# WeatherPy

## Starter Code to Generate Random Geographic Coordinates and a List of Cities

In [69]:

```
# 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

# Impor the OpenWeatherMap API key
from api_keys import weather_api_key

# Import citipy to determine the cities based on latitude and longitude
from citipy import citipy
```

### Generate the Cities List by Using the `citipy` Library

In [36]:

```
# Empty list for holding the latitude and longitude combinations
lat_lngs = []

# Empty list for holding the cities names
cities = []

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

# Create a set of random lat and lng combinations
lats = np.random.uniform(lat_range[0], lat_range[1], size=1500)
lngs = np.random.uniform(lng_range[0], lng_range[1], 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

    # 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
print(f"Number of cities in the list: {len(cities)}")
```

```
Number of cities in the list: 559
```

## Requirement 1: Create Plots to Showcase the Relationship Between Weather Variables and Latitude

### Use the OpenWeatherMap API to retrieve weather data from the cities list generated in the started code

In [37]:

```python
# Set the API base URL
url = "http://api.openweathermap.org/data/2.5/weather"

# Define an empty list to fetch the weather data for each city
city_data = []

# Print to logger
print("Beginning Data Retrieval     ")
print("-----------------------------")

# Create counters
record_count = 1
set_count = 1

# Loop through all the cities in our list to fetch weather data
for i, city in enumerate(cities):

    # Group cities in sets of 50 for logging purposes
    if (i % 50 == 0 and i >= 50):
        set_count += 1
        record_count = 0

    # Create endpoint URL with each city
    city_url = url + "?q=" + city + "&appid=<-API KEY->"

    # Log the url, record, and set numbers
    print("Processing Record %s of Set %s | %s" % (record_count, set_count, city))

    # Add 1 to the record count
    record_count += 1

    # Run an API request for each of the cities
    try:
        # Parse the JSON and retrieve data
        city_weather = requests.get(city_url).json()

        # Parse out latitude, longitude, max temp, humidity, cloudiness, wind speed, country, and date
        city_lat = city_weather["coord"]["lat"]
        city_lng = city_weather["coord"]["lon"]
        city_max_temp = city_weather["main"]["temp_max"]
        city_humidity = city_weather["main"]["humidity"]
        city_clouds = city_weather["clouds"]["all"]
        city_wind = city_weather["wind"]["speed"]
        city_country = city_weather["sys"]["country"]
        city_date = city_weather["dt"]

        # Append the City information into city_data list
        city_data.append({"City": city,
                          "Lat": city_lat,
                          "Lng": city_lng,
                          "Max Temp": city_max_temp,
                          "Humidity": city_humidity,
                          "Cloudiness": city_clouds,
                          "Wind Speed": city_wind,
                          "Country": city_country,
                          "Date": city_date})

    # If an error is experienced, skip the city
    except:
        print("City not found. Skipping...")
        pass

# Indicate that Data Loading is complete
print("-----------------------------")
print("Data Retrieval Complete      ")
print("-----------------------------")
```

```
Beginning Data Retrieval
-----------------------------
Processing Record 1 of Set 1 | iqaluit
Processing Record 2 of Set 1 | port-aux-francais
Processing Record 3 of Set 1 | brisas de zicatela
Processing Record 4 of Set 1 | masterton
Processing Record 5 of Set 1 | udachny
Processing Record 6 of Set 1 | riachao das neves
Processing Record 7 of Set 1 | grytviken
Processing Record 8 of Set 1 | mahavelona
Processing Record 9 of Set 1 | kerikeri
Processing Record 10 of Set 1 | shalqar
Processing Record 11 of Set 1 | klyuchi
Processing Record 12 of Set 1 | invercargill
Processing Record 13 of Set 1 | newman
Processing Record 14 of Set 1 | happy valley-goose bay
Processing Record 15 of Set 1 | lihue
Processing Record 16 of Set 1 | bredasdorp
Processing Record 17 of Set 1 | margaret river
```

In [38]:

```
# Convert the cities weather data into a Pandas DataFrame
city_data_df = pd.DataFrame(city_data)

# Show Record Count
city_data_df.count()
```

Out[38]:

```
City          539
Lat           539
Lng           539
Max Temp      539
Humidity      539
Cloudiness    539
Wind Speed    539
Country       539
Date          539
dtype: int64
```

In [39]:

```
# Display sample data
city_data_df.head()
```

Out[39]:

| | City | Lat | Lng | Max Temp | Humidity | Cloudiness | Wind Speed | Country | Date |
|---|---|---|---|---|---|---|---|---|---|
| **0** | iqaluit | 63.7506 | -68.5145 | 259.00 | 72 | 75 | 1.54 | CA | 1702492584 |
| **1** | port-aux-francais | -49.3500 | 70.2167 | 280.74 | 97 | 100 | 19.11 | TF | 1702492567 |
| **2** | brisas de zicatela | 15.8369 | -97.0419 | 303.21 | 48 | 75 | 2.94 | MX | 1702492640 |
| **3** | masterton | -40.9597 | 175.6575 | 288.09 | 77 | 4 | 1.27 | NZ | 1702493072 |
| **4** | udachny | 66.4167 | 112.4000 | 245.62 | 82 | 100 | 4.80 | RU | 1702492584 |

In [40]:

```
# Export the City_Data into a csv
city_data_df.to_csv(r"C:\Users\conne\OneDrive\Desktop\NU-VIRT-DATA-PT-10-2023-U-LOLC\02-Homework\06-Pytl
```

In [41]:

```
# Read saved data
city_data_df = pd.read_csv(r"C:\Users\conne\OneDrive\Desktop\NU-VIRT-DATA-PT-10-2023-U-LOLC\02-Homework\

# Display sample data
city_data_df.head()
```

Out[41]:

| City_ID | City | Lat | Lng | Max Temp | Humidity | Cloudiness | Wind Speed | Country | Date |
|---|---|---|---|---|---|---|---|---|---|
| 0 | iqaluit | 63.7506 | -68.5145 | 259.00 | 72 | 75 | 1.54 | CA | 1702492584 |
| 1 | port-aux-francais | -49.3500 | 70.2167 | 280.74 | 97 | 100 | 19.11 | TF | 1702492567 |
| 2 | brisas de zicatela | 15.8369 | -97.0419 | 303.21 | 48 | 75 | 2.94 | MX | 1702492640 |
| 3 | masterton | -40.9597 | 175.6575 | 288.09 | 77 | 4 | 1.27 | NZ | 1702493072 |
| 4 | udachny | 66.4167 | 112.4000 | 245.62 | 82 | 100 | 4.80 | RU | 1702492584 |

## Create the Scatter Plots Requested

#### Latitude Vs. Temperature

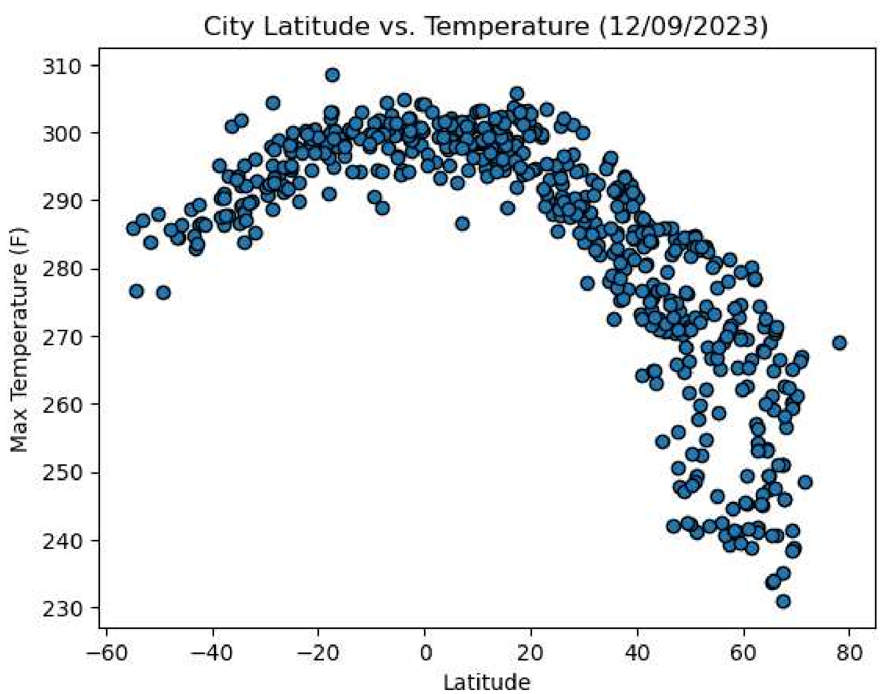
In [39]:

```
# Build scatter plot for latitude vs. temperature
# YOUR CODE HERE
plt.scatter(city_data_df["Lat"], city_data_df["Max Temp"], edgecolors="black")

plt.title("City Latitude vs. Temperature (12/09/2023)")
plt.xlabel("Latitude")
plt.ylabel("Max Temperature (F)")

# Save the figure
plt.savefig(r"C:\Users\conne\OneDrive\Desktop\NU-VIRT-DATA-PT-10-2023-U-LOLC\02-Homework\06-Python-APIs\

# Show plot
plt.show()
```




#### Latitude Vs. Humidity

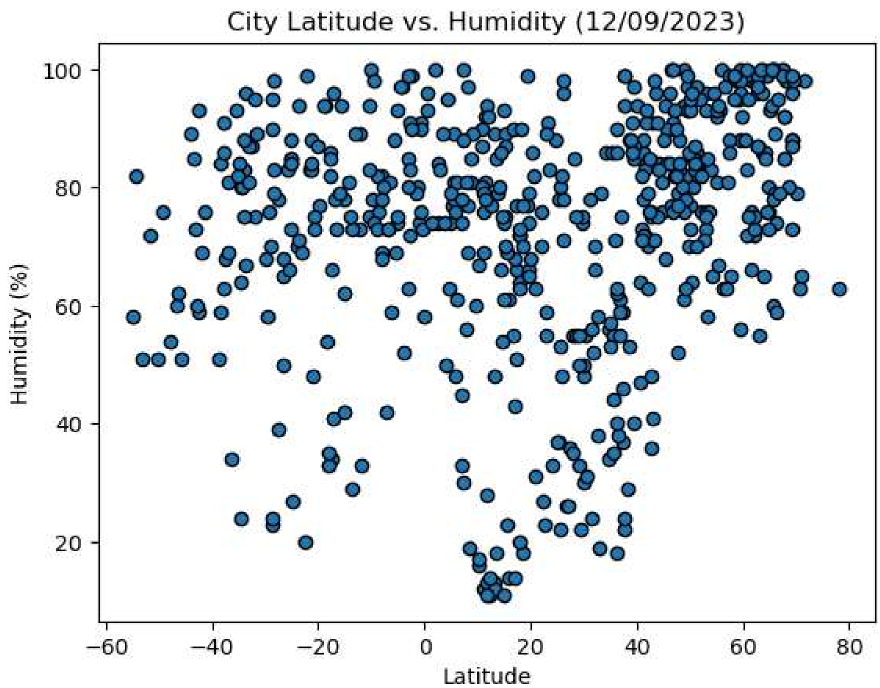
In [41]:
```
# Build the scatter plots for latitude vs. humidity
# YOUR CODE HERE

plt.scatter(city_data_df["Lat"], city_data_df["Humidity"], edgecolors="black")

plt.title("City Latitude vs. Humidity (12/09/2023)")
plt.xlabel("Latitude")
plt.ylabel("Humidity (%)")

# Save the figure
plt.savefig(r"C:\Users\conne\OneDrive\Desktop\NU-VIRT-DATA-PT-10-2023-U-LOLC\02-Homework\06-Python-APIs\

# Show plot
plt.show()
```




**Latitude Vs. Cloudiness**

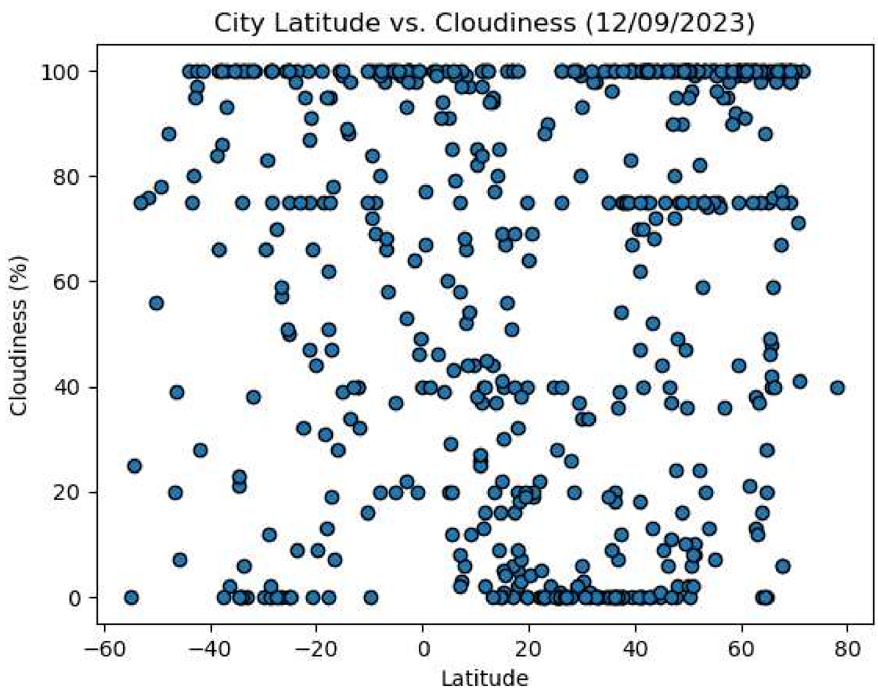
In [43]:

```
# Build the scatter plots for latitude vs. cloudiness
plt.scatter(city_data_df["Lat"], city_data_df["Cloudiness"], edgecolors="black")

plt.title("City Latitude vs. Cloudiness (12/09/2023)")
plt.xlabel("Latitude")
plt.ylabel("Cloudiness (%)")

# Save the figure
plt.savefig(r"C:\Users\conne\OneDrive\Desktop\NU-VIRT-DATA-PT-10-2023-U-LOLC\02-Homework\06-Python-APIs\

# Show plot
plt.show()
```




**Latitude vs. Wind Speed Plot**

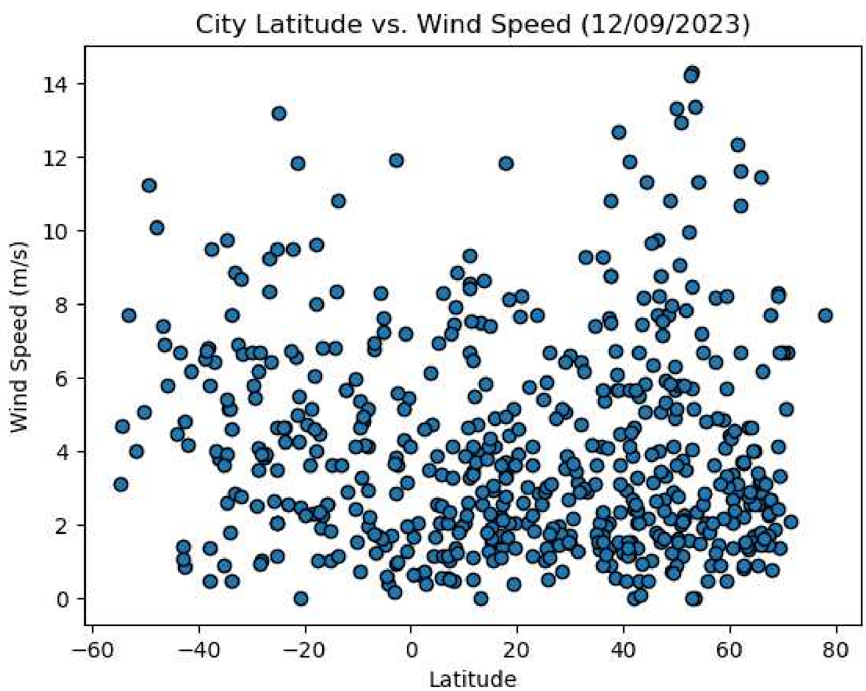
In [44]:
```
# Build the scatter plots for latitude vs. wind speed
plt.scatter(city_data_df["Lat"], city_data_df["Wind Speed"], edgecolors="black")

plt.title("City Latitude vs. Wind Speed (12/09/2023)")
plt.xlabel("Latitude")
plt.ylabel("Wind Speed (m/s)")

# Incorporate the other graph properties
# YOUR CODE HERE

# Save the figure
plt.savefig(r"C:\Users\conne\OneDrive\Desktop\NU-VIRT-DATA-PT-10-2023-U-LOLC\02-Homework\06-Python-APIs\

# Show plot
plt.show()
```




## Requirement 2: Compute Linear Regression for Each Relationship

In [80]:
```
# Define a function to create Linear Regression plots

def plot_linear_regression(x_values, y_values, title, text_corordinates):
    (slope, intercept, rvalue, pvalue, stderr) = linregress(x_values, y_values)
    regress_values = x_values * slope + intercept
    line_eq = "y =" + str(round(slope,2)) + "x + " + str(round(intercept, 2))

    plt.scatter(x_values, y_values)
    plt.plot(x_values, regress_values, "r-")
    plt.xlabel("Latitude")
    plt.ylabel(title)
    print(f"The r-value is: {rvalue**2}")
    plt.show()
```

In [81]:
```
# Create a DataFrame with the Northern Hemisphere data (Latitude >= 0)
northern_hemi_df = city_data_df.loc[(city_data_df["Lat"] >= 0)]

northern_hemi_df.head()
```

Out[81]:

| City_ID | City | Lat | Lng | Max Temp | Humidity | Cloudiness | Wind Speed | Country | Date |
|---|---|---|---|---|---|---|---|---|---|
| 0 | iqaluit | 63.7506 | -68.5145 | 259.00 | 72 | 75 | 1.54 | CA | 1702492584 |
| 2 | brisas de zicatela | 15.8369 | -97.0419 | 303.21 | 48 | 75 | 2.94 | MX | 1702492640 |
| 4 | udachny | 66.4167 | 112.4000 | 245.62 | 82 | 100 | 4.80 | RU | 1702492584 |
| 9 | shalqar | 47.8333 | 59.6000 | 261.04 | 32 | 100 | 9.95 | KZ | 1702493073 |
| 10 | klyuchi | 52.2667 | 79.1667 | 249.73 | 84 | 83 | 2.52 | RU | 1702492591 |

In [82]:
```
# Create a DataFrame with the Southern Hemisphere data (Latitude < 0)
southern_hemi_df = city_data_df.loc[(city_data_df["Lat"] < 0)]
```

In [83]:
```
# Display sample data
southern_hemi_df.head()
```

Out[83]:

| City_ID | City | Lat | Lng | Max Temp | Humidity | Cloudiness | Wind Speed | Country | Date |
|---|---|---|---|---|---|---|---|---|---|
| 1 | port-aux-francais | -49.3500 | 70.2167 | 280.74 | 97 | 100 | 19.11 | TF | 1702492567 |
| 3 | masterton | -40.9597 | 175.6575 | 288.09 | 77 | 4 | 1.27 | NZ | 1702493072 |
| 5 | riachao das neves | -11.7461 | -44.9100 | 310.02 | 22 | 4 | 2.07 | BR | 1702493072 |
| 6 | grytviken | -54.2811 | -36.5092 | 276.39 | 97 | 100 | 3.28 | GS | 1702492566 |
| 7 | mahavelona | -17.6848 | 49.5087 | 300.14 | 85 | 88 | 1.36 | MG | 1702493072 |

In [ ]:
```

```

In [ ]:
```

```

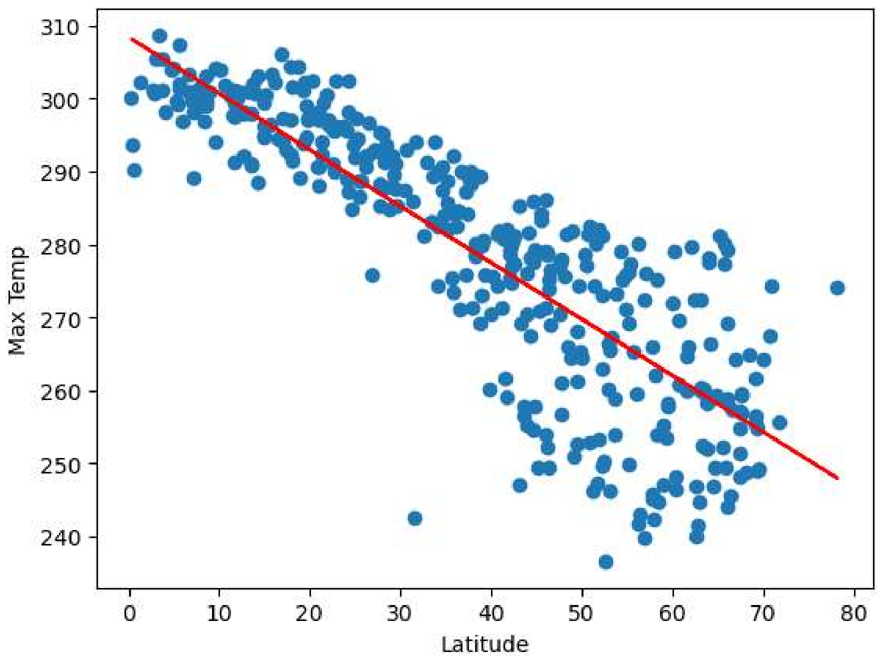
### Temperature vs. Latitude Linear Regression Plot

In [96]:
```
# Linear regression on Northern Hemisphere
# Define your X and Y values

x_values = northern_hemi_df["Lat"]
y_values = northern_hemi_df["Max Temp"]
plot_linear_regression(x_values, y_values, "Max Temp", (0,0))

# plt.text(0, 0, f"y = {round(slope, 2)}x + {round(intercept, 2)}", bbox=dict(facecolor="white", edgeco
```

```
The r-value is: 0.7151521229090637
```

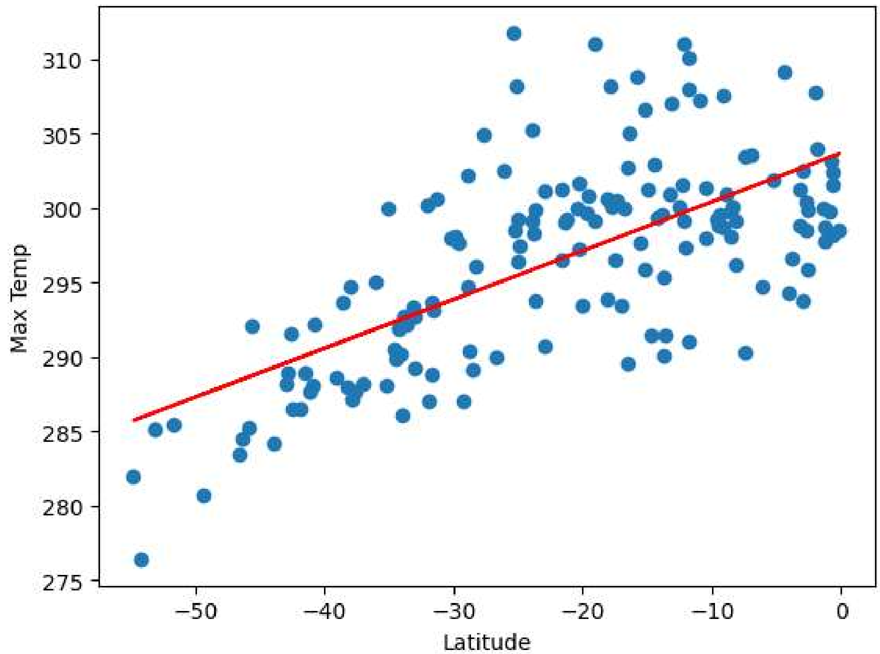


In [97]:

```
# Linear regression on Southern Hemisphere

x_values = southern_hemi_df["Lat"]
y_values = southern_hemi_df["Max Temp"]
plot_linear_regression(x_values, y_values, "Max Temp", (0,0))
```

```
The r-value is: 0.4495177362695968
```




```
# **Discussion about the linear relationship: It is clear the max temperature increases as you get closer to 0 latitude in the northern and southern hemisphere. The plots show the temperatures in cities across both hemispheres.
```

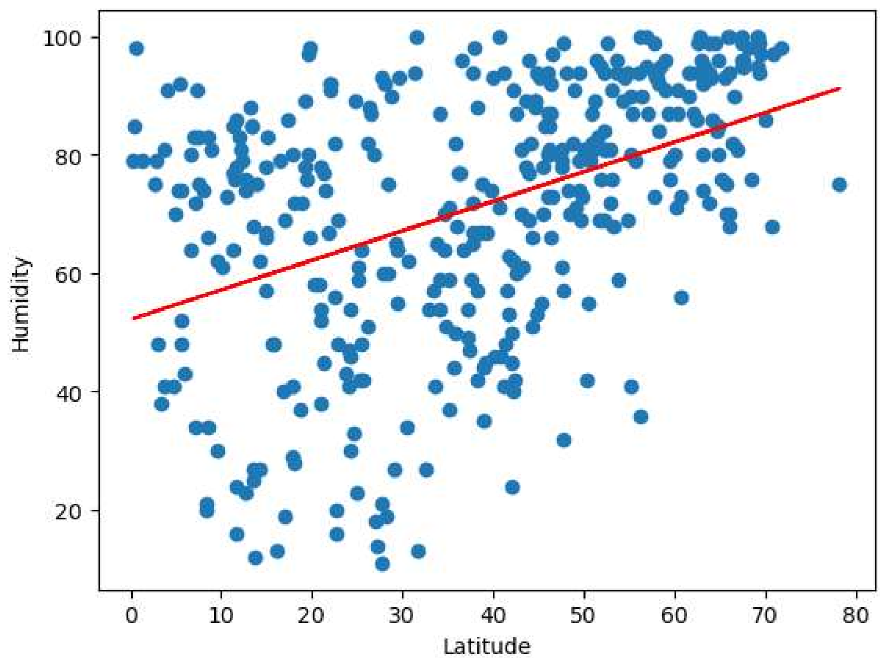
### Humidity vs. Latitude Linear Regression Plot

In [98]:

```
# Northern Hemisphere

x_values = northern_hemi_df["Lat"]
y_values = northern_hemi_df["Humidity"]
plot_linear_regression(x_values, y_values, "Humidity", (0,0))
```

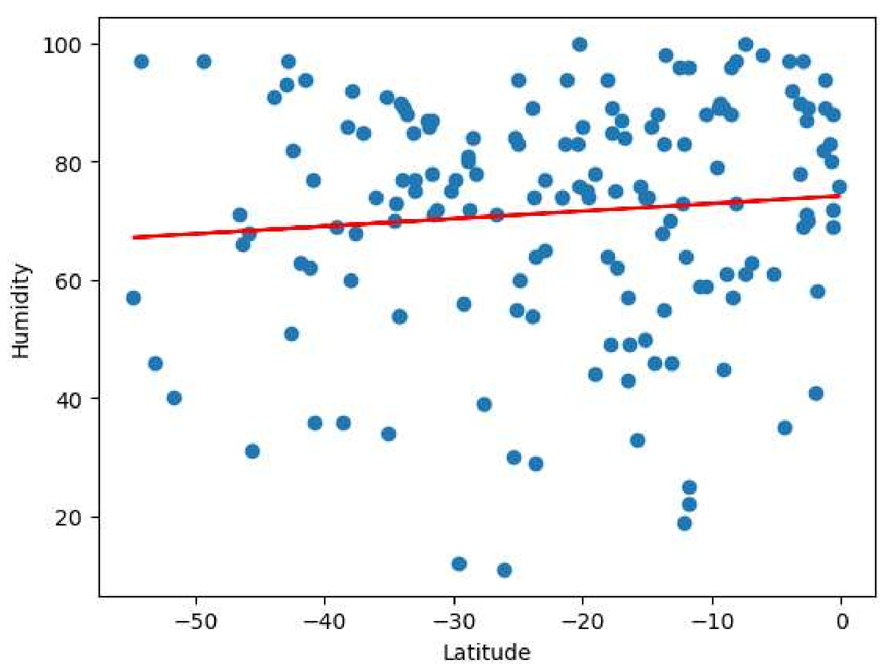
```
The r-value is: 0.19495558842745248
```




In [99]:

```
# Southern Hemisphere
x_values = southern_hemi_df["Lat"]
y_values = southern_hemi_df["Humidity"]
plot_linear_regression(x_values, y_values, "Humidity", (0,0))
```

```
The r-value is: 0.008016071168502214
```



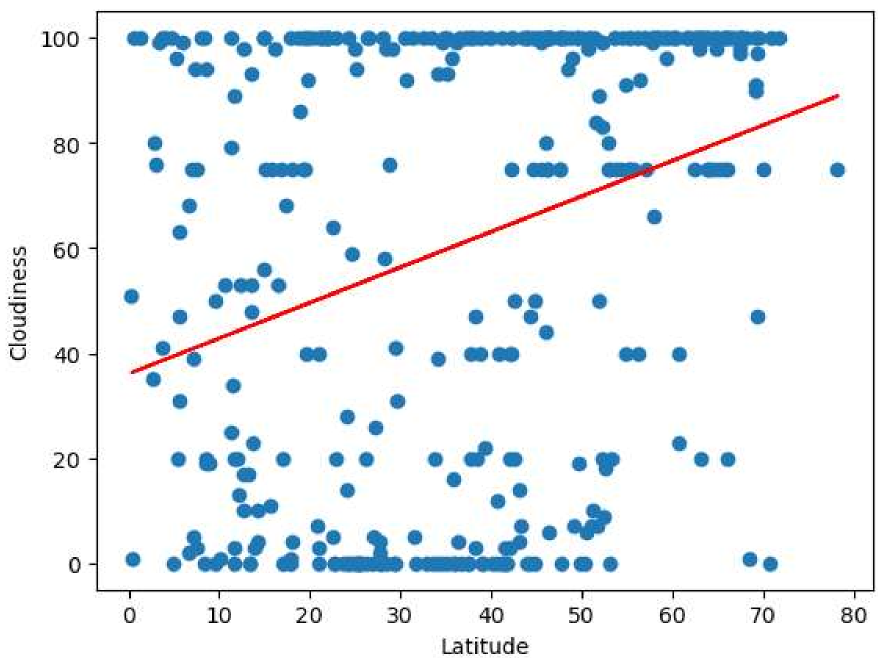
# **Discussion about the linear relationship: The two plots show the humidity for multiple cities across the nothern and southern hemispheres. While it appears that the further away you move from 0 latitude the more humid it gets in the northern hemisphere, both plots fail to produce any significant correlation based on their R-Values.

### Cloudiness vs. Latitude Linear Regression Plot

In [100]:

```
# Northern Hemisphere
x_values = northern_hemi_df["Lat"]
y_values = northern_hemi_df["Cloudiness"]
plot_linear_regression(x_values, y_values, "Cloudiness", (0,0))
```

```
The r-value is: 0.10246651124114439
```

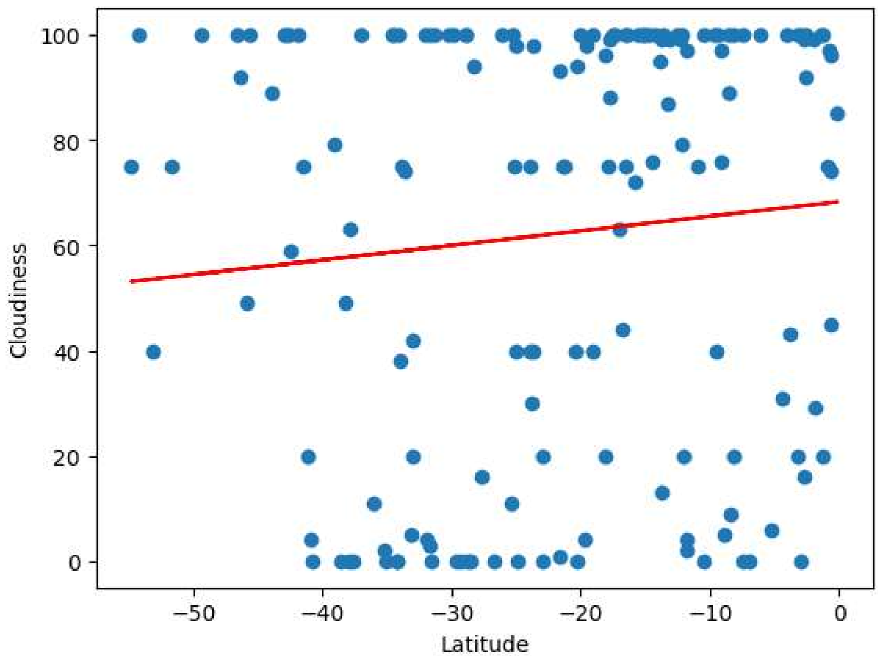


In [101]:

```
# Southern Hemisphere

x_values = southern_hemi_df["Lat"]
y_values = southern_hemi_df["Cloudiness"]
plot_linear_regression(x_values, y_values, "Cloudiness", (0,0))
```

```
The r-value is: 0.009148487769070958
```



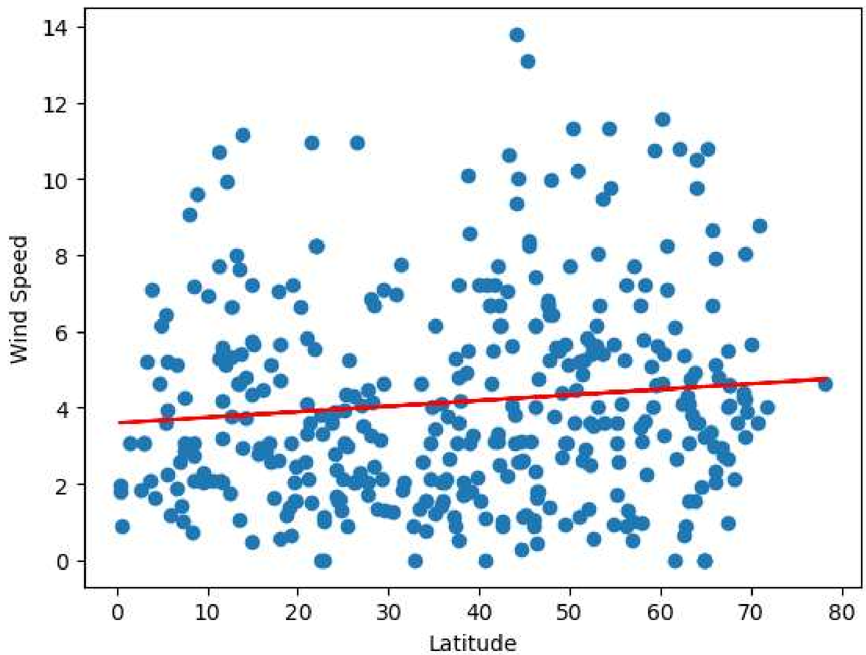

# **Discussion about the linear relationship: The plots show the level of cloud different cities experience across the northern and southern hemispheres. The data is very scattered and there does not appear to be a correlation between these two variables.

### Wind Speed vs. Latitude Linear Regression Plot

In [102]:

```
# Northern Hemisphere
x_values = northern_hemi_df["Lat"]
y_values = northern_hemi_df["Wind Speed"]
plot_linear_regression(x_values, y_values, "Wind Speed", (0,0))
```

```
The r-value is: 0.011352465571313175
```

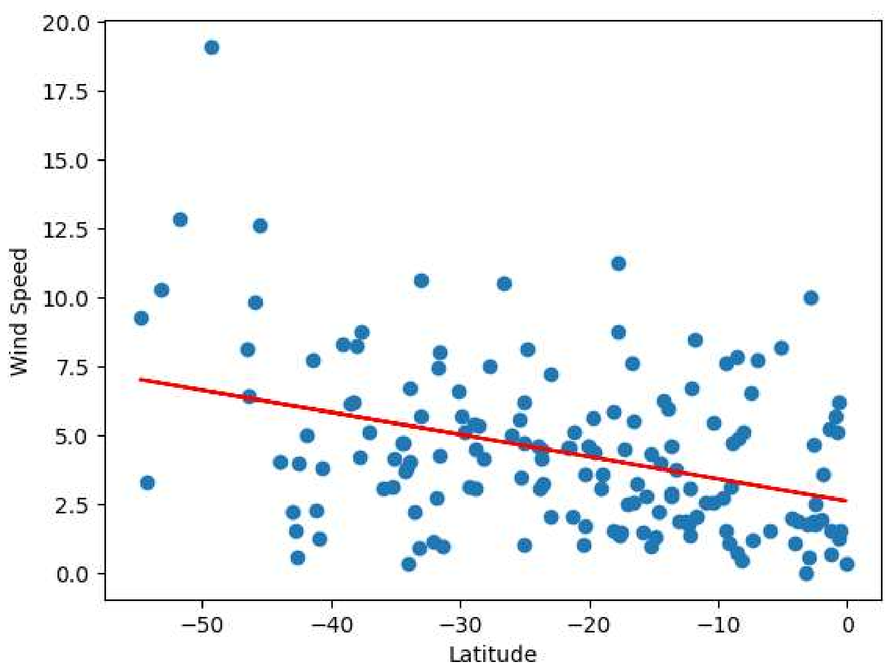



In [103]:

```
# Southern Hemisphere

x_values = southern_hemi_df["Lat"]
y_values = southern_hemi_df["Wind Speed"]
plot_linear_regression(x_values, y_values, "Wind Speed", (0,0))
```

```
The r-value is: 0.14254748813073853
```



# **Discussion about the linear relationship: The two plots show the wind speed of multiple cities across the northern and southern hemisphere. There does not appear to be any correlation between the two variables.

In [ ]: