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PREDICTING PARTICULATE MATTER CONCENTRATIONS BASED ON ATMOSPHERIC CONDITIONS

by
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AN ABSTRACT OF THE THESIS OF

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Research in Air quality Monitoring has been gaining a great importance worldwide especially in areas where pollution levels are high. The main objective of this thesis is to develop a computer model to predict ground pollution levels based on meteorological conditions. In order to build this model, daily mixing height data were used, estimated from temperature profiles collected from a simulator (WRF) for the period of nine months. The analysis was performed over the region of Beirut and involved the usage of pollution parameters, such as the PM2.5, PM4, and PM10 concentrations which were measured for this period, and meteorological parameters such as the mixing height, relative humidity, and wind speed. The study confirmed that there is strong anti-correlation between the mixing height and near ground level PM concentrations (PM 2.5 and PM10), moderate positive correlation between the relative humidity and near ground level PM concentrations, and weak negative correlation between the wind speed and near ground level PM concentrations. Regression models produced good results for the mixing height as a predictor for PM2.5 and PM10 concentrations. The mixing height was the most dominant factor in the regression analysis among other meteorological parameters including Relative Humidity and Wind Speed. Multi variable regression models (depending in two and three independent variables) were developed to predict PM concentrations based on meteorological parameters. The best regression coefficients were witnessed with the multi variable regression models developed to predict PM concentrations based on the three meteorological parameters (mixing height, relative humidity, and wind speed). These models can be applied for prediction of near ground pollution level over for the region of Beirut.

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To My

Beloved Family

CHAPTER 1

INTRODUCTION

In the past few decades much research on air quality has been conducted worldwide (Dai *et al*. 2014; Dye 2003; Holzworth 1967; Khandokar, Mofarrah and Husain 2010; Lu *et al*. 2012; Zang *et al*. 2017) in regions where pollution levels exceeded the normal values in such a way that affects people's life. Conducting such studies is crucial since it provides people with information that are very important for their health which in turn can help people avoid their exposure to unhealthy air quality levels. In addition, many communities could use this information to initiate air quality actions or awareness campaigns (Qu, Han, Wu, Gao and Wang 2017) that would help reduce air pollution levels and improve air quality as well. One of the key concerns of air quality studies is air pollution.

Air pollution can be thought of as the impurity of the atmosphere by wastes that are in the form of solid, liquid, or gas; this impurity has serious effects on people, animals, and the environment. Particulate matter, Ozone, Carbon Monoxide, Sulfur oxide, and Nitrogen Oxides are among the most effective pollutants of the atmosphere (Qu *et al*. 2017). Air Pollution has severe effects on our health.

Air pollution can lead to respiratory diseases. Tens of millions of respiratory and other diseases are caused by air pollution worldwide (SEI 2012). Since the average breathing volume per day for every person on the planet is 12,870 liters, even small amounts of air pollutants can lead to respiratory diseases. People can be affected directly by air pollution when breathing unhealthy air, and indirectly through the damage of their living environment. Not only babies and children are vulnerable to air pollution, but also people suffering from heart or respiratory diseases and elderly people as well. In particular the effects of air pollution are more severe in Asia and Western Pacific regions where millions of people die each year due to air pollution, and one billion people are exposed to air pollution levels that exceed the recommended health-based air quality level according to the World Health Organization (WHO). In addition there exists the need to avoid the exposure to pollutants especially when we have high pollution levels. In order to avoid the exposure to pollutants Air Quality researchers should predict near future conditions based on current conditions.

Many models in literature have been developed in order to predict near ground pollution levels based on meteorological conditions (temperature, relative humidity, and mixing height) (Dye 2003; Qu *et al*. 2017; Roy, Gupta and Singh 2012; Symeonidis 2017) . Previous studies relied mainly on mixing height measured directly through the use ceilometer (LIDAR) (Chen *et al*. 2013; Qu *et al*. 2017; Tang *et al*. 2016), SODAR (Zang *et al*. 2017) , or different methods applied on radiosonde data (Zang *et al*. 2017) which include the usage of complex instrumentation. Since the instrumentation is expensive and because meteorological stations are needed to conduct such Air Quality studies, computer models, which relies on software rather than hardware to predict near future conditions are particularly attractive, especially in third world countries where there are no meteorological stations and funding for such studies. In this thesis I seek to develop such a model to predict near ground pollution levels; the novelty in my approach is that meteorological parameters are predicted, rather than using an online meteorological prediction software named Weather Research and forecasting Software (WRF).

WRF is an advanced mesoscale forecasting system that is used for atmospheric research, and it can be used for research and operational forecasting.

Several meteorological agencies use it worldwide (e.g., National Centers for Environmental Forecasts, and The Air Force Weather Agencies).

One of the most important meteorological parameters used for the assessment of air quality and that was investigated in this thesis is the mixing height, which defines the height above which pollutants are mixed by means of turbulence and convection. In this thesis after I compared between the commonly used methods in literature, the mixing height was estimated using the “Parcel Method” or “Dry-Adiabatic Method” (Holzworth 1967). During my analysis, it was found that the resolution offered by WRF in its standard form was too coarse; therefore the WRF grid resolution had to be made finer. While the previous resolution included five data points from zero to four hundred meters, the finer grid included ten data points.

To validate the data offered by the WRF, I relied on a small unmanned air vehicle (UAV) equipped with a temperature sensor in order to estimate temperature profiles in the lower part of the atmosphere. The resulting measured temperature profiles were compared with those predicted using WRF in order to evaluate these profiles. The UAV used in this research was limited to a height of 150 meters because of its short flight time and low ascending speed.

The main methodology used for predicting near ground pollution levels based on atmospheric conditions was based on a measurement of ground pollution levels on one hand, and a prediction of meteorological parameters on the other hand. For this purpose WRF simulations were conducted during the period ranging from November 2016 till August 2017, where Parcel method was applied on the temperature profiles predicted using WRF to estimate the mixing height, and daily measurements of aerosols at near ground level were conducted during the same period as well. The relation between the aerosols and the mixing height was then investigated using Pearson correlation method. As a result, many linear regression models were built where the regression coefficients between the meteorological parameters and aerosols concentrations were calculated. It was found that there exists a linear relation between the mixing height and aerosols concentrations. The determination coefficient was calculated for each of these equations and it was found that the linear regression is a good estimate for the aerosols concentrations based on the mixing height as the main predictor. Multi variable regression models were built and examined taking into consideration two and three independent variables. It was found that the multi variable regression model relying on the three meteorological parameters gave the best regression coefficients in comparison with the other developed models relying on one or two of the meteorological parameters. The next chapter examines the air pollution problem and describes the mathematical and meteorological models used in air quality modeling.

CHAPTER 2

BACKGROUND

In this chapter an overview of air quality modeling and monitoring is presented. The definition of air pollution, its sources, and its main effects are explained in the first part of this chapter. The main mathematical models used for the modeling of air quality are presented in the second part of this chapter. An overview of air quality monitoring is investigated focusing on two key parameters: atmospheric aerosols and the mixing height. In the last part of this chapter the method used for the determination of the mixing height are explained, arguing that the “Parcel Method “is the most suitable approach for determining the mixing height.

2.1. Air Quality Modeling

In the first part of this section a brief description of air pollution is presented showing the main sources, and effects of air pollution. The second part of this section shows a brief view of the mathematical models used in air quality modeling.

2.1.1, Air Pollution

Air Pollution is one of the most influencing problems that is harmful to humans, animals, and the environment. Air pollution is mainly caused by emission of particulates and biological molecules into the atmosphere which are emitted into the atmosphere through natural or man-made activities. The emitted particles can be classified into two main types: primary and secondary pollutants(Arya 1999).

The primary pollutants are: Sulfur Oxides (SO_x), Nitrogen Oxides (NO_x), Carbon Monoxide (CO), Volatile organic compounds (VOC), Particulate matter (PM), Persistent free radicals, toxic metals, Chlorofluorocarbons ($CFCs$), Ammonia (NH_3), Odours, and Radioactive pollutants. The secondary pollutants include: Ground level ozone (O_3) and Peroxacetyl nitrate ($C_2H_3NO_5$). The two main sources of air pollution are natural sources and anthropogenic sources (Symeonidis 2017).

One of the main anthropogenic sources of air pollution is the burning of different types of fuels. Anthropogenic sources can be stationary (like power plants and manufacturing facilities) or mobile sources (like motor vehicles and aircrafts). Controlled burn (like practices in agriculture and forest management), Fumes (like paint, hair spray, varnish, and aerosol sprays), waste deposition, and Military resources (like nuclear weapons, toxic gases, and rocketry) are all anthropogenic sources of air pollution. Whereas, Natural sources include Dust from natural sources, Methane, Radon, smoke and Carbon Monoxide from wildfires, vegetation and volcanic activity. Air pollution has many severe effects on people, animals, and the environment (Sharma, Jain, Khirwadkar and Kulkarni 2013).

According to (Symeonidis 2017) the main effects of air pollution are:

- Health problems: it causes problems in cardiovascular and respiratory systems which may lead to asthma, chronic bronchitis, and premature death.
- Eutrophication: it causes the excess of nutrients in water or soil which is dangerous to biodiversity since the excessive growth of simple plants damages other plants, animals, rivers, and lakes.
- Acidification: it causes acidification of water and soil which damages plants, animals, and buildings.
- Physical damage: buildings are also subject to damage because of corrosion and soiling of their surfaces by the effect of particulate matter and acidification.

- Ozone depletion: man-made activities causes depletion of ozone layer which is the layer that protects earth from harmful radiation.

2.1.2. Mathematical Modeling of Air Quality

Air quality models can be classified into two types: Lagrangian models and Eulerian models. Lagrangian models examine the temporal and spatial movement of air parcel. On the other hand, Eulerian models predict atmospheric conditions using a gridded reference system. Currently the Eulerian 3d models are used primarily because they use three dimensional grids especially with advancements in IT systems that made these models highly adaptable. There are many factors that can affect an air quality model(Goyal and Kumar 2011).

According to (Symeonidis 2017) the most important factors in the air quality modelling are:

- Meteorological parameters
- Emission characteristics
- Topography

The mathematical modeling of air quality is classified into two main types. The first main type (called meteorological models) is concerned with the modeling of the atmosphere for the sake prediction of main meteorological parameters. The second type (called dispersion models) is concerned with modeling the physical and chemical processes involved in the atmosphere and will not be addressed in this thesis.

2.1.2.1. Meteorological Models

The prediction of atmospheric conditions for future times at given locations and altitudes require the usage of meteorological models which are computer programs built on to simulate the mathematical models of atmosphere, land, and oceans, and used to predict the future weather conditions based on the current conditions.

In order to predict the future weather parameters, a set of differential equations is solved which include ideal gas law equations along with primitive equations which are those for momentum, mass continuity, and energy conservation (Lions, Temam and Wang 1992). The meteorological parameters that are simulated by these models are: air density, air pressure, potential temperature, wind speed, and wind direction. The meteorological parameters are simulated through time and they highly depend on the prediction scale.

The prediction scales classifies these models into two types which are: global models and mesoscale models. Examples of global models include the Integrated Forecast System (IFS), the Global Forecast System (GFS), and the Global Environmental Multiscale Model (GEM). Whereas examples of mesoscale Models include the MM5, and the WRF. For this project the only software of interest is WRF. The rest are disregarded because we don’t have access and documentation to these software packages, and because of its wide usage in atmospheric research (Symeonidis 2017) .

2.2. Air Quality Monitoring

In this section the main pollution parameters used in this thesis are presented in the first part. In the second part the meteorological parameters used in thesis are illustrated.

2.2.1. Atmospheric Aerosols

The atmospheric aerosol is a complex mixture of solid and liquid particles that are released into the atmosphere. Atmospheric aerosols can be classified into two main types which are primary atmospheric aerosols, and secondary atmospheric aerosols. Primary aerosols are those that are directly released into the atmosphere (such as dust and smoke). Whereas secondary aerosols are formed in the atmosphere by gas-to-particles conversion processes (such as sulfates and nitrates) (Dye 2003).

The size of atmospheric aerosols varies in diameters between 0.002 and100 µm. Aerosols can be classified according to their size into two main types which are Fine particles ($d<2.5$ µm) and coarse particles ($d>2.5$ µm). Among the strongest fine particulate matter is Black Carbon. In the following sections a brief description of Particulate matter, PM2.5, and Black Carbon is presented(Dye 2003).

2.2.1.1. Particulate Matter

Another main concentration of this thesis is particulate matter, which is a complex mixture of solid and liquid particles of organic and inorganic substances suspended in the air. It mainly constitutes of sulfate, nitrates, ammonia, sodium chloride, black carbon, mineral dust and water. The size of particulate matter varies where their corresponding characteristics vary with relative to their size(Dye 2003).

The size of PM varies from about ten nanometers to ten micrometers where the particles with diameter less than 0.1 micrometers are considered ultrafine, and those of diameter between 0.1 and 10 micrometers are considered large. The diameter of the particles increases as their number decrease. The residence time of particulate matter varies with their size where the particles with diameters between 0.1 and 1 micrometers has the largest residence time, and may last from few days to weeks. The light scattering and absorption efficiencies of particulate matter varies with their size. Figure 1 shows the variation per mass of light scattering and absorption efficiencies per mass with respect to the diameter of particles. The particles with diameter of 0.5 micrometers has the highest scattering absorption efficiency (Figure 1). The below figures also shows that the absorption efficiency has a small variance with the particle diameter. Particulate matter has severe health impacts(Dye 2003).

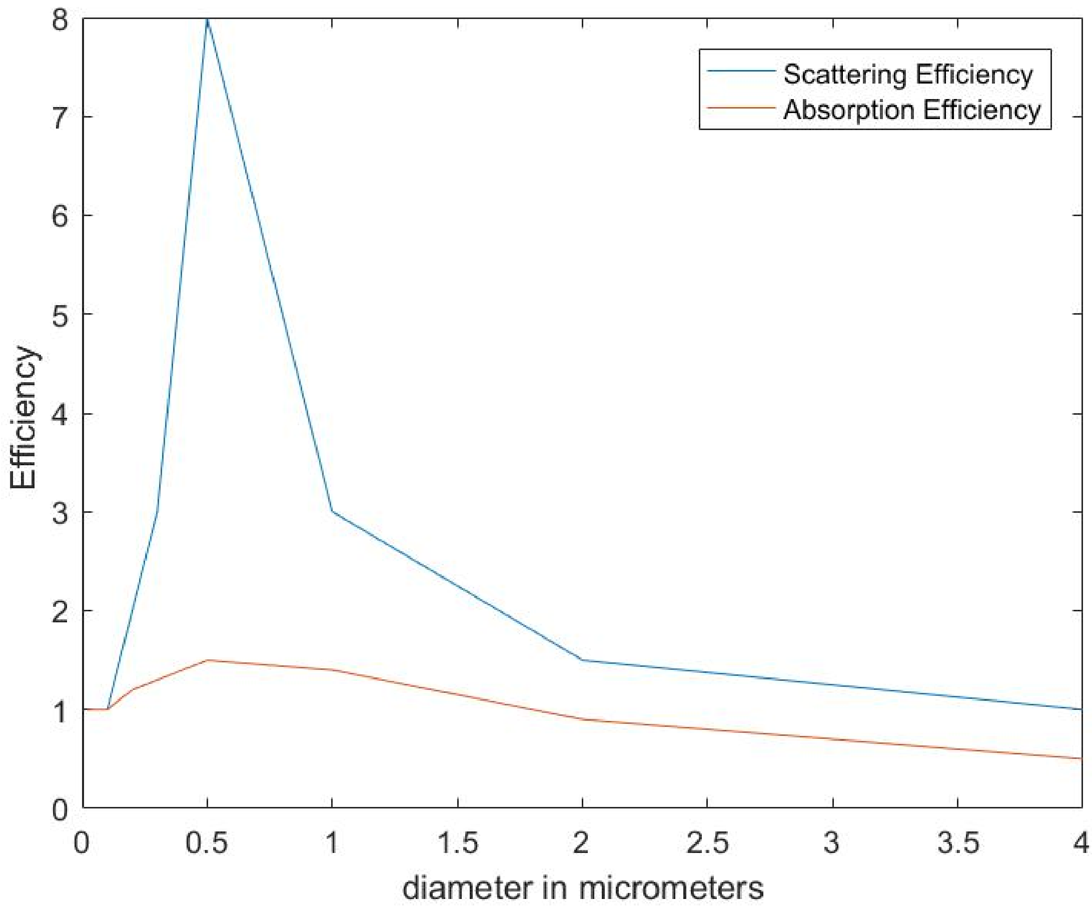


Fig. 1. Relationship between PM diameter and scattering and absorption efficiencies
Source: Dye, T.S. (2003). "Guidelines for developing an air quality". (Ozone and PM2. 5) *Iorecasting Program*.

Particulate matter has severe health impacts even in low concentrations, and there is no threshold above which health effects are not observed. Particulate matter with diameter less than 10 micros are the most dangerous since they can penetrate deep inside lungs causing cardiovascular and respiratory diseases. Also high rates of mortality is directly related to the exposure to high concentrations of small particulates (PM10 and PM2.5)(Brook *et al*. 2013).

Since PM has severe health impacts even for short-time exposure, there exists the need for the prediction of PM concentrations in order to warn people a few days before they appear in order to help them avoid exposure to them, especially on days where the concentrations of PM are expected to be high. PM2.5 and Black Carbon were studied in this thesis.

2.2.1.2. PM 2.5

PM2.5 are particulate matter of diameters less than 2.5 µm that are formed from fine particles of different sources. PM2.5 is mainly formed of: Sulfate, Nitrate, Ammonium, Salt, Organic Carbon, Elemental Carbon, and Liquid Water. PM can be classified into two main types which are primary and secondary aerosols (Dye 2003).

PM which are emitted directly into the atmosphere are called primary aerosols. Whereas PM which form when gaseous compounds are emitted are called secondary aerosols. PM2.5 has man-made and natural sources (Dye 2003).

Man-made sources include mobile sources (like vehicles, trains, and farm machinery) and stationary sources (like combustion of fuels and wood products). On the other hand, natural sources include primary sources (like dust and sea spray) and secondary sources (like ammonium sulfate and nitrate which result from oxidation of biogenetic hydrocarbons). Black carbon is among the finest and most dangerous particulate matter (Dye 2003).

2.2.1.3. Black Carbon

Black Carbon is a type of particulate matter that is considers the most harmful among particulate matter. It is composed of pure carbon and has the ability to absorb solar radiation of different wavelengths (Organization 2012). It's considered the most effective particulate matter since it has the ability to absorb solar radiation of different wavelengths. Many methods were conducted in the literature for determination of concentrations of Black Carbon, and its effects on health and climate (Apte *et al*. 2011; Organization 2012; Sasser 2012). In this thesis I use aethalometer for measuring Black Carbon concentrations.

2.2.2. Definition of the Mixing Height

One of the most important parameters for the assessment of air quality is the mixing height; it is defined as the volume within which pollutants are mixed or dispersed by means of turbulence and convection. The mixing height typically ranges from few meters to several kilometers during the day. The lowest levels of mixing height are observed during the early morning time and grow gradually to reach its maximum during the afternoon. Mixing height is based on the concept of heat transfer and it highly affects the transport and diffusion of air pollutants.

Temperature normally decreases with the increase of altitude in the troposphere, at an average of 10 °C per kilometer (Definition of Dry Adiabatic Lapse Rate). Inversion occurs when temperature increases with altitude, which results in a stable temperature profile that restricts vertical mixing. Pollution becomes more stagnant and undissipated as a result of volumes of air restricted due to inversion and causes vertical mixing or forming of mixing height. The early morning mixing height was determined from the temperature profile predicted by WRF using the " Dry-

Adiabatic Method" or "Parcel Method" (Holzworth 1967), based on the concept of air parcel.

A parcel of air that is hotter than the environment will rise at a given rate called the Dry Adiabatic Lapse Rate (Figure 2). Once the parcel becomes colder than the environment it will slow down until it stops. The point of meeting of the vertical temperature profile with the temperature of parcel is called the mixing height (Figure 3) which is the point where the environmental lapse rate is less than the dry adiabatic lapse rate. The environmental lapse rate defines the rate of change of temperature of the atmosphere with height (Figure 3). The method for determining the mixing height was chosen based on a comparison that is presented in the next section.

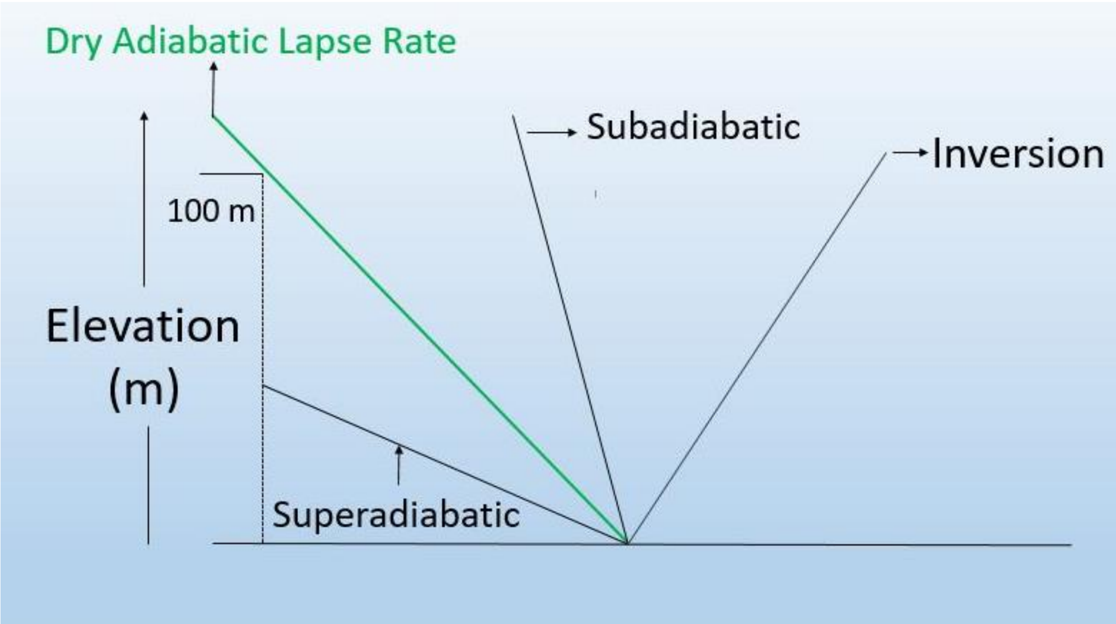


Fig. 2. Dry Adiabatic Lapse Rate

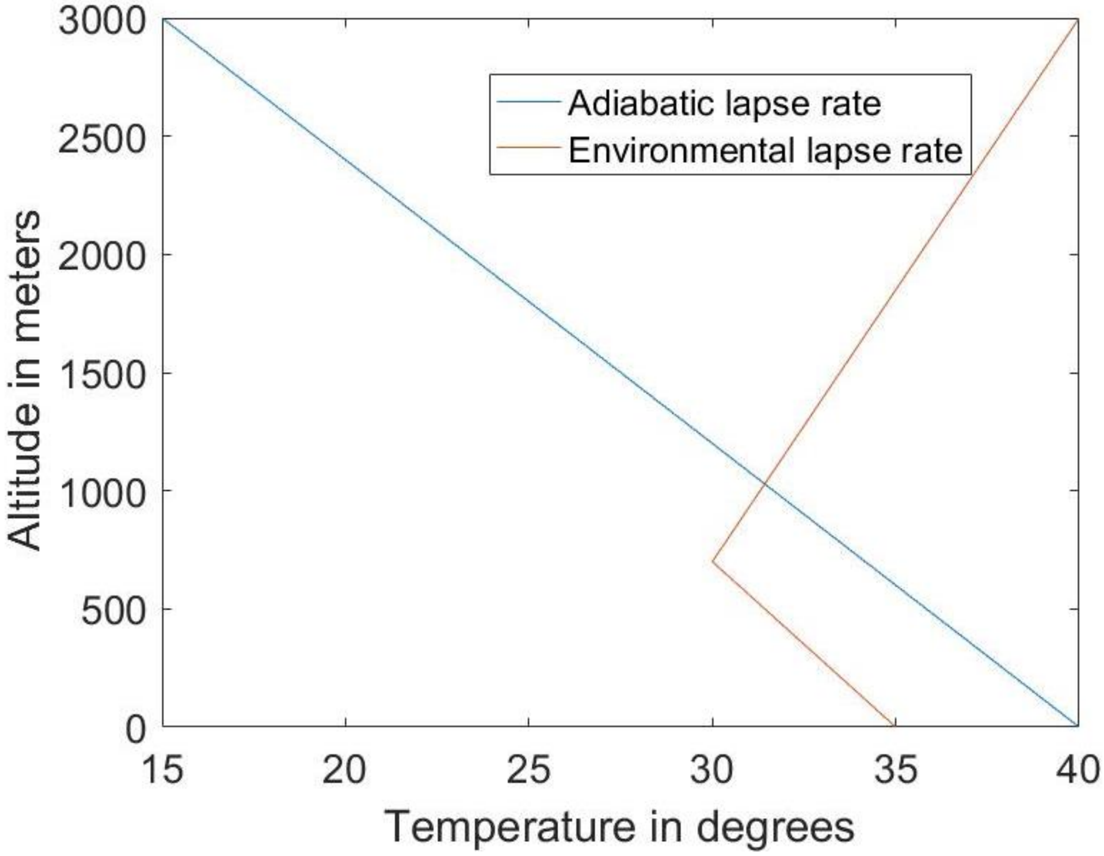


Fig. 3. The Mixing Height

2.2.2.1. Mixing Height Determination Method

In literature, several strategies have been used to determine the mixing height. Mixing height can be determined based using two main approaches: the profile measurements (direct measurement techniques) and the simple models (Parametrizations) (Seibert *et al*. 2000). Determining mixing height from profile measurements depends only on measurements whereas determining it from simple models may depend on weather forecast models and measurements.

Direct measurement methods may be classified into two types: remote sensing, and radiosoundings. Radiosoundings are the most common methods for the determination of mixing height, being considered as a standard for evaluating remote sensing methods. A radiosonde is equipped with a measurement system that is carried to high altitudes by a hydrogen or helium balloons. It measures atmospheric parameters and transmits them to a fixed receiver. The measured atmospheric parameters are: longitude, altitude, longitude, temperature, barometric pressure, and humidity. Rawinsondes differ from radiosondes that they also can measure wind speed, and direction. Using these methods mixing height can be calculated based on profiles of temperature, relative humidity, and windspeed. Mixing height can determined based on radiosounding using subjective or objective methods. The mixing height determination methods can be classified as shown in Figure 4.

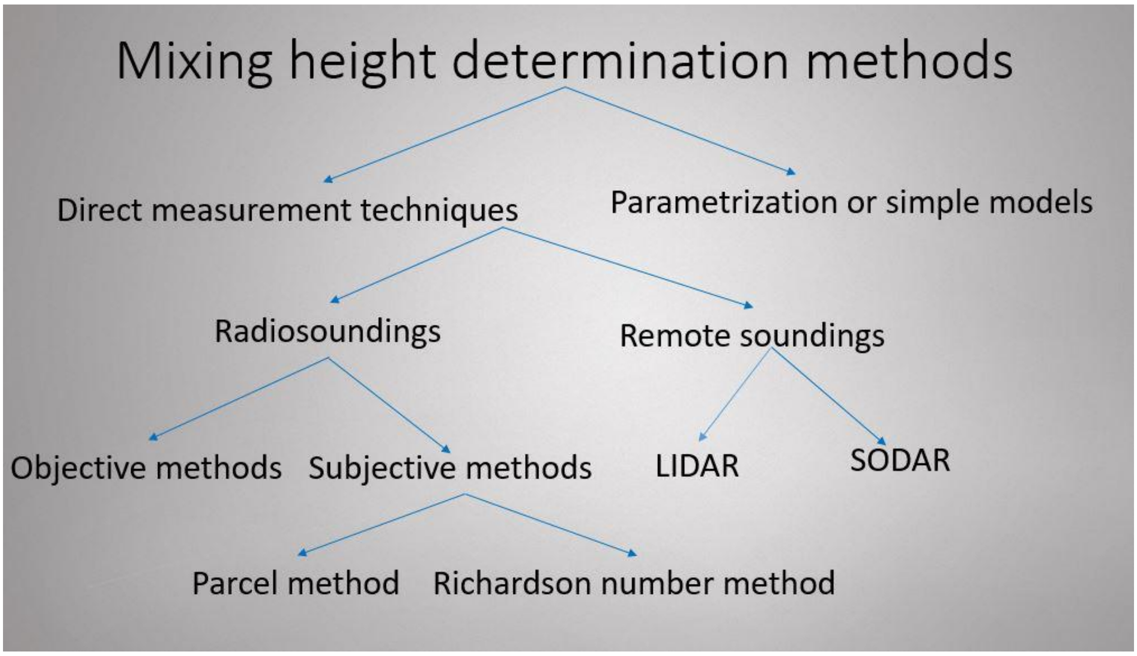


Fig. 4. Mixing height determination methods

Subjective methods depend on wind profiles and radiosondes. These methods determine mixing height as the height where we have sudden decrease in air moisture or base height of inversion layer (Dai *et al*. 2014; Lotteraner and Piringer 2016; Mues *et al*.) . On the other hand, objective methods simplify the determination of mixing height by homogenizing it's estimation under convective conditions (Holzworth 1967). The two most common objective methods are the Parcel methods and Richardson number methods.

Parcel methods strongly depend on surface temperature where the mixing height is determined by the intersection between temperature vertical profile, and dry adiabatic lapse rate starting at the surface (Holzworth 1967). Whereas Richardson methods depends on potential temperature and wind speed to determine the mixing height. The mixing height is assumed as the height which reaches a certain threshold. Richardson number can be calculated at each height from potential temperature and wind speed at that level (Zhang *et al*. 2014). Richardson methods can be used for weather forecast models since they work at certain conditions that are reliable under various atmospheric conditions. The second type used for determination of mixing height from profile measurement is remote sensing methods.

Remote sensing methods employ the use of operational systems for the direct measurement of mixing height through the use of LIDAR (Light detection and ranging) and SODAR (Sound detection and ranging). LIDAR uses laser light in to measure aerosols concentrations to measure the mixing height. The mixing height determined using Lidar is defined by sudden decrease in the aerosol concentration. Whereas SODAR (Sound detecting and ranging) uses sound waves to determine the mixing height. The mixing height in this case is the height at which sudden increases in temperature occur. Particles and aerosols mix at a height where the variance of temperature starts to increase. Remote sensing methods can be used to determine average mixing height values, but not instantaneous ones. The second main approach of mixing height determination is the usage of simple models.

Simple models are used when data profile measurement techniques aren't available. They use simple parametrization based on standard surface observations. These models use simple parametrized equations depending on a limited number of input data.

Many comparisons between these methods have been conducted in the literature (Coulter 1979; Khandokar, Mofarrah and Husain 2010; Seibert *et al*. 2000). Parametrization methods are confined for the treatment of atmospheric boundary layer in some weather forecast models. Whereas Profile measurement methods can cover up to 2-3 km above the ground, which enables mixing height determination in all seasons. These studies concluded that profile measurement methods superior are superior on parametrization methods due to the suggested reasons.

Dai *et al*. (2014) state that the Richardson number method is inadequate for most cases in comparison with other used methods. The results of (Mues *et al*.) showed that it gives comparable results at 100-m vertical resolution.

Lotteraner and Piringer (2016) presents a new method of determination of mixing height using an operational ceilometer, in contrast with Parcel, Heffer and Richardson methods applied on radiosondes profiles. It showed that the Parcel method gave the best fit to the ceilometer derived mixing height, whereas Richardson and Heffer methods overestimated the mixing height.

A comparison between subjective method and parametrization models is shown (Cheng *et al*. 2001). Dry Adiabtic (Parcel Method) is compared with Nokazi and modified Nokazi model. Parcel method determines mixing height based on surface temperature and radiation inversion, whereas Nokazi models determine it based on thermal and dynamic factors. It states that Parcel methods require sounding data whereas Nokazi models are applicable in areas where there are no sounding data. The implied results showed that the Parcel method is superior on Nokazi model for estimating the mixing height.

Seibert *et al*. (2000) state that the determination mixing height from Profile measurements is preferred on determining it from Parametrization models. This papers shows comparison between Parcel and Richardson number methods applied on radiosounding data. It proves that the Parcel method is the most reliable method for the determination of mixing height based on the sounding temperature profile.

In Seidel, Ao and Li (2010), six methods based on radiosonde data were compared concluding that the Parcel method is an obvious choice for determining the mixing height especially over the well dense and populated area. It concludes also that other methods are better for comparison with weather forecast models.

Comparison between temperature turbulence method, gradient method, low-level jet method, and parcel method is shown in (Coulter 1979). It states that Parcel Methods are more affordable than turbulence method since Temperature turbulence methods are more expensive, and can't be widely applied.

Based on the above comparisons, and since we are only measuring temperature profile without the usage of remote sensing systems the method used in this thesis is the "Dry Adiabatic Method" or "Parcel Method".

Using the Parcel method the mixing height can be determined by finding the intersection between the early morning temperature profile, and the dry adiabatic lapse rate line. Figure 5 shows how to calculate the early morning mixing depth from early morning temperature profile, by the following steps:

- Find a representative morning ground-level temperature:

$$T_{AM} = T_{min}(between\ 2\ a.m. \&\ 6\ a.m.) + 5\ ℃$$

- From point T_AM draw a line corresponding to the dry adiabatic lapse rate.
- Find the intersection between early morning temperature profile, and dry

adiabatic lapse rate line.

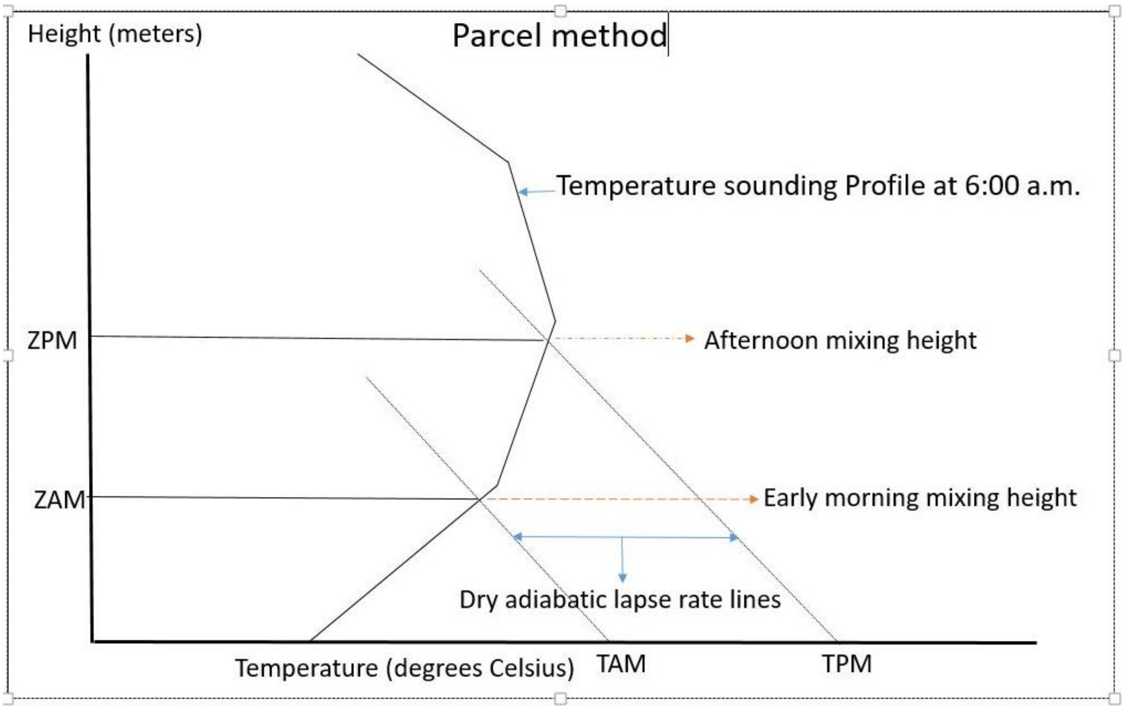


Fig. 5. Parcel Method

In this chapter an overview of the main aspects of air quality modeling and monitoring was presented. The air pollution problem and mathematical models used in air quality were described in the first part of this chapter. The meteorological parameters used in this thesis were explained in the second part which are: atmospheric aerosols and the mixing height. Finally, the method used in this thesis for the determination of the mixing height was presented showing an overview of the previous studies used, comparing between them, and explaining the method used in this thesis. In the next chapter the previous studies that were conducted for investigating the correlation between the mixing height and atmospheric aerosols are investigated.

CHAPTER 3

LITERATURE REVIEW

Many similar works have been conducted in literature to study the relation between the mixing height and PM concentrations. Most of these studies predicted PM concentrations using linear regression models, but they differed in the method applied for the estimation of the mixing height. Different correlation methods were applied to test the relation between the mixing height and meteorological parameters. The next paragraphs present an overview of these studies.

One of the previous studies focused on studying the correlation between the mixing height and PM 2.5 concentration (Qu *et al.* 2017). The study concluded that low mixing height is associated with low wind speed and high relative humidity, and that the stability of Planetary Boundary Layer (PBL) is enhanced by high PM concentrations. The study also found that the mixing height is highest in the summer and lowest in the winter and that the correlation coefficient between PM 2.5 and mixing height is -0.71, a fact which proves that there is strong anti-correlation between PM 2.5 concentration and the mixing height.

A similar study was conducted to examine the effect of mixing height on ground-level PM2.5 concentrations (Zang *et al*. 2017). A step wise regression model was built to estimate PM2.5-ground level concentrations based on surface relative humidity, mixing height, and surface temperature. The determination coefficient was found to be 0.65.

A related analysis was conducted to study the mixing layer height and its effects on air pollution(Tang *et al*. 2016). The mixing layer height was estimated using ceilometer, and it was observed to be low in autumn and winter, and high in spring and summer. A significant correlation was found between the sensible heat flux and the mixing height. The correlation between mixing height and visibility was investigated and was found to be poor.

The empirical relationship between aerosol optical depth (AOD) and of fine (PM 2.5, particles with diameters less than 2.5 µm) and coarse (PM Particles between diameter of 2.5 and 10 µm AD) mass concentrations and compositions was investigated (Chen *et al*. 2013). Continuous hourly measurement of PM 2.5 data was done, and daily average measurement of PM2.5 and PM10 were obtained. The correlation coefficient varied from 0.56 and 0.87 depending on the season. Linear regression between PM2.5 and AOD was investigated in order to allow the estimation of PM2.5 mass concentrations at the surface based on AOD data, which can be used to help interpret AOD measurements made in Central Asia and potentially over the regions of the world. The mixing height was measured by LIDAR and has a seasonal variation from 1 to 4 km. The regression equation depends on AOD, mixing height, and relative humidity. The determination coefficient varied between 0.32 and 0.38 depending on the season.

Other studies focused on the temporal variation of ventilation coefficient and estimated it using multi-linear regression models (Lu, Deng, Liu, Huang and Shi 2012). Pearson correlation analysis was conducted to investigate the relationship between mixing height and meteorological parameters. The meteorological parameters that were used in this study included: Wind speed, temperature, pressure, relative humidity, and dew point temperature. The largest correlation coefficient (0.799) was observed with the solar radiation during day time. A high correlation coefficient was observed between mixing layer, and relative humidity and temperature during day time. Multi-regression models were built based on the correlation between the mixing height and meteorological parameters. The regression models estimated the day and night hourly mixing height based on the wind speed, pressure, temperature, relative humidity, and temperature dew point.

Similarly, the relation between mixing height and atmospheric parameters was examined (Roy, Gupta and Singh 2012). Correlation coefficients were calculated to study the relation between mixing height and meteorological parameters. Regression analysis showed that mixing height is significantly affected by solar radiation and wind speed. A statistical model was developed to estimate the mixing height based on meteorological parameters.

In Sansone *et al*. (2006), a different approach was conducted to develop a multiple regression approach that forecasted PM 10 concentration. The linear regression depended on the following meteorological factors: daily means of wind speed, rain accumulation, mixing height, and thermal inversion index. The determination coefficient R^2 was calculated to test the fitness of the regression and it was evaluated as 0.75 during the period October 2001- September 2004 and as 0.72 during the Period October 2004-September 2005. The largest determination coefficient was observed between PM 10 and the mixing height with a value of $R^2 = 0.28$ which proves that the strongest correlation is between PM10 and the mixing height.

All the above studies are similar in forecasting PM concentrations using a linear regression model that depends on one or more of the meteorological parameters as the main predictor for these concentrations (Dye 2003; Qu *et al*. 2017; Roy *et al.* 2012; Symeonidis 2017). However, these studies differed in the mixing height method. One group of studies employed the use of ceilometer for determining the mixing height (Chen *et al*. 2013; Qu *et al*. 2017; Tang *et al*. 2016). Another study employed the use of SODAR for the estimation of the mixing height (Zang *et al*. 2017). A third study calculated the mixing height using different methods applied on radiosonde data (Zang *et al*. 2017). A fourth study collected the mixing height data from meteorological websites (Lu *et al*. 2012). The final study estimated the mixing height using CALMET meteorological model (Sansone *et al*. 2006). Giving the fact that most of previous studies adopted a linear regression model for forecasting PM concentrations, a multi variable linear regression model is also used to predict PM2.5, and PM4, and PM10 concentrations based on the meteorological parameters as the main predictor for these concentrations in this study. The above studies differed in the mixing height determination method where most of them relied on meteorological stations data or expensive instrumentation (LIDARs and SODARs).

To address these issues and taking into consideration the fact that my aim was for an automated and relatively inexpensive method, independent of meteorological station, I opted for a software-based-design approach, in which a current online system (WRF) would be augmented with ground pollution level information. In this respect this research is new of its kind presenting a software based approach for forecasting PM2.5, PM4, and PM10 concentrations based on meteorological parameters especially the mixing height. I estimate the mixing height using the Parcel method applied on temperature profiles predicted using WRF software. The next chapter outlines in details the methodology that was conducted for achieving the main objective of this thesis.

CHAPTER 4

METHDOLOGY

The different methods and tools that were used in this thesis to develop the linear regression models are presented in this chapter. The two main datasets that were used are PM Dataset and Meteorological dataset. A brief view of each dataset is provided in the first two sections of this chapter. The tools and methods that were used in this thesis are described briefly in the third section of this chapter. Finally the regression model that was built based on the meteorological and PM Datasets is elaborated in the fourth section of this chapter.

4.1. Description of Datasets

The following datasets were used in this study:

- PM concentration data (PM1, PM2.5, PM4, and PM10) from the station located in Beirut, Lebanon
- Meteorological Data from the WRF modeling system. The datasets were studied for the period ranging from November 2016 to August 2017

These datasets are described shortly in the next sections.

4.1.1. PM Dataset

PM Measurements from air quality station were used in order to evaluate the possible relation between the mixing height and PM concentration. PM data contained the hourly variation of PM concentration for the period between November 2016 and August 2017.

4.1.2. Meteorological Data

The Mixing Height was predicted using meteorological data (Temperature vertical profiles). The main meteorological parameters were predicted using the WRF modeling system. The main objective is to use meteorological data estimated using WRF as an input for a system model that uses this data to predict near ground particulate matter concentrations (Figure 6). WRF resolution was refined using Python scripting.

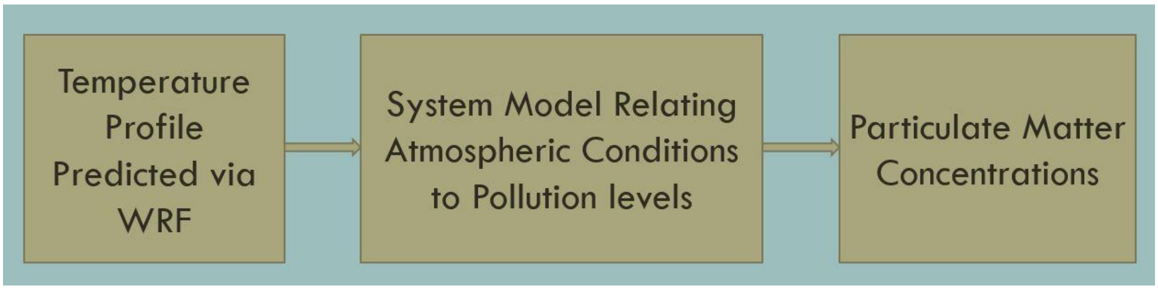


Fig. 6. Prediction of Particulate Matter Concentrations Using WRF

WRF files contained the average hourly values of parameters in the vertical layers of the model. WRF vertical resolution was refined in order help in accurately comparing between predicted temperature profiles and measured temperature profiles.

On the other hand, the relative humidity and wind speed were predicted using Beirut underground weather forecast website.

4.2. Tools and Methods

In order to achieve the main objective, different tools and methods were used to develop the main system model. The WRF datasets preprocessing was mostly performed using custom Python scripts. Microsoft Excel was used in order to produce the monthly or seasonal averages of PM concentrations and mixing height values .MATLAB software and tools were used in this study to analyze and visualize the PM and meteorological datasets and to investigate the relation between them. MATLAB provides advanced statistical tools including descriptive statistics, correlations, and regression analysis.

MATLAB curve fitting tool was used in order to build the regression equations between PM concentrations and the mixing height where statistical analysis was performed. The overall process workflow is presented in the image below (Figure 7).

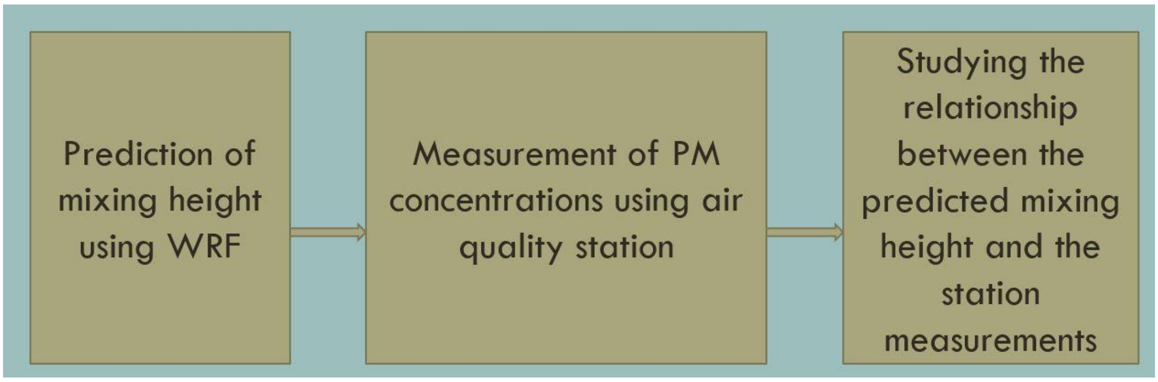


Fig. 7. Basic Methodology

Moreover, SPSS software was used to develop the multi variable linear regression models. Many models were developed relying on two or three of the above stated meteorological parameters, where these models were then compared to determine the best equations that can be used for the prediction of PM concentrations based on atmospheric conditions.

CHAPTER 5

SYSTEM MODEL

The onsite PM measurements, and the WRF model are briefly described in the first and second sections of this chapter respectively. The developed regression model is described in the third section.

5.1. Onsite PM Measurements

The PM daily average concentrations were assessed over the region of Beirut. This data was provided by the Chemistry Department at the American University of Beirut. The location of this station is shown in the map below (Figure 8).

Fig. 8. Location of PM station
Source: Google Map, 2017.

5.2. WRF

The advanced research WRF (ARW) is a modeling system that has been designed for atmospheric system. It's a flexible software suited for many kinds of applications including: hurricane research, forecast research, regional climate research, data assimilation research, and many other ones. WRF simulations were carried out with WRF 3.8.1 version. WRF was used in a 210 km domain with 45 levels, in which the first ten levels up to a height of 2 km were used. Simulation time was set to 24 h, with a 60s time step. WRF was used to predict vertical temperature profiles. Mixing height was then determined using Dry Adiabatic Method as shown in Figure 9. The mixing height was determined by the intersection between the temperature vertical profile predicted using WRF at 6 a.m. with the dry adiabatic lapse rate line assuming the surface temperature as the minimum temperature between 2 & 6 a.m. in addition to five degrees to compensate between urban and rural areas as discussed before. The basic flowchart of WRF is shown in Figure 9 whereby the WRF workflow consists of two consecutive main parts. The first part is the WRF Preprocessing System (WPS) which contains the tools that prepare the data that WRF uses (geogrid, ungrib, and metgrid). These tools were used as processers for static data and driving model data as well. The second main part is the WRF model. It consists of two consecutive parts which are:

- Real.exe which is the initialization program
- Wrf.exe which is the numerical integration program

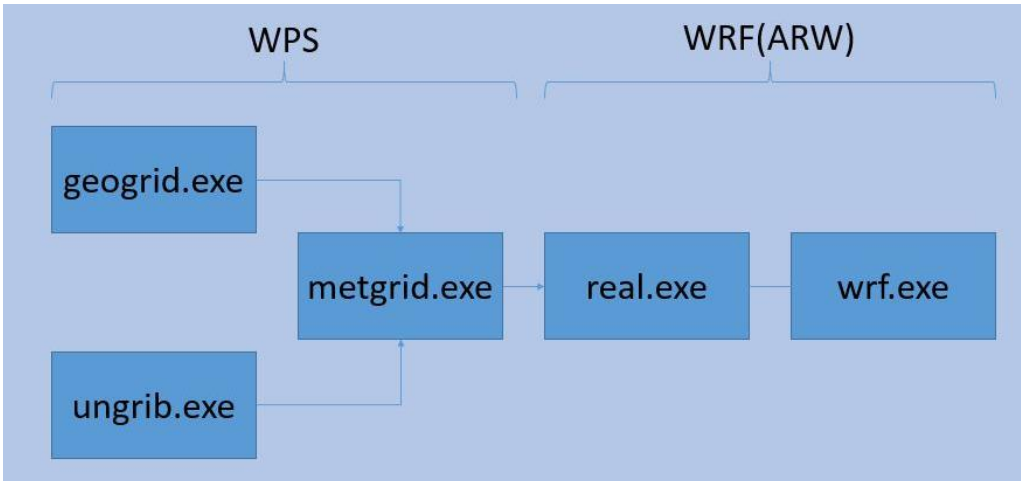


Fig. 9. Basic WRF flowchart
Source: Tran, 2014

5.3. Creation of Regression Models between the PM station Data and the Model Data

In this study, the correlation between Mixing Height predicted using WRF and PM concentrations measured by air quality station was studied. The hypothesis was tested over the area of Beirut, since Beirut is a very dense area, where a large population is affected by air pollution especially those exceeding the regulation limits. Thus, monitoring air quality in this area is of high importance. To achieve this goal many steps were taken.

First, the mixing height was predicted using WRF, and PM station data were extracted. The available data was then compiled, where regression analysis was performed. The condition that was examined is that of PM concentrations with the meteorological parameters. The result of this analysis showed that there is a significant relation between these variables and the mathematical relationship between them was investigated statistically. Linear regression models between the meteorological parameters and PM concentrations (which have high correlation coefficients with the mixing height) were developed, and coded using MATLAB software (taking into consideration the methodology described in the previous chapter) and SPSS software. The developed regression equations, and results of statistical analysis are shown in Chapter 7. In the next chapter, the main software and hardware used for the validation of WRF in this study are presented.

CHAPTER 6

VALIDATION OF WRF

The different hardware and software that were used for the validation of WRF in this thesis are presented and described. The hardware consists of: temperature sensors, Arduino Uno, Aethalometer, and an Unmanned Aerial Vehicle (UAV). Critical instrumentation were used in this thesis which are less commonly used in other methods of literature. These descriptions are confined to the measurement of temperature, and Black Carbon concentration. The results of flights are shown in the last section of this chapter.

6.1. Description of Software and Hardware Involved

6.1.1. Arduino Uno

Arduino is open-source physical board, which has many applications for reading data from different kinds of sensors, switches, and controlling motors, and many other actuators. The projects built using Arduino are easily communicated with various software. The Arduino can be powered via a USB connection or external power supply. There are different kinds of Arduino models such as the Arduino UNO, the Arduino Leonardo, and the Arduino zero; I opted for the Arduino UNO since it has the lowest price among other Arduino models, and because according to the technical specifications of the sensors, the specifications of Arduino Uno are adequate.

6.1.1.1. Specifications of Arduino UNO

The main specifications of Arduino UNO used in this thesis is shown in Table

1 below.

Table 1. Specifications of Arduino UNO

Operating Voltage	5V
Input Voltage	7-12V
Digital Input/output Pins	14
Analog Input Pins	6
DC Current for Input/output Pins	40 mA
Clock Speed	16 MHz
Flash Memory	32 KB
SRAM	2 KB
EPROM	1 KB

6.1.2. Temperature Sensors

6.1.2.1. SHT75

SHT75 is sensor of temperature and relative humidity. It is fully and has lower power consumption with excellent long-term stability. It can be easily integrated since the chip contains an amplifier, A/D converter, OTP memory, and digital interface. The main specifications of SHT75 for sensing relative humidity and temperature are shown in Tables 2 and 3 respectively.

Table 2. Relative Humidity Sensing Specifications

Parameter	Value	Units
Resolution	0.05-0.4	%RH
Accuracy	1.8	%RH
Repeatability	0.1	%RH
Hysteresis	1	%RH
Response time	8	%RH
Operating range	0-100	%RH
Long time drift	<0.5	%RH/yr

Table 3. Temperature Sensing Specifications

Parameter	Value	Units
Resolution	0.01-0.04	℃
Accuracy	0.3	℃
Repeatability	0.1	℃
Response time	5	℃
Operating range	-40-124	℃
Long time drift	<0.04	℃/yr

As shown in Tables 2 and 3, the response time of the SHT75 sensor for sensing relative humidity and temperature is 5 and 8 s respectively, which is incompatible with the desired sensor specifications of the temperature sensor that can be used for meteorological applications (Figure 11).

6.1.2.2. MCP9808

MP9808 is a digital temperature sensor that converts temperatures to digital mean with maximum accuracy of ± 0.25 degrees Celsius. The sensor comes with user-programmable registers that provide flexibility for temperature sensing applications allowing accurate temperature measurements. The specifications of the MCP9808 temperature sensor are shown in Table 4.

Table 4. MCP9808 Temperature Sensor Specifications

Sensor	Type	Range	Accuracy	Response time
MCP9808	High accuracy temperature sensor	-40-12 ℃	+/- 0.25℃	0,7 s

As shown on Table 4, the response time of the MCP9808 temperature sensor is 0.7 s. The response time of the temperature sensor was tested experimentally by recording the time required by the sensor to shift from room temperature to freezer temperature. It was found that the temperature sensor needed more than one minute to shift from room to freezer temperature, which makes this sensor inapplicable. This is because the total flight time of the drone is six minutes, and a fast enough temperature sensor in this case.

6.1.2.3. 503 ET

Many temperature sensors were implemented and tested for the sake of determination of vertical temporal variation (Jacob *et al*. 2017). The used temperature sensor is bead thermistor 503ET-3H87L-20073. This sensor was chosen since it has high accuracy, fast response time, and long reliability(Jacob *et al*. 2017). It utilizes the concept of decreasing resistance for increasing temperature where the resistance is transformed to voltage by the use of voltage divider. The PCB schematic diagram of the circuit is shown in Figure 10, as can be seen, the sensor is connected to Arduino via a voltage divider which transforms the output current to output voltage. This voltage is filtered by a low pass filter R2 & C1, and sent to ADC A0. Then the data is saved as a text file in a microSD card with a SPI interface.

Table 5 presents the technical specifications of the 503ET temperature sensor.

Table 5. Technical Specifications of the Used Temperature Sensor

Parameter	Value	Units
Rate zero-power resistance at 37℃	29.615-30.263	KΩ
B value by rate zero-power resistance between 30 and 45℃	3944$\pm$0.5	%
Dissipation factor	0.7	mW/℃
Thermal time constant	0.8	s
Rated maximum power dissipation (at 25℃)	3.5	mW
Temperature range	-40-100	℃

The specifications of a sensor that can be used for meteorological applications are shown in Figure 11. Based on these specifications, the temperature sensor was chosen since it has faster response than the other two sensors.

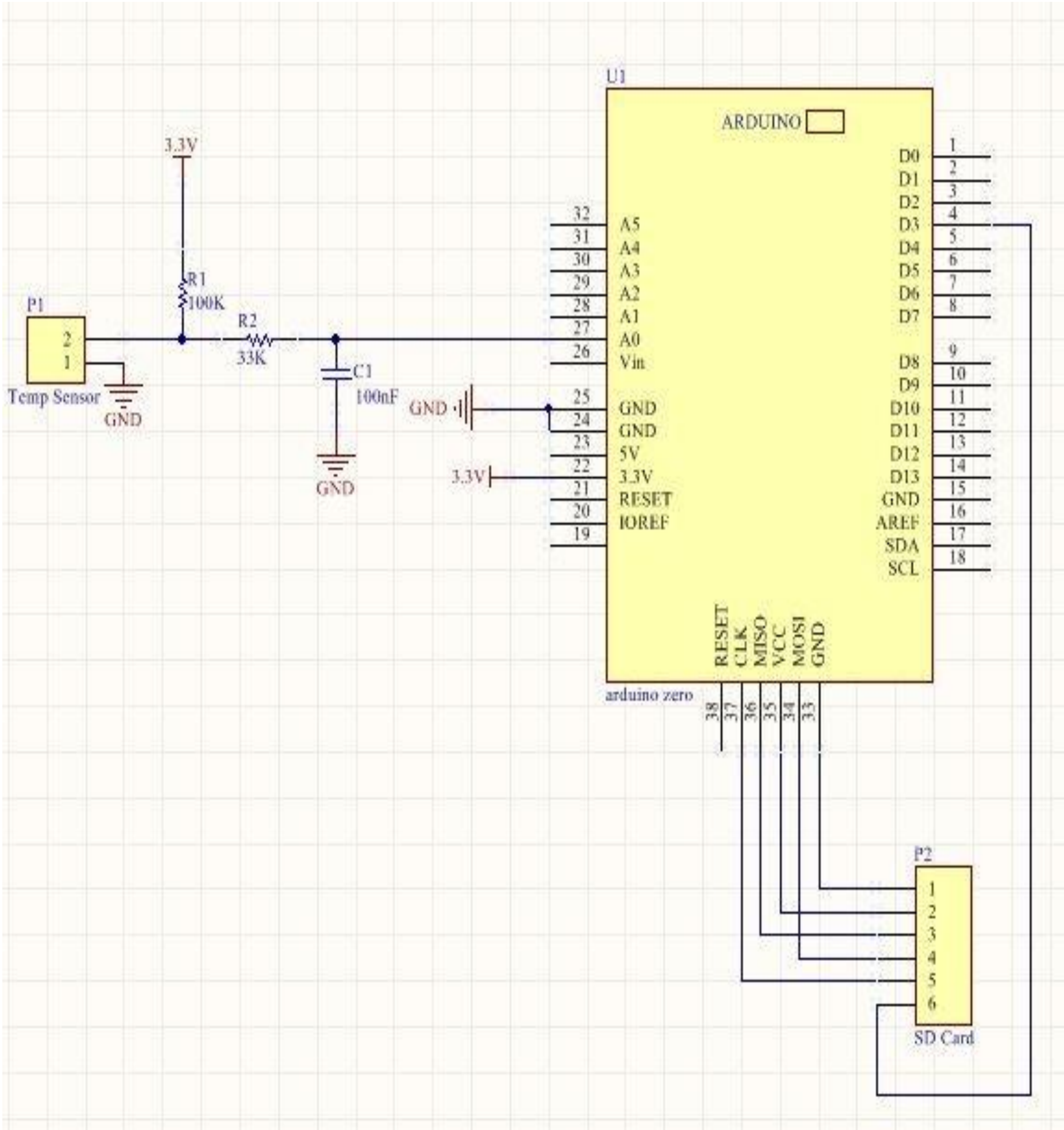


Fig. 10. Schematic of Temperature Measurement System

Desired Sensor Ranges and Accuracies	
Temperature	-30 – 40 C, +/- 0.2 C
Relative Humidity	0 – 100 %, +/- 5.0%
Pressure	+/- 1.0 hPa
Wind Speed	0 – 45 m/s, +/- 0.5 m/s
Wind Direction	+/- 5 Degrees Azimuth
Sensor Response Time	< 5 s (Preferably < 1 s)

Fig. 11. Meteorological Sensor Specifications
Source: Jacob *et al.* (2017). Unmanned Aerial Systems for Atmospheric Research: Instrumentation Issues for Atmospheric Measurements.

6.1.3. Aethalometer

The model used for measurement of Black Carbon concentrations in real time is the “microAeth AE51 “(Figure 12). The main uses of aethalometers is for air quality measurements, with data being used for studies of the impact of air pollution on health, climate, and visibility. In many measurements, including planes, trains, bicycles, weather balloons and UAVs, it constitutes one of the fundamental principles for acquiring information about aerosol Black Carbon concentration in real time (Organization 2012; Sasser 2012). Other measurements include the emission of Black Carbon from combustion sources such as vehicles, industrial processes, and biomass burning, both in wildfires and in domestic and industrial settings (Apte *et al*. 2011).

In this thesis, an aethalometer is used to determine the near ground level Black Carbon concentration. The model I selected can work for 24 hours on a single battery charge. The air sample is collected on T60 (Teflon coated glass fiber) filter media which can be easily replaced by simple handling in the field. Data is collected by the means of collection of aerosol deposit on a filter. The measurement resolution and precision are 0.001 μg $BC/m3$ and $\pm$ 0.1 μg $BC/m3$ respectively. In this research, the chosen time base and resolution set to the aethalometer are 5 min and 100 ml/min respectively. According to the operating manual, the individual data point noise associated with this time setting base and flow rate is less than $0.05 ug/m^3$. Data is stored in a microSD card which is mounted inside the aethalometer. The Black Carbon concentration is collected during the time of flight.

Fig. 12. The Aethalometer

6.1.4. Unmanned Aerial Vehicle

The UAV used in this thesis is 3DR RTF X8 (2013) (Figure 13). The quadcopter has powerful motors and high-speed propellers. The quadcopter has three modes of flight which are: stabilize, manual, and autonomous modes. In this research, the UAV is set to autonomous flight mode in order to perform vertical measurement of temperature since we have defined vertical waypoints where the quadcopter can hover for a small time to collect data. Two 5200 mAh/11.1 V was used for each flight giving the quadcopter a total flight time of 6 minutes. The ascending and descending speeds that were set to the drone were 1.25 and 0.8 m/s respectively. Using RC transmitter the communication between the quadcopter and the laptop were handled. Mission Planner software was used to communicate with the drone during flights, and store flight missions on a laptop. Quadrotor flights are conducted at AUB over the Green Field (Figure 14) that is located near to Paris Street, a high source of air pollution, where population and industries concentrate at Beirut city. The quadrotor was set to autonomous flight mode where temperature profiles were recorded up to a height of 150 meters.

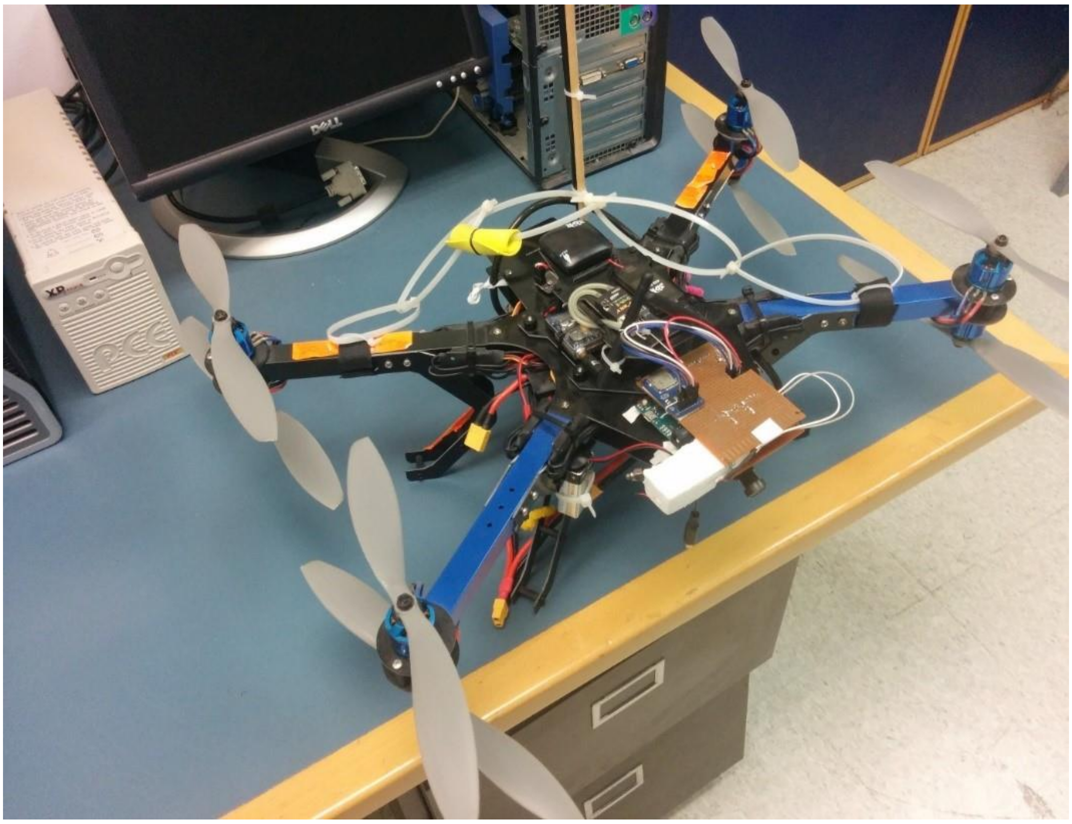


Fig. 13. Quadrotor with Temperature Sensor

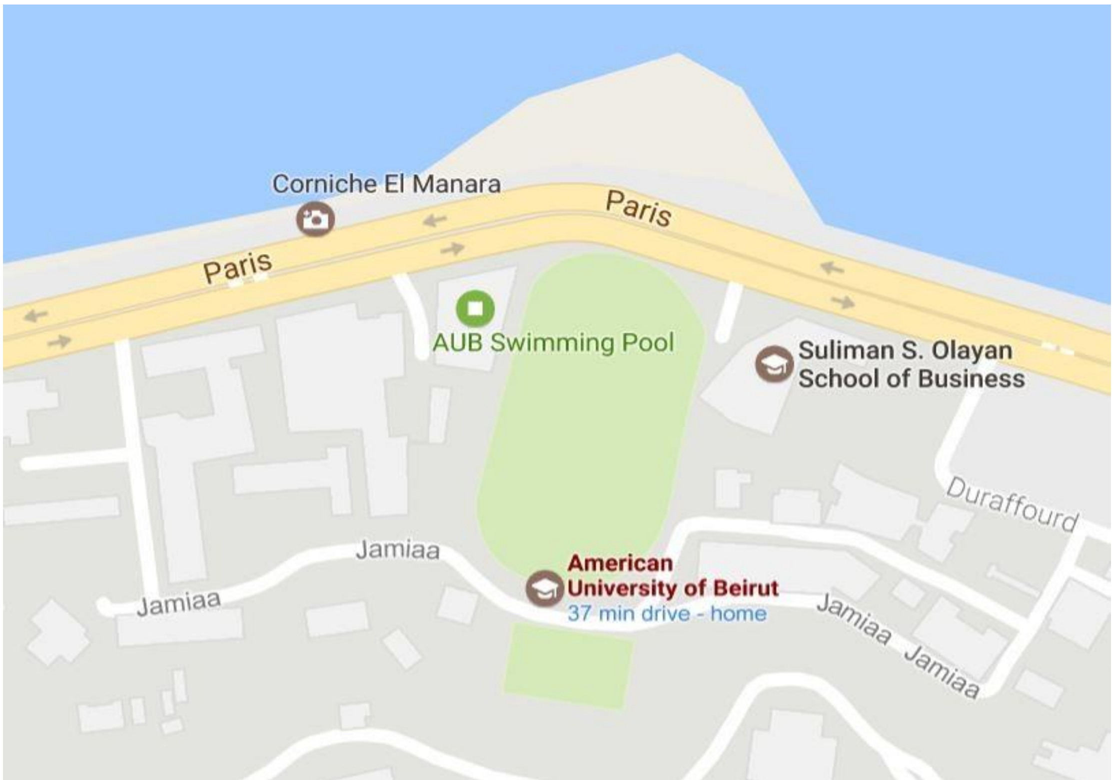


Fig. 14. AUB Green Field Location
Source: Google Map, 2017.

6.2. Results of flights

In order to validate WRF eight flights were conducted, where the temperature was measured to a height of 150 meters. The temperature profiles resulting from the flights were then compared with the temperature profiles predicted using WRF. Samples of resulting temperature profiles and temperature profiles predicted using WRF (during the same timing of flights) are shown in Figure 15. The mean, variance, and standard deviation of the error were calculated, whereby the error represents the difference between measured and predicted temperature.

Table 6 shows the coefficients calculated for the sake of comparison between the measured and predicted profiles using 503 ET temperature sensor.

Table 6. Results of comparison between predicted and measured temperature profiles using 503 ET temperature sensor

Mean of error	1.76℃
Variance	1.1 ℃
Standard deviation	1.2 ℃

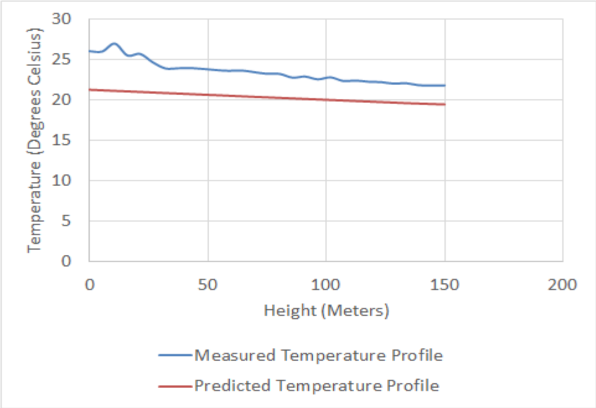
As shown in Table 6, the error has a mean of 1.76℃, a variance of 1.1 ℃ , and a standard deviation of 1.2℃. The obtained results show that WRF is different than temperature measurements by 1.76℃.

Similarly, a sample of the results of temperature measurements conducted using SHT75 is shown in Figure 16. Five flights were conducted, of which we have four flights up to a height of 70 meters, and one flight up to a height of 150 meters.

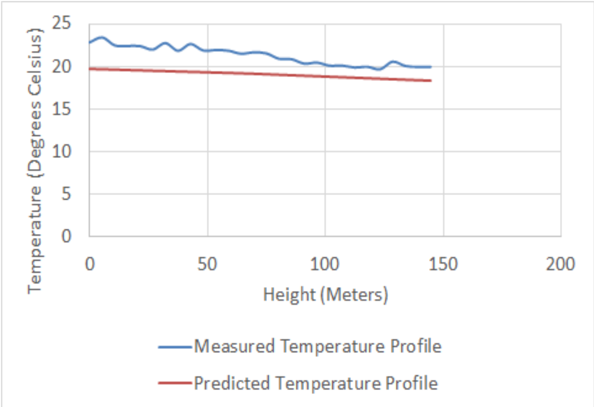
Table 7 shows the coefficients calculated for the sake of comparison between the measured and predicted profiles using SHT75 temperature sensor.

Table 7. Results of comparison between predicted and measured temperature profiles using SHT75 temperature sensor

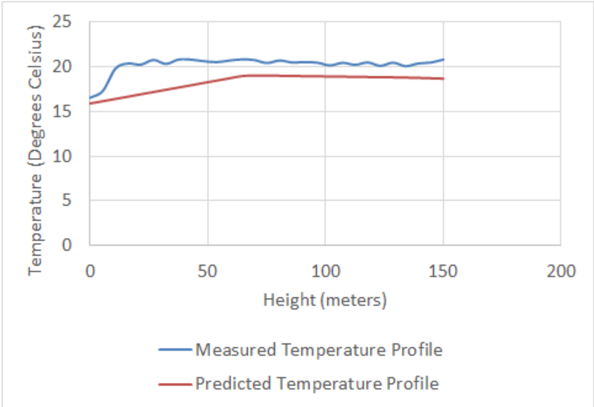
Mean of error	0.822921611 ℃
Variance	1.364782397 ℃
Standard deviation	1.862630991 ℃



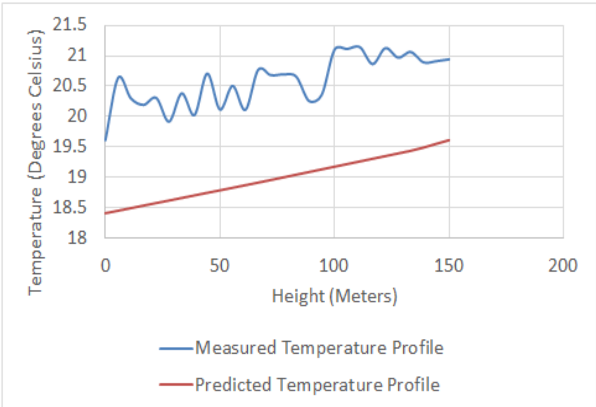
(a)



(b)

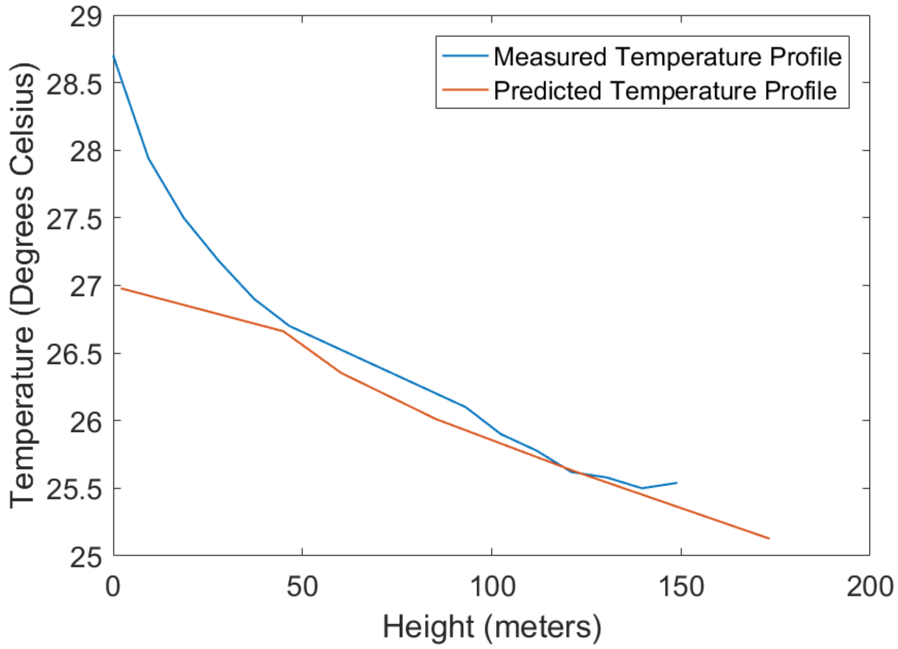


(c)

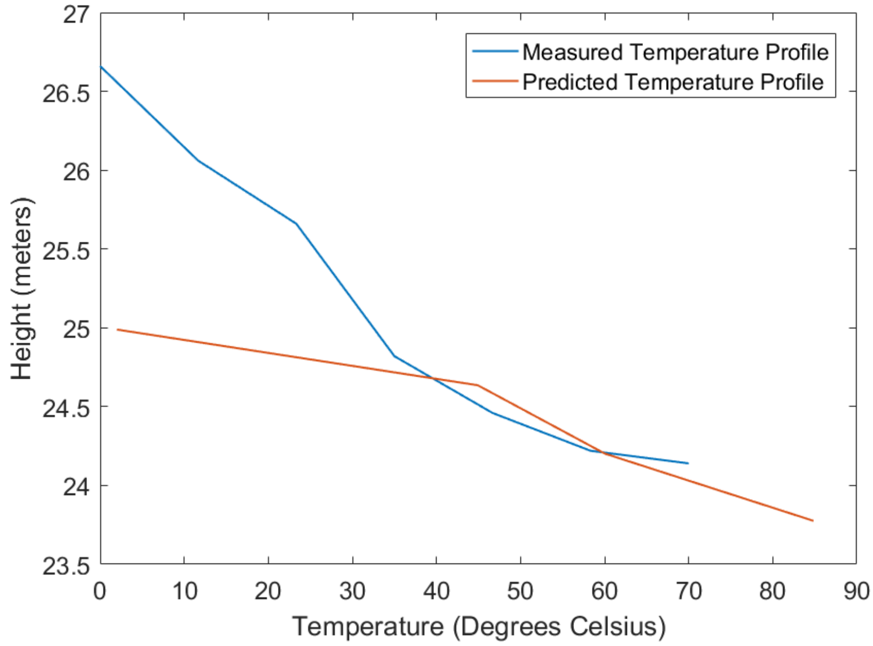


(d)

Fig. 15. Samples of Resulting Flights Using 503ET Temperature Sensor



(a)



(b)

Fig. 16. Samples of Resulting Flights Using SHT75 Temperature Sensor

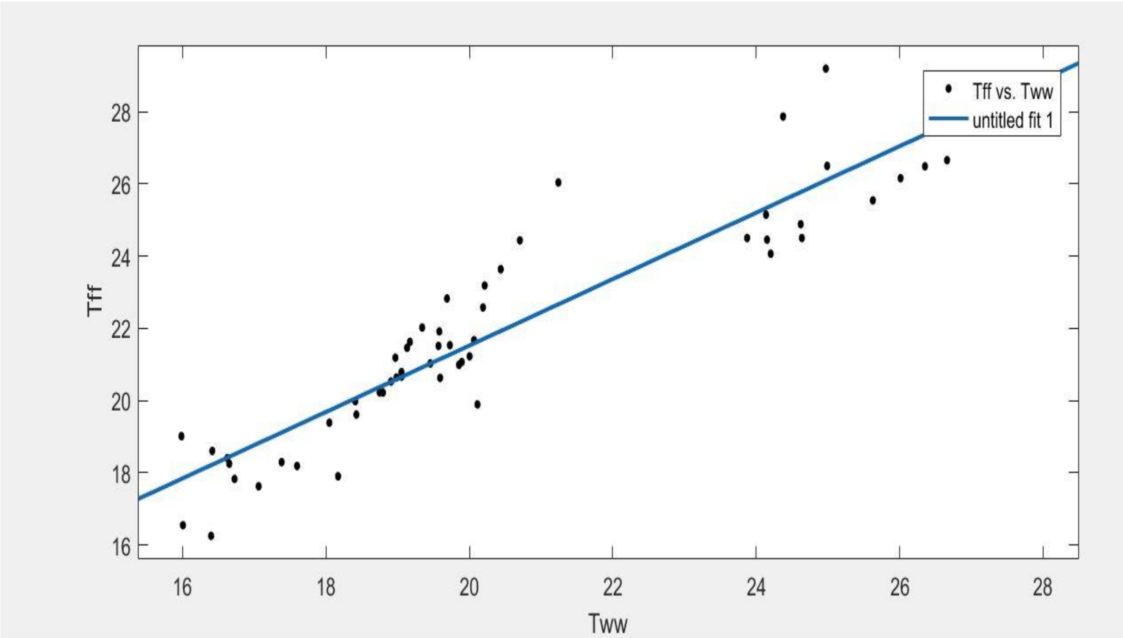


Fig. 17. Scatter Plot of Measured Temperature Profiles with Measured Temperature Profiles

The scatter plot of the relation between predicted and measured temperature profile is shown in Figure 17. The coefficient of determination (R-squared) between the measured with predicted temperature profiles is 0.8661, which proves that the mixing height predicted relying on temperature profile predicted using WRF is quite accurate.

CHAPTER 7

RESULTS

7.1. WRF Simulations

WRF simulations were conducted from November 2016 till August 2017 in order to extract temperature profiles. A large number of data were collected intermittently within the mentioned period, and below are some samples from different seasons. Moreover, Parcel Method was applied on the resulting temperature profiles to estimate the mixing height during this period. The dry adiabatic lapse rate line is shown in the figure below. As stated before the mixing height is the intersection between the dry adiabatic lapse rate line, and the temperature profile curve. Two samples from each month are shown in the below Figures (18-25).

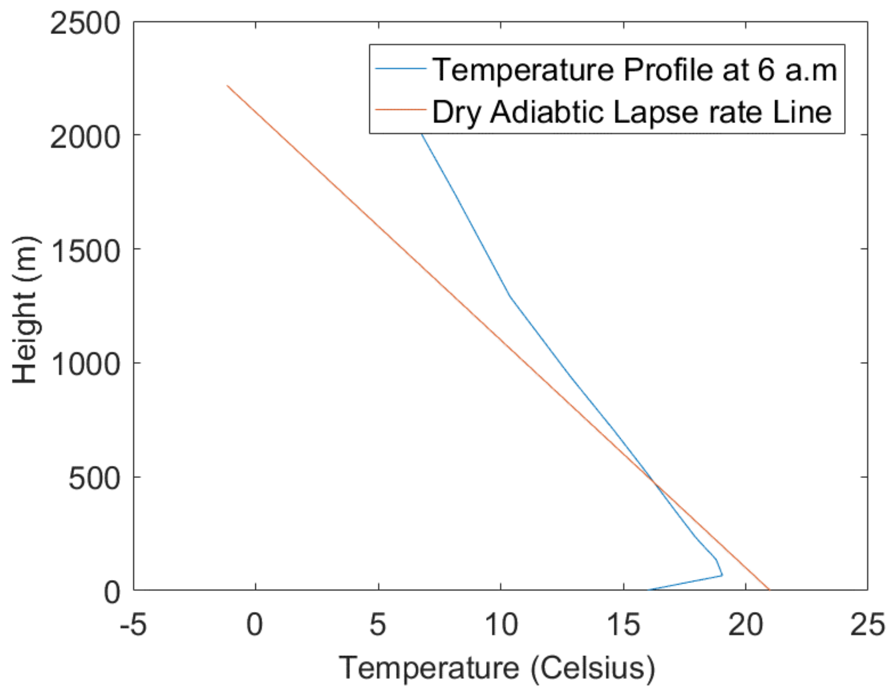


Fig. 18. Sample of WRF Simulations from November

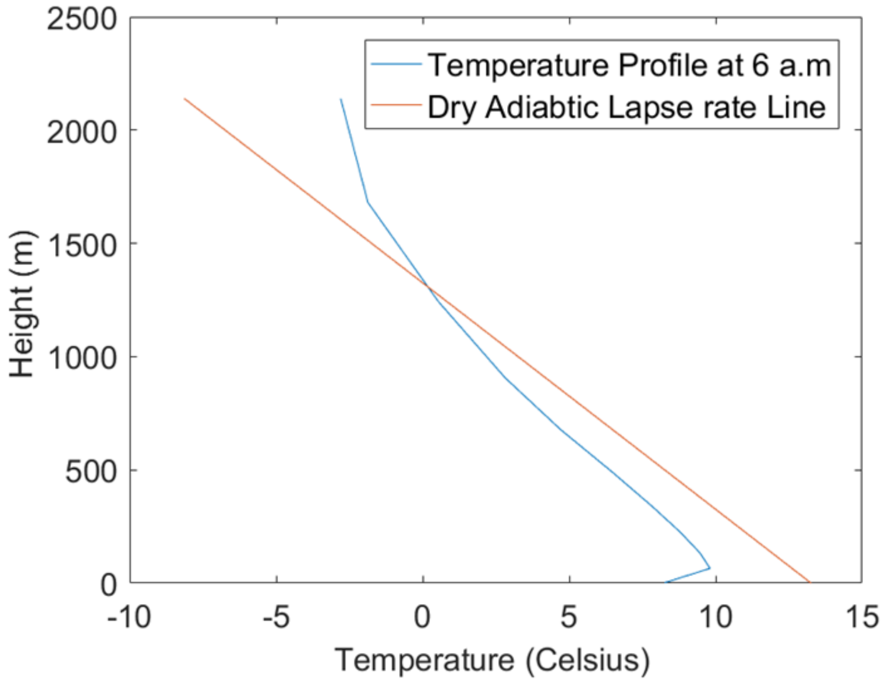


Fig. 19. Sample of WRF Simulations from December

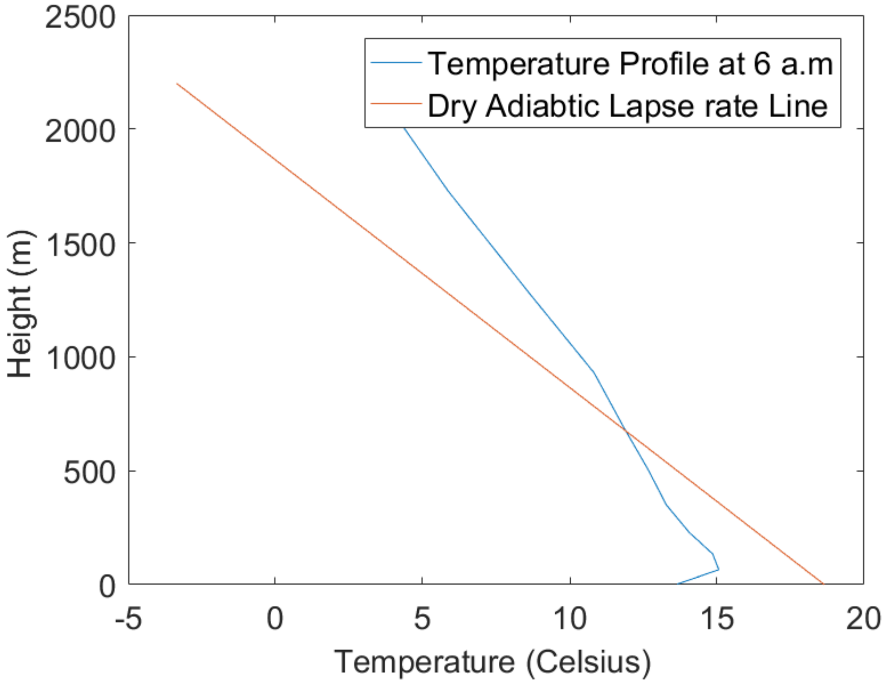


Fig. 20. Sample of WRF Simulations from March

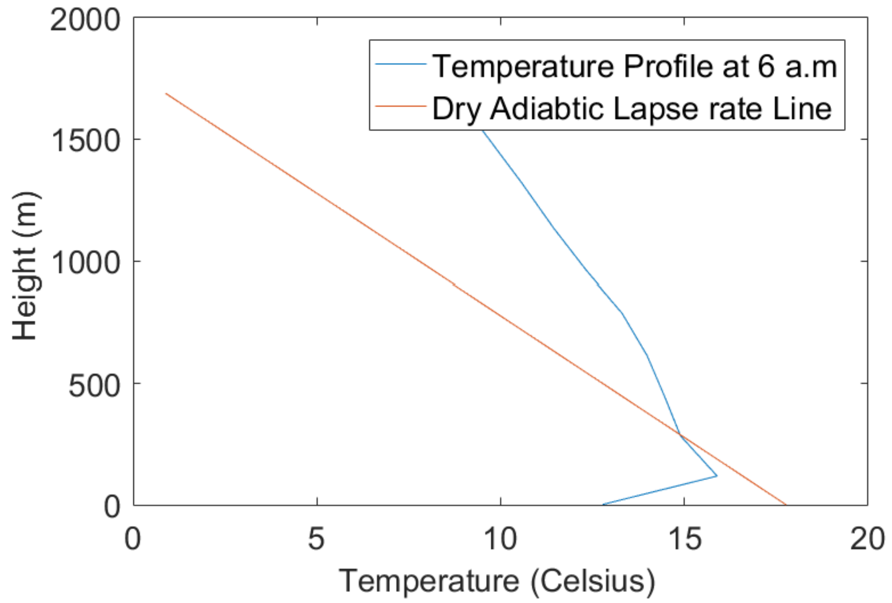


Fig. 21. Sample of WRF Simulations from April

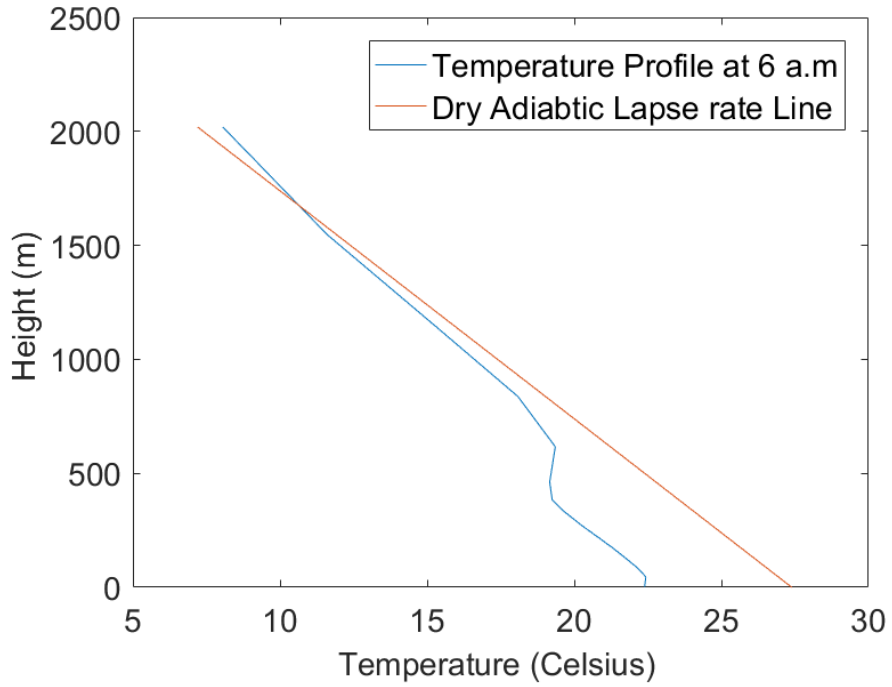


Fig. 22. Sample of WRF Simulations from May

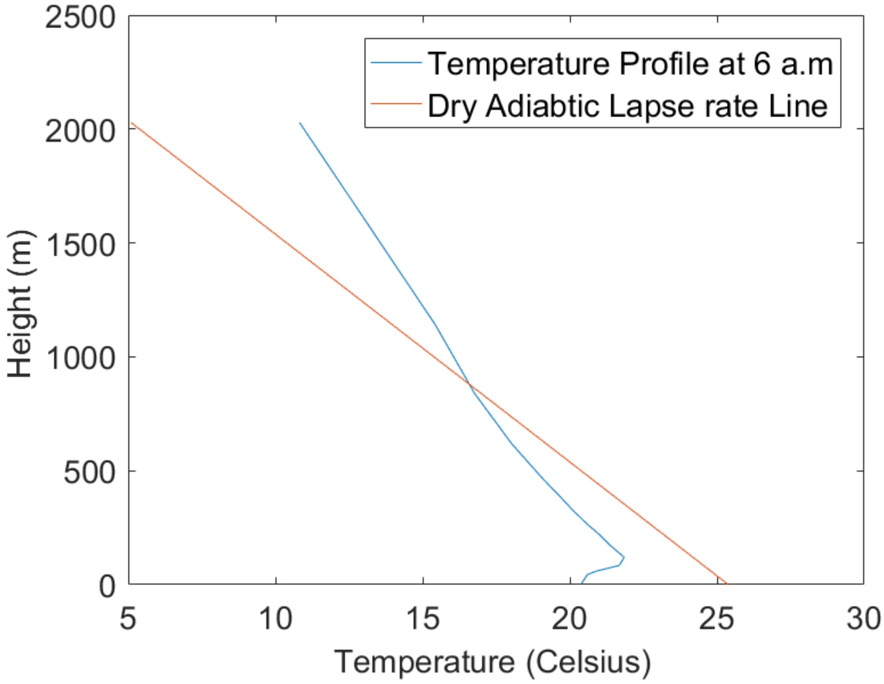


Fig. 23. Sample of WRF Simulations from June

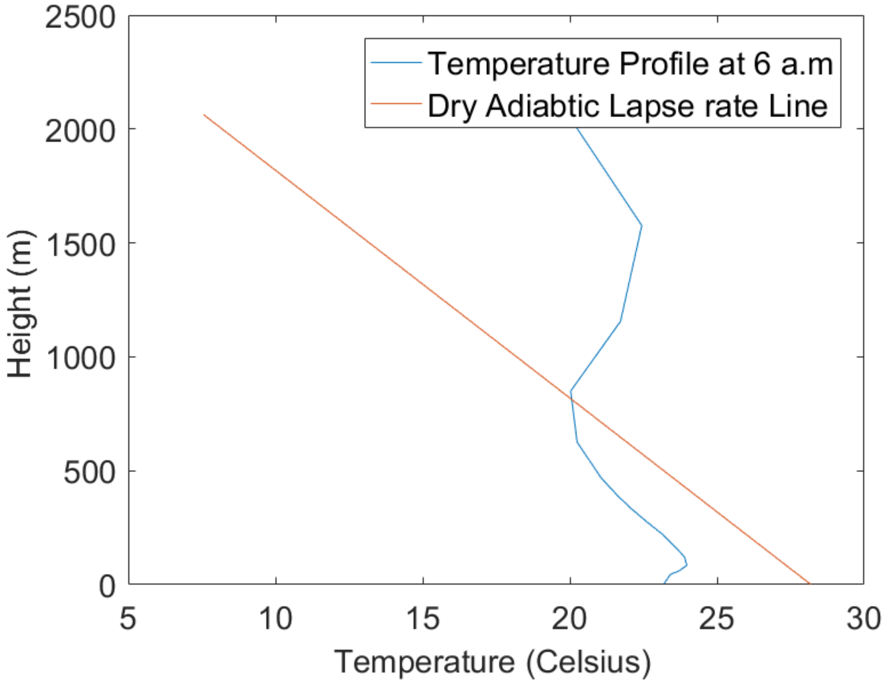


Fig. 24. Sample of WRF Simulations from July

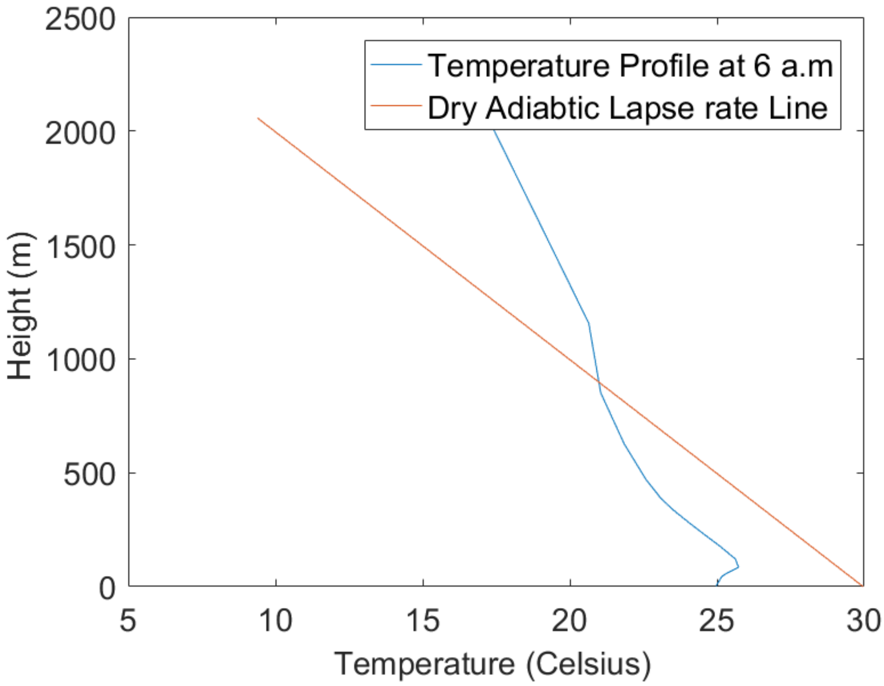


Fig. 25. Sample of WRF Simulations from August

7.1.1. Temporal Variation of the Mixing Height

Since we don't know when each season begins and ends, the monthly average of the mixing height was calculated in order to plot its monthly variation. The monthly variation of the mixing height is shown in Figure 26. The Mixing height has its maximum value during the month of December and its minimum value during July. The maximum value of the mixing height was witnessed in the winter and the minimum one in the summer.

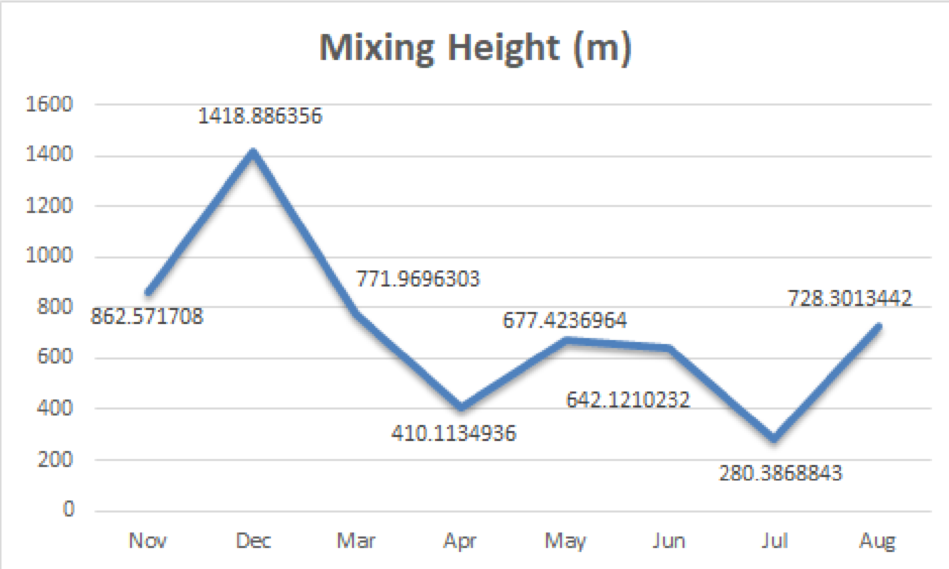


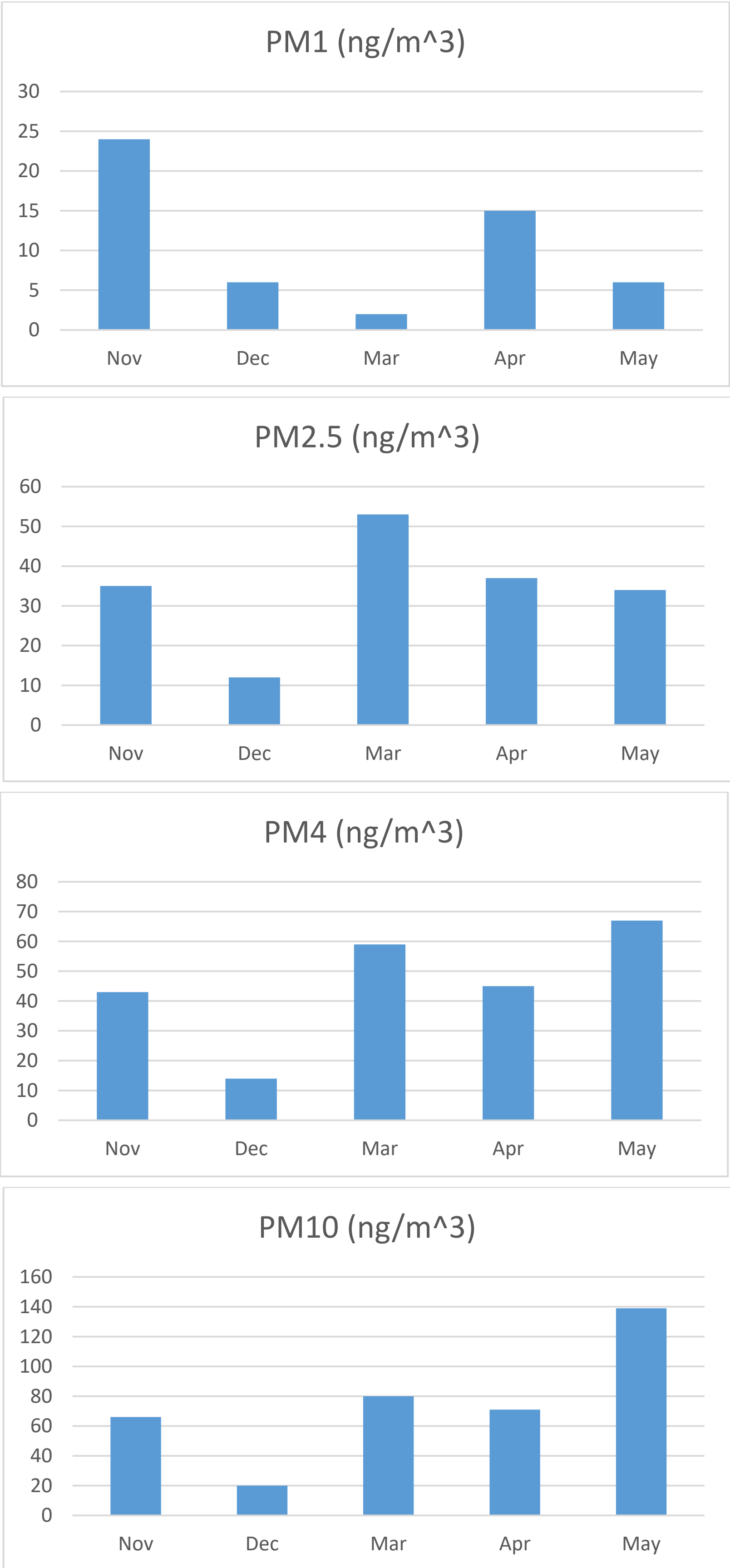
Fig. 26. Monthly Variation of the Mixing Height

7.2. PM Measurements

Similarly measured PM data was provided by the Chemistry Department at the American University of Beirut. 45 samples of different days from November to August were obtained, and below are a few examples that correspond to the same timings of the WRF simulations (Figure 27).

7.2.1. Temporal variation of Aerosols

Similarly, the monthly average of the PM concentrations (PM1, PM2.5, PM4, and PM10) were calculated in order to plot its monthly variation. The monthly variation of the PM1, PM2.5, PM4, and PM10 are shown in Figures 28, 29, 30, and 31 respectively. These plots are based on monthly averages



(a) **(b)** **(c)** **(d)**

Fig. 27. Samples of PM data from different months

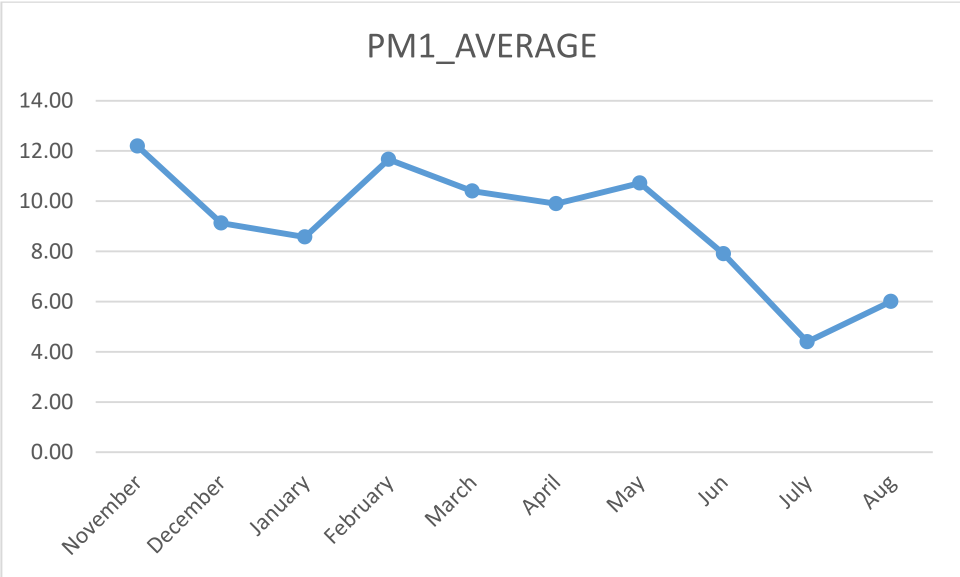


Fig. 28. Monthly Variation of PM1 Concentrations

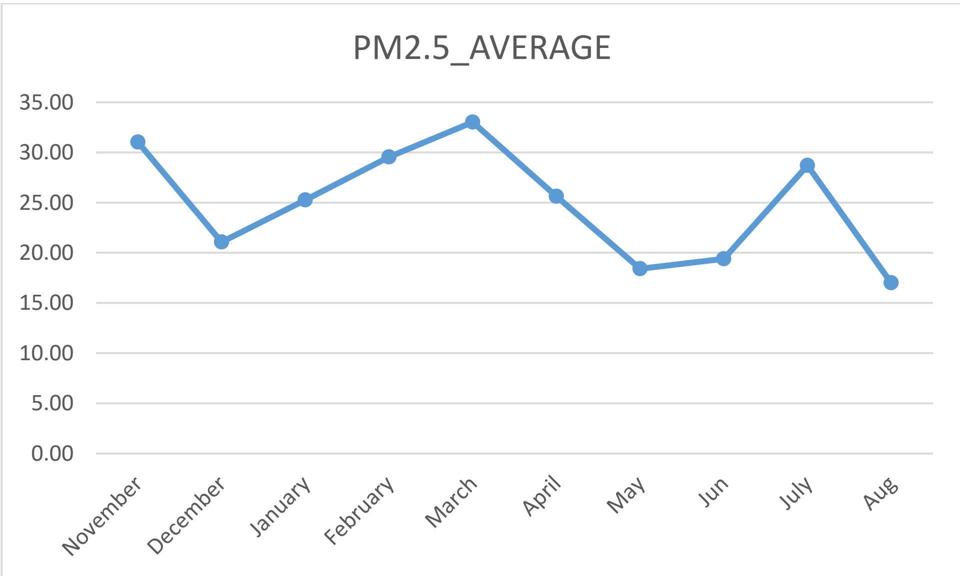


Fig. 29. Monthly Variation of PM2.5 Concentrations

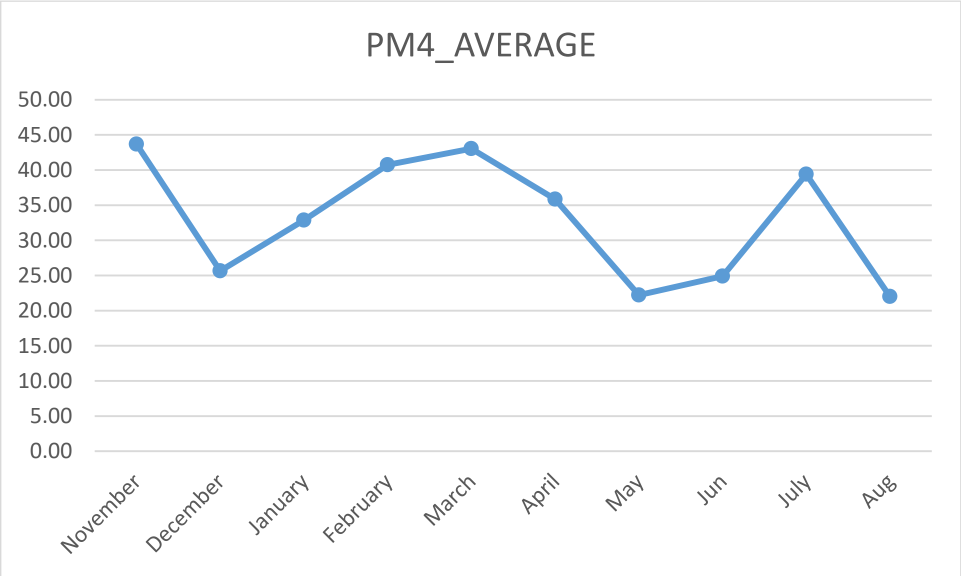


Fig. 30. Monthly Variation of PM4 Concentrations

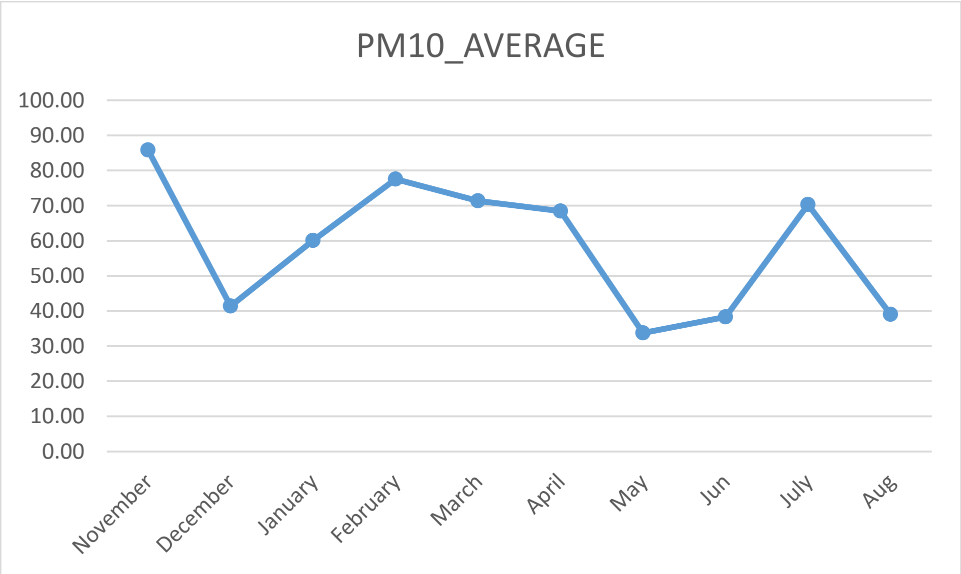


Fig. 31. Monthly Variation of PM10 Concentrations

7.2.2. Temporal Variation of PM Concentrations

As shown in Figures 28 to 31, the Lowest PM concentrations were witnessed during December and the highest in November.

7.3. Results of Statistical Analysis of the Relation the Mixing Height-PM Concentration

In order to figure out the relation between the mixing height and the measured PM data, statistical analysis was investigated. We applied Pearson correlation methods for this sake which are shown in Table 8.

Table 8. Analysis Using Pearson Correlation Method

	PM 1	PM 2.5	PM4	PM10
R	-0.116	**-0.592**	-0.51	-0.359
PVAL	0.2696	**4.2563e-05**	0.0145	4.9474e-04

The correlation coefficients between PM concentrations and the Mixing Height are shown in Table 8 above. These coefficients show a quantitative measure of the statistical relationship between these variables. The greater the value of correlation coefficient the stronger is the correlation. Table 8, values in bold demonstrate the highest correlation which is between PM2.5 concentration and the Mixing Height. It is clear that there is a strong correlation between PM4 and the Mixing Height with Pearson correlation coefficients of 0.51. The correlation between PM10 and the mixing height is moderate with Pearson correlation coefficient of 0.359. The correlation between PM2.5 and the Mixing Height is clearly shown in the scatter plot in Figure 32.

The suggested hypothesis is that there is correlation between the mixing height, and PM concentrations. In order to investigate this hypothesis, coefficients (r) and P Values (PVAL) were calculated using the two mentioned methods. From the above table we note that the highest association exists between PM2.5 and mixing height. Since the correlation coefficient has a negative sign then there is a negative correlation between the mixing height and PM concentrations. Taking into consideration a significance level of 0.5 % (0.005), PM1 would be considered not statistically significant since its P Values are greater than the significance level. Whereas the P-values of PM2.5, PM4, and PM10 are less than the significance level which proves the suggested hypothesis since the smaller the P-values are, the more confident we are regarding the suggested hypothesis. According to Cohen's convention the correlation between the mixing height, PM2.5, and PM4 would be considered strong since the correlation coefficient is greater than 0.5, but the correlation between PM2.5 and the mixing height would be stronger than that of PM4 since we have greater correlation coefficient.

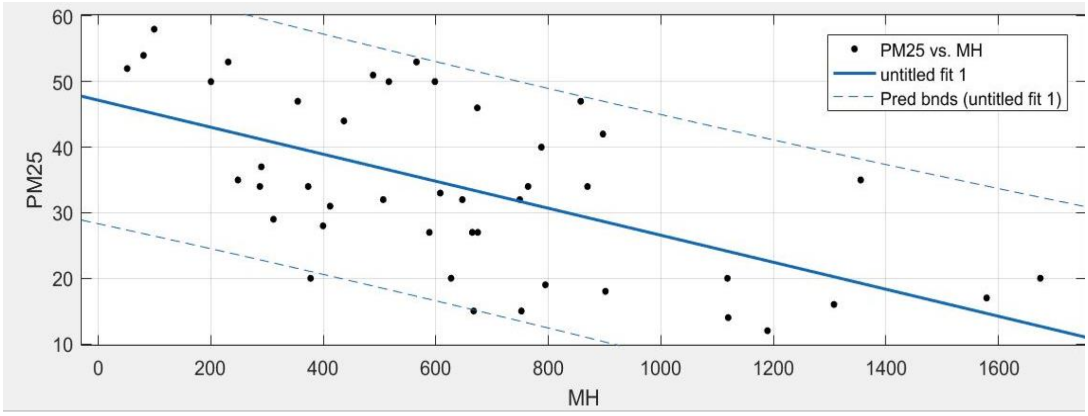


Fig. 32. Scatter Plot of PM2.5 concentrations with the Mixing Height over Beirut

The coefficient of determination, R^2 and regression equation were calculated for this case.

The regression equation is expressed as:

$$PM\ 2.5 = P1 + P2 * MH$$

Table 9 presents the regression results and coefficients for the examined case.

N represents the sample size used in the regression analysis. The other values in the table are the coefficients of the regression equations:

Table 9. Regression Coefficients of the relation PM2.5-MH

N	R	R^2	P1	P2
45	0.592	0.35	-0.02	47.662

Table 9 proves that there is a good correlation between PM2.5 and the Mixing Height.

The correlation between PM4 and the Mixing Height is clearly shown in the scatter plot in Figure 33.

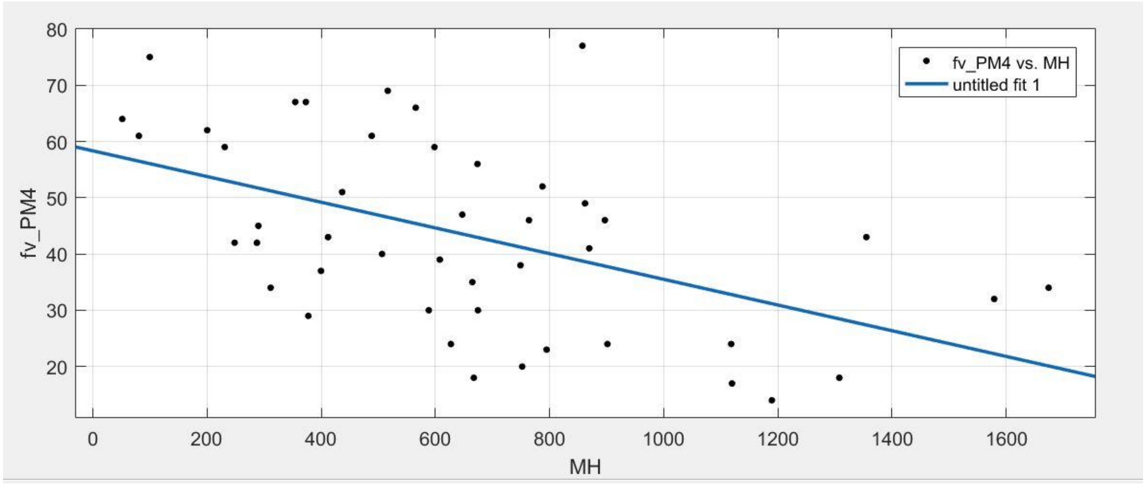


Fig. 33. Scatter Plot of PM4 concentrations with the Mixing Height over Beirut

The coefficient of determination, R^2 and regression equation were calculated for this case.

The regression equation is expressed as:

$$PM\,4 = P1 + P2 * MH$$

Table 10 presents the regression results and coefficients for the examined case. N represents the sample size used in the regression analysis. The other values in the table are the coefficients of the regression equations:

Table 10. Regression Coefficients of the relation PM4-MH

N	R	R^2	P1	P2
45	0.51	0.26	-0.023	58.37

Table 10 proves that there is a good correlation between PM4 and the Mixing Height

The correlation between PM10 and the Mixing Height is clearly shown in the scatter plot in Figure 34.

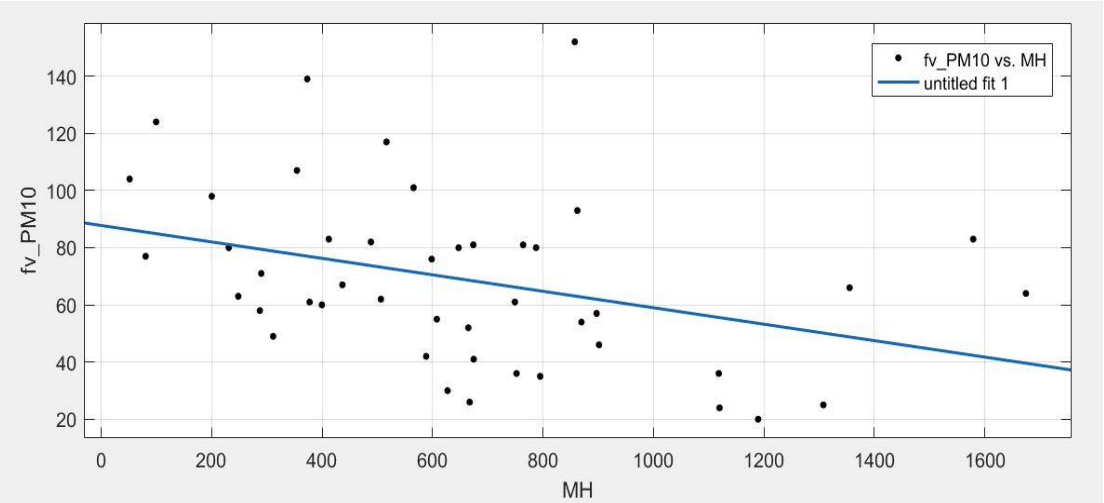


Fig. 34. Scatter Plot of PM10 concentrations with the Mixing Height over Beirut

The coefficient of determination, R^2 and regression equation were calculated for this case.

The regression equation is expressed as:

$$PM\ 10 = P1 + P2 * MH$$

Table 11 presents the regression results and coefficients for the examined case. N represents the sample size used in the regression analysis. The other values in the table are the coefficients of the regression equations:

Table 11. Regression Coefficients of the relation PM10-MH

N	R	R^2	P1	P2
45	0.359	0.129	-0.029	87.758

7.4. Results of Statistical Analysis of the Relation the Wind Speed/Relative Humidity-PM Concentrations

In order to figure out the relation between the wind speed, relative humidity and the measured PM data, statistical analysis was investigated. We applied Pearson correlation methods for this sake which is shown in Table 12 for the relation between PM concentrations and the mixing height. The same methods were applied also to investigate the relation between the PM concentrations and the wind speed and are shown in Tables 13.

Table 12. Analysis of the Relation PM Concentration- Wind Speed Using Pearson Correlation Method

	PM 1	PM 2.5	PM4	PM10
r	0.134	0.243	0.162	0.036
PVAL	0.379	0.108	0.286	0.817

Table 13. Analysis of the Relation PM Concentration- Relative Humidity Using Pearson Correlation Method

	PM 1	PM 2.5	PM4	PM10
R	0.107	0.269	0.35	0.312
PVAL	0.486	0.074	0.019	0.037

The correlation coefficients between PM concentrations and the Wind Speed are shown in Table 12 above. It is clear that there is a weak anti-correlation between PM concentrations and the Wind Speed with Pearson correlation coefficients less than 0.3 for all PMs.

The suggested hypothesis is that there is correlation between the Wind Speed, and PM concentrations. Since the correlation coefficient has a negative sign then there is a negative correlation between the Wind Speed and PM concentrations. Taking into consideration a significance level of 0.5 % (0.005), the relation between PM concentrations and Wind Speed would be considered not statistically significant since their P Values are greater than the significance level.

Moreover, the correlation coefficients between PM concentrations and the Relative Humidity are shown in Table 13 above. It is clear that there is a moderate correlation between PM4, PM10, and the relative humidity with Pearson correlation coefficients of 0.35 and 0.312 respectively .The correlation between PM1, PM2.5, and the relative humidity is weak with Pearson correlation coefficients of 0.107 and 0.269 respectively.

The suggested hypothesis is that there is correlation between the Relative Humidity, and PM concentrations. From the above tables we note that the highest association exists between PM4 and the Relative Humidity. Since the correlation coefficient has a positive sign then there is a positive correlation between the Wind

Speed and PM concentrations. Taking into consideration a significance level of 0.5 % (0.005), the relation between PM1, PM2.5, and Relative Humidity would be considered not statistically significant since their P Values are greater than the significance level.

7.5. Results of Multi Variable Regression Analysis Depending on Two Independent Variables

In order to figure out if there is a relation between the mixing height, wind speed, relative humidity and the measured PM data, multivariable regression models were developed. We developed three models for the prediction of PM concentrations based on relative humidity, the mixing height, and wind speed depending on two of these variables for each case. Table 14 presents the multi variable regression coefficients calculated for the sake of the determination of PM concentrations based on the relative humidity and the mixing height. The results presented in Table 14 shows that PM2.5 and PM4 concentrations can be predicted relying on the mixing height and relative humidity since the correlation coefficients (R), R-squared values, and p-values were good for these two cases.

Table 14. Prediction of PM Concentrations Based on the Mixing Height and Relative Humidity

RH/MH	PM1	PM2.5	PM4	PM10
R	0.166	0.678	0.65	0.502
R2	0.028	0.46	0.423	0.252
Pvalue (95% confidence interval)	0.555	0	0	0.002
b0	8.44	21.821	18.143	25.403
b1	-0.002	-0.022	-0.025	-0.032
b2	0.064	0.393	0.623	0.967
PM=b0+b1*MH+b2*RH				

Similarly, Table 15 presents the results of regression analysis of the relation between PM concentrations, the mixing height, and the wind speed. The results presented in Table 15 shows that PM 2.5 concentrations can be predicted relying on the mixing height and wind speed since it gave good results for the regression analysis performed where the correlation coefficient, R-squared and P-value were good for this case.

Table 15. Prediction of PM Concentrations Based on the Mixing Height and Wind Speed

WS/MH	PM1	PM2.5	PM4	PM10
R	0.148	0.593	0.516	0.389
R2	0.022	0.352	0.267	0.151
Pvalue	0.63	0	0.001	0.032
b0	13.061	46.7	56.936	83.365
b1	-0.001	-0.021	-0.025	-0.035
b2	-0.134	0.119	0.358	1.31
PM=b0+b1*MH+b2*WS				

Table 16 presents the results of regression analysis performed for the sake of determination of PM concentrations based on the wind speed and relative humidity. The resulting regression coefficients revealed the fact that PM concentrations can’t be predicted relying on the wind speed and relative humidity since it gave weak results all calculated regression coefficients.

Table 16. Prediction of PM Concentrations Based on the Relative Humidity and Wind Speed

WS/RH	PM1	PM2.5	PM4	PM10
R	0.174	0.367	0.389	0.315
R2	0.03	0.135	0.152	0.099
Pvalue	0.526	0.048	0.032	0.111
b0	8.819	17.623	12.085	13.97
b1	0.058	0.325	0.543	0.859
b2	-0.179	-0.726	-0.646	-0.292
PM=b0+b1*RHp+b2*WS				

7.6. Results of Multi Variable Regression Analysis Depending on Three Independent Variables

In order to compare between multi variable regression models, multi variable regression models were developed to test the relation between PM concentrations and the three meteorological parameters (wind speed, relative humidity, and the mixing height). These models used three independent variables to predict PM concentrations. The results shown in Table 17 shows that the developed multi variable regression models gave the best results among all regression models presented in sections 6.3 to 6.5 giving better values for correlation coefficients, R-squared, and P-values. The developed regression models can be used to predict PM2.5, PM4, and PM10 concentrations relying on the mixing height, wind speed, and relative humidity.

Table 17. Prediction of PM Concentrations Based on the Mixing Height, Wind Speed, and Relative Humidity

WS/RH/MH	PM1	PM2.5	PM4	PM10
R	0.188	0.68	0.657	0.526
R2	0.035	0.462	0.432	0.277
Pvalue	0.683	0	0	0.004
b0	9.021	21.163	16.338	20.023
b1	-0.001	-0.022	-0.027	-0.038
b2	0.062	0.394	0.627	0.978
b3	-0.13	0.147	0.403	1.2
PM =b0+b1*MH+b2*RHp+b3*WS				

CHAPTER 8

CONCLUSION

In this thesis, I developed a model for predicting ground level particulate matter concentrations based on the mixing height, wind speed, and relative humidity. Many simulations were conducted using WRF to extract temperature profiles for the period November 2016-August 2017. Parcel Method was applied on these profiles in order to determine the mixing height. This height was correlated with the particulate matter concentration near ground level. It was observed that there is strong negative correlation between the mixing height and the near ground level PM2.5, PM4, and PM10 concentrations, moderate positive correlation between the relative humidity and near ground level PM concentrations, and weak negative correlation between the wind speed and near ground level PM concentrations. The strongest correlation was observed between PM2.5 and the mixing height among other used meteorological parameters. Simple linear regression model was built to predict PM concentrations relying on the mixing height as the main predictor based on the results of correlation analysis performed between PM concentrations and the three meteorological parameters (the mixing height, wind speed, and relative humidity). The study concluded that the mixing height is the most dominant meteorological parameter that can be used for the estimation of near ground PM concentrations. PM2.5 and PM4 gave good results for regression analysis with determination coefficients of 0.3504 and 0.2596 respectively. However, PM10 gave week results for regression analysis even though the calculated correlation coefficient was good. Multi variable regression models were developed to predict PM concentrations based on two or three independent parameters. PM2.5, PM4, and PM10 gave better results than simple linear regression model with determination coefficients of 0.462, 0.433, and 0.277 respectively. The best regression coefficients were observed for the regression models developed for the sake of the prediction of PM concentrations based on three independent variables which are: the mixing height, relative humidity, and wind speed. The three regression equations were calculated to predict PM2.5, PM4, and PM10 concentrations. UAV was used to validate WRF software, where a set of thirteen flights were conducted. The results of flights revealed that temperature measurements differs from temperatures predicted using WRF by 1.7℃ and 0.8℃ using the 503ET and SHT75 temperature sensors respectively. The coefficient of determination between the resulting temperature profiles and temperatures profiles predicted using WRF was 0.8661. This means that the mixing height estimated relying on WRF is quite accurate. In the future, the developed model will rely on WRF to predict near ground pollution levels based on atmospheric conditions. These predictions can help in improving people's life and would be of a great benefit on the whole country and the region as well.

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