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THESIS TITLE:

INTERANNUAL VARIATION OF WHEAT ECOSYSTEM RESPIRATION

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1.0 INTRODUCTION

The term "global carbon budget" refers to an assessment of the amount of carbon dioxide (CO_2) emissions caused by both human activities and natural sources, as well as how they are distributed between the atmosphere, oceans, and land. Carbon budgets essentially measure the flow of carbon between different parts of the Earth's system (Le Quéré et al., 2018). These elements include terrestrial ecosystems, oceans, and the atmosphere. Therefore, there is a dire need to understand the global carbon cycle which will help to develop climate policies and future projections for climate change. Since the beginning of the Industrial Revolution, there has been a significant rise in atmospheric CO_2 levels, increasing from approximately 277 parts per million (ppm) in 1750 to 417 ppm in 2022, Lan et al., 2023. The primary cause for the high levels of CO_2 in the atmosphere prior to the industrial era was the initial discharge of carbon emissions due to land-use alteration activities and deforestation. (Ciais et al., 2013, Friedlingstein et al., 2020).

Greenhouse gases are gases that trap heat in the Earth's atmosphere, leading to the phenomenon known as the greenhouse effect. These gases include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), fluorinated gases, and ozone (O_3). The concentration of most GHGs is increasing because of anthropogenic emissions, and the high GHG concentrations causes the global warming. Human activities, such as burning fossil fuels, deforestation, and industrial processes, have significantly increased the concentration of greenhouse gases in the atmosphere, leading to global warming and climate change. The burning of fossil fuels is the primary source of CO_2 emissions, while agriculture and livestock farming are the main sources of CH_4 and N_2O emissions (Pachauri et al., 2014). The relationship between total emissions and global temperature change brings up new possibilities for climate mitigation strategies (Matthews et al., 2012) and for forecasting the regional climate consequences linked to a particular emission route.

Climate change refers to the alteration of long-term temperatures and weather patterns, which can occur naturally as a result of changes in the sun's activity or significant volcanic eruptions. However, since the 1800s, climate change has primarily been caused by human activities such deforestation, extensive cultivation, and burning of fossil fuels like oil and gas due to high energy demand. The rise in greenhouse gases, such as CO_2, is contributing to the phenomenon of climate change that we are currently experiencing.

In response to the growing concern over the climatic effects of greenhouse gas (GHG) emissions, efforts are being conducted globally to increase carbon sequestration and decrease CO_2 emissions (Sierra et al., 2013). Agricultural croplands are able to capture and store CO_2 and other greenhouse gases (GHGs), which significantly reduces the potential negative effects of climate change in the future. Changing farming practices has a notable effect on reducing global GHG emissions, as largely recognized by UNEP in 2013. Hence, more management practices should be adopted to decrease CO_2 emissions and increase carbon sequestration (Lal, 2011). The estimation of the net carbon sequestration potential is difficult because of the numerous linkages and vast regional variability in cropping systems and management practices (Hutchinson et al., 2007). The eddy covariance approach has become the most crucial tool for estimating the direct estimates of mass and energy exchange between vegetation surfaces and the atmosphere. When using the eddy covariance approach, fast-response instruments of 10–20 Hz are installed above plant canopies, and the fluxes are computed as the covariance of the vertical velocity fluctuations and the fluctuations of various scalars such as CO_2, water vapor, and temperature. This method makes it possible to quantify the net exchange of CO_2 directly and without causing any damage to the vegetation. This net exchange is the so-called Net Ecosystem Exchange (NEE) which is the balance between the amount of carbon dioxide (CO_2) absorbed by a given ecosystem through photosynthesis, and the amount of CO_2 released by that ecosystem through respiration. Moreover, the evapotranspiration (loss of water from land and plants) and sensible heat flux (transfer of heat due to temperature differences) in an ecosystem can also be measured by eddy covariance towers. This method can provide estimates of daily, monthly, or yearly carbon exchange by the ecosystem. Furthermore, eddy covariance data is important for verifying and adjusting models that quantify carbon balance at regional and canopy levels. Nonetheless, this approach has limitations such as the high costs of setting it up, requirement of uniform and flat vegetation at the site, and challenges in measuring fluxes accurately during low wind conditions. Advantages include measurements that are nearly continuous and spatial averaging over 10-100 hectares and measurements have a negligible effect on the systems that were studied. Data missing due to the influence of weather and equipment is a common feature of eddy covariance measurements. Accurate estimation and understanding of the regional to global scale carbon cycling of croplands are essential for developing effective policies and management practices that can contribute to the stabilization of atmospheric CO_2 concentrations (Glenn et al., 2010). According to estimates, croplands account for the greatest amount of carbon that Europe loses to the atmosphere each year, however, this estimate is the least certain of any land use type (Janssens et al., 2003). According to Janssens et al. (2003), croplands in Europe that extend as far east as the Urals lose roughly 300 Mt of carbon annually. Cropland soil carbon loss figures are highly uncertain (Janssens et al., 2003) and there is clear scope to reduce the uncertainty surrounding it by ensuring accurate estimation of the NEE of the cropland. Therefore, precise measurements of carbon emissions from numerous cropland ecosystems are required to find the most effective methods over a long period of time. There is limited information regarding the estimation of nighttime ecosystem respiration (RE) in croplands by using the eddy covariance setup. At present, there are limited relevant research studies that analyze and depict the extended-term trends of ecosystem respiration in croplands during various growing seasons. The main objective of this study is to determine the interannual variation patterns in the RE of croplands during the growing season by using Eddy Covariance The goals are to assess how the interannual differences in temperature affects ecosystem respiration (RE). Previous research had shed light on the underlying processes causing fluctuation in agroecosystem RE. The research will provide insight into the interannual variation of RE and also contribute to the development of accurate models that will forecast long-term trends in greenhouse gas emissions.

2.0 LITERATURE REVIEW

2.1 Methods for Measuring Net Ecosystem Exchange

Eddy covariance and Bowen-ratio/energy balance (BREB) are the two approaches for estimating NEE that are most frequently used. The fundamental idea behind these micrometeorological techniques is that air parcels are displaced from the soil surface to the measurement height by eddies, which then move gas from the soil surface. The Eddy-covariance method calculates the net rate of CO_2 exchange between a plant canopy and the atmosphere by analyzing the relationship between the fluctuations of the vertical wind speed and fluctuations in the CO_2 mixing ratio. This technique determines the covariance between these variables. (Baldocchi et al., 2003. The BREB method employs a surface energy balance to determine the net CO_2 fluxes by utilizing flux-gradient associations among water vapor, CO_2, and heat. This method assumes that the turbulent exchange coefficients for sensible heat, latent heat, and momentum are the same, as indicated by Gilmanov et al. in 2005. However, the accuracy of the CO_2 flux measurements obtained through the BREB technique can be affected by the assumed equivalence of the turbulent exchange coefficients and the measurement errors associated with input variables like net radiation, temperature, and humidity gradients. Compared to chamber-based techniques, non-intrusive micrometeorological approaches like eddy covariance and BREB systems have less impact on the microenvironments of the soil surface (Dugas, 1993). According to Baldocchi (1997), those methods have the ability to observe the continuous release of CO_2 for extended durations and cover vast surface areas while considering the irregularity of the surroundings due to natural turbulence. However, for these techniques to work effectively, certain conditions must be met, such as having a wide and uniform area upwind and maintaining consistent atmospheric conditions (Baldocchi and Meyers,1991). According to Jensen (1996), micrometeorological techniques may not be suitable for measuring small-scale phenomena because of their expensive implementation costs.

2.2 Temperature Sensitivity of Ecosystem Respiration

The temperature has a significant impact on ecosystem respiration, which is a crucial component of the terrestrial carbon cycle on a worldwide scale. According to Sierra (2011), temperature sensitivity is the rate at which a process changes as the temperature rises or falls while other factors remain constant. The time at which the growth component is prominent is determined by phenology and growth trends (Ceschia et al., 2002). Thus, seasonal fluctuations in photosynthesis, mobilization and utilization of stored carbohydrates, and differences in the physiological growth stages of plant organs are the causes of the varied responses of soil respiration and ecosystem respiration to environmental factors (Jassal et al., 2007). Ecosystem respiration can be partitioned into above-ground autotrophic respiration (R_{aa}) from plant canopy and soil respiration (R_s), or it can be divided into heterotrophic respiration (R_h) from microbial decomposition of residues and soil organic matter and autotrophic respiration (R_a) from plants. Soil respiration can be also separated into Rh and below-ground autotrophic respiration (R_{ab}) from plant roots. Yiqi and Xuhui (2010) stated that soil respiration involves the interdependence of respiration, microbial breakdown of litter and organic soil elements, and fauna, all of which contribute to the removal of carbon dioxide from the soil through ecological processes. Changes in temperature and soil water content had a greater impact on ecosystem respiration than on soil respiration (Jassal et al., 2007).

In terrestrial ecosystems, the temperature sensitivity of ecosystem respiration (Q) is a key measure for establishing a causal relationship between respiratory carbon flux and global warming (Reichstein et al., 2007). Earth system models (ESMs) frequently produce carbon dynamics using a constant Q value of 2 for ER (Friedlingstein et al., 2006). Nevertheless, using the FLUXNET database created from a global collection of eddy covariance CO_2 flux datasets, a mean Q value of 1.6 for ER was generated (Mahecha et al., 2010). Furthermore, there is mounting evidence that Q of ER is not constant but rather changes with changes in air temperature, precipitation, atmospheric CO_2, atmospheric nitrogen deposition, precipitation (Araki et al., 2017; Li et al., 2019), plant phenology and biomass (Ceschia et al., 2002). Besides that, disturbance activities including harvest, fire, bark beetle epidemic, wind throw, insect defoliation, fungal assault, and droughts have a significant impact on the overall Q of ER because they change the amount of coarse woody debris (CWD) and leaf area (Williams et al., 2016). Hence, the ability of process-based models to precisely simulate the size of climate-carbon feedback is limited by the erroneous parameterization in the Q of ER (Tang et al., 2008). Even though the eddy covariance technique has made it possible to detect ER continuously, tower-based flux measurements do not directly reveal the component fluxes (Tang et al., 2008). As a result, comparing Q_{10} in the key ER components is essential for decreasing model uncertainties and correctly forecasting carbon dynamics (Chi et al.,2020).

Several types of investigations have been carried out to estimate the carbon balance in the ecosystem, although they have mainly focused on a single vegetation type that is typically homogeneous in nature. Various crops like wheat, maize, soybeans, paddy rice, sugar beet, and potatoes have been studied for their RE patterns using micrometeorology in previous research by different authors such as Schmidt et al. (2012), Du and Liu (2013), Kutsch et al. (2010), Saito et al. (2005), and Aubinet et al. (2009). Recent research has indicated that the annual RE differs depending on factors like the type of crop, geographical region, climate zone, and farming practices employed, as reported by Chen et al. (2019). The variability in RE from year to year in agricultural ecosystems is affected by factors such as temperature, precipitation, soil moisture, and plant growth, as observed by Guo et al. (2019). The soil temperature directly affects the RE, provided that the soil moisture level is optimal, according to research conducted by Chang et al. (2016) and Flanagan and Johnson (2005).

2.2 Components of Net Ecosystem Exchange

Net Ecosystem Exchange (NEE) is the difference between the total amount of CO_2 produced by all respiration processes combined (RE) and the carbon that is taken in by photosynthesis. GPP is the total carbon uptake by photosynthesis by plants, whereas RE is the total carbon excretion by all species' respiration processes. The NEE of CO_2 between ecosystems and the atmosphere is measured using the eddy covariance (EC) technique. A crucial first step to comprehending the underlying mechanisms restricting ecosystem function is the estimation of GPP and RE. Furthermore, EC estimates of GPP and RE are helpful for modeling, supporting process-based models, parameterization and validation, data assimilation, and vegetation attributes retrieval by model inversion (van der Tol, & Frankenberg, 2019; Pacheco-Labrador et al., 2019), as well as estimates of photosynthesis based on remote sensing (e.g., Verrelst et al., 2016).

2.2.1 Ecosystem respiration

Ecosystem respiration (RE) is a substantial and unique component of carbon cycling that will be crucial in determining how terrestrial ecosystems react to climate change (Valentini et al., 2000). Ecosystem respiration (RE) is crucial for managing ecosystem carbon balances and regulating atmospheric CO_2 levels (Valentini et al., 2000). Ecosystem respiration (RE) is frequently represented as a combined variable directly related to temperature (Lloyd & Taylor, 1994; Enquist et al., 2003). For a better understanding of the dynamics of the ecosystem's carbon balance, it is crucial to quantify components of RE. Moreover, partitioning RE into its aboveground (canopy respiration) and below-ground (soil respiration) components is necessary to comprehend the reasons for RE seasonal and interannual fluctuation. Among all, temperature, precipitation, and substrate availability can all affect how the above- and below-ground components of RE respond (Ekblad et al., 2005). RE encompasses plant autotrophic respiration both above and below ground, as well as the respiration of heterotrophic species (Xu et al., 2001). According to Trumbore (2006), each of these components responds differently to environmental conditions and ecological traits. Gaumont-Guay et al. (2008) suggest that microbial respiration is significantly influenced by certain environmental factors such as the temperature and moisture content of the soil. Due to the intricacy of RE, it is very difficult to forecast how global change will affect ecosystem functioning. As a result, it is expected that the relationship between Rs and RE would change periodically, and this change may shed light on how ecosystems react to changing weather and climatic conditions (kirschbaum, 2019).

2.2.2 Net primary production

Net primary production (NPP) refers to the annual productivity of plants within an ecosystem, and it is determined by the balance between the carbon assimilated by photosynthesis and the carbon lost through plant respiration. NPP takes into account the energy that autotrophs absorb and their respiration. The gross primary production (GPP) represents the amount of CO_2 that an ecosystem grossly absorbs and utilizes for photosynthesis. About half of the photosynthesis from GPP is consumed by autotrophic respiration (Ra), which is necessary for synthesizing new plant tissues and maintaining live tissues. NPP is the amount of photosynthates that remain after respiration and are available for other processes. This can be expressed in terms of GPP and Ra as follows.

$$GPP = NPP + Ra$$

It can be difficult to accurately measure the total Net Primary Productivity (NPP) due to the loss of organic material through various processes, such as emission of volatile organic compounds (more common in forests than croplands), exudation from roots, and carbon transfer to root symbionts. The majority of NPP is used to produce above and below-ground biomass, but quantifying the fractions associated with exudation and volatile losses is challenging because the biomass may have been harvested or lost to pests/herbivores at the time of measurement. Corrections must be made for this lost biomass when calculating NPP from measured biomass. Additionally, estimating root turnover is challenging as it occurs year-round and varies depending on vegetation type. Therefore, NPP estimations are uncertain. Every year, a portion of the generated biomass is added to the soil's litter and carbon pools, each with different residence times.

The carbon stored in certain areas is susceptible to decay caused by microorganisms, a process called heterotrophic respiration (Rh). Rh includes the breakdown of current-year plant material and previously accumulated organic matter that has been in the environment for decades, centuries, or even millennia. The contrast between the rate of Net Primary Productivity (NPP) and Rh is referred to as Net Ecosystem Productivity (NEP) (Ciais et al., 2010). Ecosystem respiration (RE) encompasses Rh and another process called autotrophic respiration (Ra), with soil respiration being a component of RE. Thus, in practical terms, NEP can be determined by subtracting RE from Gross Primary Productivity (GPP).

2.3 Ecosystem Respiration Estimation

According to Pries et al. (2017), ecosystem respiration comprises both autotrophic and heterotrophic respiration. The decomposition of plant roots and aerial parts by soil organisms is the primary cause of heterotrophic respiration, whereas autotrophic respiration pertains to respiration by plants' roots and aerial parts. The net ecosystem exchange (NEE) is the amount of carbon measured by the eddy covariance system, obtained by adding gross ecosystem primary productivity (GPP) and ecosystem respiration (RE). Since photosynthesis only takes place during daylight hours, gross primary productivity (GPP) is nonexistent at night. As a result, the net ecosystem exchange (NEE) during the night is equivalent to the ecosystem respiration. The flux of daytime respiration or the intercept of the day flux response to light flux can be determined by calculating the total ecosystem respiration from nighttime eddy covariance fluxes using a temperature and soil water response model. The eddy covariance approach is reliable and energy-efficient enough to be used for years at a time, and it can measure the net exchange of CO_2 over typical areas of several hundred square meters (Baldocchi, 2003). To estimate the daily and yearly RE values for ecosystems, respiratory models require several specified model parameters. There are three models that are frequently used to measure carbon emissions from ecosystems: the Van't Hoff model, the Arrhenius model, and the Lloyd and Taylor model.

2.3.1 Van't Hoff model

The Van't Hoff model written in the form of the Van't Hoff equation, is a thermodynamic equation that describes the relationship between temperature and equilibrium constant for a chemical reaction. In 1884, a chemist named Jacobus Henricus Van't Hoff, who hailed from the Netherlands, was the first to suggest this concept. The equation is as follows:

$$\ln (K_2/K_1) = \Delta H/R \, [(1/T_1) - (1/T_2)]$$

where K_1 and K_2 are the equilibrium constants at temperatures T_1 and T_2 respectively, ΔH is the enthalpy change of the reaction, R is the gas constant, and ln denotes the natural logarithm.

The equation shows that the natural logarithm of the ratio of equilibrium constants for a reaction is proportional to the inverse of temperature. The constant of proportionality is ΔH/R, which represents the enthalpy change of the reaction over the gas constant. The Van't Hoff model can be employed to approximate the impact of temperature on chemical reactions and to ascertain the enthalpy alteration of a reaction based on temperature information. Law (2021) explains that the equation is obtained by applying the Gibbs free energy equation, which elucidates the correlation among temperature, enthalpy, entropy, and Gibbs free energy.

Van't Hoff equation also links changes in a chemical reaction's equilibrium constant (Keq) to changes in temperature, T, given the reaction's standard enthalpy change, rH. The Van't Hoff and Arrhenius equations have been extensively utilized to forecast how respiration and decomposition rates will alter as temperature changes (Atkins and Paula, 2010). The Van't Hoff rule states (Van't Hoff, 1884) assumes that the reaction's enthalpy change remains constant over the temperature range studied, which is not always the case. Additionally, the equation applies only to reactions at equilibrium and cannot be used to predict reaction rates. For instance, every 10° C, the rate of biological reactions doubles. It can be expressed as follows;

$$RE = RE_{\mathrm{ref}} \exp\left(B\left(T_s - T_{ref}\right)\right)$$

2.3.2 Arrhenius model

The Arrhenius equation describes many physical and chemical reactions, the relationship between reaction rate and temperature (Koerner et al. 1992) as given below

$$\mathrm{k} = \mathrm{k}_0 \mathrm{e}^{-(\mathrm{E}/\mathrm{RT})}$$

Where k is the kinetic reaction rate, k_0 is rate constant, E is the activation energy, R is the universal gas constant and T is the absolute temperature. By evaluating the logarithm of both sides of the above equation, a more useful form of the relationship is derived.

$$\ln (k) = \ln (k_0) - \mathrm{E}/\mathrm{RT}$$

Time is not specifically included as a variable in the equation, despite the fact that it describes the rate of reaction. As temperature increases, the exponential factor e^(-Ea/RT) becomes smaller, and the rate constant k becomes larger. This means that the reaction proceeds faster at higher temperatures. The Arrhenius model is useful for predicting how the rate of a chemical reaction will change as the temperature changes, and it has many practical applications, such as in the design of chemical reactors and in the study of reaction kinetics.

2.3.3 Lloyd and Taylor's model

The Lloyd-Taylor function explains that the relationship between temperature and respiration is a nonlinear one, where the logarithm of respiration increases with temperature but at a decreasing rate. This is because the impact of temperature on respiration is greater at lower temperatures and diminishes as temperature increases. When the temperature is exceptionally high, the respiration rate reaches a plateau, and the Q10 value decreases. To compare statistical models, the Lloyd-Taylor function was fitted using non-linear least squares regression with the dependent variable being the respiration rate. The starting values for the parameters a and b were obtained through linear regression with 1/T as the independent variable. The parameter c was set to zero to initiate the non-linear fitting process.

$$RE = RE_{\mathrm{ref}} \exp\left[E_0\left(\frac{1}{T_{\mathrm{ref}} - T_0} - \frac{1}{T_{\mathrm{s}} - T_0}\right)\right]$$

where Ts refers to the temperature of a surface in degrees Celsius. RE_{ref} is the rate of a specific process at a reference temperature (T_{ref}) of 10°C. B is a parameter used in a mathematical model to describe the relationship between two variables. E_a represents the amount of energy required for a reaction to occur in joules per mole. R is the gas constant, which is equal to 8.314 joules per Kelvin per mole. E_0 is a parameter linked with the activation energy, which affects how sensitive the rate of the process is to temperature. T_0 is a fixed parameter representing a constant temperature value of -46.02°C by Lloyd and Taylor (1994).

2.4 Soil Respiration

Soil respiration refers to the release of CO_2 by living organisms in the soil, including plants roots, microorganisms, and soil animals, as they carry out their biological functions. The standard measure of soil respiration is µmol CO_2 m^{-2} s^{-1}. Unlike total ecosystem respiration, which includes the respiration of aboveground parts such as leaves, trunks, branches, twigs, and dead wood, soil respiration accounts for the respiration of both soil microorganisms and roots. In temperate and boreal regions, there may be discrepancies in seasonal patterns between aboveground and belowground processes, as changes in soil temperature lag behind changes in air temperature. In certain environments, plants may have access to deep soil water, which can protect them from drought stress compared to heterotrophs located closer to the soil surface. The ratio of Rs/RE can change periodically, and this variability can provide insight into how ecosystems respond to fluctuations in weather and climate conditions. Soil respiration is often as important as or even more significant than aboveground respiration in ecosystems, and it determines whether the ecosystem acts as a source or sink of CO_2. The emission of CO_2 from the soil can increase due to global warming, which could lead to a faster acceleration of climate change. Soil respiration research since the 1990s has focused on how it affects carbon storage in terrestrial ecosystems and how it reacts to alterations in land use and the surroundings.

2.4.1 Soil respiration measurement

Soil respiration is usually measured using soil respiration chambers. Soil respiration chambers are essentially enclosed containers that are placed over a section of soil, allowing for the measurement of CO_2 flux between the soil and the atmosphere. The chambers are left in place for a period of time, during which the CO_2 concentration inside the chamber increases as the soil respires. The rate of CO_2 accumulation inside the chamber is measured over time, usually by taking gas samples at regular intervals and analysing them using a gas analyzer. By measuring the rate of CO_2 flux between the soil and the atmosphere, soil respiration chambers allow researchers to estimate the total amount of carbon that is being respired by the soil ecosystem. This data holds significance in comprehending the function of soils in the worldwide carbon cycle, and in anticipating how soils will react to modifications in climate and land use (Davidson and Janssens, 2006). By putting soil respiration chambers on bare soil patches, we can measure the amount of CO_2 released by the soil alone, which is soil respiration.

Indirect techniques such as measuring NEE or ecosystem respiration can provide useful information about soil respiration, which is an important component of the carbon cycle and can help us understand the role of soil in regulating atmospheric CO_2 concentrations (Baldocchi et al., 2003). It remains highly difficult to partition the measured NEE into soil respiration, respiration by plants above ground, and photosynthesis occurring in the canopy while preserving the original meaning. Eddy flux measurements taken at night above the canopy or analysis of daylight readings can be used to determine ecosystem respiration (Falge et al., 2000). It is impossible to differentiate between respiration from soil and respiration from aboveground plant parts without empirical estimations or additional observations. To estimate the soil CO_2 efflux over a larger area, the eddy-covariance flux can be correlated with chamber data. Other indirect methods for determining soil respiration include carbon balance based on the litterfall-soil respiration ratio, nocturnal observations of CO_2 concentration profiles in the planetary boundary layer, and lagrangian analysis of canopy carbon source and sink profiles. An example of this is the Lagrangian dispersion model used by Katul et al. (1997) to estimate soil respiration by analyzing canopy CO_2 profiles and determining that near-ground air was a source of CO_2.

3.0 MATERIALS AND METHODS

3.1 Study Site

Crop Net Ecosystem Exchange (NEE) is measured at the premises of Gödöllői Tangazdaság Zrt by an eddy covariance station built by the Department of Plant Physiology and Plant Ecology, Institute of Agronomy, Hungarian University of Agriculture and Life Sciences. The study site is at the edge of Kartal (47.658° N, 19.532° E, 153 m a.s.l.) and it is in operation since October 2017.

3.2 Description of the Eddy Covariance Method

The eddy covariance technique is measuring the net amount of CO_2 crossing the measurement plane, i.e., going toward the surface and coming from the surface. This net amount is the Net Ecosystem Exchange (NEE), which is the resultant CO_2 taken up by assimilation and released by respiration by the plants. The technique provides a half-hourly NEE of assimilation and respiration output. In addition, a number of environmental factors (such as temperature, precipitation, global and photosynthetic active radiation, soil water content, etc.) are recorded at both locations on an hourly basis. The eddy-covariance tower is equipped with a CSAT3 a sonic anemometer, which can measure the wind speed 10 times per second, and a LI-7500 gas analyzer, which can simultaneously measure the air's water vapor and carbon dioxide content. The temperature, precipitation, global and photosynthetic active radiation, and soil water content were measured using a 105T Thermocouple probe, ARG 100 Tipping Bucket Rain gauges, CM3 Kipp and Zonen PyranometerSKP215 Quantum Sensor, and CS615 Water Content Reflectometer respectively.

3.3 Dataset

Data were collected from the five years long dataset periods, where the wheat was grown at the study site, and were selected and used for the present work. The periods are presented below:

- Period 1: 2017-10-13 - 2019-06-19,
- Period 5: 2019-11-17 - 2020-07-01,
- Period 9: 2021-11-08 - 2022-06-17.

The used data include the Temperature of air (Tair), Soil Temperature (Ts), Short wave incoming radiation (SWIN), Soil Water Content (SWC), precipitation, and Net Ecosystem Exchange (NEE) recorded as cflux.

3.4 Temperature Response Curves

In each growing season, the data set was split into three subperiods as follows;

- October-February: normally referred to as the dormant period or no intensive growth.
- March-April: intensive growth with increasing growing intensity that gives rise to an increasing trend in cflux.
- May-June: intensive growth but with decreasing growing intensity that results in decreasing trend in cflux.

The R-Stat software was used to analyze the eddy covariance data. Data in each subperiod was filtered by "The Inter Quartile Range (IQR) criterion, which states that data points that fall below q0.25-1.5·IQR or above q0.75+1.5·IQR are considered outliers. The first quartile (q0.25), and the third quartile (q0.75), are used to calculate the IQR, which is the difference between them. The IQR criterion is important in the detection and removal of outliers.

Temperature response curves were fitted to nighttime data, on a half-hourly basis when the global radiation (SWIN) was below 5 W m^{-2} were considered as nighttime. To estimate the daily response of RE to temperature, non-linear fitting algorithms were used to fit the different model parameters of the Van't Hoff model, Arrhenius model, and Lloyd and Taylor models as follows;

$$RE = RE_{ref} exp \left(B\left(T_s - T_{ref}\right)\right) \qquad (1)$$

$$RE = RE_{ref} exp \left[\left(\frac{E_a}{R}\right)\left(\frac{1}{T_{ref}} - \frac{1}{T_s}\right)\right] \qquad (2)$$

$$RE = RE_{ref} exp \left[E_0\left(\frac{1}{T_{ref}-T_0} - \frac{1}{T_s-T_0}\right)\right] \qquad (3)$$

where Ts refers to the temperature of a surface in degrees Celsius. RE_{ref} is the rate of a specific process at a reference temperature (T_{ref}) of 10°C. B is a parameter used in a mathematical model to describe the relationship between two variables. E_a represents the amount of energy required for a reaction to occur in joules per mole. R is the gas constant, which is equal to 8.314 joules per Kelvin per mole. E_0 is a parameter linked with the activation energy, which affects how sensitive the rate of the process is to temperature. T_0 is a fixed parameter representing a constant temperature value of -46.02°C by Lloyd and Taylor (1994).

4.0 RESULTS AND DISCUSSION

4.1 Results

4.1.1 Meteorological conditions

Figure 1 shows the annual and seasonal fluctuations in the daily mean air temperature (Ta), daily mean soil temperature (Ts), the daily sum of precipitation, and the daily mean soil water content (Ws) at a 5 cm depth at the site. In most years, the highest and lowest values of Ta and Ts were observed between July and August and between November and January, respectively. Figure 2 illustrates that the variations in Ta and Ts throughout the seasons follow a bell-shaped curve with a single peak.

During the years 2017-2022, the daily mean air and soil temperature, ranged from 5.3°C to 19.9°C and 2.8°C to 18.9°C, respectively. The coldest temperatures were typically observed between October and February, followed by March and April, with the warmest temperatures occurring in May and June in each of the three periods. Additionally, during the winter periods, the air temperature was slightly lower than the soil temperature. In Period 5, the mean air temperature in March-April and May-June was the lowest, while Period 9 was relatively warmer and drier. Finally, Figure 2 shows that in Period 1, the lowest and highest mean soil temperatures were observed during the October-February and May-June subperiods, respectively.

The average annual precipitation sum for the whole period (2017-2022) was 534 mm, above the 10-year average (2011-2020) of a nearby meteorological station. The annual sum of precipitation was highest in 2019 with 643 mm and lowest in 2021 with 435 mm as a result of drought in that year. The amount of precipitation in March-April and May-June was lowest in period 5 and period 9 respectively while the highest was observed in October-February of period 1 which is moist and cooler (Figure 1).

The soil water content (W_s) also varies across the three periods but follows a regular pattern as the W_s decreases from winter to summer for all three periods. It ranges from 20.0 m^3m^{-3} to 36.68 m^3m^{-3} at the site and. The daily mean W_s has its maximum value during winter and minimum value in the summer as shown in Figure 3. The mean W_s of March-April and May-June subperiod was lowest in period 9, while the highest occurs in October-February of period 1.

Table 1. Showing the Mean variation of the Meteorological Conditions Across the Periods.

		mean air temp.	mean soil temp.	mean SWC	Sum of prec.
Period 1	Oct _ Febr	5.32	2.77	36.68	172.8
	March-Apr	8.95	8.63	34.80	73.6
	May-June	19.67	20.14	30.54	160.4
Period 5	Oct _ Febr	9.29	4.80	27.00	217.6
	March-Apr	3.37	9.21	29.47	19.3
	May-June	17.33	18.10	25.88	152.0
Period 9	Oct _ Febr	4.37	5.67	24.95	112.7
	March-Apr	7.25	7.55	28.27	71.1
	May-June	19.86	18.89	20.02	69.0

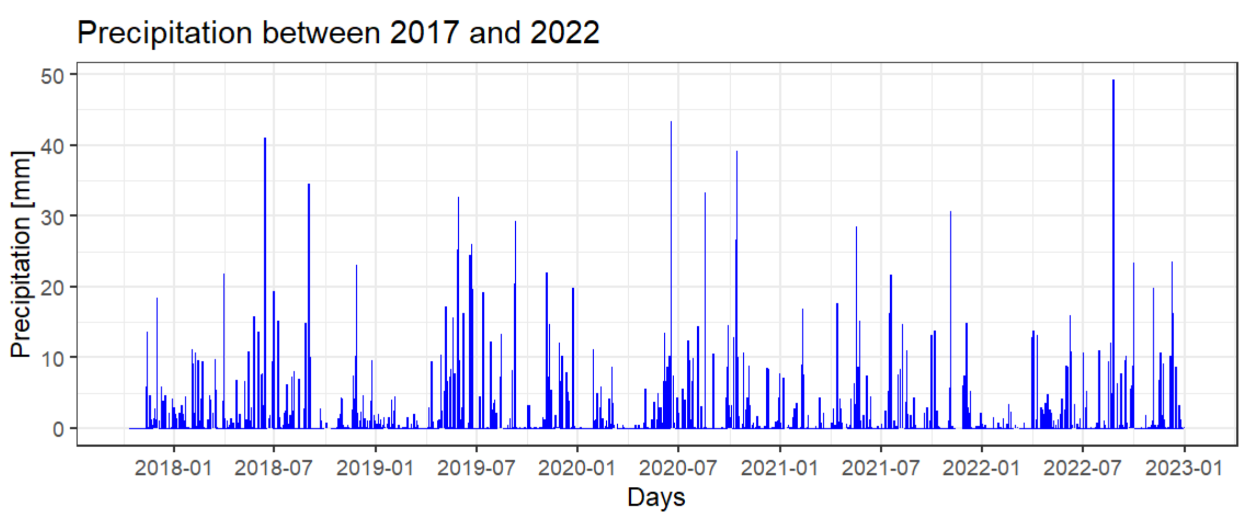

Figure 1. Daily sum of precipitation for the Kartal eddy covariancs site between 2017 and 2022.

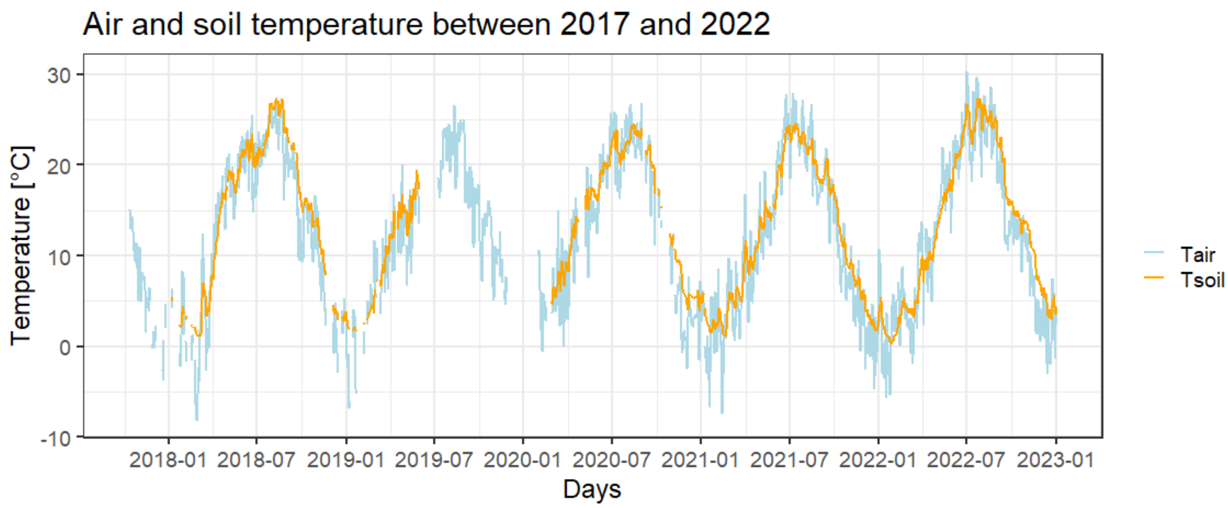

Figure 2. Variations in the daily mean air temperature (T_a, ^0C) soil temperature ($T_s{}^0C$) at the Kartal eddy covariance site between 2017 and 2022.

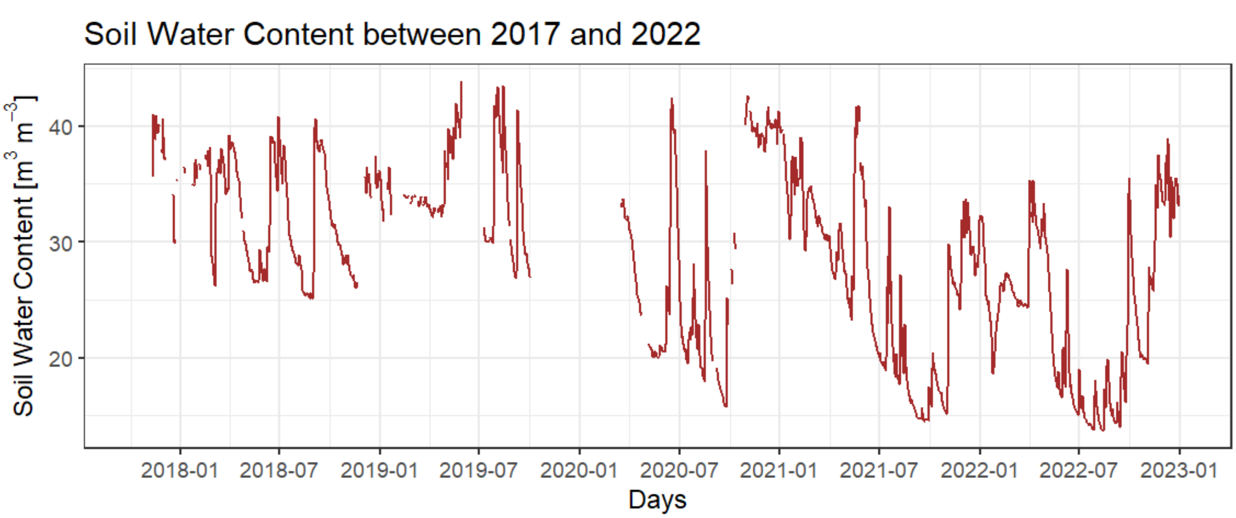

Figure 3. Variations in the daily mean soil water content (W_s) at the Kartal eddy covariance site between 2017 and 2022.

4.1.2 Comparing the three models based on the three periods

The Van't Hoff, Arrhenius, and Lloyd and Taylor models were used to calculate the RE for the three time periods. In order to choose the most accurate model, the application of each model varies depending on the criteria and parameters related to it. To evaluate the accuracy of the models, nighttime data (measured) from the three time periods 2017/2018, 2019/2020, and 2021/2022 were used. Table 2 displays the statistical details of the three models' correlations between parameters and correlation coefficients. It shows that different periods and models' nonlinear regression equations for the parameters and correlation coefficients produced various temperature response curves and correlation coefficients (R2). The most precise model for determining Re in the crop fields during the three selected growing seasons was the Lloyd and Taylor model. This model displayed the strongest sensitivity to temperature and had the highest regression coefficient.

4.1.3 Seasonal and periodic variation in RE

The Van't Hoff, Arrhenius, and Lloyd and Taylor models were used to estimate the seasonal changes in ecosystem respiration (RE) during three different periods of the year. Among these models, the Lloyd and Taylor model was found to be the most significant, as shown in Figures 4, 5, and 6. In each growing season, the data set were further splitted into three subperiods namely October-February, March-April, and May-June. During the subperiods of the wheat growing season around October-February, the CO_2 release was still considerable even though there might have been plants, although small growing in the field (Figure 7). The decrease in RE values during winter could be attributed to the low temperature, which hinders the breakdown of soil organic matter, and a decrease in aboveground biomass due to slow growth. However, as winter turned to spring and winter wheat began to grow rapidly, there was an increase in RE, with the most significant increase occurring in March due to rising temperatures and plant growth. RE levels usually peaked in late April in wheat fields but declined as the crop matured. In May and June, CO_2 emissions were likely caused by the decomposition of soil organic matter due to warm soil conditions as temperatures increased towards summer. Therefore, the primary contributors to RE during this period were the decomposition of soil organic carbon and root respiration of the wheat.

The Van’t Hoff Model as shown in Figure 8 was used to test the correlation between the carbon flux and temperature for Period 1 between October and June, it gave the correlation coefficient

(R^2) values of 0.04, 0.56, and 0.081 for the October-February, March-April, and May-June subperiods. During the period 5 growing season, there is no correlation at the beginning but rather at the mid and end of the period with R^2 coefficients 0.23 and 0.19 for the March-April, and May-June subperiods respectively. Further correlations were also observed for period 9, with R^2 values of 0.09 and 0.57 for October-February and March-April respectively, but the May-June subperiods have no correlation between the parameters.

The three seasons were also subjected to the temperature response curve using the Arrhenius model (Figure 9) based on the three periods (1,5 & 9) in order to check the correlation between them. Period 1 has R^2 values of 0.04, 0.62, and 0.081 for the October-February, March-April, and May-June subperiods of the 2017/2018 season respectively. The October-February subperiod in Period 5 does not have an R^2 value except in March-April, and May-June subperiods with 0.24 and 0.020 respectively. Period 9 also has a missing correlation value in the subperiod of May-June due to no growth activity but it was present in October-February, and March-April, with the values 0.09 and 0.57 accordingly. The Arrhenius R^2 was quite similar to Van't Hoff Model but still the temperature response curve is not well fitted to the carbon dioxide fluxes which makes it necessary to try the next model.

Lloyd and Taylor's model was also used to calculate the R^2 for the three periods. The R^2 for period 1 based on the three subperiods are 0.042, 0.58, and 0.086 as shown in Table 2. Period 5 has the following correlation coefficient for the subperiods of March-April, and May-June as 0.23, and 0.19 respectively but was totally absent in the October-February subperiod. The R^2 values for Periods 9 are 0.17, 0.59, and null for October-February, March-April, and May-June respectively.

The degree of correlations in the subperiods of October-February and May-June relative to the whole seasons were the lowest ranging from 0.04 to 0.19 and the highest values occurring in the March- April subperiod across all three periods of the growing seasons.

TABLE 2. THE STATISTICAL FEATURES OF THE RELATIONSHIPS BETWEEN THE FITTED COEFFICIENTS AND R^2 VALUES FOR ALL THE 3 PERIODS IN ALL THE 3 YEARS.

Period/Year	**2017/2018**			**2019/2020**			**2021/2022**		
	a	B	R^2	A	B	R^2	a	B	R^2
	Van't Hoff model								
October-February	2.611	0.1188	0.0421	-	-	-	1.64	0.0913	0.1737
March-April	3.893	0.09979	0.5576	2.495	0.07313	0.2293	4.064	0.1782	0.5833
May-June	8.972	0.04636	0.08794	3.074	0.06185	0.1856	-	-	-
	Arrhenius model								
October-February	1.373	5.409	0.03967	-	-	-	1.045	3.003	0.9223
March-April	5.011	68.92	0.6214	2.647	55.67	0.2425	4.376	77.88	0.5695
May-June	13	139.4	0.08138	1.974	177.6	0.1988	-	-	-
	Lloyd and Taylor's model								
October-February	2.361	285.6	0.04216	-	-	-	1.563	229.7	0.173
March-April	4.105	320.9	0.5827	2.523	231.8	0.2331	4.133	527.1	0.5869
May-June	9.608	197.3	0.08631	2.833	259.9	0.1899	-	-	-

R^2, correlation coefficient, a and b – coefficients/parameters of the model

4.2 Discussion

4.2.1 Ecosystem respiration models comparison with other croplands

This research compared how the response of CO_2 flux to temperature differs based on three models: Van't Hoff, Arrhenius, and Lloyd and Taylor. The results indicated that the Lloyd and Taylor model produced better temperature curves than the other two models. According to X. Bao et al (2020), an eight-year study of changes in RE residue incorporated rotation croplands and a similar two-year study by Li et al. (2015) of a rain-fed maize ecosystem in China both found that the Lloyd and Taylor model was more accurate than the other two models. The accuracy of the Van't Hoff and Arrhenius models was limited due to improper approximations that led to inaccuracies in the numerical values of the activation enthalpies (Keleti, 1993).

The results of the three models obtained from the wheat field show a good correlation between temperature and CO_2 flux with seasonal and periodic variations. The RE value starts increasing gradually during the winter, reaches its maximum during the active growth period (March-April), and finally declines when wheat ripens. The wheat CO_2 flux was usually higher during the mid-season period when compared with the other parts of the growing periods. The increasing trend of CO_2 flux at the mid-season periods may be explained by the optimum air and soil temperature, and precipitation as required by the plants during the intensive growing period except in some periods like 2019 where there was drought occurrence. According to Guo et al. (2019), temperature, precipitation, soil moisture, and plant development, all contribute to the interannual variability in agroecosystem RE. The increase in temperatures from winter to summer has an impact on ecosystem respiration (RE) due to the negative impact of extreme temperatures on gas flow within the ecosystem. This could be caused by the influence of climate change. One key factor in identifying a correlation between global warming and respiratory carbon flux in land-based ecosystems is the temperature sensitivity of ecosystem respiration (Q) (Reichstein et al., 2007). The Ws decreases when the temperature of the soil and air rise together, which causes an increase in the activity of microorganisms in the soil (Fisher and Whitford's findings in 1995). This boosts soil fertility, leading to better plant growth and a subsequent increase in the exchange of CO_2 flux. Jassal et al., (2007) noted that changes in soil moisture and temperature had a more significant impact on ecosystem respiration than on soil respiration. RE comprises both below-ground (soil) and above-ground (plant) components. Numerous factors, such as leaf area index

(LAI), fine root biomass, soil temperature and moisture, photosynthetic carbon allocation, size of the soil organic carbon pool, microbial biomass, and composition of the microbial community, can influence both plant RE and soil RE, which consist of primary heterotrophic and autotrophic components. Thus, all these factors play a crucial role in determining RE (Cheng et al., 2015; Huang et al., 2016).

This study discovered a substantial and positive correlation in period 1 between temperature and carbon flux. (Fig. 3a) using Lloyd and Taylor model. At the beginning of period 1, the relationship between the two parameters was weak despite high precipitation and W_s but low Ta and Ts as a result of slow plant growth and low vegetation cover. During the Mid-period (March-April), the T_a and T_s start to increase gradually and the precipitation decreases but the CO_2 exchange is high due to intensive plant growth with more vegetation. The correlation shows a good temperature response curve in Fig. 3a indicating that the increase in soil temperature has a significant effect on CO_2 flux. In the same period 1, we examined the response of high temperature with CO_2 flux around May-June where there was a decline in growth and result in less intense CO_2 release despite the temperature reaching its peak.

Period 5 indicated no significant correlation between the T_s and CO_2 at the beginning of October as a result of drought at the early start of the season in 2019 which leads to low regeneration despite high precipitation in later months. This also affects the soil temperature because it was a major contributing factor to RE than precipitation as any variation in it may alter CO_2 exchange. Several research investigations have demonstrated that the optimal level of soil moisture can be directly impacted by changes in soil temperature, which in turn affects the RE (Chang et al., 2016). However, the CO_2 flux tends to improve around March-April when intensive growth occurs but still, the correlation was very weak due to the effect of drought at the beginning of the season. The CO_2 flux trend decline after reaching its peak as the season approaches June as no active plant growth but soil organic matter decomposition. It can be inferred that little change in precipitation pattern had a big effect on the Ts and further disturbs the CO_2 balance within the ecosystem.

During the period 9, there is a notable correlation between Ts and CO_2, which persisted from the beginning of the season (October-February) until the active growth phase (March-April), where the correlation was considerably strong. A further correlation was not observed at the end of period 9 despite the high temperature but the precipitation was quite low when compared with the other periods. Furthermore, at the end of period 9, plant growth and activities ceased due to drought caused by insufficient in the year 2022. The amount of precipitation was decreasing annually which may disturb the interannual variation of soil moisture and thereby affects the soil and air temperature. It can be inferred that the effect of global warming would affect the carbon dioxide emissions of croplands as a result of variation in the climatic factors annually around the globe.

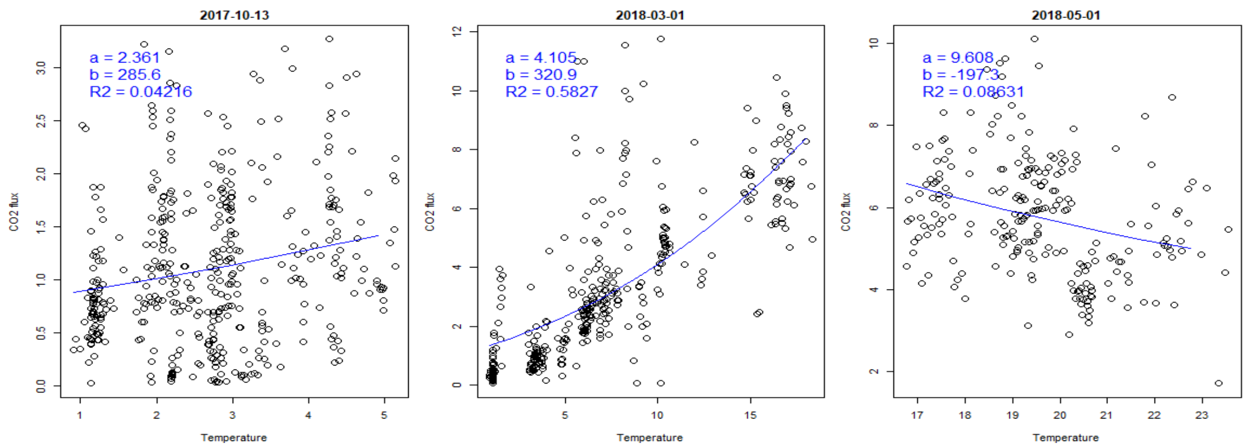

Figure 3. Temperature Response Curves of Period 1 Using Lloyd and Taylor Model.

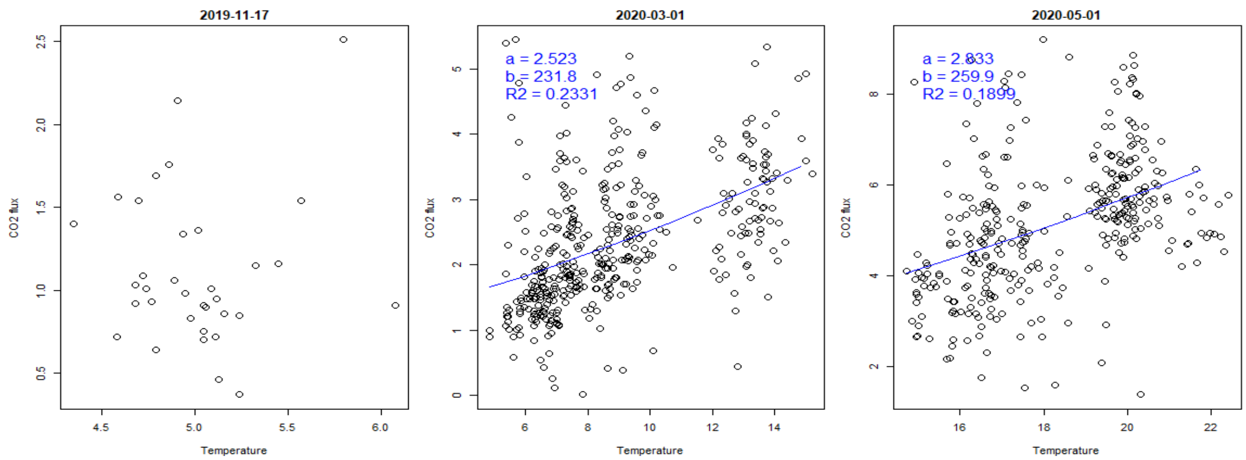

Figure 4. Temperature Response Curves of Period 5 Using Lloyd and Taylor Model.

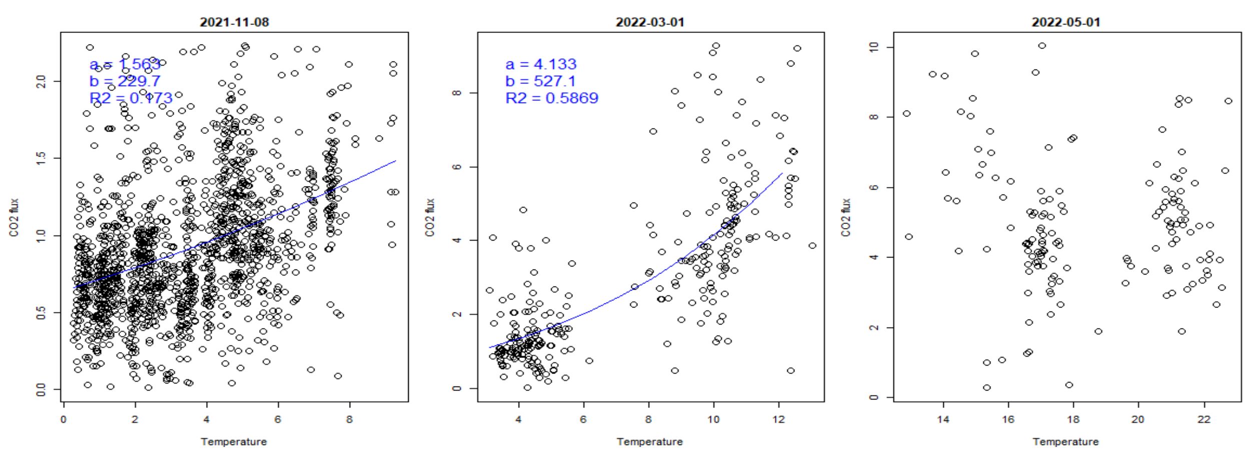

Figure 5. Temperature Response Curves of Period 9 Using Lloyd and Taylor Model.

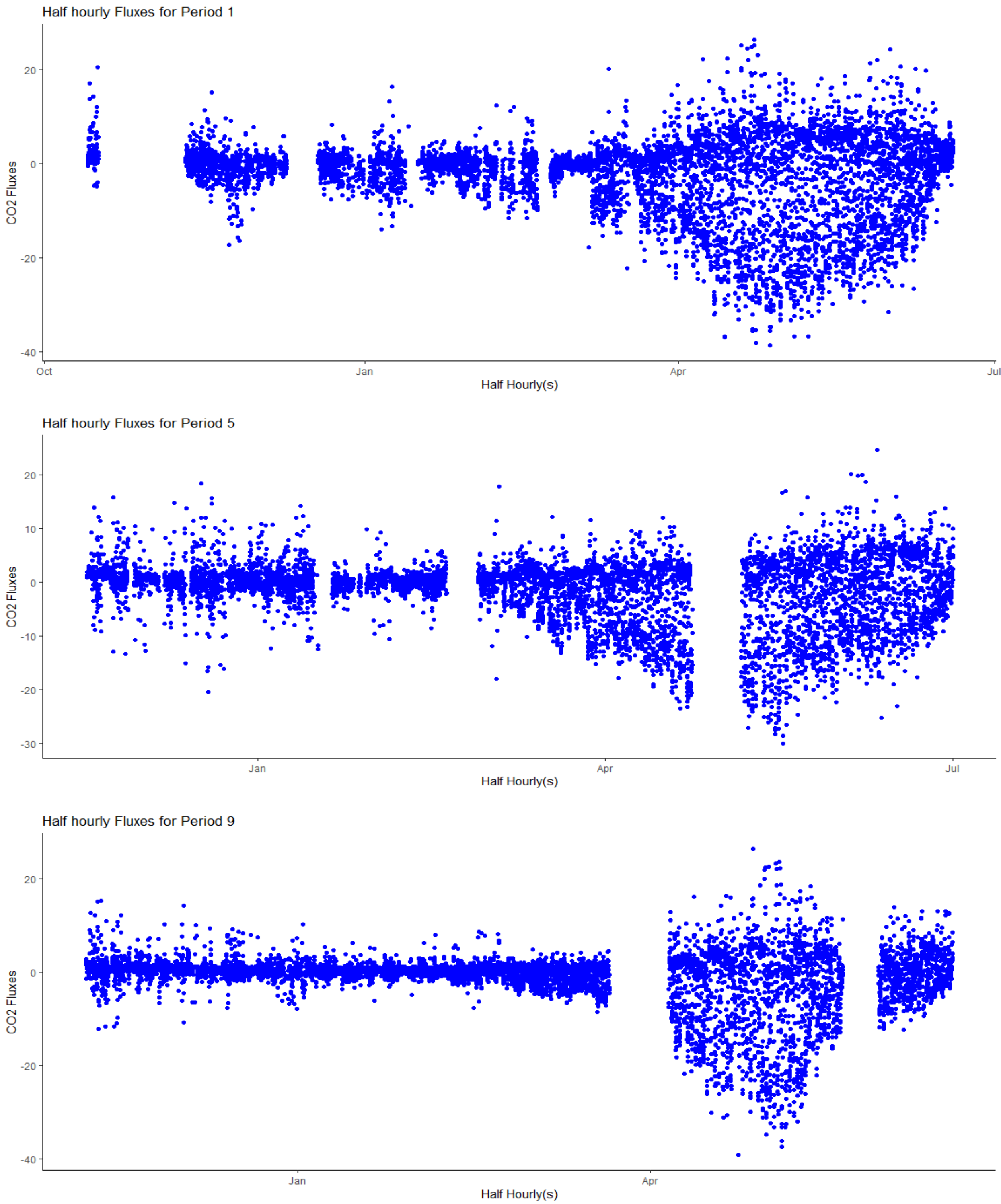

Figure 6. Half hourly fluxes of CO_2 (NEE) for the three selected growing periods at the Kartal eddy covariance site.

5.0 CONCLUSION AND RECOMMENDATION

Using five years of eddy covariance data, we characterized the year-to-year fluctuations in total ecosystem respiration (RE) for a wheat crop in the field, and investigated how temperature influenced these variations across three growing seasons. We also assessed the performance of three different RE models that accounted for temperature dependence. Our results showed that Lloyd and Taylor's model was the most appropriate, as it had the best fit with the correlation coefficient values observed over the five-year period. The R^2 values for the wheat crop were quite high during the March-April subperiod with 0.59 while it was weak during the October-February and May-June subperiods ranging from 0.04 to 0.19. Initially, it appeared that changes in wheat CO_2 emissions from year to year were primarily influenced by Ts and precipitation. However, after conducting further analysis using the Lloyd and Taylor model, it became apparent that the respiration rate (RE) was actually affected more significantly by Ts and drought, rather than just Ta. These findings suggest that the relationship between wheat RE and Ws was only occasional, and that interannual changes in CO_2 emissions were mainly governed by Ts, Ta, and Precipitation. While the seasonal CO_2 flux differed, the net source and net sink activities during periods 1 and 9 were quite similar. However, in period 5, there were significant differences, which were largely attributed to an early winter drought in 2019 that impacted the entire season during that period. Ecosystem temperature had a greater impact on total ecosystem respiration compared to the suppression caused by drought stress. Alternatively: Total ecosystem respiration was less affected by drought stress than by ecosystem temperature. Our study indicated that the effect of global warming would affect the carbon dioxide emissions of croplands as a result of variations in climatic factors annually around the globe.

In the early years of eddy covariances measurements, numerous studies have been done on the estimation of the carbon balance in agroecosystems, they are typically restricted to one specific vegetation type that is largely homogeneous in nature. Due to the significant efforts in last decades, the estimation of the carbon balance between the atmosphere and ecosystem has seen significant progress and nowadays this method is widely used to measure carbon balance of various ecosystems (e.g., grasslands, croplands and forests) in the frame of networks like the Integrated Carbon Observation System (ICOS) in Europe or AmeriFlux in the USA. Based on this huge amount of data, more research should be done to compare the carbon budget of various vegetation concurrently, including forests and croplands, grassland and forests, etc., which is of great importance.

6.0 SUMMARY

Accurate assessment of the terrestrial ecosystem respiration (RE) from carbon dioxide emissions of croplands is essential for the development of regional- to global-scale carbon budgets. In order to quantify the fluctuations in ecosystem respiration (RE) using temperature sensitivity and other parameters, continuous measurements of nighttime RE were obtained in wheat fields using the eddy covariance method from 2017 to 2022 growing periods. Based on correlation analysis, there was a relationship between the average soil temperature, CO_2 flux, and the interannual variations in the wheat field. The temperature response curve for three periods (1, 5, and 9) from October to June was analyzed using Van't Hoff, Arrhenius, and Lloyd and Taylor's models. Lloyd and Taylor's model was the most precise and well-suited to the data among the three models in the March-April subperiod where it has the maximum correlation coefficients (R^2) of 0.23 to 0.59 and lowest in the other subperiods namely October-February and May-June respectively. The correlation in period 5(0.23) of March-April was weak due to the low amount of precipitation and drought in 2019 and the absence of correlation indicated dormant or no growth periods in the field. The variation in RE of the wheat field was significantly influenced by soil and air temperature, and precipitation but less influenced by soil water content. The interannual variations in the wheat field showed a connection between the average soil temperature and CO_2 flux, as indicated by the results of the correlation analysis. It was suggested that day and night period ecosystem respiration be studied and compared in heterogeneous ecosystems to arrive at a clear conclusion in CO_2 flux as influenced by various climatic factors within the environment.

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APPENDIX

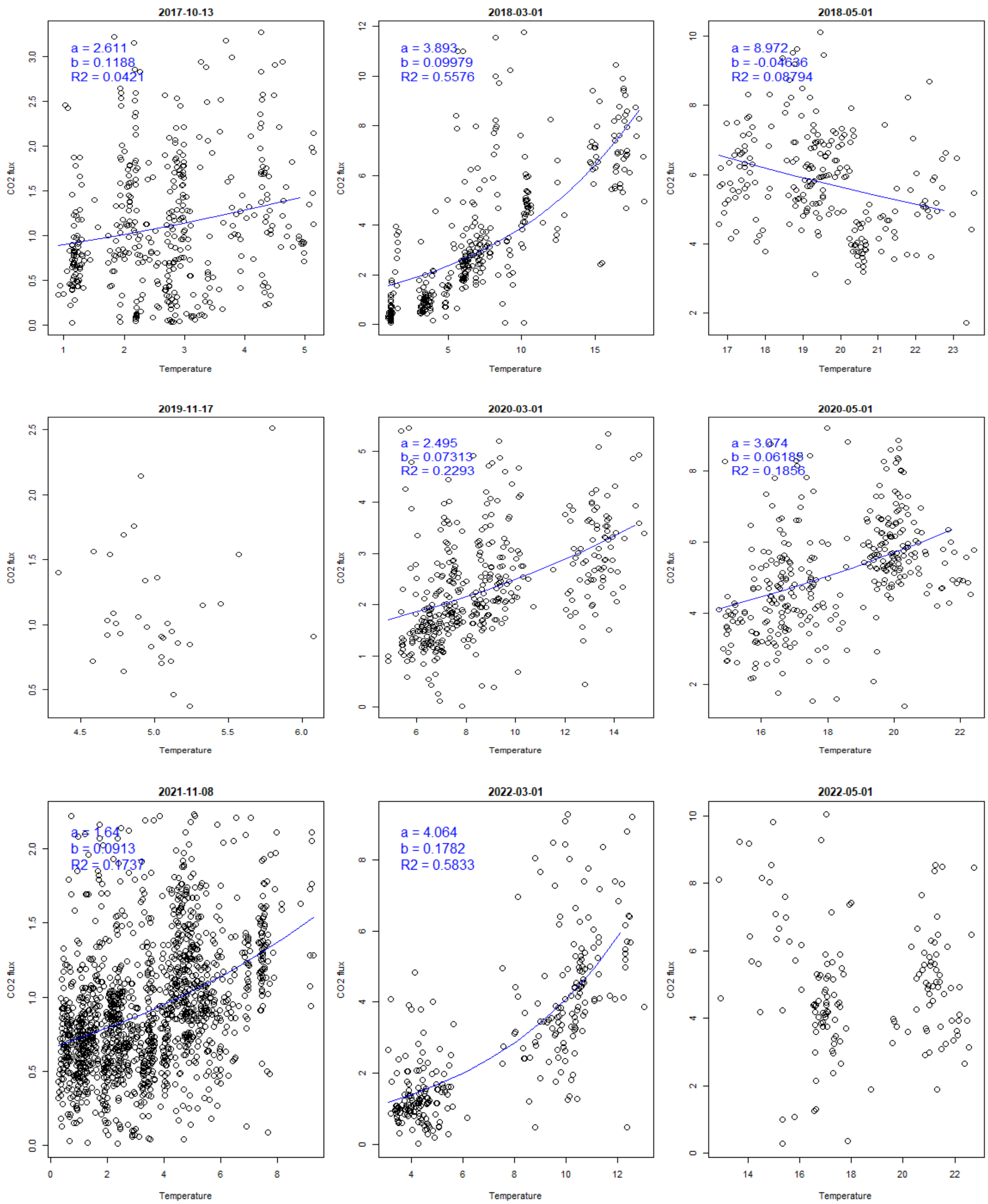

Figure 7. Temperature Response Curves of the Three Periods Using Van't Hoff Model.

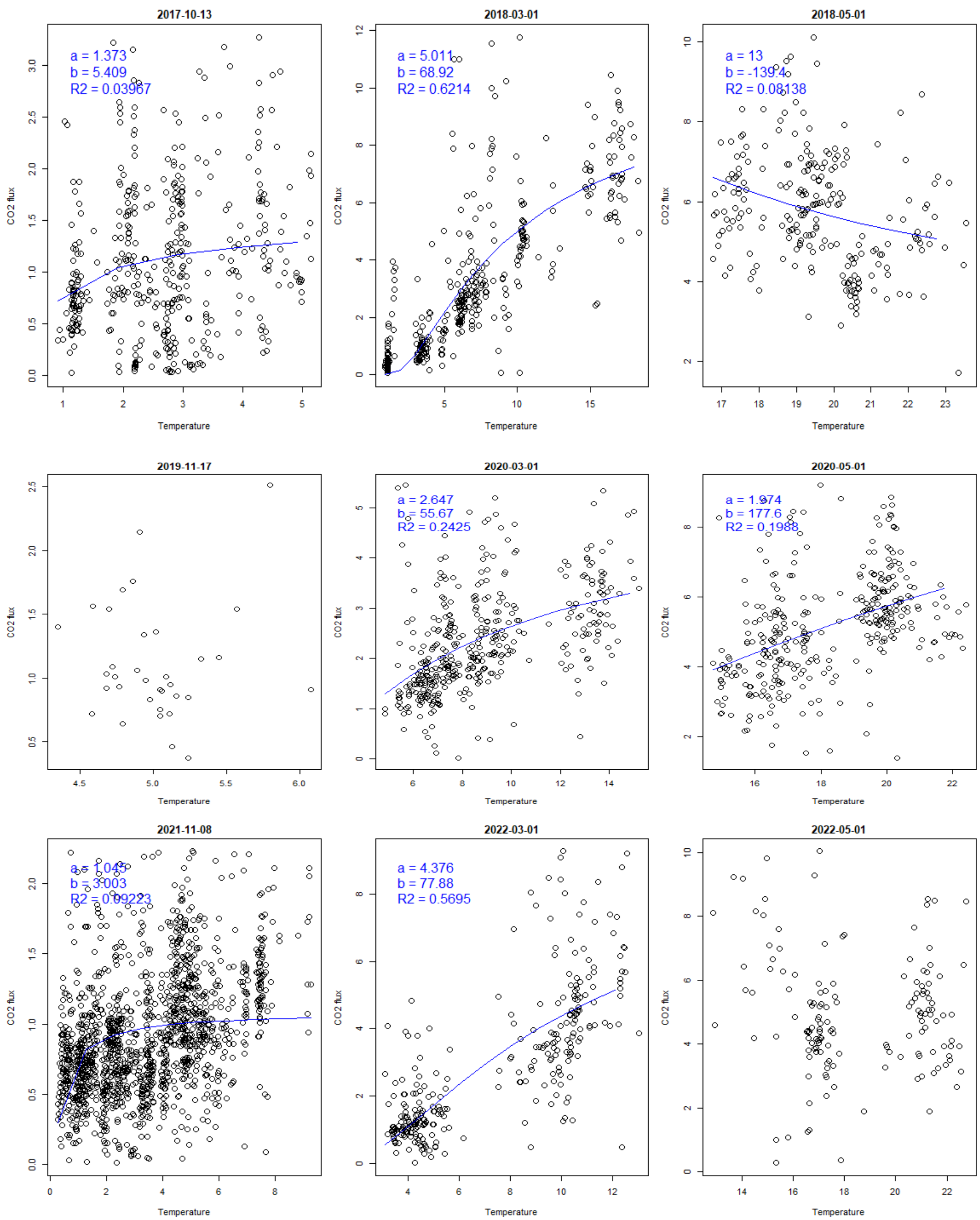

Figure 8. Temperature Response Curves of the Three Periods Using Arrhenius Model.

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