WeatherPy

Note

- Instructions have been included for each segment. You do not have to follow them exactly, but they are included to help you think through the steps.

In [5]:

```
# Dependencies and Setup
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import requests
import time
from scipy.stats import linregress
from scipy import stats

# Import API key
from api_keys import weather_api_key

# Incorporated citipy to determine city based on latitude and longitude
from citipy import citipy

# Output File (CSV)
output_data_file = "output_data/cities.csv"

# Range of latitudes and longitudes
lat_range = (-90, 90)
lng_range = (-180, 180)

```

Out[5]: 'e6b224e4b358cbcbca0782ff11081b44'

Generate Cities List

In [6]:

```
# Set up a List for holding lat_lngs and cities
lat_lngs = []
cities = []

# Create a set of random lat and lng combinations
lats = np.random.uniform(low=-90.000, high=90.000, size=1500)
lngs = np.random.uniform(low=-180.000, high=180.000, size=1500)
lat_lngs = zip(lats, lngs)

# Identify nearest city for each lat, lng combination
for lat_lng in lat_lngs:
    city = citipy.nearest_city(lat_lng[0], lat_lng[1]).city_name
    print(city)
    # If the city is unique, then add it to a our cities list
    if city not in cities:
        cities.append(city)

# Print the city count to confirm sufficient count
len(cities)
```

```
jamestown
ulladulla
batagay-alyta
puerto ayora
ancud
jamestown
belushya guba
rikitea
carnarvon
new norfolk
hobart
rikitea
kuva
ponta do sol
hilo
samarai
butaritari
tumannyy
punta arenas
```

Perform API Calls

- Perform a weather check on each city using a series of successive API calls.
- Include a print log of each city as it'sbeing processed (with the city number and city name).

In [7]:
```
# define URL for weather
base_url = "http://api.openweathermap.org/data/2.5/weather?"
units = "imperial"

# Build a partial query URL
query_url = f"{base_url}appid={weather_api_key}&units={units}&q="
query_url
```

Out[7]:
```
'http://api.openweathermap.org/data/2.5/weather?appid=e6b224e4b358cbcbca0782ff11081b44&units=imperial&q='
```

In [9]:
```
# Create empty list to hold the values
cities_name = []
cloudinesses = []
countries = []
dates = []
humidities = []
lats = []
lngs = []
max_temps = []
wind_speeds = []

# set up the counter
count_one =0
set_one = 0
```

In [10]:

```
# create a for loops to loop throught each variable

for city in cities:
    # create a seach query, make request and store in json
#     query_url = query_url + city
    response = requests.get(query_url + city)
    response_json = response.json()

    # Try to grab the cities values if they are available in the Weather API
    try:
        countries.append(response_json['sys']['country'])
        cloudinesses.append(response_json['clouds']['all'])
        dates.append(response_json['dt'])
        humidities.append(response_json['main']['humidity'])
        lats.append(response_json['coord']['lat'])
        lngs.append(response_json['coord']['lon'])
        max_temps.append(response_json['main']['temp_max'])
        wind_speeds.append(response_json['wind']['speed'])


        if count_one > 50:
            count_one = 1
            set_one += 1
            cities_name.append(city)
        else:
            count_one += 1
            cities_name.append(city)

        print(f"Processing Record {count_one} of {set_one} | {city}")

    # Handle exceptions for a value that is not available on Weather API

    except:
        # Append null values
        print("City not found. Skipping...")

```

```
Processing Record 1 of 0 | jamestown
Processing Record 2 of 0 | ulladulla
Processing Record 3 of 0 | batagay-alyta
Processing Record 4 of 0 | puerto ayora
Processing Record 5 of 0 | ancud
```

```
City not found. Skipping...
Processing Record 6 of 0 | rikitea
Processing Record 7 of 0 | carnarvon
Processing Record 8 of 0 | new norfolk
Processing Record 9 of 0 | hobart
City not found. Skipping...
Processing Record 10 of 0 | ponta do sol
Processing Record 11 of 0 | hilo
Processing Record 12 of 0 | samarai
Processing Record 13 of 0 | butaritari
City not found. Skipping...
Processing Record 14 of 0 | punta arenas
Processing Record 15 of 0 | waihi beach
Processing Record 16 of 0 | cabedelo
```

In [14]:

```
print('--------------------')
print('Data Retrieval Complete')
```

```
--------------------
Data Retrieval Complete
```

Convert Raw Data to DataFrame

- Export the city data into a .csv.
- Display the DataFrame

In [15]:

```
# create a dictionary
weather_dict = {
    "City":cities_name,
    "Cloudiness":cloudinesses,
    "Country":countries,
    "Date":dates,
    "Humidity":humidities,
    "Lat":lats,
    "Lng":lngs,
    "Max Temp":max_temps,
    "Wind Speed":wind_speeds
}
weather_dict
```

Out[15]:

```
{'City': ['jamestown',
  'ulladulla',
  'batagay-alyta',
  'puerto ayora',
  'ancud',
  'rikitea',
  'carnarvon',
  'new norfolk',
  'hobart',
  'ponta do sol',
  'hilo',
  'samarai',
  'butaritari',
  'punta arenas',
  'waihi beach',
  'cabedelo',
  'salalah',
  'hervey bay',
  'ketchikan',
```

In [60]:

```
# Create a Data Frame to storage the results
weather_data_frame = pd.DataFrame(weather_dict)

# Exports results to csv file
weather_data_frame.to_csv(output_data_file)

# Count output results
weather_data_frame.count()
weather_data_frame.head()
```

Out[60]:

	City	Cloudiness	Country	Date	Humidity	Lat	Lng	Max Temp	Wind Speed
0	jamestown	90	US	1579998908	97	42.10	-79.24	36.00	5.82
1	ulladulla	29	AU	1579998970	49	-35.35	150.47	89.60	8.05
2	batagay-alyta	0	RU	1579998962	54	67.80	130.41	-34.38	4.38
3	puerto ayora	75	EC	1579999060	78	-0.74	-90.35	78.80	8.05
4	ancud	100	CL	1579998934	68	-41.87	-73.82	66.20	6.93

Plotting the Data

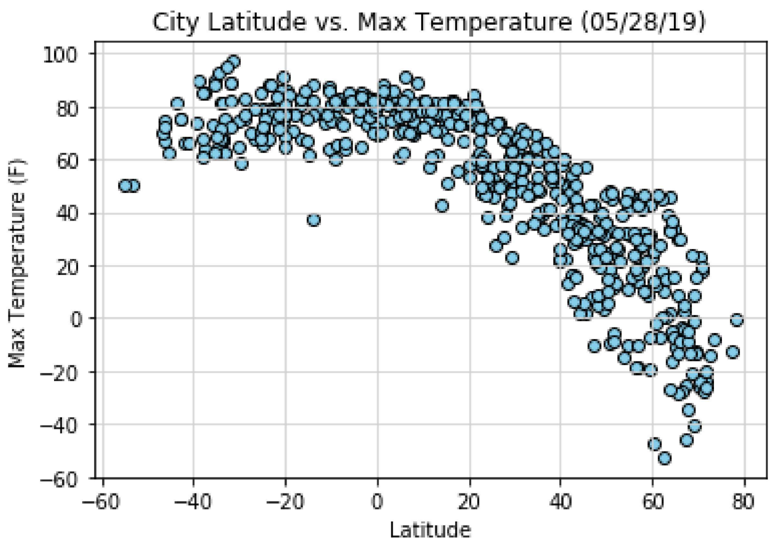
- Use proper labeling of the plots using plot titles (including date of analysis) and axes labels.
- Save the plotted figures as .pngs.

Latitude vs. Temperature Plot

```
Observations:
- Temperature has a strong correlation with latitude, the temperature is higher on the places near to the equator (latitude zero degree)
- On the data plot, I observed that North Hemisphere is lower than south.
- Temperature has a correlation with latitude, the temperature is higher on the places near to the equator

The cities locates far from the equator present lower temperature, these cities will be closer to the north pole or sout pole
```

In [22]:

```
# Build Scatter Plot of  City Latitude vs. Max Temp (F)
plt.scatter(weather_data_frame["Lat"],weather_data_frame["Max Temp"],edgecolors="black",facecolors="skyl

# Add properties to the graph
plt.title("City Latitude vs. Max Temperature (05/28/19)")
plt.xlabel("Latitude")
plt.ylabel("Max Temperature (F)")
plt.grid (b=True,which="major",axis="both",linestyle="-",color="lightgrey")

#save the picture to a folder
plt.savefig("output_data/CityLatitudeVsTemperature.png")
plt.show()
```

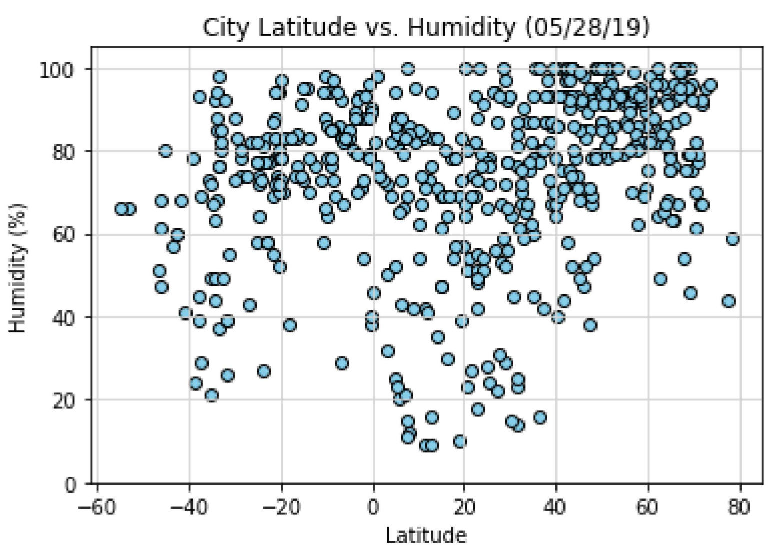


Latitude vs. Humidity Plot

```
Analysis Humidity:
- There is no strong relationship between latitude and humidity.
- On the Northern hemisphere cities, there is high number of cities with humidity greater than 50%.
```

In [23]:

```
# Build Scatter Plot of  City Latitude vs. Humidity
plt.scatter(weather_data_frame["Lat"],weather_data_frame["Humidity"],edgecolors="black",facecolors="skyl

# Add properties to the graph
plt.title("City Latitude vs. Humidity (05/28/19)")
plt.xlabel("Latitude")
plt.ylabel("Humidity (%)")
plt.ylim(0,105)
plt.grid (b=True,which="major",axis="both",linestyle="-",color="lightgrey")

#save the picture to a folder
plt.savefig("output_data/CityLatitudeVsHumidity.png")
plt.show()
```



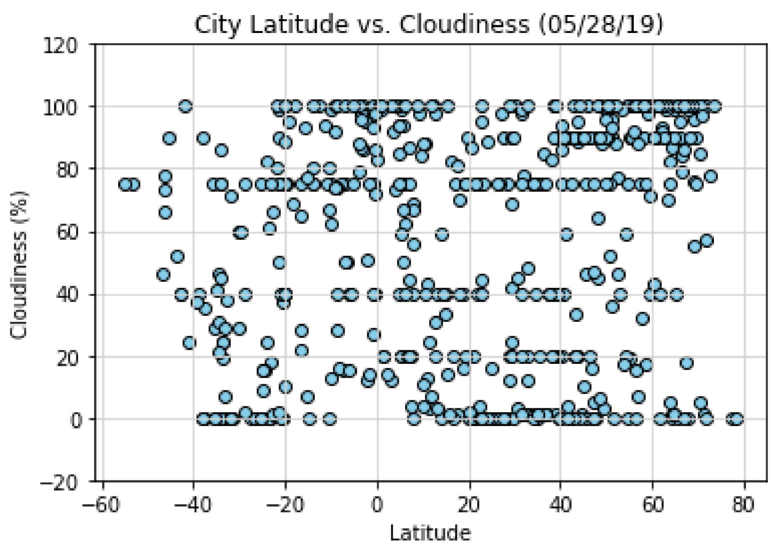
Latitude vs. Cloudiness Plot

```
Analysis Cloudiness:
- There is not correlation between latitude and cloudiness, in one set of value of latiotude close to zero
you can see value of cloudiness varies from 0 to 100
```

```
- There is strong band of cities near 0, 20%, 75%, and 100% cloudiness.
```

In [24]:

```
# Build Scatter Plot of  City Latitude vs. Cloudiness
plt.scatter(weather_data_frame["Lat"],weather_data_frame["Cloudiness"],edgecolors="black",facecolors="s

# Add properties to the graph
plt.title("City Latitude vs. Cloudiness (05/28/19)")
plt.xlabel("Latitude")
plt.ylabel("Cloudiness (%)")
plt.ylim(-20,120)
plt.grid (b=True,which="major",axis="both",linestyle="-",color="lightgrey")

#save the picture to a folder
plt.savefig("output_data/CityLatitudeVsCloudiness.png")
plt.show()
```

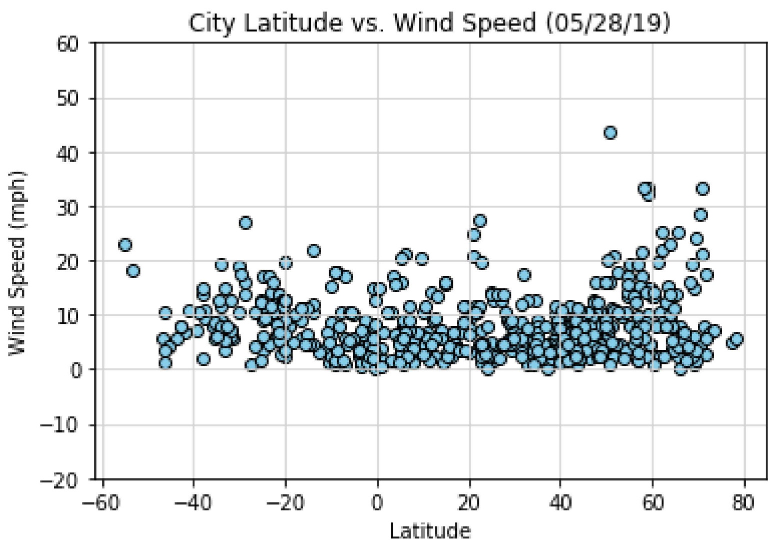


Latitude vs. Wind Speed Plot

```
Analysis Wind Speed:
There is no strong relationship between latitude and wind speed.
Wind speed tends to generally be betweeen 0 and 15 mph regardless of latitude
In northern hemispheres, there are small amount of cities with wind speed over 20 mph
There is one city on the extreme south latitud with wind speed close to 45 mph

```

In [25]:

```
# Build Scatter Plot of  City Latitude vs. Wind Speed
plt.scatter(weather_data_frame["Lat"],weather_data_frame["Wind Speed"],edgecolors="black",facecolors="s

# Add properties to the graph
plt.title("City Latitude vs. Wind Speed (05/28/19)")
plt.xlabel("Latitude")
plt.ylabel("Wind Speed (mph)")
plt.ylim(-20,60)
plt.grid (b=True,which="major",axis="both",linestyle="-",color="lightgrey")


plt.savefig("output_data/CityLatitudeVsWindSpeed.png")
plt.show()
```



Linear Regression

```
# Run linear regression on each relationship, only this time separating them into Northern and Southern Hemisphere
# Northern Hemisphere: latitude is greater than or equal to 0 degrees
# Southern Hemisphere: latitude is less than 0 degre
# OPTIONAL: Create a function to create Linear Regression plots

```

In [19]:
```
# Range of latitudes for Northern Hemisphere
lat_range = (0, 90)
```

In [26]:
```
# Run linear regression on each relationship, only this time separating them into Northern and Southern
# Define axis x and y
x_values = weather_data_frame['Lat']
y_values = weather_data_frame['Max Temp']

# Perform a linear regression on temperature vs. latitude
(slope, intercept, rvalue, pvalue, stderr) = stats.linregress(x_values, y_values)

# Get regression values
regress_values = x_values * slope + intercept
print(regress_values)
```

```
0       34.917975
1       93.044329
2       15.630082
3       67.069466
4       97.937599
          ...
556     67.054456
557    101.134737
558     81.666723
559     35.210671
560     22.827393
Name: Lat, Length: 561, dtype: float64
```

In [27]:

```
# Define axis x and y
x_values = weather_data_frame['Lat']
y1_values = weather_data_frame['Cloudiness']

# Perform a linear regression on temperature vs. latitude
(slope, intercept, rvalue, pvalue, stderr) = stats.linregress(x_values, y1_values)

# Get regression values
regress_values = x_values * slope + intercept
print(regress_values)
```

```
0      58.982097
1      42.300820
2      64.517395
3      49.755164
4      40.896534
         ...
556    49.759472
557    39.979010
558    45.565999
559    58.898098
560    62.451889
Name: Lat, Length: 561, dtype: float64
```

In [28]:

```
# Define axis x and y
x_values = weather_data_frame['Lat']
y2_values = weather_data_frame['Humidity']

# Perform a linear regression on temperature vs. latitude
(slope, intercept, rvalue, pvalue, stderr) = stats.linregress(x_values, y2_values)

# Get regression values
regress_values = x_values * slope + intercept
print(regress_values)
```

```
0      78.298107
1      65.731872
2      82.467923
3      71.347332
4      64.674004
         ...
556    71.350577
557    63.982820
558    68.191576
559    78.234830
560    80.911949
Name: Lat, Length: 561, dtype: float64
```

In [29]:

```
# Define axis x and y
x_values = weather_data_frame['Lat']
y3_values = weather_data_frame['Wind Speed']

# Perform a linear regression on temperature vs. latitude
(slope, intercept, rvalue, pvalue, stderr) = stats.linregress(x_values, y3_values)

# Get regression values
regress_values = x_values * slope + intercept
print(regress_values)
```

```
0      8.130160
1      7.876597
2      8.214298
3      7.989906
4      7.855252
         ...
556    7.989972
557    7.841305
558    7.926229
559    8.128883
560    8.182902
Name: Lat, Length: 561, dtype: float64
```

In [24]:

```
# Create Northern and Southern Hemisphere DataFrames
```

In [30]:

```
# Northern Hemisphere - Temperature (F) vs. Latitude
northern_hemisphere_df = weather_data_frame.loc[weather_data_frame['Lat']>0,:]
northern_hemisphere_df.head()
```

Out[30]:

	City	Cloudiness	Country	Date	Humidity	Lat	Lng	Max Temp	Wind Speed
0	jamestown	90	US	1579998908	97	42.10	-79.24	36.00	5.82
2	batagay-alyta	0	RU	1579998962	54	67.80	130.41	-34.38	4.38
9	ponta do sol	20	PT	1579999061	67	32.67	-17.10	60.80	5.82
10	hilo	90	US	1579998933	57	19.73	-155.09	80.60	6.93
12	butaritari	12	KI	1579998927	72	3.07	172.79	85.03	10.56

In [31]:

```
# Southern Hemisphere - Temperature (F) vs. Latitude
southern_hemisphere_df = weather_data_frame.loc[weather_data_frame['Lat']<0,:]
southern_hemisphere_df.head()

```

Out[31]:

	City	Cloudiness	Country	Date	Humidity	Lat	Lng	Max Temp	Wind Speed
1	ulladulla	29	AU	1579998970	49	-35.35	150.47	89.60	8.05
3	puerto ayora	75	EC	1579999060	78	-0.74	-90.35	78.80	8.05
4	ancud	100	CL	1579998934	68	-41.87	-73.82	66.20	6.93
5	rikitea	18	PF	1579998882	77	-23.12	-134.97	79.25	14.03
6	carnarvon	15	AU	1579998931	74	-24.87	113.63	78.80	17.22

Northern Hemisphere - Max Temp vs. Latitude Linear Regression

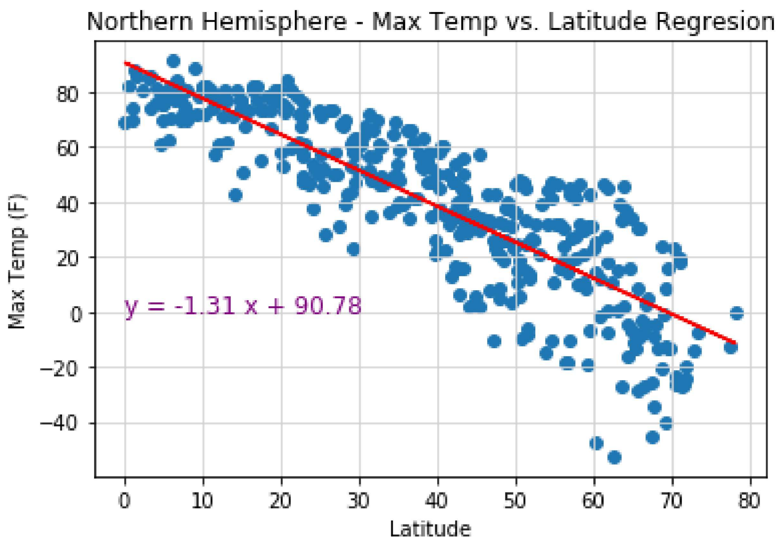
In [32]:

```
# OPTIONAL: Create a function to create Linear Regression plots
def regresion_plot(df,title_name,y_name,y_label,file_name,xy):
    x_values = df['Lat']
    y_values = df[y_name]
    (slope, intercept, rvalue, pvalue, stderr) = linregress(x_values, y_values)
    regress_values = x_values * slope + intercept
    line_equation = "y = " + str(round(slope,2)) + " x + " + str(round(intercept,2))
    plt.scatter(x_values, y_values)

    plt.plot(x_values, regress_values, "r-")
    plt.title(title_name)
    plt.xlabel("Latitude")
    plt.ylabel(y_label)
    plt.grid (b=True,which="major",axis="both",linestyle="-",color="lightgrey")
    plt.annotate(line_equation, xy, fontsize=12, color="purple")

    print(f"The r-squared is: {rvalue}")

    plt.savefig(file_name)
```

In [37]:

```
# Create the plot for Max Temp vs. Latitude linear regression
# Apply the regresion
regresion_plot(northern_hemisphere_df,\
               'Northern Hemisphere - Max Temp vs. Latitude Regresion',
               'Max Temp', 'Max Temp (F)', 'output_data/Northern_LatitudeRegresion_vs_MaxTemp.png',(0,0

```

```
The r-squared is: -0.8561817643548616
```



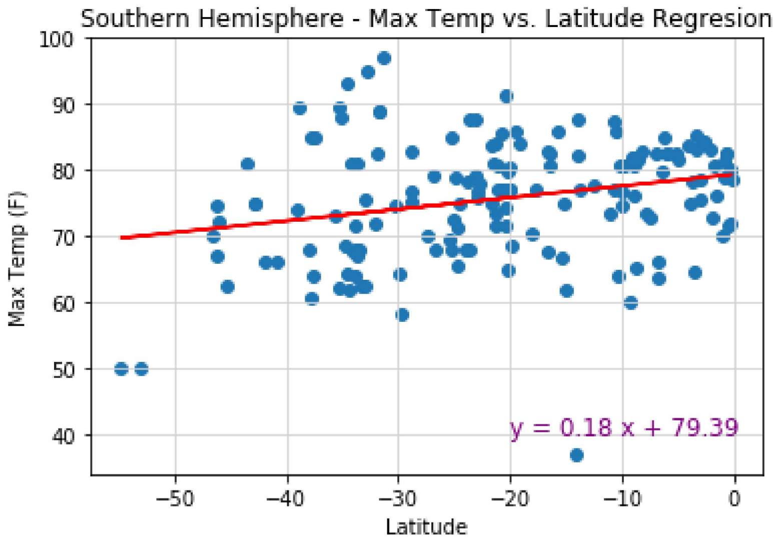

```
This model show that there is a negative correlation between Max Temp and Latitude Regresion in the Northern Hemisphere.
The Max Temp increase when the city get closer to the equator but this correlation has not quite strong R-square.

R-squared is a handy, seemingly intuitive measure of how well the linear model fits a set of observations.
However, as we saw, R-squared doesn’t tell us the entire story. I recommend evaluate R-squared values in conjunction with residual plots, other model statistics in order to round out the picture.
```

Southern Hemisphere - Max Temp vs. Latitude Linear Regression

In [46]:

```
# Southern Hemisphere - Temperature (F) vs. Latitude
# # Apply the regresion
regresion_plot(southern_hemisphere_df,\
                'Southern Hemisphere - Max Temp vs. Latitude Regresion',
                'Max Temp', 'Max Temp (F)', 'output_data/Southern_LatitudeRegresion_vs_MaxTemp.png',(-20
```

```
The r-squared is: 0.2587106114152503
```



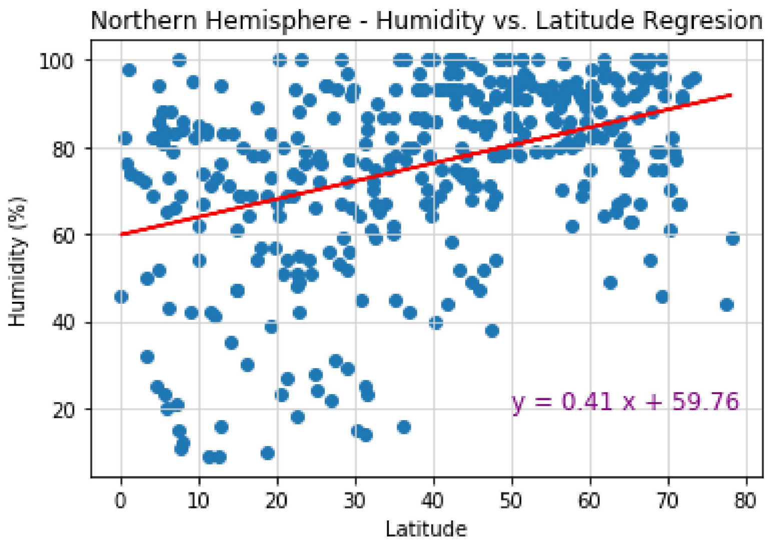

```
There is a positive correlation between Max Temp and Latitude Regresion in the Southern Hemisphere.
The Max Temp increase when the city get closer to the equator but this correlation has not strong R-square
(close to 100%)
```

Northern Hemisphere - Humidity (%) vs. Latitude Linear Regression

In [36]:

```
# * Northern Hemisphere - Humidity (%) vs. Latitude
# Apply the regression
regresion_plot(northern_hemisphere_df,\
               'Northern Hemisphere - Humidity vs. Latitude Regresion',
               'Humidity', 'Humidity (%)', 'output_data/Northern_LatitudeRegresion_vs_Humidity.png',(50
```

```
The r-squared is: 0.3909767019362812
```



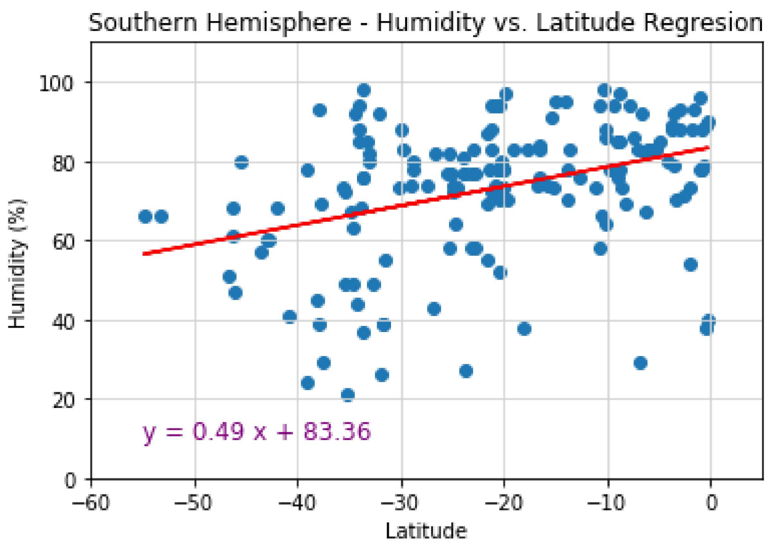

```
There is a positive correlation between Humidity and Latitude Regresion in the Northern Hemisphere.
The humidity increase when the city get futher from the equator but this correlation has not strong R-square (close to 100%)
```

Southern Hemisphere - Humidity (%) vs. Latitude Linear Regression

In [53]:

```
# * Southern Hemisphere - Humidity (%) vs. Latitude
# Define limit to center the plot
plt.xlim([-60, 5])
plt.ylim([0, 110])

# Apply the regresion
regresion_plot(southern_hemisphere_df,\
               'Southern Hemisphere - Humidity vs. Latitude Regresion',
               'Humidity', 'Humidity (%)', 'output_data/Southern_LatitudeRegresion_vs_Humidity.png',(-5


```

```
The r-squared is: 0.37287279008218643
```



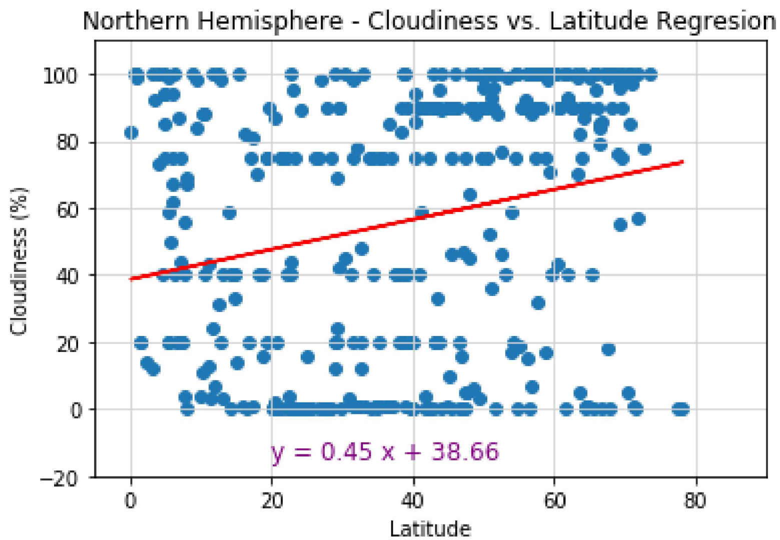

```
There is a positive correlation between Humidity  and Latitude Regresion in the Southern Hemisphere.
The humidity increase when the city get closer to the equator but this correlation has not high R-square (close to 100%)
```

Northern Hemisphere - Cloudiness (%) vs. Latitude Linear Regression

In [54]:

```
#  Northern Hemisphere - Cloudiness (%) vs. Latitude
# Define limit to center the plot
plt.xlim([-5, 90])
plt.ylim([-20, 110])

# Apply the regresion
regresion_plot(northern_hemisphere_df,\
               'Northern Hemisphere - Cloudiness vs. Latitude Regresion',
               'Cloudiness', 'Cloudiness (%)', 'output_data/Northern_LatitudeRegresion_vs_Cloudiness.png
```

```
The r-squared is: 0.2285912959243647
```



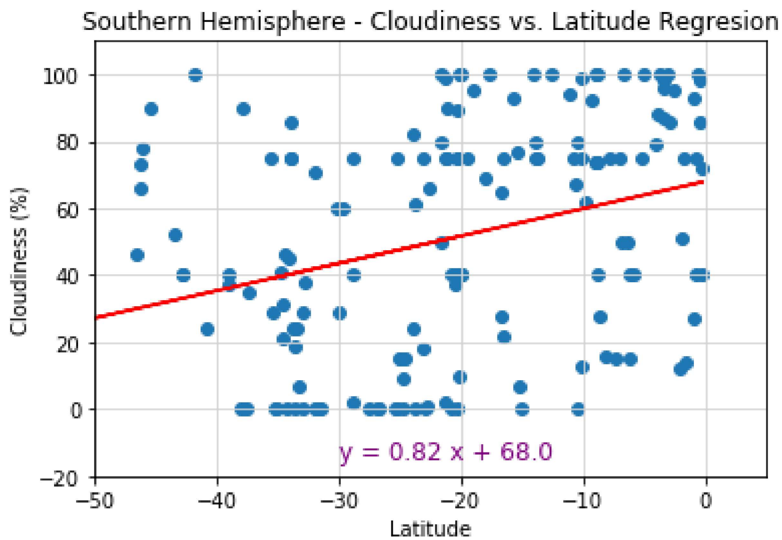

```
There is a positive correlation between Cloudiness  and Latitude Regresion in the Northern Hemisphere.
The cloudiness increase when the city get further from the equator but this correlation has not high R-square (close to 100%)
While R-squared provides an estimate of the strength of the relationship between the model and the response variable, it does not provide a formal hypothesis test for this relationship. I recommend to evaluate the p value or other statistic metrics
```

Southern Hemisphere - Cloudiness (%) vs. Latitude Linear Regression

In [57]:

```python
# Southern Hemisphere - Cloudiness (%) vs. Latitude
# Define limits to center the plot
plt.xlim([-50, 5])
plt.ylim([-20, 110])

# Apply the regresion
regresion_plot(southern_hemisphere_df,\
               'Southern Hemisphere - Cloudiness vs. Latitude Regresion',
               'Cloudiness', 'Cloudiness (%)', 'output_data/Southern_LatitudeRegresion_vs_Cloudiness.pn
```

```
The r-squared is: 0.30914679879568924
```



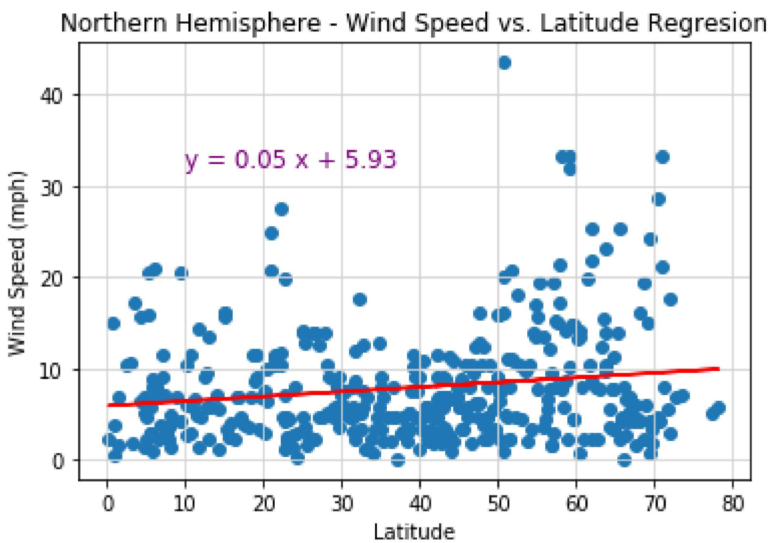

```
There is a positive correlation between Cloudiness  and Latitude Regresion in the Southern Hemisphere.
The cloudiness increase when the city get closer to the equator but this correlation has not hig R-square (close to 100%)
```

Northern Hemisphere - Wind Speed (mph) vs. Latitude Linear Regression

In [58]:

```
# * Northern Hemisphere - Wind Speed (mph) vs. Latitude
# # Apply the regresion
regresion_plot(northern_hemisphere_df,\
                'Northern Hemisphere - Wind Speed vs. Latitude Regresion',
                'Wind Speed', 'Wind Speed (mph)', 'output_data/Northern_LatitudeRegresion_vs_WindSpeed.p
```

```
The r-squared is: 0.16735985690946031
```



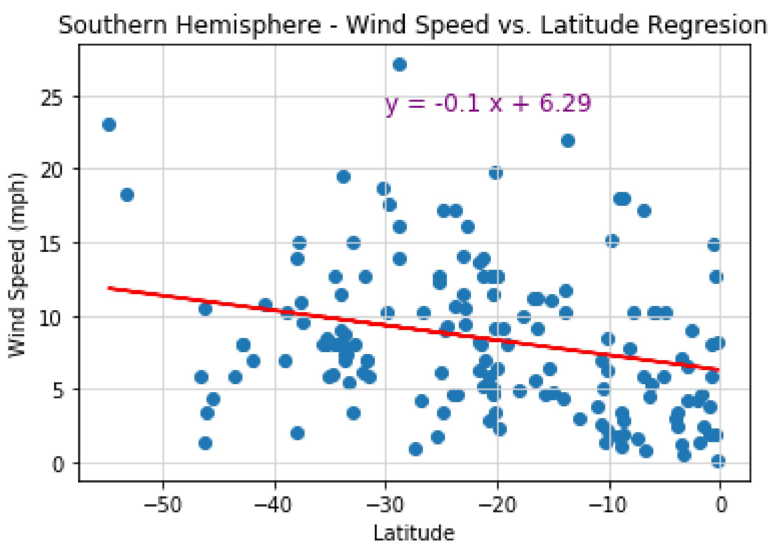

```
There is a positive correlation between Wind Speed and Latitude Regresion in the Northern hemisphere.
The wind speed slighly increase when the city get futher from the equator.
R-square of 0.18 suggest that this regresion model is not strong and it doesn't fit the set of obsevations.
```

Southern Hemisphere - Wind Speed (mph) vs. Latitude Linear Regression

In [59]:

```
# * Southern Hemisphere - Wind Speed (mph) vs. Latitude
# Apply the regression
regresion_plot(southern_hemisphere_df,\
               'Southern Hemisphere - Wind Speed vs. Latitude Regresion',
               'Wind Speed', 'Wind Speed (mph)', 'output_data/Southern_LatitudeRegresion_vs_WindSpeed.p
```

```
The r-squared is: -0.26003079698191506
```




```
There is a negative correlation between Wind Speed and Latitude Regresion in the Southern Hemisphere.
The wind speed slighly increase when the city get futher from the equator. Similar behaviour than Northern hemisphere.
R-square negative (approx. -0.30) indicates that lineal regression model doesn't fits the set of obsevations.
```

```
Reference:
Minitag Blog. R-squared. URL: https://blog.minitab.com
```