

In [65]:
```python
# Select the dataset to include only the selected features
df_forecast = df_forecast[feature_lst_2].copy()
df_forecast['Count'] = 1
# df_forecast.head()
```

In [66]:
```python
df_forecast.Timestamp = pd.to_datetime(df_forecast.Start_Time, format='%Y-%m-%d %H:%M:%S')
```

In [67]:
```python
df_forecast['Start_Time_date'] = pd.DatetimeIndex(df_forecast.Timestamp).date
# df_forecast.head()
```

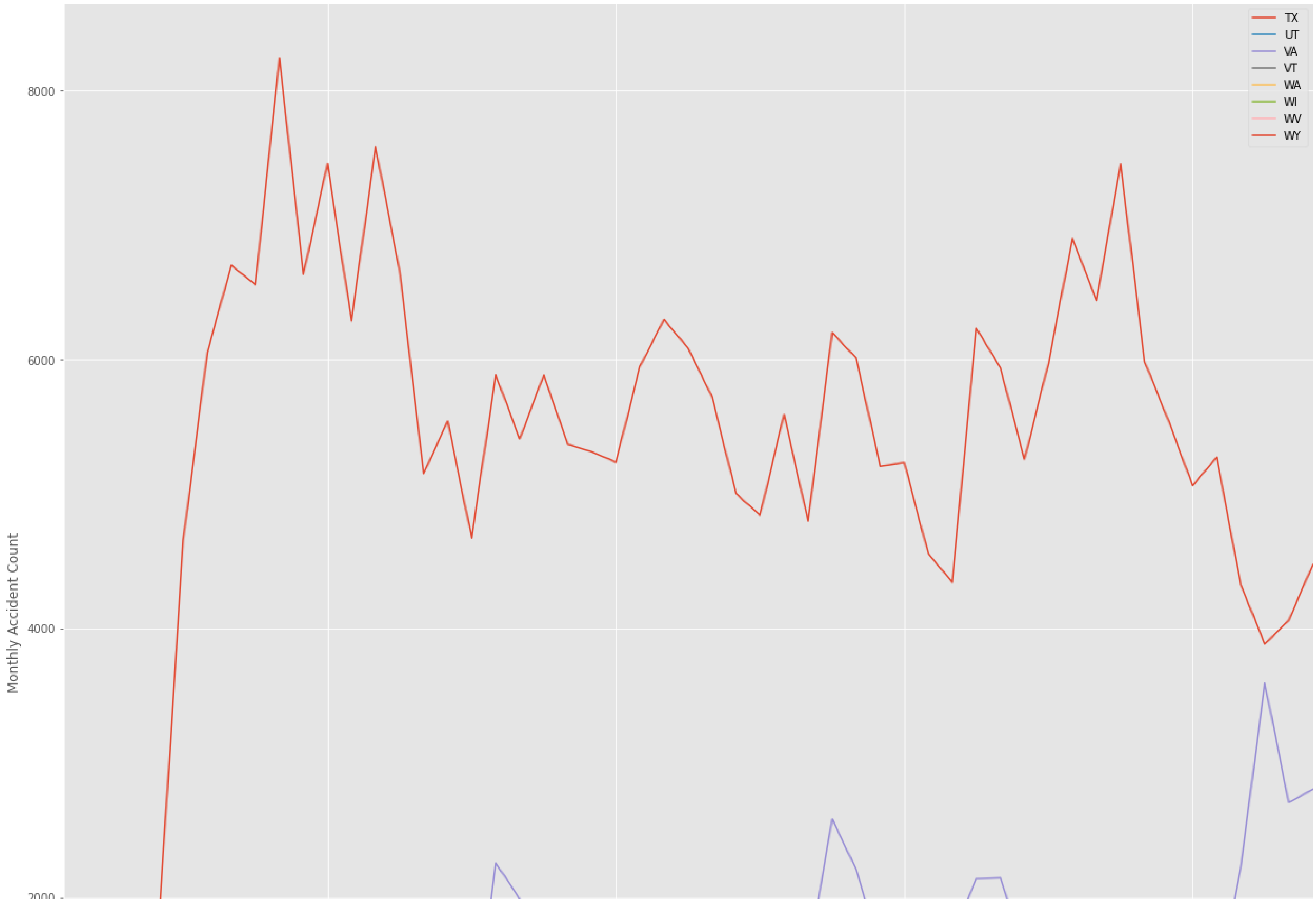
In [68]:

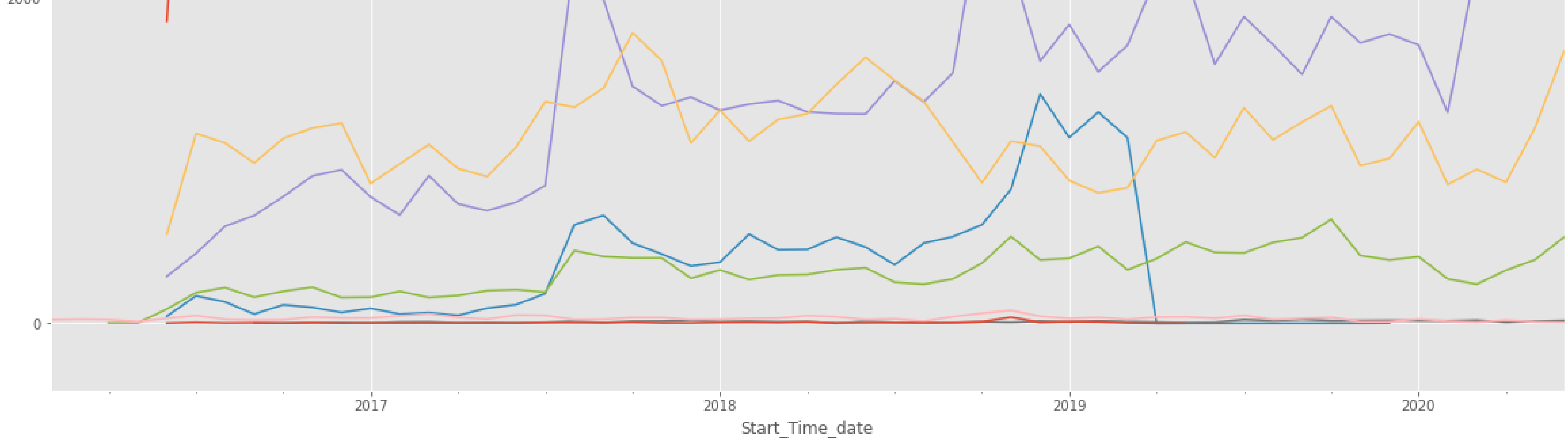
```
df_forecast_1 = df_forecast[['Start_Time_date','State']].copy()
df_forecast_1['Count'] = 1
df_forecast_1['Start_Time_date'] = pd.to_datetime(df_forecast_1.Start_Time_date, format='%Y-%m-%d')
df_forecast_1.groupby(['Start_Time_date']).count()
# df_forecast_1
```

Out[68]:

	State	Count
Start_Time_date		
2016-02-08	45	45
2016-02-09	29	29
2016-02-10	26	26
2016-02-11	71	71
2016-02-12	8	8
...	...	...
2020-06-26	4033	4033
2020-06-27	1760	1760
2020-06-28	1493	1493
2020-06-29	2134	2134
2020-06-30	1195	1195

In [55]:
```python
state_list = ['TX', 'UT', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY']
fig, ax = plt.subplots(figsize=(20, 20))
ax.set_ylabel('Monthly Accident Count')

# for item in df_forecast_1.State.unique():
for item in state_list:
    df_temp = df_forecast_1[df_forecast_1['State'] == item]
    df_temp.rename(columns={'Count':str(item)},inplace=True)
    df_temp.groupby(pd.Grouper(key='Start_Time_date', freq='1M')).sum().plot(ax = ax)
```





In [10]:

```
# Select TX to build a forecast model
df_tx_fc = df_forecast.loc[df_forecast.State == 'TX'].copy()
df_tx_fc.drop('State', axis = 1, inplace = True)
df_tx_fc.drop('Start_Time', axis = 1, inplace = True)
df_tx_fc['Start_Time_date'] = pd.to_datetime(df_tx_fc.Start_Time_date, format='%Y-%m-%d')
df_tx_fc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 275742 entries, 198647 to 2774776
Data columns (total 15 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Severity           275742 non-null  int64
 1   Start_Lng          275742 non-null  float64
 2   Start_Lat          275742 non-null  float64
 3   Distance(mi)       275742 non-null  float64
 4   Side               275742 non-null  object
 5   Temperature(F)     275742 non-null  float64
 6   Humidity(%)        275742 non-null  float64
 7   Pressure(in)       275742 non-null  float64
 8   Visibility(mi)     275742 non-null  float64
 9   Wind_Speed(mph)    275742 non-null  float64
 10  Weather_Condition  275742 non-null  object
 11  Traffic_Signal     275742 non-null  int64
 12  Hour               275742 non-null  int64
 13  Weekday            275742 non-null  object
 14  Start_Time_date    275742 non-null  datetime64[ns]
dtypes: datetime64[ns](1), float64(8), int64(3), object(3)
memory usage: 33.7+ MB
```

In [11]:
```
df_tx_fc.sort_values('Start_Time_date', inplace=True)
df_tx_fc
```

Out[11]:

	Severity	Start_Lng	Start_Lat	Distance(mi)	Side	Temperature(F)	Humidity(%)	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	Weather_Condition	Tra
231555	2	-96.683105	32.871536	0.0	L	88.0	61.0	29.78	10.0	8.1	Scattered Clouds	
231557	2	-95.365791	29.757492	0.0	L	86.0	66.0	29.84	8.0	9.2	Clear	
231556	2	-95.368080	29.821486	0.0	L	84.2	70.0	29.84	8.0	9.2	Clear	
231554	2	-96.719559	32.860638	0.0	R	90.0	57.0	29.77	10.0	10.4	Partly Cloudy	
231553	2	-97.703049	30.335411	0.0	L	89.1	61.0	29.80	10.0	5.8	Clear	
...	...	...	...	...	...	...	...	...	...	...	...	
442931	2	-97.019234	32.837791	0.0	R	93.0	52.0	29.13	10.0	18.0	Partly Cloudy	
442930	3	-97.023819	32.675663	0.0	R	91.0	49.0	29.19	7.0	18.0	Fair	
442925	2	-97.662491	30.451880	0.0	R	82.0	74.0	29.26	5.0	16.0	Mostly Cloudy	
442922	2	-97.764374	30.197924	0.0	R	86.0	70.0	29.32	9.0	16.0	Cloudy	
442928	2	-97.062920	32.705818	0.0	R	91.0	49.0	29.20	7.0	10.0	Fair	

275742 rows × 15 columns

In [12]:
```
df_tx_fc['Count'] = 1
df_tx_fc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 275742 entries, 231555 to 442928
Data columns (total 16 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Severity           275742 non-null  int64
 1   Start_Lng          275742 non-null  float64
 2   Start_Lat          275742 non-null  float64
 3   Distance(mi)       275742 non-null  float64
 4   Side               275742 non-null  object
 5   Temperature(F)     275742 non-null  float64
 6   Humidity(%)        275742 non-null  float64
 7   Pressure(in)       275742 non-null  float64
 8   Visibility(mi)     275742 non-null  float64
 9   Wind_Speed(mph)    275742 non-null  float64
 10  Weather_Condition  275742 non-null  object
 11  Traffic_Signal     275742 non-null  int64
 12  Hour               275742 non-null  int64
 13  Weekday            275742 non-null  object
```

In [13]:
```
df_tx_fc1 = df_tx_fc.groupby(pd.Grouper(key='Start_Time_date', freq='1M')).sum()
df_tx_fc1
```

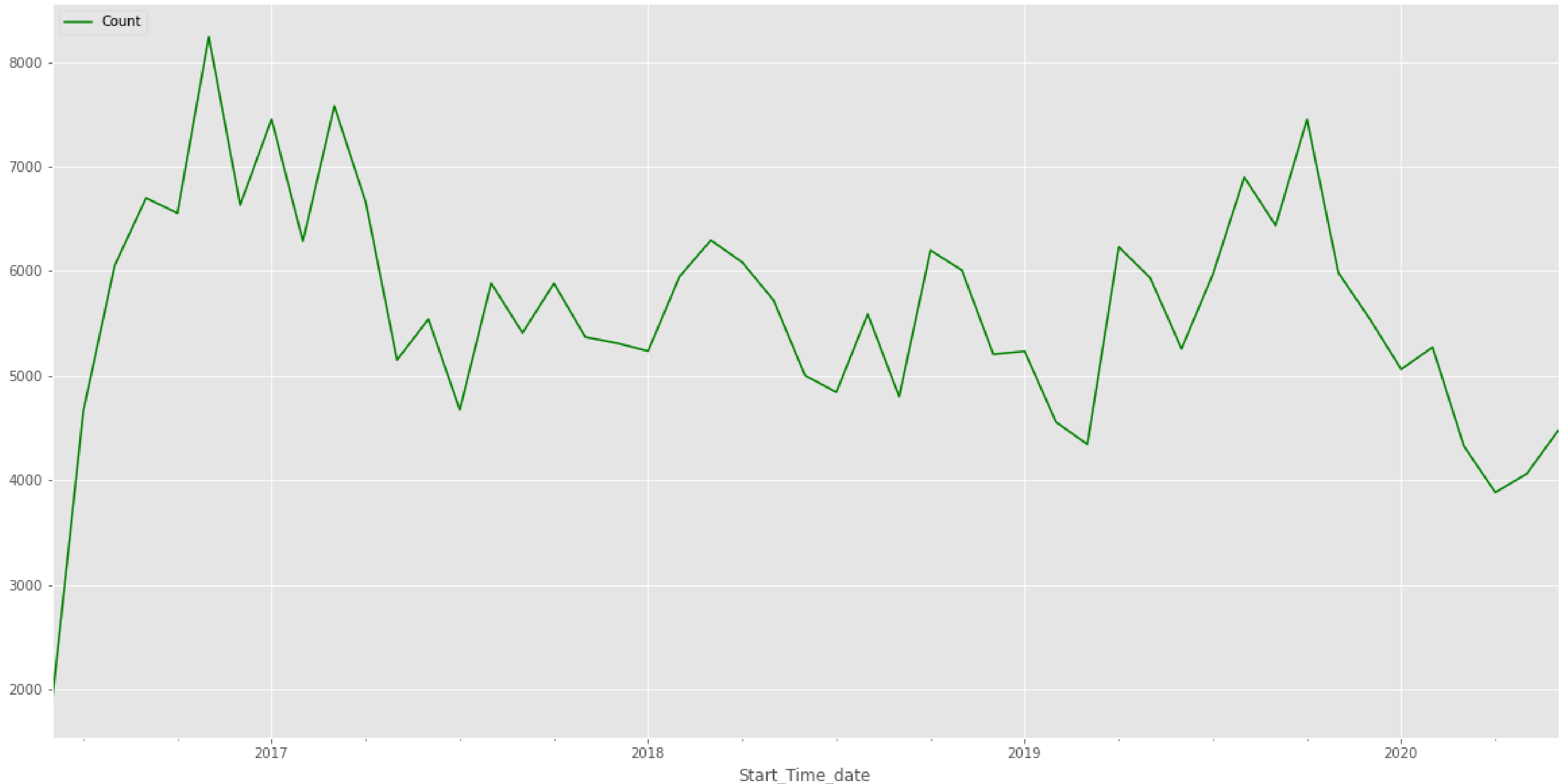
Out[13]:

Start_Time_date	Severity	Start_Lng	Start_Lat	Distance(mi)	Temperature(F)	Humidity(%)	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	Traffic_S
2016-06-30	4200	-179769.760496	57617.859417	251.633000	162391.2	108563.0	55605.81	18563.1	14784.0	
2016-07-31	10650	-451456.925907	144782.093067	540.664000	414800.6	270021.0	139507.67	46017.2	43350.3	
2016-08-31	13684	-586298.326588	187467.647806	603.612000	518994.4	398374.0	181348.01	58409.5	46042.7	
2016-09-30	15112	-648302.307555	208008.675026	545.065000	559928.4	415543.0	200994.88	66161.7	51391.4	
2016-10-31	14860	-633743.326597	203825.842013	703.822000	511423.4	410996.0	196774.87	64831.1	55838.3	
2016-11-30	18516	-795151.356745	253778.596462	840.288000	565817.6	541801.0	247830.65	77742.7	70241.4	
2016-12-31	15001	-640102.398722	204790.210395	834.163000	367624.8	428449.0	200023.33	59819.1	58529.9	
2017-01-31	16701	-718865.523473	229363.018255	895.353000	440702.3	465785.0	224082.36	68652.0	72001.9	
2017-02-28	14355	-606759.521289	194001.472619	796.267000	407486.9	391092.0	188517.48	58441.1	63525.6	
2017-03-31	17121	-732300.162025	234157.195799	798.718000	521719.4	464264.0	227971.70	70428.3	78208.4	

In [14]:
```
df_tx_fc1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 49 entries, 2016-06-30 to 2020-06-30
Freq: M
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Severity         49 non-null     int64
 1   Start_Lng        49 non-null     float64
 2   Start_Lat        49 non-null     float64
 3   Distance(mi)     49 non-null     float64
 4   Temperature(F)   49 non-null     float64
 5   Humidity(%)      49 non-null     float64
 6   Pressure(in)     49 non-null     float64
 7   Visibility(mi)   49 non-null     float64
 8   Wind_Speed(mph)  49 non-null     float64
 9   Traffic_Signal   49 non-null     int64
 10  Hour             49 non-null     int64
 11  Count            49 non-null     int64
dtypes: float64(8), int64(4)
memory usage: 5.0 KB
```

In [15]:
```
df_tx_fc1['Count'].plot(figsize=(20,10), color='g')
plt.legend(loc='upper left')
plt.show()
```



In [16]:
```
forecast = 10
df_tx_fc1['Prediction'] = df_tx_fc1[['Count']].shift(-forecast)
X = np.array(df_tx_fc1.drop(['Prediction'], 1))
X = preprocessing.scale(X)
X_forecast = X[-forecast:]
X = X[:-forecast]
y = np.array(df_tx_fc1['Prediction'])
y = y[:-forecast]
```

In [19]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 9) #34666

clf = LinearRegression()
clf.fit(X_train, y_train)
confidence = clf.score(X_test, y_test)
confidence
```

Out[19]:
```
-3.514460093114899
```

In [20]:
```
y_test.shape
```

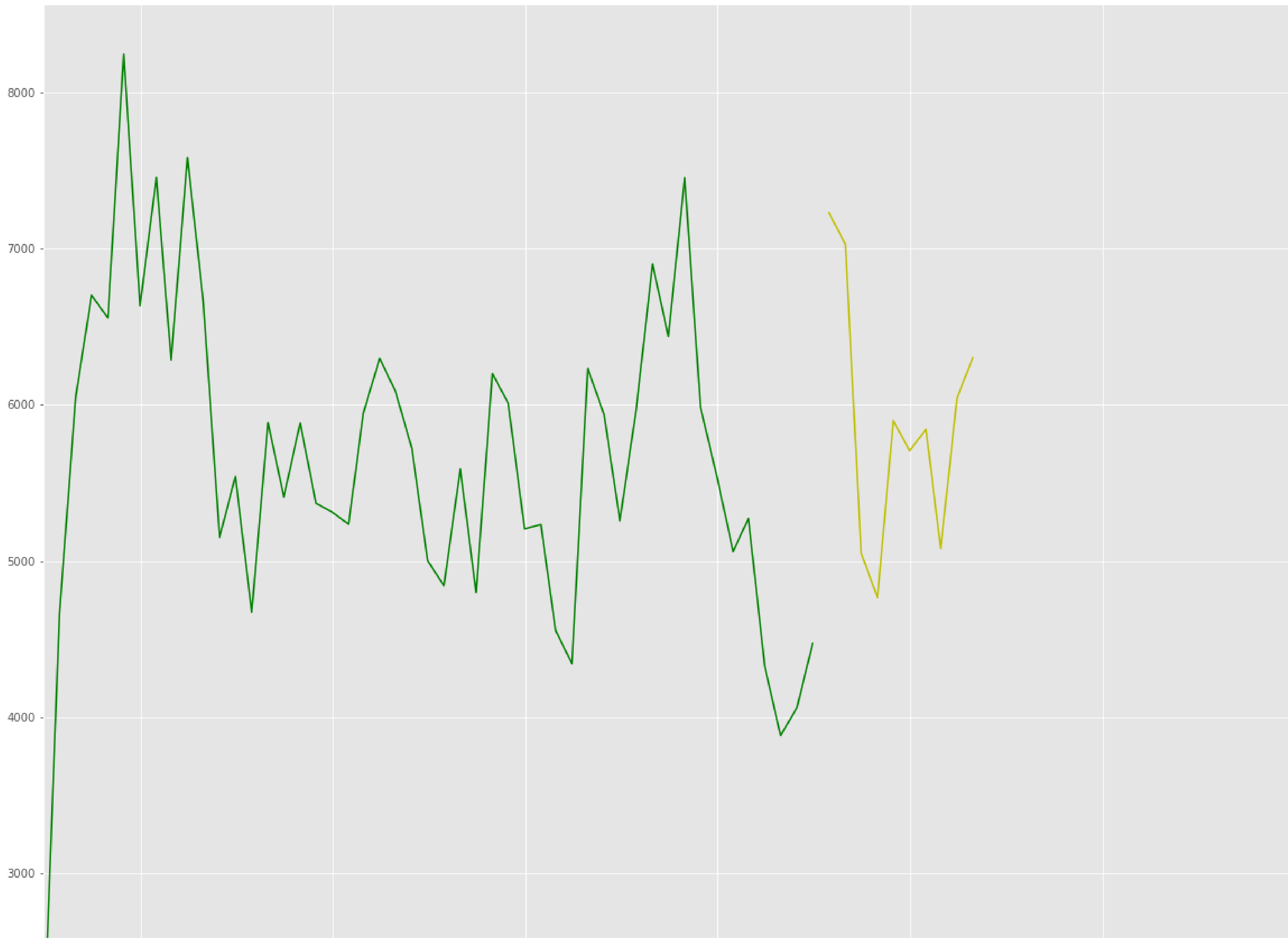
Out[20]:
```
(10,)
```

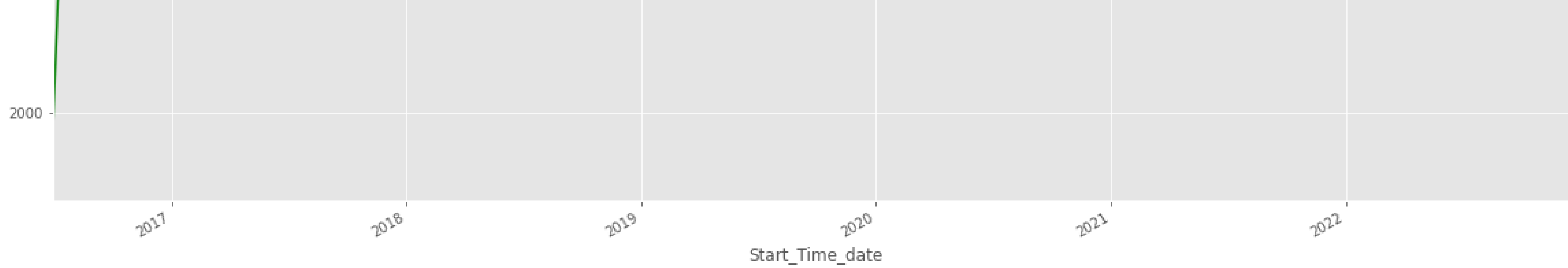
In [21]:
```
forecast_predicted = clf.predict(X_test).round()
print(forecast_predicted)
```

```
[7227. 7027. 5050. 4765. 5897. 5706. 5842. 5079. 6043. 6301.]
```

In [22]:
```
fig, ax = plt.subplots(figsize=(20, 20))
monthes = pd.date_range(start = "2020-07-31", end = "2021-04-30", freq='1M')
plt.plot(monthes, forecast_predicted, color = 'y')
df_tx_fc1['Count'].plot(color = 'g')
plt.xlim(xmin = datetime.date(2016, 6, 30), xmax = datetime.date(2022, 12, 31))
```

Out[22]:
```
(16982.0, 19357.0)
```





Time Series Forecasting For Road Accidents in one specific State

Auto Regressive Integrated Moving Average (ARIMA) model

In [8]:
```python
from pylab import rcParams
import statsmodels.api as sm
```

In [367]:
```python
# Check out the Data for a specific State
df_fc_spe = df_forecast.loc[df_forecast.State == 'CA'].copy()
df_fc_spe.head()
```

Out[367]:

	Start_Time	Severity	Start_Lng	Start_Lat	Distance(mi)	Side	State	Temperature(F)	Humidity(%)	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	W
1963360	2016-03-22 21:40:18	2	-122.307788	37.881038	0.17	R	CA	55.0	67.0	30.26	10.0	8.1	
71541	2016-03-22 22:17:27	2	-118.186256	34.028297	0.00	L	CA	62.1	30.0	30.01	10.0	8.1	
71539	2016-03-22 22:09:58	3	-118.418961	34.031689	0.01	R	CA	62.1	28.0	30.04	10.0	8.1	
71537	2016-03-22 20:27:30	2	-117.196167	33.148216	0.01	R	CA	59.0	72.0	30.03	10.0	3.5	
71540	2016-03-22 22:07:02	2	-118.242271	34.155743	0.01	R	CA	62.1	30.0	30.01	10.0	8.1	

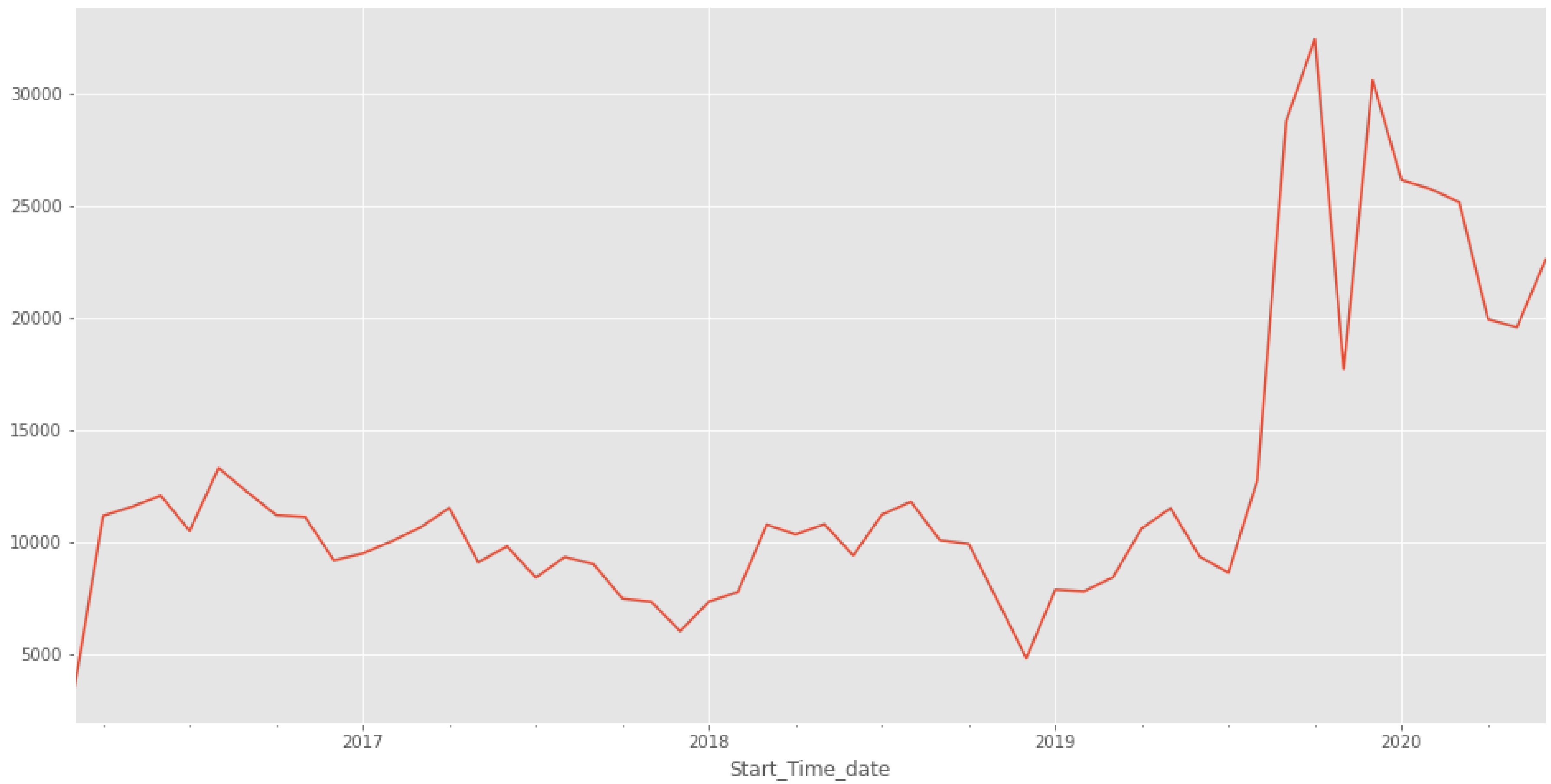
In [368]:
```
# Set the Date for index
df_fc_spe['Start_Time_date'] = pd.to_datetime(df_fc_spe.Start_Time_date, format='%Y-%m-%d')
acc_spec = df_fc_spe.set_index('Start_Time_date')
acc_spec.index
```

Out[368]:
```
DatetimeIndex(['2016-03-22', '2016-03-22', '2016-03-22', '2016-03-22',
               '2016-03-22', '2016-03-22', '2016-03-22', '2016-03-22',
               '2016-03-22', '2016-03-22',
               ...
               '2020-06-30', '2020-06-30', '2020-06-30', '2020-06-30',
               '2020-06-30', '2020-06-30', '2020-06-30', '2020-06-30',
               '2020-06-30', '2020-06-30'],
              dtype='datetime64[ns]', name='Start_Time_date', length=650415, freq=None)
```

In [369]:
```
y_spec = acc_spec['Count'].resample('M').sum()
```

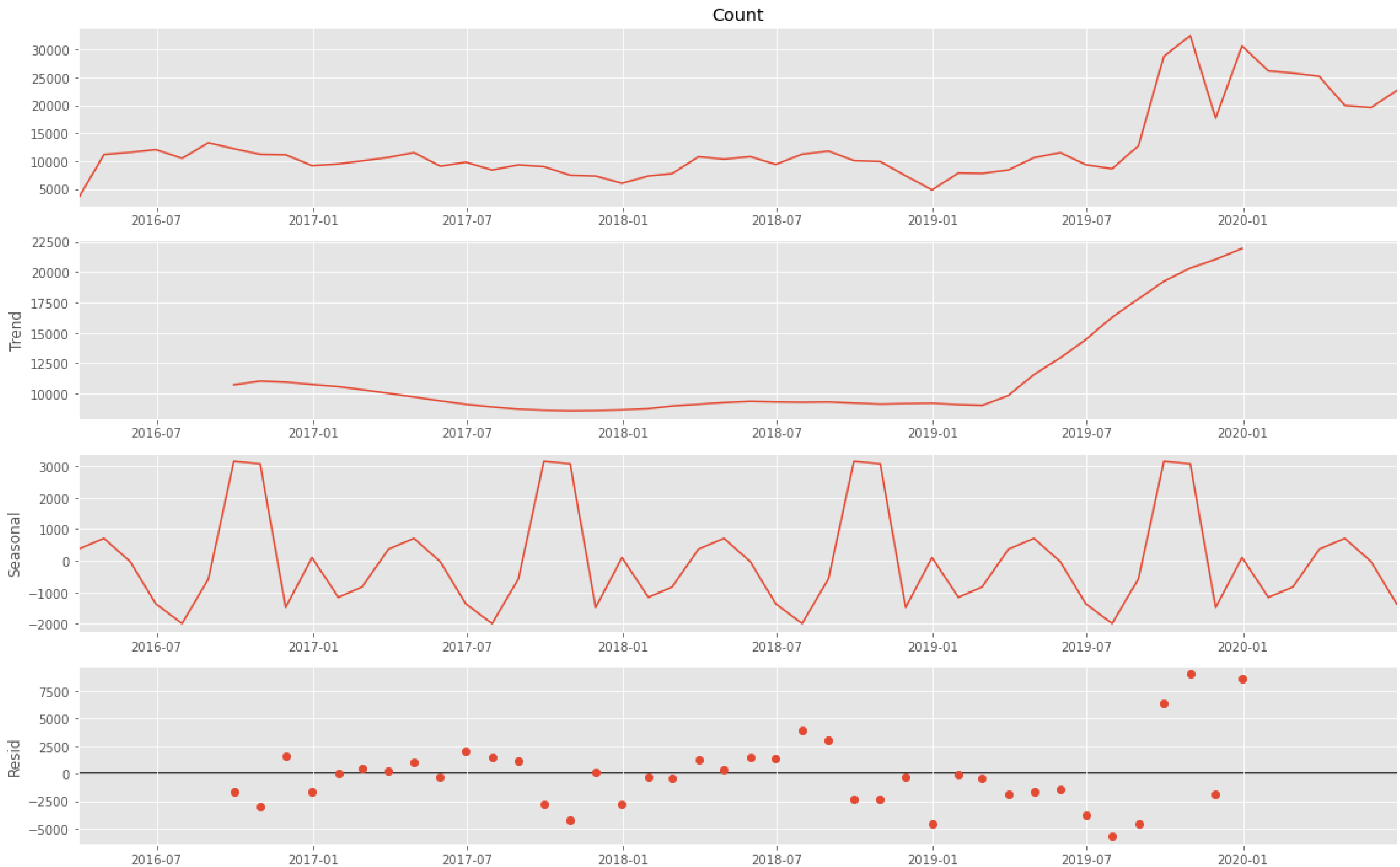
In [370]:
```
rn_spec = np.where(y_spec.index == '2019-12-31')
n = int(rn_spec[0]) + 1
```

```
In [371]: y_spec.plot(figsize=(16, 8))
          plt.show()
```



In [373]:

```
# visualise the data using time-series decomposition which decompose time series into three distinct components:
# trend, seasonality, and noise.
rcParams['figure.figsize'] = 16, 10
decomposition = sm.tsa.seasonal_decompose(y_spec, model='additive')
fig = decomposition.plot()
plt.show()
```



In [24]:
```
# Parameter combinations for seasonal ARIMA
p = d = q = range(0, 2)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]
# print('Examples of parameter combinations for Seasonal ARIMA...')
# print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
# print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[2]))
# print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[3]))
# print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[4]))
```

In [377]:

```python
# use a “grid search” to find the optimal set of parameters that yields the best performance for ARIMA model
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(y_spec[:n],
                                            order = param,
                                            seasonal_order = param_seasonal,
                                            enforce_stationarity = False,
                                            enforce_invertibility = False)
            results = mod.fit()
            print('ARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, results.aic))

        except:
            continue
```

```
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:979.4273732610349
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:1365.5727695260152
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:682.9871031272089
ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:444.90524281681127
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:704.7926489651738
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:1367.6904076447106
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:465.68332435176467
ARIMA(0, 0, 0)x(1, 1, 1, 12)12 - AIC:441.4333327812981
ARIMA(0, 0, 1)x(0, 0, 0, 12)12 - AIC:932.3783544649402
ARIMA(0, 0, 1)x(0, 0, 1, 12)12 - AIC:3827.6458355236273
ARIMA(0, 0, 1)x(0, 1, 0, 12)12 - AIC:652.407333493177
ARIMA(0, 0, 1)x(0, 1, 1, 12)12 - AIC:417.5398967809095
ARIMA(0, 0, 1)x(1, 0, 0, 12)12 - AIC:689.5481512815007
ARIMA(0, 0, 1)x(1, 0, 1, 12)12 - AIC:3539.145187675308
ARIMA(0, 0, 1)x(1, 1, 0, 12)12 - AIC:457.1584276451849
ARIMA(0, 0, 1)x(1, 1, 1, 12)12 - AIC:419.5377203858947
ARIMA(0, 1, 0)x(0, 0, 0, 12)12 - AIC:860.0212165535962
ARIMA(0, 1, 0)x(0, 0, 1, 12)12 - AIC:1270.5687945583882
ARIMA(0, 1, 0)x(0, 1, 0, 12)12 - AIC:638.343520325064
```

TX: ARIMA(0, 1, 1)x(0, 1, 1, 12) yields the lowest AIC 366.44. CA: ARIMA(1, 1, 0)x(1, 1, 0, 12) yields the lowest AIC 529.57.

In [378]:

```python
# Fitting the ARIMA Model
mod = sm.tsa.statespace.SARIMAX(y_spec[:n],
                                order = (0,1,1),
                                seasonal_order = (0,1,1,12),
                                enforce_stationarity = False,
                                enforce_invertibility = False)
results = mod.fit()
# print(results.summary().tables[1])
```

```
In [379]: pred = results.get_prediction(start = pd.to_datetime('2020-01-31'), dynamic = False)
          pred_ci = pred.conf_int()
          ax = y_spec['2016':].plot(label = 'observed')
          pred.predicted_mean.plot(ax = ax,
                                   label = 'Accident Forecast',
                                   alpha = .7,
                                   figsize = (14, 7))
          ax.fill_between(pred_ci.index,
                          pred_ci.iloc[:, 0],
                          pred_ci.iloc[:, 1], color = 'k', alpha = .2)
          ax.set_xlabel('Date')
          ax.set_ylabel('Monthly Accident Count')
          plt.legend()
          plt.show()
```

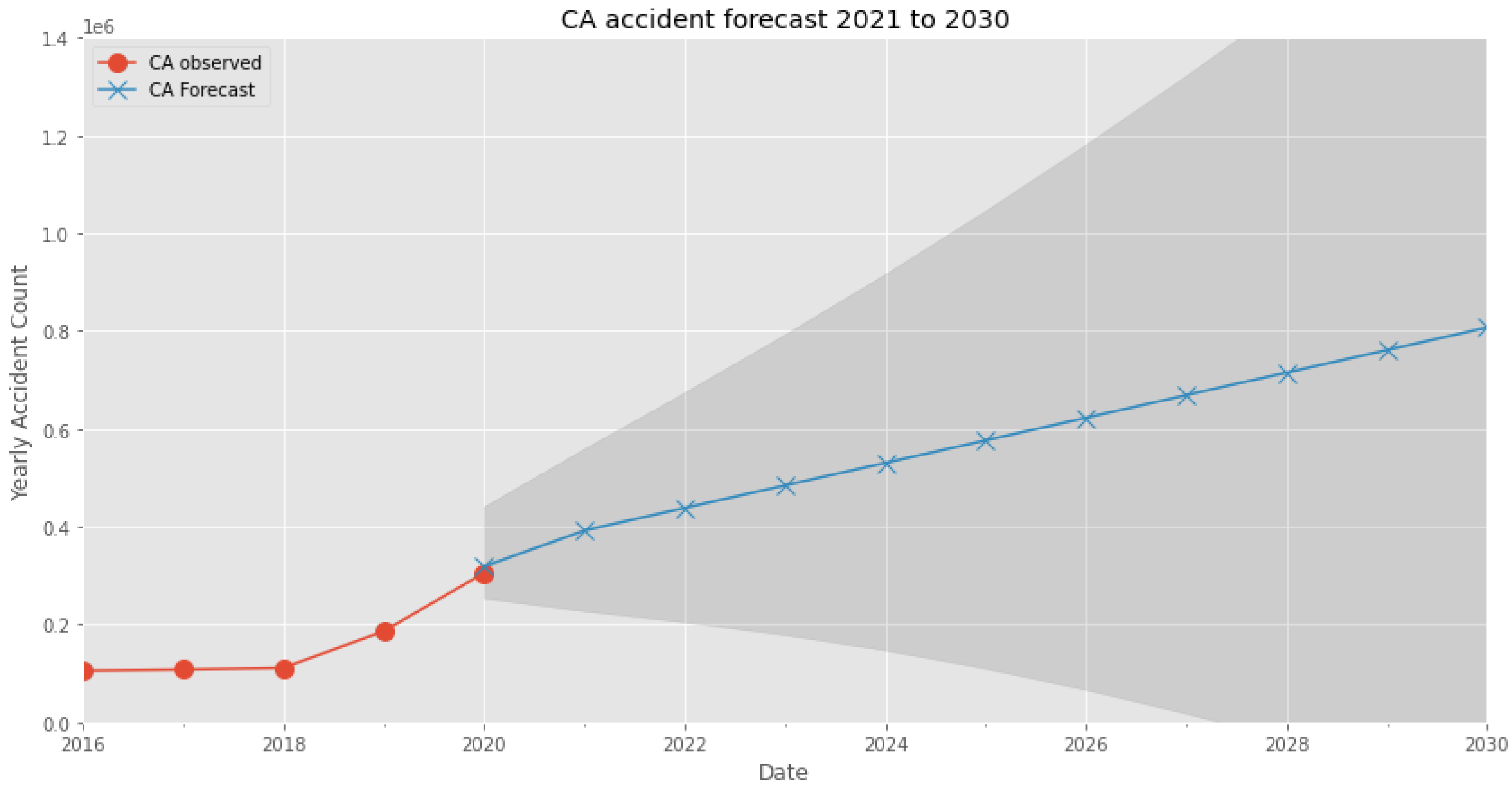
```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-379-6682faf61933> in <module>
      8 ax.fill_between(pred_ci.index,
      9                 pred_ci.iloc[:, 0],
---> 10                 pred_ci.iloc[:, 1], color = 'k', alpha = .2)
     11 ax.set_xlabel('Date')
     12 ax.set_ylabel('Monthly Accident Count')

~\Anaconda3\lib\site-packages\matplotlib\__init__.py in inner(ax, data, *args, **kwargs)
   1436     def inner(ax, *args, data=None, **kwargs):
   1437         if data is None:
-> 1438             return func(ax, *map(sanitize_sequence, args), **kwargs)
   1439
   1440         bound = new_sig.bind(ax, *args, **kwargs)

~\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py in fill_between(self, x, y1, y2, where, interpolate, step, **kwargs)
   5301         return self._fill_between_x_or_y(
   5302             "x", x, y1, y2,
-> 5303             where=where, interpolate=interpolate, step=step, **kwargs)
   5304
   5305     if _fill_between_x_or_y.__doc__:

~\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py in _fill_between_x_or_y(self, ind_dir, ind, dep1, dep2, where, interpolat
e, step, **kwargs)
   5288
   5289         # now update the datalim and autoscale
-> 5290         pts = np.row_stack([np.column_stack([ind[where], dep1[where]]),
   5291                             np.column_stack([ind[where], dep2[where]])])
   5292         if ind_dir == "y":

<__array_function__ internals> in column_stack(*args, **kwargs)
```

```
~\Anaconda3\lib\site-packages\numpy\lib\shape_base.py in column_stack(tup)
    654             arr = array(arr, copy=False, subok=True, ndmin=2).T
    655         arrays.append(arr)
--> 656     return _nx.concatenate(arrays, 1)
    657 
    658 

<__array_function__ internals> in concatenate(*args, **kwargs)

TypeError: invalid type promotion
```

In [380]:
```python
# Use mean squared error (MSE) to check the accuracy of this model
y_forecasted = pred.predicted_mean
y_truth = y_spec['2020-01-01':]
mse = ((y_forecasted - y_truth) ** 2).mean()
print('The Mean Squared Error of the forecasts is {}'.format(round(mse, 2)))
```

```
The Mean Squared Error of the forecasts is 636637.42
```

In [389]:
```
# Visualising the number of road accident in USA in next years
pred_uc = results.get_forecast(steps = 132)
pred_ci = pred_uc.conf_int(alpha = 0.5).resample('Y').sum()
pred_y_s = pd.concat([y_spec[-6:], pred_uc.predicted_mean[6:]]).round()
obse_y_s = pd.concat([y_spec, pred_uc.predicted_mean[:6]]).round()
ax = obse_y_s.resample('Y').sum().plot(label = 'CA observed', figsize = (14, 7), marker='o', markersize = 10)
pred_y_s.resample('Y').sum().plot(ax = ax, label = 'CA Forecast', marker='x', markersize = 10)
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.10)
ax.set_xlabel('Date')
ax.set_ylabel('Yearly Accident Count')
plt.title('CA accident forecast 2021 to 2030')
plt.legend(loc = 2)
plt.ylim(ymin = 0, ymax = 1400000)
plt.show()
```



Time Series Forecasting For Road Accidents in US and each state

In [357]:
```
# as_index=False
df_forecast['Count']=1
df_forecast['Start_Time_date'] = pd.to_datetime(df_forecast.Start_Time_date, format='%Y-%m-%d')
```

In [358]:
```
# forecasting for the US
# Set the Date for index
df_forecast.sort_values('Start_Time_date', inplace = True)
accident_US = df_forecast.set_index('Start_Time_date')
```

In [359]:
```
temp = df_forecast[['Start_Time_date', 'State','Count']].copy()
temp['Start_Time_date'] = pd.to_datetime(temp.Start_Time_date, format='%Y-%m-%d')
a = temp.groupby([pd.Grouper(key='Start_Time_date', freq='1M'),'State']).sum()
a
```

Out[359]:

		Count
Start_Time_date	**State**	
	IN	47
	KY	26
2016-02-29	**MI**	9
	OH	587
	PA	27
...	**...**	...
	VA	2802
	VT	16
2020-06-30	**WA**	1672
	WI	529
	WV	5

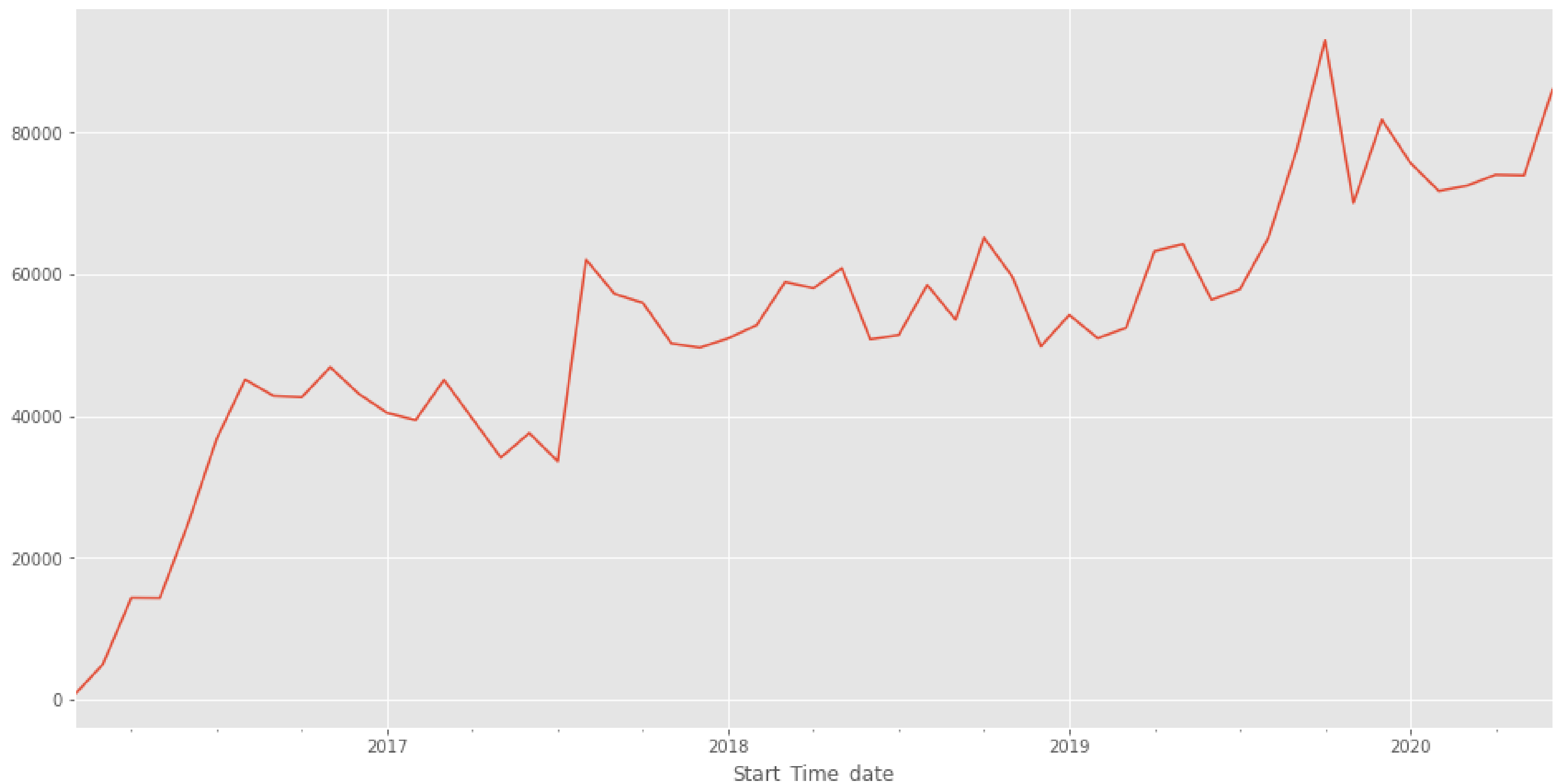
2316 rows × 1 columns

In [123]:
```python
# temp['Start_Time_date' == '2019-12-31']
# temp.State.unique().count()
# temp['Start_Time_date'=='2019-12-31']
print('2019-12-31' + '\n' + str(a.loc[('2019-12-31'),:].count()))
print('2020-1-31' + '\n' + str(a.loc[('2020-1-31'),:].count()))
print(a.loc[('2020-1-31'),:].count())
```

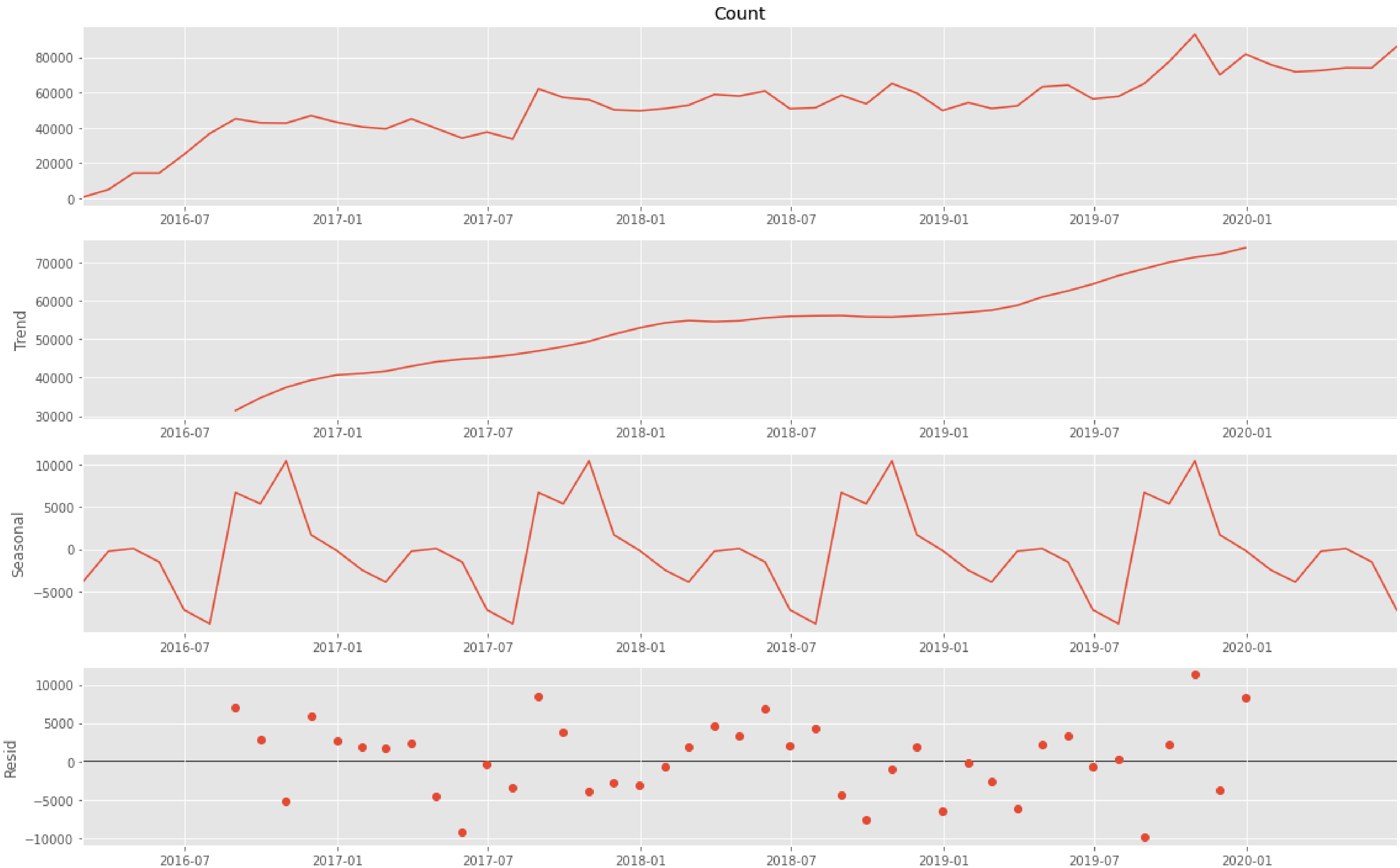
```
2019-12-31
Count    43
dtype: int64
Count    41
dtype: int64
```

In [360]:
```python
y = accident_US['Count'].resample('M').sum()
# y
```

In [361]:
```python
y.plot(figsize=(16, 8))
plt.show()
```



In [362]:
```
rcParams['figure.figsize'] = 16, 10
decomposition = sm.tsa.seasonal_decompose(y, model='additive')
fig = decomposition.plot()
plt.show()
```



In [101]:

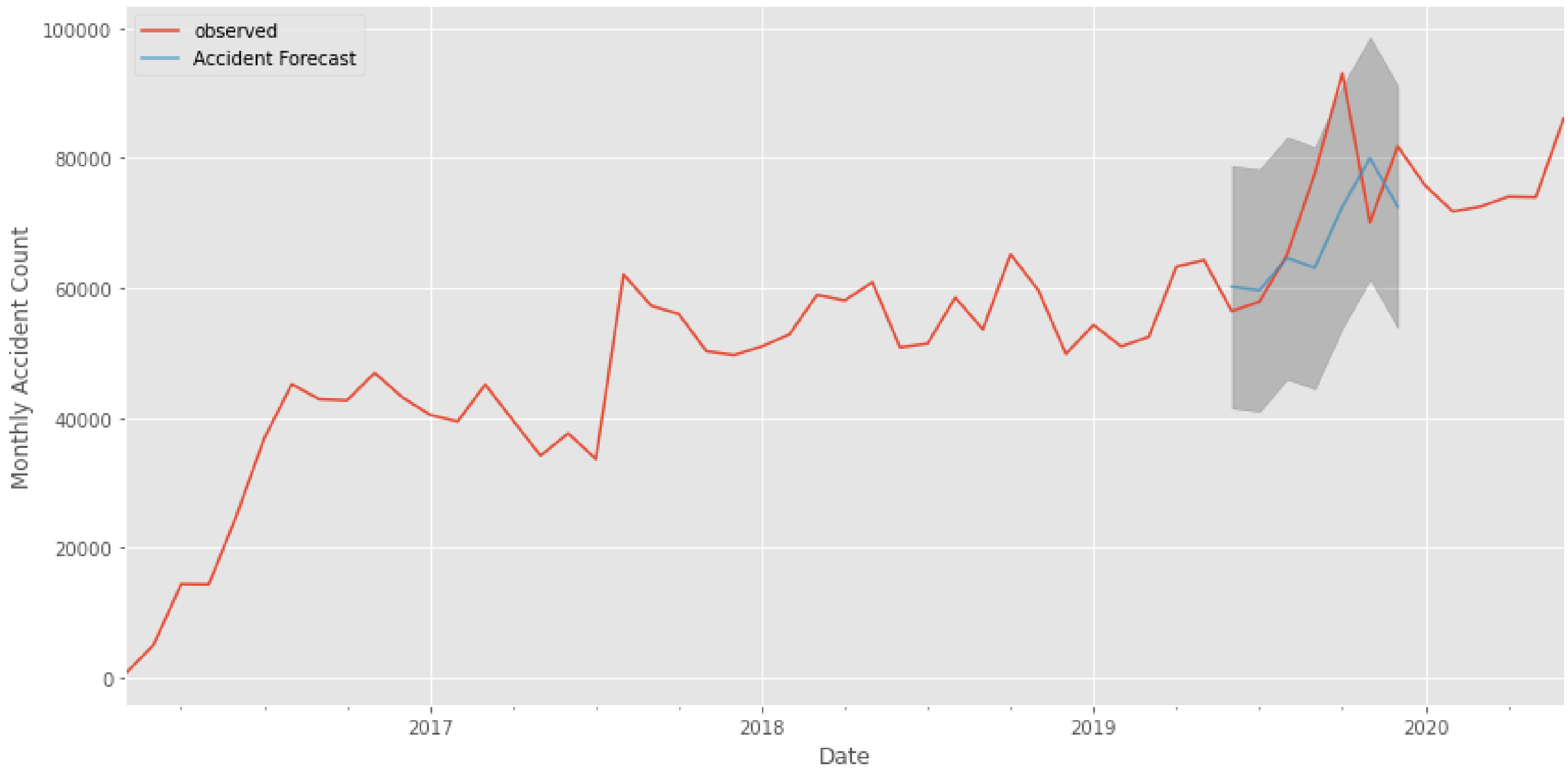
```python
# use a “grid search” to find the optimal set of parameters that yields the best performance for ARIMA model
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(y,
                                            order = param,
                                            seasonal_order = param_seasonal,
                                            enforce_stationarity = False,
                                            enforce_invertibility = False)
            results = mod.fit()
            print('ARIMA{}x{}12 - AIC:{}'.format(param, param_seasonal, results.aic))

        except:
            continue
```

```
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:1286.840593578298
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:980.0272023834661
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:892.6664979530045

C:\Users\AS\Anaconda3\lib\site-packages\statsmodels\base\model.py:568: ConvergenceWarning: Maximum Likelihood optimization fa
iled to converge. Check mle_retvals
  ConvergenceWarning)

ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:1355.1000686386908
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:901.1914822409857
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:878.0193453364288
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:641.7244497755037

C:\Users\AS\Anaconda3\lib\site-packages\statsmodels\base\model.py:568: ConvergenceWarning: Maximum Likelihood optimization fa
iled to converge. Check mle_retvals
  ConvergenceWarning)

ARIMA(0, 0, 0)x(1, 1, 1, 12)12 - AIC:1371.1817736160676
ARIMA(0, 0, 1)x(0, 0, 0, 12)12 - AIC:1231.321363796586
ARIMA(0, 0, 1)x(0, 0, 1, 12)12 - AIC:938.4144712541566
```

In [274]:
```python
# Fitting the ARIMA Model
mod = sm.tsa.statespace.SARIMAX(y[:47],
                                order = (0,1,1),
                                seasonal_order = (1,1,1,12),
                                enforce_stationarity = False,
                                enforce_invertibility = False)
results = mod.fit()
print(results.summary().tables[1])
```

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.5605      0.226     -2.483      0.013      -1.003      -0.118
ar.S.L12       0.1308      0.582      0.225      0.822      -1.010       1.271
ma.S.L12      -0.8725      0.447     -1.951      0.051      -1.749       0.004
sigma2      8.948e+07   2.79e-09    3.2e+16      0.000    8.95e+07    8.95e+07
==============================================================================
```

In [275]:
```
pred = results.get_prediction(start = pd.to_datetime('2019-06-30'), dynamic = False)
pred_ci = pred.conf_int()
ax = y['2016':].plot(label = 'observed')
pred.predicted_mean.plot(ax = ax,
                         label = 'Accident Forecast',
                         alpha = .7,
                         figsize = (14, 7))
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color = 'k', alpha = .2)
ax.set_xlabel('Date')
ax.set_ylabel('Monthly Accident Count')
plt.legend()
plt.show()
```



In [275]:
```python
# Use mean squared error (MSE) to check the accuracy of this model
y_forecasted = pred.predicted_mean#.resample('Y').sum()
y_truth = y['2020-01-01':]
mse = ((y_forecasted - y_truth) ** 2).mean()
print('The Mean Squared Error of the forecasts is {}'.format(round(mse, 2)))
```

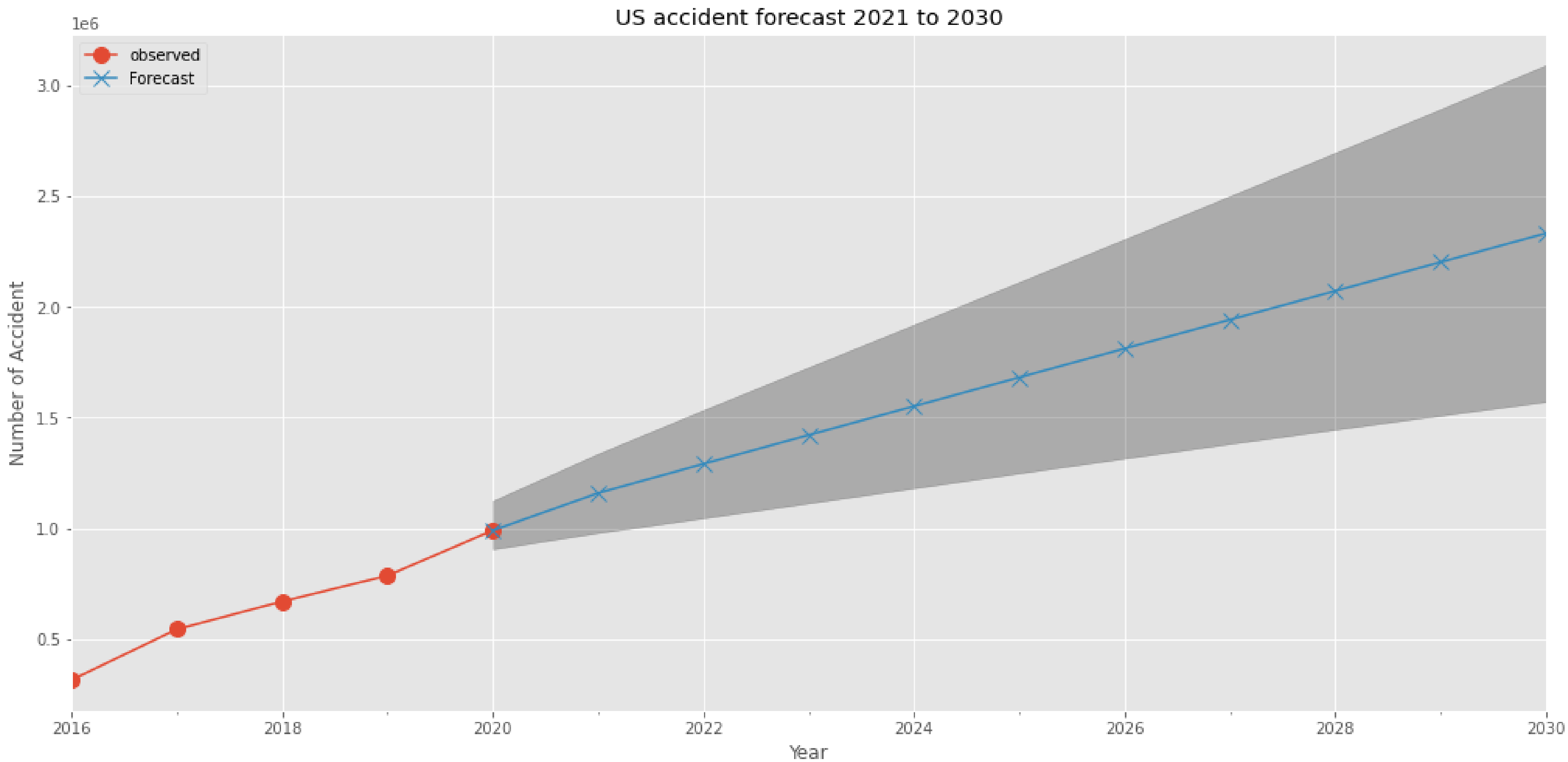
Out[275]:
```
Start_Time_date
2020-01-31    76496.227341
2020-02-29    76061.289314
2020-03-31    76459.065719
2020-04-30    77388.555615
2020-05-31    76541.792538
2020-06-30    74906.018021
Freq: M, Name: predicted_mean, dtype: float64
```

In [184]:
```python
# index_us = y[y.index == '2019-12-31'].index.tolist()
# row_number_us = np.where(y.index == '2019-12-31')[0].tolist()
# print(row_number_us)
y[-6:]
```

Out[184]:
```
Start_Time_date
2020-01-31    26157
2020-02-29    25754
2020-03-31    25166
2020-04-30    19933
2020-05-31    19573
2020-06-30    22619
Freq: M, Name: Count, dtype: int64
```

In [276]:

```
# Visualising the number of road accident in USA in next years
pred_uc = results.get_forecast(steps = 132)
pred_ci = pred_uc.conf_int(alpha = 0.5).resample('Y').sum()
pred_y = pd.concat([y[-6:], pred_uc.predicted_mean[6:]]).round() # add observed 2020 6 month to the beginning of prediction for y
obse_y = pd.concat([y, pred_uc.predicted_mean[6:12]]).round() # add predicted 2020 6 month to the end of observed for yearly coun
ax = obse_y.resample('Y').sum().plot(label = 'observed', figsize = (17, 8), marker='o', markersize = 10)
pred_y.resample('Y').sum().plot(ax = ax, label = 'Forecast', marker='x', markersize = 10)
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.25)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('US accident forecast 2021 to 2030')
plt.legend(loc = 2)
plt.show()
```



Forecast for all states

In [37]:
```
warnings.filterwarnings("ignore")
```

In [256]:
```
state_info = df_forecast.State.unique()
print(sorted(state_info))
```

```
['AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'IA', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA', 'MD', 'ME', 'MI',
'MN', 'MO', 'MS', 'MT', 'NC', 'ND', 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'RI', 'SC', 'SD', 'TN', 'TX', 'U
T', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY']
```

In [185]:
```python
state_list = ['AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'IA', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA', 'MD',
              'ME', 'MI', 'MN', 'MO', 'MS', 'MT', 'NC', 'ND', 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'RI',
              'SC', 'SD', 'TN', 'TX', 'UT', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY']

for item in state_list:

    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2020-06-30')[0].tolist()
    print('%s: '%item + '%s'%row_number)
```

```
AL: [48]
AR: [48]
AZ: [48]
CA: [51]
CO: []
CT: [51]
DC: [48]
DE: [51]
FL: [48]
GA: [48]
IA: [51]
ID: [48]
IL: [50]
IN: [52]
KS: [48]
KY: [52]
LA: [48]
MA: [51]
MD: [51]
```

state_manu = ['CO', 'MT', 'ND', 'NM', 'SD', 'UT', 'WY']

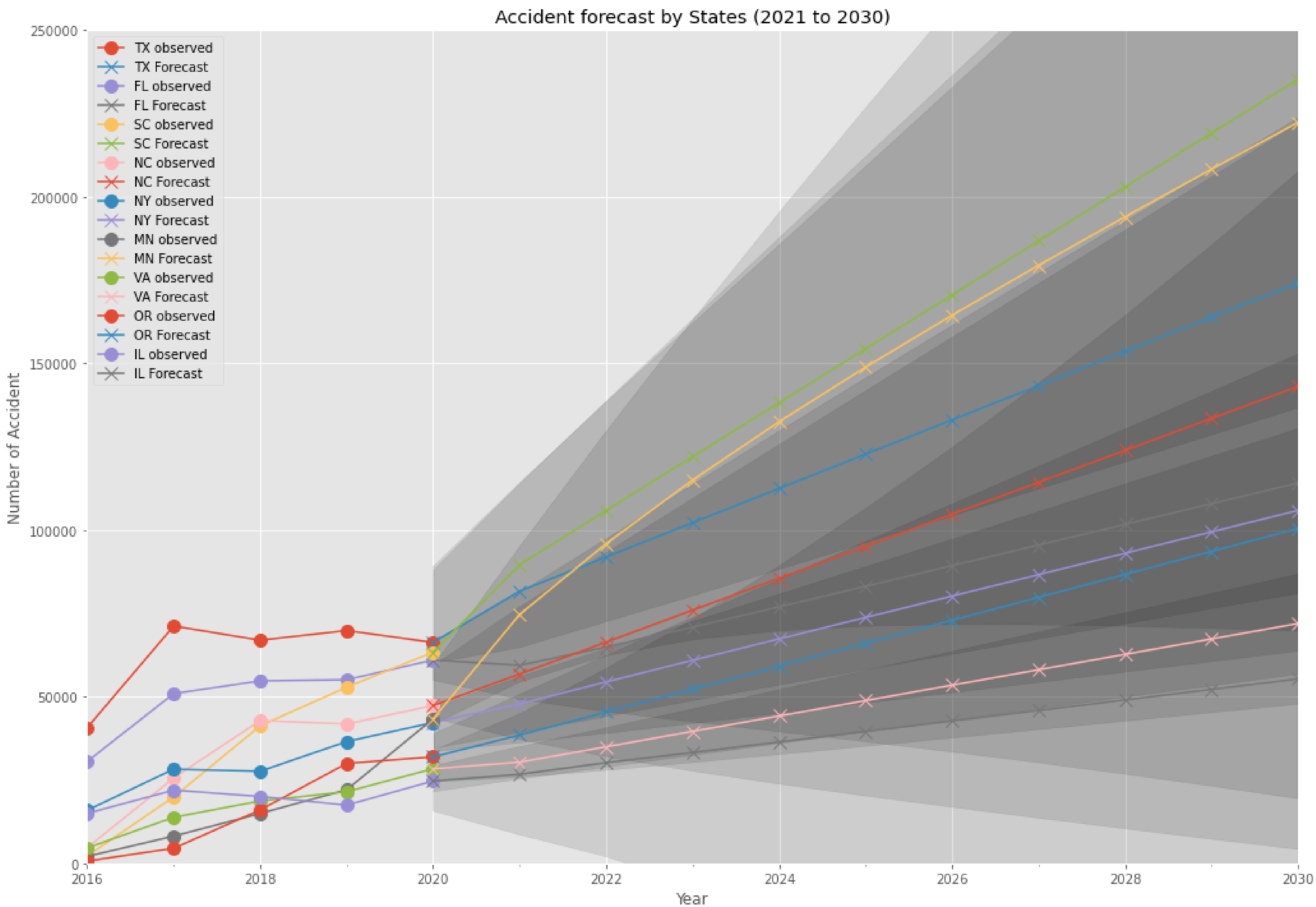
In [316]:
```
accident_US.State.value_counts().sort_values(ascending = False)
```

Out[316]:
```
CA    650415
TX    275742
FL    222472
SC    140687
NC    137023
NY    128063
IL     86061
MI     81875
PA     80408
GA     75293
VA     72860
OR     65230
MN     61626
TN     59079
WA     56593
AZ     55411
OH     54988
LA     53369
OK     52930
```

state_list_1 = ['CA', 'TX', 'FL', 'SC', 'NC', 'NY'] state_list_2 = ['IL', 'MI', 'PA', 'GA', 'VA', 'OR'] state_list_3 = ['MN', 'TN', 'WA', 'AZ', 'OH', 'LA'] state_list_4 = ['OK', 'NJ', 'AL', 'MD', 'MA', 'MO'] state_list_5 = ['IN', 'CT', 'NE', 'KY', 'WI', 'RI'] state_list_6 = ['IA', 'NH', 'MS', 'DE', 'NV', 'KS'] state_list_7 = ['DC', 'ME', 'WV', 'AR', 'ID', 'VT']

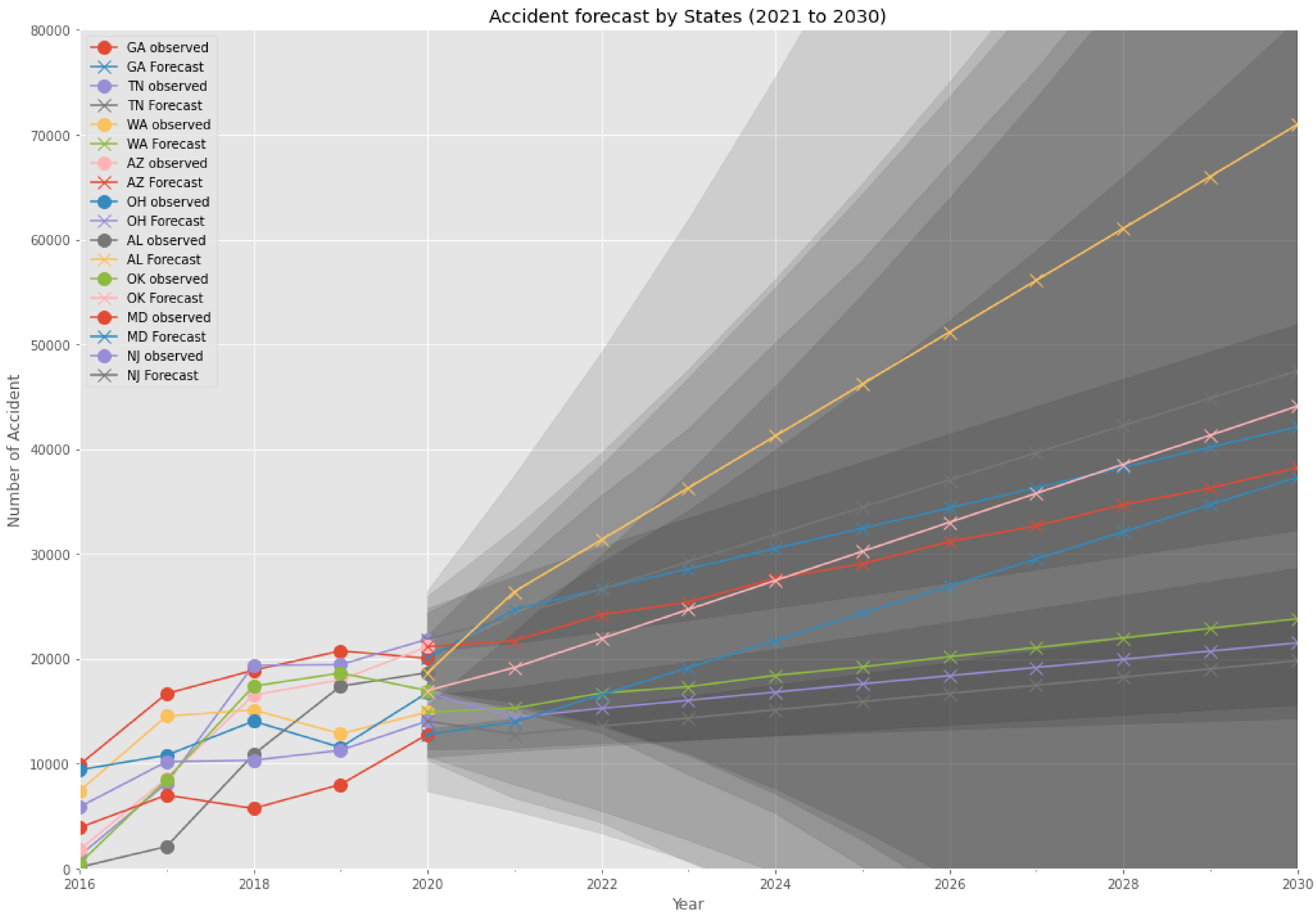
In [350]:
```
state_list_1 = ['TX', 'FL', 'SC', 'NC', 'NY', 'MN', 'VA', 'OR', 'IL']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 250000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_1:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = True,
                                                enforce_invertibility = True)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = True,
                                    enforce_invertibility = True)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' Forecast', marker='x', markersize = 10)
```

```
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
plt.legend(loc = 2)
```



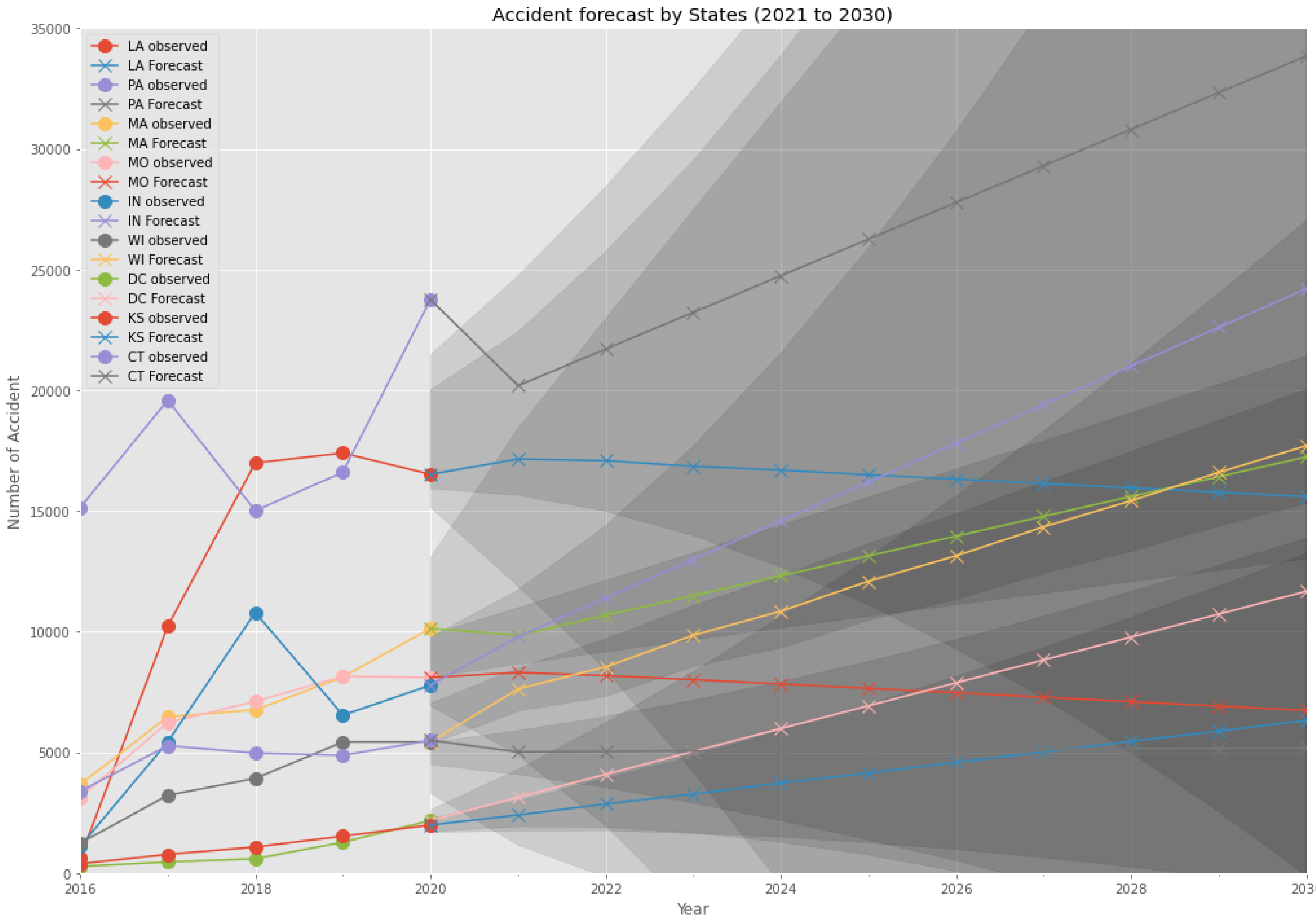
In [351]:
```python
state_list_2 = ['GA', 'TN', 'WA', 'AZ', 'OH', 'AL', 'OK', 'MD', 'NJ']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 80000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_2:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = False,
                                                enforce_invertibility = False)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = False,
                                    enforce_invertibility = False)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' Forecast', marker='x', markersize = 10)
```

```
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
    plt.legend(loc = 2)
```



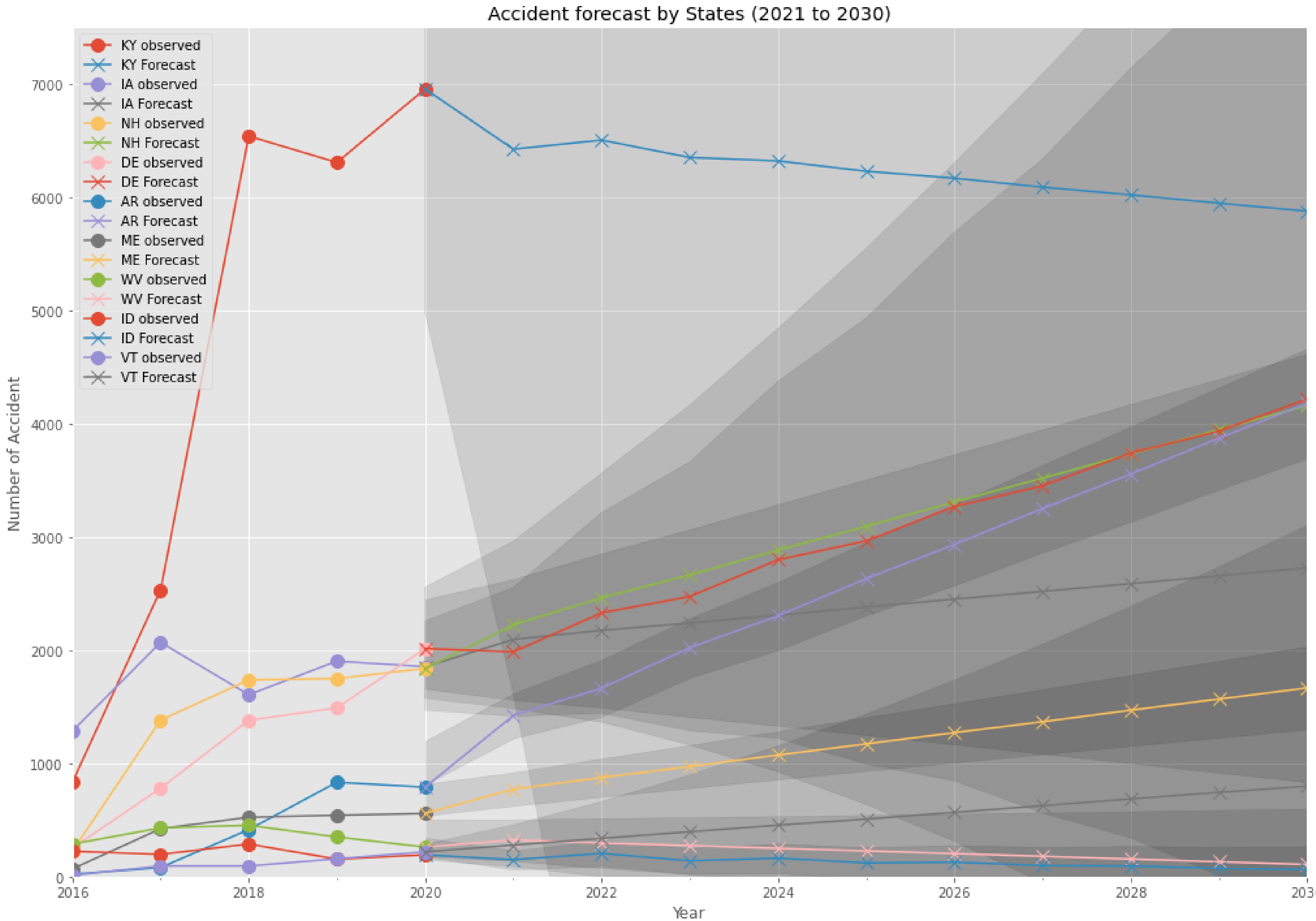
In [355]:
```
state_list_3 = ['LA', 'PA', 'MA', 'MO', 'IN', 'WI', 'DC', 'KS', 'CT']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 35000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_3:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = False,
                                                enforce_invertibility = False)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = False,
                                    enforce_invertibility = False)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' Forecast', marker='x', markersize = 10)
```

```
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
    plt.legend(loc = 2)
```



In [363]:
```python
state_list_4 = ['KY', 'IA', 'NH', 'DE', 'AR', 'ME', 'WV', 'ID', 'VT']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = 0, ymax = 7500)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_4:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = False,
                                                enforce_invertibility = False)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = False,
                                    enforce_invertibility = False)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' Forecast', marker='x', markersize = 10)
```

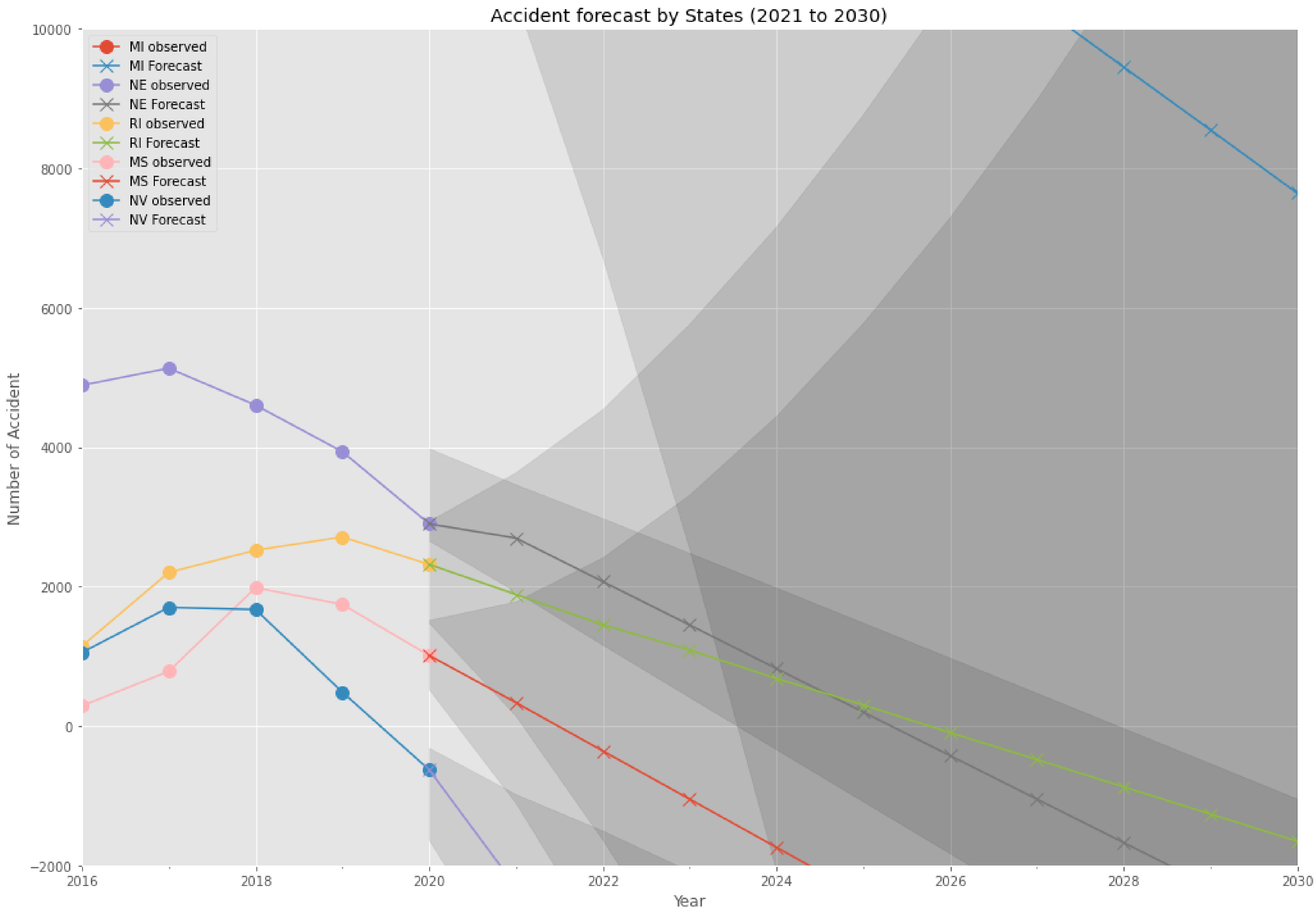
```
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
plt.legend(loc = 2)
```



In [366]:

```
state_list_5 = ['MI', 'NE', 'RI', 'MS', 'NV']
fig, ax = plt.subplots(figsize=(17, 12))
plt.ylim(ymin = -2000, ymax = 10000)
ax.set_xlabel('Year')
ax.set_ylabel('Number of Accident')
plt.title('Accident forecast by States (2021 to 2030)')

# for item in df_forecast_1.State.unique():
for item in state_list_5:

    results_aic = []
    df_temp = accident_US[accident_US['State'] == item]
    y_state = df_temp['Count'].resample('M').sum()
    row_number = np.where(y_state.index == '2019-12-31')
    n = int(row_number[0]) + 1

    p = d = q = range(0, 2)
    pdq = list(itertools.product(p, d, q))
    seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q))]

    for param in pdq:
        for param_seasonal in seasonal_pdq:
            try:
                mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                                order = param,
                                                seasonal_order = param_seasonal,
                                                enforce_stationarity = True,
                                                enforce_invertibility = True)
                results_ite = mod.fit()
            except:
                continue
            res_aic = results_ite.aic
            if results_ite.aic <= res_aic:
                res_aic = results_ite.aic
                results_aic=([param, param_seasonal, results_ite.aic])

    mod = sm.tsa.statespace.SARIMAX(y_state[:n],
                                    order = results_aic[0],
                                    seasonal_order = results_aic[1],
                                    enforce_stationarity = True,
                                    enforce_invertibility = True)
    results = mod.fit()

    pred_uc_state = results.get_forecast(steps = 132)
    pred_ci_state = pred_uc_state.conf_int(alpha = 0.5).resample('Y').sum()
    pred_y_state = pd.concat([y_state[-6:], pred_uc_state.predicted_mean[6:]]).round()
    obse_y_state = pd.concat([y_state, pred_uc_state.predicted_mean[6:12]]).round()
    obse_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' observed', marker='o', markersize = 10)
    pred_y_state.resample('Y').sum().plot(ax = ax, label = str(item)+' Forecast', marker='x', markersize = 10)
```

```python
    ax.fill_between(pred_ci_state.index,
                    pred_ci_state.iloc[:, 0],
                    pred_ci_state.iloc[:, 1], alpha=.10, color='k')
plt.legend(loc = 2)
```



```
In [ ]:
```