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PERSON-SPECIFIC VARIABLES PREDICT DEPRESSION SYMPTOMS BETTER THAN ENVIRONMENTAL AND WEATHER VARIABLES

INIMESEKOHASED MUUTUJAD ENNUSTAVAD DEPRESSIOONI SÜMPTOMEID KESKKONNA- JA ILMAMUUTUJATEST EDUKAMALT

Master's Thesis

Environmental Governance and Adaptation to Climate Change

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Major depression is one of the most prevalent mental health disorders, which symptoms include lowered mood, energy, and anhedonia. Research on psychological variables, green and blue spaces, and weather variables have all shown promising results in reducing depression symptoms. Even though there is no clear indication of which has the most significant effect on depression symptoms. This master thesis aims to combine person-specific, environmental, and weather variables to compare which of the three shows the highest effect on depression symptoms. Three wave samples, mainly collected in January 2021, May 2021 and January 2022, consisting of 2339 participants (*M=847, F=1492*), were analysed. Five linear regression and correlation analysis results indicate that person-specific variables outperformed environmental and weather variables, as none of the environmental and weather variables could predict depression symptoms significantly. More emotion regulation difficulties and post-traumatic stress disorder symptoms, high neuroticism, and low extraversion lead to more depression symptoms. Data waves differed from each other, as each wave presented a new highest predictor. In the January 2021 model more emotion regulation difficulties, the May 2021 model more post-traumatic stress symptoms, and the January 2022 model high neuroticism displayed the most substantial effect on depression symptoms. This master thesis' results suggest focusing on person-specific variables rather than changing home address nearer to a blue area or an area with higher vegetation cover or tree height to affect depression symptoms. Future research should aim to collect and analyse data in an area with less green and blue areas to see if results are replicable.			

Keywords: Mental health, Green and Blue Spaces, Weather, Effect size, PTSD symptoms

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Depressioon on üks sagedamini esinevaid vaimseid häireid, mille sümptomid väljenduvad alanenud meeleolus, energiatasemes ning anhedoonias. Eelnevalt avaldatud artiklid sini- ja rohealade ning ilmaandmete kohta seostavad keskkonnategureid kõrgema heaolu ning vähemate depressiooni sümptomitega. Sellegipoolest ei ole teada, kas inimesepõhised, keskkonna- või ilmatunnused mõjutavad vaimset tervist enim. Selle magistritöö eesmärk on kaasata nii inimesepõhised, keskkonna- ja ilmaandmed, et võrrelda nende efekti depressiooni sümtomitele. 2021. aasta jaanuaris ja mais, ning 2022. aasta jaanuaris toimunud kolmes andmekogumislaines osales kõikides lainetes 2339 vastajat (*M= 847, N=1492*). Andmetel viidi läbi lineaarne regressioonanalüüs ning korrelatsioonanalüüs, mille tulemustest selgus, et inimesekesksed muutujad olid selgelt paremad depressiooni sümptomite ennustajad. Keskkonna- ja ilmamuutujad ei ennustanud depressiooni sümptomeid. Rohkemad emotsiooni regulatsiooni raskused, enam post-traumaatilise stresshäire sümptomeid, kõrge neurootilisus ja madal ekstravertsus viisid enamate depressiooni sümptomiteni. Andmelained erinesid omavahel, kuna kõigis kerkis esile uus tugevaim depressiooni sümptomite ennustaja. Jaanuar 2021 mudelis oli emotsiooni regulatsiooni raskuste, Mai 2021 mudelis post-traumaatilise stresshäire sümptomite ning Jaanuar 2022 mudelis kõrge neurootilisus olulisim depressiooni sümptomite selgitaja. Magistritöö tulemuste põhjal on depressiooni sümptomaatika alandamiseks olulisem keskenduda inimesekesksete tegurite muutmisele kui rohe-või siniala lähedal paiknevasse kohta kolimisele. Tulevased uuringud vähema sini- või rohealaga piirkonnas annaksid ülevaate, kas tulemused saavad kinnitust ka teistsugustes loodustingimustes.			

Märksõnad: Vaimne tervis, rohe- ja sinialad, ilm, efekti suurus, PTSD sümptomid

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1. Introduction

Depression is one the most burdening mental health disorders in the world, as epidemiological studies suggest lifetime prevalence estimates up to 16.9%, the disorder often reoccurs and is the leading cause of disability in the world (Kessler & Bromet, 2013a; LeMoult & Gotlib, 2019). Depression affects mood, thoughts, energy level, concentration capacity, and attention (LeMoult & Gotlib, 2019). Depression develops due to genetic, psychological, and environmental factors, which interact and influence one another (Ettman et al., 2020; LeMoult & Gotlib, 2019; Perlstein & Waller, 2022). The last decades have welcomed research on depression, green and blue spaces, showing potential to support mental health and well-being (Kaplan, 1995; Ulrich et al., 1991; White et al., 2021; Yao et al., 2021). Meta-analytic evidence from 18 countries relates higher well-being with more nature visits, living nearer to a park with lower depression symptoms, and more often visiting blue spaces to higher well-being (Georgiou et al., 2021; Pouso et al., 2021b; White et al., 123 C.E.). Research combining weather data and mood has also sparked interest but has not enjoyed the same popularity as green and blue spaces (Kööts et al., 2011; Yang et al., 2015). Laypeople often presume that weather influences their current affect and mood, but published results are conflicting (Huibers et al., 2010; Kööts et al., 2011; O'Hare et al., 2016; Yang et al., 2015). Differences are visible between different locations, and some areas might even show location-specific weather and mood patterns (Yang et al., 2015). To add, some weather variables like wind speed are often left out, and therefore there is no knowledge if it influences mood or well-being (Bielinis et al., 2021). To the author's knowledge, previous research has not combined person-specific variables with environmental and weather variables to estimate and compare effect sizes on depression symptoms or well-being. This makes it challenging to know which variable would be more important to influence if resources are limited. This master thesis aims to combine person-specific, environmental, and weather variables to compare their effect on depression symptoms. Data collected in three waves from January 2021 to February 2022 will be analysed in five linear regression models and correlation analysis. Mental health and person-specific data were collected with Estonian National Mental Health Research; environmental and weather variables are available in public databases. Based on the aim of the research and previously published literature, three research questions were raised:

1) Are person-specific, environmental, or weather variables the strongest predictors of depression symptoms score?
2) Which weather variables will predict depression symptoms score?
3) Are variables predicting depression symptoms score differently between January-February 2021, May-June 2021, and January-February 2022 data waves?

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2. Literature review

2.1 Depression

Depression in the DSM-V is defined as a mood disorder lasting at least two weeks, exhibiting symptoms of lowered mood, decreased interest and motivation (LeMoult & Gotlib, 2019). Other symptoms include changes in appetite, sleep rhythm, hopelessness, suicidal thoughts; and depression is often co-morbid with anxiety and other disorders (Cummings et al., 2014). According to the Global Burden of Disease Study, depression is the leading contributor to disability (Liu et al., 2020; Moreno-Agostino et al., 2021). Epidemiological studies before Covid-19 estimated the lifetime prevalence of depression up to 16.9%, and peri-Covid-19 studies report prevalence of 18.3% (Kessler & Bromet, 2013b; Schafer et al., 2022). During the last decades likelihood of suffering from depression has increased, this effect seems to be not explained by study differences and publication bias (Liu et al., 2020; Moreno-Agostino et al., 2021).

Gender bias is evident in depression. Females experience a twofold risk of suffering from depression, also, divorced or separated people report higher rates of depression than married people (Kessler & Bromet, 2013b). People with higher income have a lower risk of developing depression, the same pattern is visible for people with higher education levels (Kessler & Bromet, 2013b). Another possible risk factor for depression could arise from living in a city, as people living in rural areas have lower depression symptoms (Romans et al., 2011).

2.2 Environmental Factors and Mental Health

People living in some locations have lower depression symptoms and higher well-being (de Bell et al., 2020; Vries et al., 2016; Yao et al., 2021). A study conducted in 18 countries showed that countries with higher well-being also had the most nature visits and higher nature connectedness (White et al., 2023). Visiting natural environments is associated with decreased salivary control, state-of-anxiety, self-reported stress, diastolic and systolic blood pressure

(Yao et al., 2021). Lower levels of depression symptoms have been linked with living near a park (<300m) and visiting it more than 4 hours per week (Pouso et al., 2021a). Higher well-being and lower depression symptoms are also evident among people with access to a private garden or natural view from home (de Bell et al., 2020; Pouso et al., 2021a). Recreational visits might be even more important than living near a natural area, as more recreational visits to green and blue spaces were associated with lower mental distress, effect for blue space were slightly stronger (White et al., 2023).

Previous research has also highlighted the positive impact of blue spaces on physical and mental health (Georgiou et al., 2021; Vries et al., 2016). Larger amounts of and spending more time in blue areas link with higher physical activity levels and higher restoration (Georgiou et al., 2021). Furthermore, blue space is negatively associated with diagnosed mood (depression, bipolar disorder, and dysthymia) and anxiety disorders (panic disorder, agoraphobia, social phobia, and generalised anxiety disorder) (Vries et al., 2016).

According to a meta-analysis, exposure to natural environments was associated with positive affect with a median effect size of *0.28*, while negative affect had an effect size of *-0.11* (McMahan & Estes, 2015). Therefore, the effect of nature exposure is rather carried out by increases in positive affect than decreases in negative affect (McMahan & Estes, 2015). Effects for blue spaces are more substantial than for green spaces (Vries et al., 2016). Natural area's ability to facilitate restoration from attentional fatigue (attention restoration theory) and reduce stress (stress recovery theory) could potentially explain higher well-being and lower levels of stress-related disorders near green and blue spaces (Hartig et al., 2014; Kaplan, 1995; Markevych et al., 2017; Ulrich et al., 1991).

2.3 Weather and Mental Health

Previous research has focused chiefly on temperature, luminance, precipitation and barometric pressure's effect on mood, while snow cover and wind speed have received less attention (Kööts et al., 2011). According to Estonian data, temperature is positively related to negative affect, indicating a little bit more negative emotions with higher temperatures but less tiredness (Connolly, n.d.; Kööts et al., 2011). Days with higher maximum temperatures resulted in greater odds of transitioning to manic mood states in bipolar populations, while other meteorological variables did not predict clinically relevant mood change (Bullock et al., 2017).

Similarly, higher temperatures resulted in more interpersonal and intergroup violence (Hsiang et al., 2013). Peng and colleagues offer a potential threshold of 24.6 degrees Celsius, as from there, hospital admissions significantly rose for all mental disorders (Peng et al., 2017). In contradiction, monthly average temperature had no significant effect on depressive symptoms in O'Hare and colleagues' (2016) and Huibers et al. (2010) research.

In Ireland, participants living in areas with heavier rainfall reported more significant depression symptoms, while participants from sunnier locations had fewer depression symptoms (O'Hare et al., 2016). Higher luminance, sunshine duration and global radiation result in more positive affect, less depressive symptoms and less tiredness, cloud coverage links weakly with more depressive symptoms (Kööts et al., 2011; Sarran et al., 2017; Xu et al., 2020). Days with less than one hour of sunlight during the previous 7 and 3 days related to a higher amount of suicide attempts in Japan, monthly average sunlight hours did not associate (Kadotani et al., 2014). But at the same time, days with more than half of the day filled with sunlight result in higher risk-aversive behaviour (Bassi et al., 2013). Some research suggests that average rainfall duration differences did not relate to depressive symptoms (Huibers et al., 2010).

In Estonia, less relative humidity indicated more negative affect, e.g. less humid days might result in less negative emotions (Kööts et al., 2011). Similar results were found with UK affective disorder admissions (Salib & Sharp, 2009).

Overall, higher luminance, greater sunshine duration, and global radiation result in less depressive symptoms, while overcast weather could foreground more symptoms (Kööts et al., 2011; Sarran et al., 2017; Xu et al., 2020). Even though not all research papers find an effect, location-specific differences exist and effect sizes mostly range from small to medium (Kööts et al., 2011; Yang et al., 2015). Differences also arise from the length of the measurement period, as some research focused on intraday, others on monthly averages, which might result in different or even opposite effects. Research lacks results about wind and snow cover. Integrating local surroundings, like blue or green spaces could make us better understand the potential impact on the environment.

2.4 Person-Specific Factors and Mental Health

Person-specific factors like genetics, biological variables, cognition, certain personality traits or disorders, emotion regulation, quality of social relationships, chronic psychosocial stressors and childhood adversity increase the risk of developing depression (Hölzel et al., 2011; Klumparendt et al., 2019; Riso et al., 2002). In addition, younger age of onset, longer episodes, family history of mood disorders and comorbidity with anxiety, personality and substance abuse disorders also increase the risk for depression to turn comorbid (Hölzel et al., 2011). As many factors could influence the formation of an episode of depression, from here on, we will focus more on genetics, emotion regulation, personality, PTSD symptoms, Covid-19 stress and social relationships.

2.4.1 Genetics and Mental Health

Meta-analysis consisting of 5 family studies indicated that the heritability rate of depression is 37%, while other factors account for 63% of variance (Shadrina et al., 2018; Sullivan et al., 2000). First-degree relatives of people suffering from depression have a two- to threefold increased risk for depression (Shadrina et al., 2018; Sullivan et al., 2000). Depression is a polygenetic disorder composed of many genetic variants that individually represent small effect sizes (Hyde et al., 2016; Mullins & Lewis, 2017; Wray et al., 2014). As the heritability rate of depression is lower than other psychiatric disorders, this indicates that risk alleles might have smaller effect sizes (Mullins & Lewis, 2017), as the heritability of schizophrenia and bipolar disorder ranges approximately around 70% (Sullivan et al., 2000). 23andMe study resulted in correlating self-report measurements of depression and GWAS results, which showed a correlation of 0.72, indicating an overlap between different depression subtypes and common variant genetic overlap (Hyde et al., 2016). But if subtypes of depression were not differentiated, three wide-scale studies (Cai et al., 2015; Howard et al., 2018, 2019; Hyde et al., 2016) failed to find replicable results of genetic variants. When the results of these studies were combined, the meta-analysis identified 102 independently segregating genetic variations associated with depression in 101 loci (Howard et al., 2019). Overall, early onset and often reoccurring depression might have a more heritable background (Levinson, 2006; Mullins & Lewis, 2017; Sullivan et al., 2000). Unfortunately, Genetic data was unavailable for this master thesis, but the effect should not be left unnoticed.

2.4.2 Personality and Mental Health

Personality is often measured with a Five Factor model, which organises personality into five domains: Extraversion, Neuroticism, Agreeableness, Openness to Experience and Consciousness (Costa & McCrae, 2008). Furthermore, five domains could be divided into facets and nuances (Mõttus et al., 2017). A meta-analysis and longitudinal study resulted that high neuroticism, low extraversion and low conscientiousness predict depression symptoms (Hakulinen et al., 2015; Hyde et al., 2016). Depression symptoms were linked to changes in all personality domains, the highest association was with neuroticism and conscientiousness (Hakulinen et al., 2015). Interestingly, openness to experience score is higher among people suffering from the seasonal subtype of depression, driven by facets openness to aesthetics, feelings and values (Bagby et al., 1996; Enns et al., 2006; Oginska & Oginska-Bruchal, 2014).

2.4.3 Emotion Regulation and Mental Health

Emotion regulation difficulties have been evident among depressed patients (Joormann & Stanton, 2016; Visted et al., 2018). Emotion regulation can be seen as the ability to influence which, when, how to feel and express the emotions individual is experiencing (Gross, 1998). Some emotion regulation strategies are more effective than others, despite differences between situations. Healthy strategies are acceptance, problem-solving, reappraisal, also self-compassion (Visted et al., 2018). Maladaptive strategies include avoidance, rumination, and suppression (Visted et al., 2018). Also, higher usage of maladaptive strategies has been linked with psychopathology (Aldao et al., 2015; Joormann & Stanton, 2016; Sloan et al., 2017). Individuals with major depressive disorder report higher avoidance, rumination and suppression usage than healthy controls (Joormann & Stanton, 2016; Visted et al., 2018). Downregulating positive affect with dampening rumination and lack of access to positive memories also aligns with depressive symptoms (Joormann & Stanton, 2016). Repetitive negative thinking is more often associated with depressive symptoms than positive reappraisal (Everaert & Joormann, 2020). Underneath emotion regulation difficulties could lie cognitive biases like interpretation bias, brooding and attention bias (Everaert et al., 2016).

2.4.5 Traumatic Experiences and Mental Health

Rates of traumatic events may vary between societies, but in the example of the USA, 15% of the population reported experiencing rape, physical attack, molestation or have been involved in combat (Kessler et al., 1995; B. van der Kolk, 2022). A wide-scale adverse childhood experience study with over 8000 respondents asked about traumatic experiences taking place inside one's household, including physical, emotional and sexual abuse, also including living with a family member suffering from mental illness, and 52% of respondents reported experiencing at least one event (Felitti et al., 1998). Participants reporting more adverse childhood experiences had a higher risk for depression, alcoholism, drug abuse and suicide attempts (Felitti et al., 1998; Panagioti et al., 2012; Porche et al., 2011). Also, risks for physical illnesses like ischemic heart disease, cancer, chronic lung disease and liver disease were higher among respondents reporting more adverse childhood experiences (Felitti et al., 1998). These adverse childhood experiences might also lead to a diagnosis of post-traumatic stress disorder. Post-traumatic stress disorder (PTSD) is an anxiety disorder that develops one to six months after a traumatic event (B. van der Kolk, 2022). PTSD symptoms include intrusive thoughts about the event, avoidance of certain situations or locations, hyperarousal, nightmares, difficulties concentrating and flashbacks (B. A. van der Kolk & Fisler, 1995). The estimated lifetime prevalence of post-traumatic stress disorder is around 7.8% (Kessler et al., 1995). Even though it is important to note that not all people develop post-traumatic stress disorder or symptoms after a threatening event, and events differ from each other (B. van der Kolk, 2022). Regaining consciousness during surgery led to PTSD for 56% of patients, being raped led to PTSD for 48.4% of patients, while 10.7% of men who witnessed death or severe injury afterwards reported PTSD (Kessler et al., 1995; B. van der Kolk, 2022). Women more often report severer post-traumatic stress symptoms (B. van der Kolk, 2022; Merikangas et al., 2010). For men, more traumatic events are associated with strangers, but for women, more events are linked with people they know (B. van der Kolk, 2022).

A meta-analysis of 57 studies concluded that 52% of patients with post-traumatic stress disorder also have co-occurring major depressive disorder (Rytwinski et al., 2013). Suffering from two mental health disorders leads to greater distress and impairment (Rytwinski et al., 2013). People once suffering from PTSD or PTSD symptoms are at higher risk of redeveloping symptoms during another traumatic experience ng a stressful period (B. van der Kolk, 2022).

2.4.6 Covid-19 Stress and Mental Health

The Covid-19 pandemic introduced a wide-scale health crisis with social distancing restrictions and lockdowns. Harsher lockdown rules might have led to worse mental health, higher depression and anxiety symptoms (Pouso et al., 2021b). Research conducted among university students showed that 40% of participants reported moderate to severe anxiety symptoms, and 72% had depression symptoms (Faisal et al., 2022). Path analysis in the same research linked knowledge and attitudes about the severity of Covid-19 with more depressive symptoms (Faisal et al., 2022). This aligns with a global study incorporating participants from 63 nations reporting high anxiety and depression symptoms (Varma et al., 2021). Even though they stated that anxiety symptoms were more prevalent, 59% of respondents met the criteria for clinically significant anxiety, while 39% suffered from severe depression symptoms (Varma et al., 2021). Age-group differences were also visible, as younger age groups were more vulnerable to depression and anxiety symptoms (Varma et al., 2021). Screening of post-traumatic stress symptoms showed that according to PC-PTSD-5 34.1% of participants might have PTSD (Kar et al., 2021). If PTSD symptoms were measured in addition to depression and other anxiety disorder symptoms, percentages for depression (15%) and severe anxiety (21.2%) were lower, indicating that some of the previously presented high numbers of depression and anxiety symptoms might contain symptoms of PTSD (Kar et al., 2021). After Covid-19, depression lifetime prevalence has risen by more than 1% (Kessler & Bromet, 2013b; Schafer et al., 2022).

2.4.7 Social Relations and Mental Health

Social support has received less attention than genetics, neurobiology, personality and emotion regulation in psychology (Wang et al., 2018a). Loneliness can be seen as fewer social interactions than one wishes. Loneliness can be divided into emotional and social loneliness (Golden et al., 2009). Social loneliness is concerned that the amount of social relations is lower than desired, emotional loneliness stands for lower amount of intimacy wished for (Holvast et al., 2015). Loneliness is more present among people suffering from depression than in the wider population (Wang et al., 2018a). According to eleven studies, higher loneliness or lower levels of perceived social support resulted in higher depressive symptoms at follow-ups, no differences between sexes were visible (Golden et al., 2009; Holvast et al., 2015; Wang et al., 2018a). Holvast and colleagues (2015) study connected higher follow-up depressive symptoms severity with both emotional and social loneliness, the effect was higher for emotional loneliness. People suffering from depression could exhibit higher vulnerability towards social exclusion, as depressed patients showed stronger emotional reactions (Holvast et al., 2015; Reinhard et al., 2019). Also, slower recovery from depression was evident among patients with lower social support (Bosworth et al., 2002; Holvast et al., 2015; Leskelä et al., 2006). Similar results are visible for people with bipolar disorder, as lower perceived social support predicted greater depression over time and greater impairment in functioning (Koenders et al., 2015; Wang et al., 2018a). Lower perceived social support also predicted more severe anxiety for people suffering from generalized anxiety disorder, social anxiety, panic disorder and post-traumatic stress disorder (Dour et al., 2014; Wang et al., 2018a). Research on the protective factors of social support also yields essential aspects. Chao (2011) compared social network size, network composition, frequency of social contact, proximity, types of support received, helping others, and satisfaction with social support protective effect on depression symptoms among the Chinese elderly. The author found that satisfaction with social support had the highest impact, while other social support factors had smaller effect sizes, indicating the need to tailor social support to the recipient's needs (Chao, 2011).

3. Methodology

3.1 Participants

Data for this master thesis were collected within the *Estonian National Mental Health Research.* Data was collected in three waves: January-February 2021, May-June 2021, and January-February 2022. This thesis sample consisted of participants who answered all three data waves. This means that the targeted sample consisted of 2339 participants, making up 12.1% of the participants. Of the selected sample, 847 participants were male (36.2%), and 1492 were female (63.8%). The average age was 59.52 years (*SD=17.93*), the youngest participant was 18, and the oldest was 97 years old. 969 participants (44.3%) answered the questionnaire on paper and sent it in through post, and 1171 (55.7%) answered the questionnaire online. The whole Estonian National Mental Health Research sample consisted of 19275 participants, from 9672 (50.2%) male and 9603 female (49.8%). The average age of the whole sample was 47.95 years (*SD=21.03*), the youngest participants was 15 years old, and the oldest was 100 years old.

3.2 Data Collection

Mental Health data was collected in three waves through the Estonian National Mental Health Research, which took place from January 2021 to February 2022 online and with paper questionnaires, which were sent in through post (*Eesti Rahvastiku Vaimse Tervise Uuring Lõpparuanne*, 2022). Green and blue space measurements were retrieved from open-access Estonian Land Board Topographic Maps (Estonian Land Board, 2023). Weather Variables were retrieved from Estonian Environment Agency open access weather data historical datasets (Estonian Environment Agency, 2023).

3.3 Materials

3.3.1 Person-specific variables

3.3.1.1 Descriptive variables

Sex, education level, income, marital status, and settlement type data were collected in the Estonian National Mental Health Study. Information concerning sex was withdrawn from the Estonian population register, and other variables were self-reported by participants. While reporting education level, respondents were able to choose from 8 options. Answer 1 accounted for primary education, option eight master's or doctoral degree. Participants answered questions about their income during the last 12 months, option 1 indicated no income, and option 10 was 2501 and more euros. Regarding marital status, respondents could choose from five options: single, living with a partner, associated with a partner but not living together, divorced, or widowed. Settlement type was assessed with three options: one was living in an area with less than 1000 residents, option 2 accounted for 1000-10 000 residents, and option three was living in an area with more than 10 000 residents. Aside from sex and settlement type, all questions were asked in three data waves, and each data wave model included data collected from the same wave. Data about settlement type was gathered in the first data wave.

3.3.1.2 Emotional State Questionnaire 2

Emotional State Questionnaire (ESTQ-2) consists of 28 self-reported questions answered on a five-point Likert scale from 1 to 5 created by Aluoja and colleagues (Aluoja et al., 2009). One stands for not at all, five often. The questionnaire consists of 6 subscales: depression, generalised anxiety disorder, panic disorder, social anxiety disorder, tiredness, and insomnia. For this master thesis, only the depression subscale results were used (ESTQ-D), which consists of eight questions. More depression symptoms align with higher scores on EST-Q2-D. ESTQ-2 is a screening test; therefore, it enables to assess risk for depression but not diagnose the disorder. ESTQ-2 was administered in all three waves.

3.3.1.3 Personality Measurements

Five personality domains were measured: Extraversion, Neuroticism, Openness to Experiences, Agreeableness and Consciousness. Extraversion, Neuroticism and Consciousness were measured with four, Agreeableness and Openness with five items taken from the 100 Nuances of Personality Items Pool (Henry & Mõttus, 2021). Items were presented on a 5-point Likert scale and were self-reported. A higher score indicates a higher resemblance with the personality domain. Personality data was gathered in the third data wave.

3.3.1.4 Emotion Regulation Difficulties

Three questions were taken from the Difficulties in Emotion Regulation Scale (Gratz & Roemer, 2004). The three questions measured rumination, disbelief in changing the situation and ability to regulate emotion during the last three months. The questions were posed on a 5-point scale, where one stands for never and 5 for almost always. Therefore, higher scores presented more difficulties in emotion regulation.

3.3.1.5 Post-Traumatic Stress Symptoms

Post-traumatic stress disorder symptoms were measured with three questions adapted from PTSD Checklist (Weathers et al., 1993). The questions regarded flashbacks, high distress due to a traumatic situation and avoidance of the situation. Answers were self-reported, and presented on a 5-point Likert scale. Answer one was not disturbed at all, and answer five often disturbed. Data was collected in the first wave.

3.3.1.6 Covid-19 Stress

The variable stress caused by Covid-19 measures to prevent the spread of the virus was created by Estonian National Mental Health Research conductors and was presented as a dichotomous variable. The data was based on 20 self-reported questions raised on a Likert scale from 1 to 4.

Option one was “this does not concern me”, and option four was “causes significant stress” data was collected in all three waves.

3.3.1.7 Perceived Social Support

Perceived social support was assessed with one question. The question was measured with a four-point self-reported scale. Answer one indicated high satisfaction and four lack of satisfaction. Perceived social support was measured in the first data wave.

3.3.2 Environmental Variables

Seven environmental variables were added to the models. Vegetation height, tree cover, open areas, lake area and river length were available at three buffer areas of 100, 500 and 1000 meters from participants' home location registered at the Estonian population register. Distance from sea and inland waterbody variables were also added to the analysis. Environmental variables data were taken from Estonian Topographic Maps Collection (Estonian Land Board, 2023). Afterwards, data was put together with registered home addresses presented in the Estonian population register. Anto Aasa and Jürgen Pikk created these variables.

3.3.3 Weather Variables

Weather data was taken from the Estonian Environmental Agency Historical Weather database (Estonian Environment Agency, 2023). Anto Aasa collided person-specific and environmental data with the nearest Metrological Station to participants’ registered home address according to the Estonian population register. The author was not able to add data herself due to security restrictions. Afterwards, author cleaned data from participants replying to the questionnaire through post, as their exact response time was unknown. The author added six weather variables to the person-specific and environmental dataset for every data wave. In total, this includes 18 variables for each suitable participant. Weather variables were total sunshine radiation in the last hour (W/m2), atmospheric pressure at the metrological station (hPa), total precipitation in the previous hour (mm), relative humidity (%), average temperature (°C) and average wind speed during last 10 minutes (m/s).

3.4 Statistical Analysis

Five linear regression models and one correlation analysis were performed to analyse data. Before data analysis requirements for specific data analysis were checked. Most variables met the criteria, if not, some adjustments were made. Weather variables were added to the dataset in Excel, statistical analysis were conducted in IMB SPSS 27.

4 Results

4.1 Buffer Area Multiple Linear Regression Analysis

Firstly, I will compose three liner regression analysis to find the best buffer zone for environmental variables. The variables filled the requirements for linear regression. Environmental variables were available in 100-, 500- and 1000-meter buffer zones from participants' registered home addresses. As previously published literature does not indicate the most accurate distance from a household, these linear regression analyses will give us input on which buffer zone are best to use in further analysis. In addition to environmental variables, person-specific and weather variables are added to the analyses. All the analyses are performed on data gathered in the first data wave, the exception is personality data, which was collected in the third wave. All three models predict ESTQ-2 depression symptoms combined score collected in the first data wave. The results of linear regression analysis are presented in Table 1.

Table 1. Multiple linear regression analysis on environmental variables' buffer areas

Buffer zone	**100m**		**500m**		**1000m**	
Predictors	Standardized beta	P	Standardized beta	p	Standardized beta	p
Constant	na	0.80	na	0.77	na	0.75
Sex	-0.05	0.44	-0.05	0.44	-0.05	0.43
Marital status	0.00	0.99	0.00	0.99	-0.00	0.99
Educational status	-0.02	0.75	-0.02	0.75	-0.02	0.79
Income	0.01	0.85	0.01	0.86	0.02	0.82
Settlement type	0.04	0.64	0.05	0.54	0.08	0.39

Extraversion	-0.16	0.09	-0.15	0.09	-0.15	0.09
Neuroticism	**0.16**	**<0,05**	**0.16**	**<0,05**	**0.15**	**<0,05**
Openness to Experience	-0.01	0.90	-0.01	0.90	-0.01	0.91
Conscientiousness	-0.01	0.88	-0.01	0.88	-0.01	0.87
Agreeableness	0.04	0.62	0.04	0.63	0.04	0.63
Emotion regulation difficulties	**0.41**	**<0.001**	**0.40**	**<0.001**	**0.40**	**<0.001**
PTSD symptoms	**0.23**	**<0.005**	**0.23**	**<0.005**	**0.24**	**<0.005**
Perceived social support	0.11	0.10	0.11	0.10	0.11	0.10
Covid-19 stress	0.09	0.14	0.10	0.13	0.09	0.13
Sunshine duration	-0.00	0.97	-0.00	0.99	0.00	0.99
Air pressure	0.01	0.87	0.01	0.84	0.01	0.82
Precipitation	-0.02	0.74	-0.02	0.76	-0.02	0.78
Relative humidity	-0.02	0.74	-0.03	0.72	-0.03	0.70
Temperature	-0.01	0.90	-0.00	0.93	-0.00	0.96
Wind speed	0.05	0.47	0.05	0.49	0.04	0.51
Distance from sea	0.02	0.78	0.03	0.73	0.03	0.70
Distance from inland waterbody	0.04	0.68	0.04	0.67	0.04	0.61
Vegetation height	-0.02	0.87	-0.02	0.88	-0.04	0.79
Tree height	-0.01	0.94	0.02	0.89	0.04	0.77
Open areas	0.03	0.71	0.04	0.70	0.06	0.55
Lake area	0.02	0.81	-0.02	0.75	-0.02	0.95
Length of river	0.03	0.66	0.02	0.80	0.01	0.81

	R^2=0.52; p<0.001	R^2=0.52; p<0.001	R^2=0.52; p<0,001
Model statistics	F (27,112)= 6.55	F (27,122) = 6.55	F (27,122)= 7.41

Note. The dependent variable is the EST-Q2 depression symptoms combined score gathered in the first data wave.

All three linear regression models presented similar results, with minimal differences between predictive ability and statistically significant predictors. All models were statistically significant; none of the weather nor environmental variables were statistically significant predictors. Therefore, there is no clear indication of which buffer area to choose. This option is chosen because the 500-meter buffer area is the medium between 100- and 1000-meter buffer area.

4.3 Correlation Analysis

Secondly, correlation analysis was performed to see associations between different variables, and Pearson's R was used. Results are visible in Table 2 and Table 3 under appendix B and C, the list describing both tables is visible under appendix A. The strongest associations were between depression symptom scores measured in different data waves (*r=0.75-0.81*), between vegetation height and tree cover (*r=0.80*) and negatively between distance from inland waterbodies and sea (*r=-0.69*).

4.3.1 Person-specific variables

Person-specific variables had the highest correlations with depression symptom scores. Higher usage of maladaptive emotion regulation techniques aligns with higher depression symptoms (*r=0.56-0.67*). Higher neuroticism (*r=0.54-0.63*) and lower extraversion (*r=-0.42-0.50*) link with higher depression symptoms scores. More post-traumatic stress symptoms go together with more depression symptoms (*r=0.49-0.68*). The effects between more stress caused by Covid-19 and higher depression symptoms were medium (*r=0.27-0.37*). Similar results were present for low perceived social support and depression symptoms (*r=0.34-0.38*).

4.3.2 Environmental variables

In addition to the negative link between distance from inland waterbodies and distance from sea and the association between vegetation height and tree height, open areas link negatively with more intensely populated areas (*r=-0.62*). Similarly, more intensely populated areas have lower vegetation height (*r=-0.37*). Correlations between environmental variables and depression symptom scores were weak (*r=0.01-0.05*).

4.3.3 Weather variables

Weather variables showed weak correlations with person-specific and environmental variables (*r=0.00-0.10*), but somewhat higher correlations between each other. Relative humidity showed the highest correlations, especially with sunshine intensity and atmospheric pressure. Effects were stronger for May 2021 measurements. Correlations were lower for both winter measurements.

4.4 Data Waves Multiple Linear Regression Analysis

Thirdly, linear regression analysis was performed on person-specific, environmental, and weather variables. The dependent variable is the EST-Q2 depression symptoms score, which were gathered in three separate data waves. Linear regression requirements were fulfilled. Results are presented in Table 4. Models were named January 2021, May 2021 and January 2022, representing the period when most of the data was collected.

Table 4. Linear regression analysis on person-specific, environmental, and weather variables on data gathered in three different data waves.

Data wave	**January 2021**		**May 2021**		**January 2022**	
Predictors	Standardized beta	p	Standardized beta	p	Standardized beta	p
Constant	na	0.77	na	0.20	na	0.87
Sex	-0.05	0.44	-0.07	0.27	-0.05	0.44
Marital status	0.00	0.99	-0.05	0.38	-0.02	0.81
Educational status	-0.02	0.75	0.05	0.42	-0.01	0.91
Income	0.01	0.86	0.01	0.82	-0.00	0.99
Settlement type	0.05	0.54	0.08	0.32	0.05	0.60
Extraversion	-0.15	0.09	**-0.20**	**<0,05**	**-0.29**	**<0,05**
Neuroticism	**0.16**	**<0.05**	0.12	0.08	**0.35**	**<0.001**
Openness	-0.01	0.90	-0.01	0.92	0.03	0.71
Conscientiousness	-0.01	0.88	-0.02	0.80	-0.04	0.60
Agreeableness	0.04	0.63	0.04	0.57	0.06	0.45
Emotion regulation difficulties	**0.40**	**<0.001**	**0.21**	**<0.01**	**0.19**	**<0,05**
PTSD symptoms	**0.23**	**<0.005**	**0.53**	**<0.005**	**0.16**	**0.05**
Social support	0.11	0.10	0.04	0.59	0.11	0.23
Covid-19 stress	0.10	0.13	0.09	0.12	0.11	0.09
Total radiance	-0.00	0.99	-0.07	0.29	0.02	0.75
Air pressure	0.01	0.84	0.08	0.25	0.01	0.93
Precipitation	-0.02	0.76	0.03	0.56	0.02	0.77

Relative humidity	-0.03	0.72	0.09	0.24	0.02	0.85
Temperature	-0.00	0.93	0.06	0.43	-0.02	0.80
Wind speed	0.05	0.49	0.05	0.37	-0.01	0.77
Distance from sea	0.03	0.73	0.06	0.45	0.05	0.61
Distance from inland waterbodies	0.04	0.67	0.09	0.28	0.03	0.76
Vegetation height	-0.02	0.88	-0.16	0.23	-0.02	0.90
Tree height	0.02	0.89	0.13	0.28	0.02	0.90
Open areas	0.04	0.70	0.01	0.91	0.03	0.79
Lake area	-0.02	0.75	-0.04	0.47	0.03	0.71
Length of river	0.02	0.80	-0.02	0.69	0.00	0.99
	R^2=0.52; p<0.001		R^2=0.61; p<0.001		R^2=0.50; p<0,001	
Model statistics	F (27,112)= 6.55		F (27,112) = 9.03		F (27,112)= 6.13	

Note. The dependent variable is EST-Q2 depression symptoms score gathered in the first, second and third data waves.

Results of the linear regression analysis indicate that there is a significant collective effect between person-specific, environmental, and weather variables in all three models. Only extraversion, neuroticism, emotion regulation difficulties and post-traumatic stress symptoms could predict depression symptom scores. Other person-specific, environmental, and weather variables were non-significant in all three models. All models were able to predict more than 50% of depression symptoms score variance, May 2021 model had the highest predictive power ($R^2=0.61; p<0.001$).

The emotion regulation difficulties variable was the strongest predictor of depression symptom scores in January 2021 model, in May 2021 model, it ranked second and January 2022 model third. Post-traumatic stress symptoms score increases by 0.53 points with every one-point increase in depression symptoms score in May 2021 model. Post-traumatic stress symptoms variable was the strongest predictor in May 2021 model but had a weaker effect in both winter models. Neuroticism had a significant effect on depression symptoms score only in both

January models, in January 2022 model neuroticism was the strongest predictor. Higher extraversion predicted lower depression scores in May 2021 and January 2022 model but was insignificant in the January 2021 model.

5 Discussion

This master thesis aimed to combine person-specific, environmental, and weather variables to compare which have the highest effect on depression symptoms**.** Three research questions were raised.

The first research question emphasised on comparing person-specific, environmental, and weather variables to predict depression symptoms score. Person-specific variables clearly have the most substantial effect in all analyses, as none of the environmental nor weather variables were statistically significant in any of the multiple linear regression analyses. Also, correlations between depression symptoms, environmental and weather variables were weak. These results are rather surprising, as different environmental variables often link to higher well-being and lower depression symptoms, also links are sometimes visible between mood and weather variables (de Bell et al., 2020; Vries et al., 2016; White et al., 2023.; Yao et al., 2021). To the author's knowledge, none of the previously published studies incorporate person-specific, environmental, and weather variables to predict psychological well-being or depression symptoms. More often, studies emphasise only finding the effect of spending time in or living near a natural area on well-being, rather than comparing effects with other variables, which could also potentially affect the dependent variable. Results presented in this thesis indicate the need to start comparing effect sizes between different variables to find the most influential factors in lowering depression symptoms.

One potential reason for the environmental variables' non-significant effect on depression symptoms could arise from the way blue and green spaces were conceptualised. Distance from blue area, height of vegetation and tree cover and amount of open area in a 500-meter buffer zone could not be the best way to measure green and blue spaces' potential effect on depressive symptoms, as we do not know how much a participant spends time in that specific green or blue area. Even though, Pauso and colleagues' research shows that living nearer to a park (<300m) and visiting it for at least four hours per week during the Covid-19 lockdown resulted in lower odds for depression and anxiety symptoms (Pouso et al., 2021b). Still, in Pauso and colleagues' research, variables time spent in and the characteristics of the Covid-19 lockdown could influence these results, and the effect could not arise from green space distance from the participant's home. Another potential reason is no clear indication of the best buffer area. To the author's knowledge, there is no clear guidance on best practice in previously published research articles. This master thesis also conducted analysis on 100- and 1000-meter buffer areas on the January-February 2021 data and saw no apparent differences. Therefore, the results presented in this thesis should not depend on a chosen buffer area.

A potential explanation of environmental variables non-significant effects on depression symptoms could arise from the conceptualisation of mental health. Previous meta-analytic data argues that exposure to natural environments rather enhances positive affect than lowers negative affect (McMahan & Estes, 2015). Analysing the impact on depression symptoms rather than on positive affect or well-being could therefore lead to lower effect sizes (McMahan & Estes, 2015). Possibly, if well-being or positive affect were to be measured instead of depression symptoms, environmental variables could perhaps change to significant predictors. Even though effect sizes were relatively constant for person-specific variables, therefore environmental variables' effect would probably still stay weaker than for person-specific variables.

The second research question aimed to determine which weather variables predict depression symptoms. None of the weather variables significantly predicted depression symptoms in multiple linear regression analysis. Correlations between depression symptoms and weather variables in different data waves were mostly insignificant or weak. This somewhat aligns with previous research, as relationships between weather variables and mood or mental health factors are often weak or non-existent and might differ between locations (Huibers et al., 2010; Kööts et al., 2011; O'Hare et al., 2016; Yang et al., 2015). Previous research published on Estonian data linked temperature and less relative humidity to negative affect and greater amounts of sunlight to positive affect, but again, the effects were weak (Kööts et al., 2011). These master thesis results raise the possibility that published effects might be overpowered. Previous research suggests using as time- and location-specific measurements as possible, which is fulfilled in this research (Yang et al., 2015).

Another possible reason for insignificant results might lie in missing extreme results. More intense weather conditions could induce higher mood effects. For example, Peng et al (2017) paper stating that the increase of hospital admissions for mental health disorders rising from 24.6 degrees Celsius and Hsiang et al. (2013) article showing a higher amount of violence occurring with higher temperatures. As all three data waves mostly lacked extreme weather conditions, this could also partially account for the insignificant results.

Person-specific variables out-predicted environmental and weather variables, but not all were significant. Emotion regulation difficulties, PTSD symptoms, extraversion and neuroticism predicted depression symptom scores at least in some of the data waves, but perceived social support, Covid-19 stress, openness to experience, agreeableness and conscientiousness presented insignificant associations. To add, sex, income, marital status, and education also lacked importance on depression symptoms. This conflicts with previous knowledge on perceived social support, Covid-19 stress and descriptive features (Faisal et al., 2022; Golden et al., 2009; Holvast et al., 2015; Wang et al., 2018a). Higher perceived social support consistently links with lower depression symptoms, with effects ranging from weak to medium (Chao, 2011; Wang et al., 2018b). Thus, these results are rather intriguing. One possible explanation could emerge from the methodology, as social support was only measured with one question and only included support from friends. If other social relations had been included, then analysis could have led to different results. Another answer might arise from effect sizes, as possibly, other person-specific significant variables could just have more substantial effects than perceived social support. Higher stress due to Covid-19 has also previously aligned with higher anxiety and depressive symptoms (Faisal et al., 2022; Kar et al., 2021). As Covid-19 stress was added to the analysis to control if there were differences between data waves due to higher Covid-19 restrictions during January-February 2021 than during other data waves and, therefore possibly impacting stress levels, we could conclude that stress due to Covid-19 restrictions did not affect the amount of depression symptoms. As Covid-19 stress has presented higher effects with anxiety, if the dependent variable included other anxiety scales in addition to PTSD Checklist, the results could possibly be different (Varma et al., 2021). But again, the effect could still be weaker than other person-specific variables. Interestingly, none of the descriptive variables showed significant relationships with depressive symptoms. Published research has established that females, divorced, those suffering from financial difficulties and people with less education more often suffer from depression (Kessler & Bromet, 2013a, 2013b). This could come from other person-specific factors adding significantly more value to the models.

Personality domains openness to Experience, agreeableness and conscientiousness did not display any ability to predict depression symptoms. Results on openness to experience and agreeableness align with published articles, as mostly no relationship is present (Hakulinen et al., 2015; Hyde et al., 2016). Results collide on conscientiousness, which usually is lower among people suffering from depression (Hakulinen et al., 2015). Even though, there the effect is still lower than for Neuroticism (Hakulinen et al., 2015). Conscientiousness describes the ability to follow order and has high self-discipline, also being fond of traditions. As a person suffering from depression could have difficulties maintaining self-discipline and being responsible, it is unsurprising that they could have lower conscientiousness during the active phase of illness. But it might not be the other way around, as people already low in Conscientiousness could not exhibit signs of depression. Due to that, the results of this master's thesis might not holly go against previous research on depression symptoms and personality domains.

The third research question compared differences between data waves. January 2021 data wave model showed that more emotion regulation difficulties, PTSD symptoms and higher neuroticism lead to more depression symptoms. Emotion regulation difficulties variable had the highest predictive power. May 2021 model highlighted the importance of more PTSD symptoms, more emotion regulation difficulties and lower extraversion as depression symptoms predictors, respectively ranking in effect size. January 2022 model marked all the previously mentioned four as significant predictors. Higher neuroticism leads the list according to predictive power, followed by low extraversion, emotion regulation difficulties and PTSD symptoms. May 2022 model showed the highest predictive power, explaining more than 60% of the variance of depression symptoms. January 2021 and 2022 models also had high predictive power. These results follow the footsteps of published articles, as PTSD symptoms, low extraversion, high neuroticism and more emotion regulation difficulties all lead to more depressive symptoms (Hakulinen et al., 2015; Hyde et al., 2016; Rytwinski et al., 2013; Visted et al., 2018). Higher neuroticism can be described as a tendency to experience more negative feelings, anxiety, anger and self-doubt and the domain has been linked with depression in metanalytic findings (Hakulinen et al., 2015; Hyde et al., 2016). As one is more susceptive towards negative feelings, it might more often lead to more depressive symptoms. Possible solutions to lower the effect of neuroticism to make a person more susceptible to depression might arise from cognitive behaviour therapy, emotion regulation techniques like mindfulness and reappraisal, and if possible, lowering the amount of experienced stress (Visted et al., 2018). Higher extraversion can be seen as a protective factor from depression (Hakulinen et al., 2015; Hyde et al., 2016). Extraversion can be viewed as seeking positive emotions and excitement, higher activity, sociability and warmth towards others, and being more assertive. These personality facets might lead to more positive emotions, hence lowering the risk for depression symptoms. Emotion regulation difficulties also often align with depression (Joormann & Stanton, 2016; Visted et al., 2018). Applying avoidance of situation or emotion, rumination and suppression more likely leads to negative emotions, therefore raising the risk for depression symptoms or contributes to the preservation of symptoms (Everaert & Joormann, 2020).

Adopting more effective emotion regulation strategies such as mindfulness, reappraisal and attention refocusing might lead to fewer depression symptoms (Visted et al., 2018).

Intriguingly, all models differed in strongest predictors. Emotion regulation difficulties listed first in January 2021 model and neuroticism in January 2022 model could be explained with methodological decisions, as personality domains were measured in the third and emotion regulation difficulties in the first wave. PTSD symptoms in the May 2021 model outrank all predictors from other models, and the model has the highest predictive value. Meta-analytic evidence suggests that 52% of people suffering from PTSD also experience depression symptoms, which is in accordance with this master thesis results (Felitti et al., 1998). These results emphasise the importance of also assessing PTSD symptoms while collecting information about depression symptoms. To add, May 2021 model aligns with Solt and colleagues' research (1996), which shows PTSD patients' admission to hospital peaking in May. A possible explanation might rise from higher suicidality during May but could only partially be explained by that. Another explanation for this thesis results might also be influenced by Covid-19, which might have been more difficult for people who have PTSD (B. van der Kolk, 2022). As PTSD symptoms might emerge one up to six months after the traumatic event, if Covid-19 second distancing had a negative or traumatic or retraumatizing effect, this might be more visible only in May 2021 data rather than in January 2021 data. This could also be amplified by anniversaries of trauma, but this is a rather personal variable and might influence only some participants.

This master thesis amplifies the importance of comparing effect sizes, as person-specific variables clearly out-predicted environmental and weather variables. These results clearly suggest focusing on person-specific variables rather than changing home address nearer to a blue area or to an area with higher vegetation cover or tree height to lower depression symptoms. Focusing on person-specific variables depends on participant and their needs, but for example, could be learning healthier emotion regulation techniques or lowering PTSD symptoms by attending cognitive behaviour therapy or other research-based therapies. But completely dismissing green or blue areas and weather variables' effect on mental health or well-being would be a wrong way to interpret these results, as previous research has replicated the effect and presented meta-analytic evidence (Yao et al., 2021). The effects need to be compared with other variables to make more accurate claims. Future research should collect data and conduct analysis in less green and blue area intense locations to see if results are also replicable in different environmental surroundings.

5.1 Strengths

This thesis fills the gap of, to author's knowledge, previously non-existent research on combining person-specific, environmental, and weather variables to predict depression symptoms to find the most influential variables. Also, average wind speed was added to the analysis, which has not been done on Estonian data and is rarely included in other research papers. This research was based on three data waves, which enabled to compare effect sizes on three different occasions and build three models, not only representing cross-sectional results. Another strength is the sample size, which allows to draw firmer conclusions.

5.2 Limitations

One limitation of this research emerges from the Estonian landscape, which is filled with many green and blue spaces in comparison with some other European countries. This might interfere with presented results, as research in areas with less green and blue spaces might lead to different conclusions. Depression and PTSD symptoms were self-reported, therefore, the results might be somewhat different than what acquaintances or medical personnel would report. There is no good solution to the problem, but both used questionnaires are validated and often used in research articles. Also, both depression and PTSD questionnaire assessed risk to develop disorders but are not diagnostic interviews. Therefore, claims can be made only based on symptoms, but not on diagnosed illnesses.

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6. Conclusions

This master thesis aimed to combine person-specific, environmental, and weather variables to compare, which of the three have the highest effect on depression symptoms. Three research questions were raised, which hoped to find out, what weather variables predicted depression symptoms, if the three data waves differed from each other and if person-specific, environmental, or weather variables were the strongest predictors of depression symptoms. Five linear regression analysis and correlation analysis were performed to answer research questions. The first three linear regression analysis helped to find the best buffer area for environmental variables, which was at 500 meters, even though differences were minimal between models. Correlation analysis showed associations between variables, environmental and weather variables had weak or non-significant links with depression symptoms. Almost all person-specific variables had at least weak associations with depression symptoms, except for some descriptive variables. Linear regression analysis between three data waves mainly collected in January 2021, May 2021 and January 2022 resulted in person-specific variables out-predicting environmental and weather variables, none of the environmental or weather variables showed statistically significant results. Not all person-specific variables had effects on depression symptoms. Covid-19 stress, perceived social support, openness to experience, agreeableness, conscientiousness, and descriptive variables failed to influence depression symptoms. Higher neuroticism, lower extraversion, more emotion regulation difficulties, and higher post-traumatic stress symptoms predicted higher depression symptoms score in at least some of the data waves. January 2021, May 2021, and January 2022 models revealed differences between data waves. According to January 2021 model respectively more emotion regulation difficulties, higher post-traumatic stress symptoms and higher neuroticism predicted more depression symptoms. May 2021 model emphasised the importance of more post-traumatic stress symptoms, more emotion regulation difficulties and low extraversion as variables leading to more depression symptoms, ranked in accordance with predictive power. January 2022 model listed high neuroticism, low extraversion, more emotion regulation difficulties, and more post-traumatic stress symptoms, in the order or effect size, predicting depression symptoms. All models had rather high ability to explain the variance of depression symptoms, ranging from 50-61%. Differences between leading predictors might have been caused by methodological choices in January 2021 and 2022 models, as variables measured during the same data wave were the strongest predictors there. May 2021 model differed from other models, as it had the highest predictive ability, but also showed the importance of post-traumatic stress symptoms measured in the first data wave. This could possibly be caused by long-term impact from Covid-19 restrictions as post-traumatic stress symptoms might appear one to six months after the distressing event, but also previously published articles show the height of post-traumatic stress disorder admissions to hospitals in May. The overall results of this master thesis suggest focusing on person-specific variables rather than changing home address nearer to a blue area or to an area with higher vegetation cover or tree height to effect depression symptoms. Future research should see if these master thesis results are replicable in less green and blue area intense areas.

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8 Appendixes

8.1 Appendix A. List of variables presented in Tabel 2 and Tabel 3 under appendix B and appendix C.

1. EST-Q2-DEP in the First Data Wave
2. EST-Q2-DEP in the Second Data Wave
3. EST-Q2-DEP in the Third Data Wave
4. Sex
5. Family Status
6. Education
7. Income
8. Type of settlement
9. Extraversion
10. Neuroticism
11. Openness to Experience
12. Conscientiousness
13. Agreeableness
14. Emotion regulation difficulties
15. PTSD Symptoms
16. Perceived social support
17. Covid-19 stress in the first data wave
18. Covid-19 stress in the second data wave
19. Covid-19 stress in the third data wave
20. Total sun radiation in the first data wave
21. Atmospheric pressure in the first data wave
22. Precipitation in the first data wave
23. Relative humidity in the first data wave
24. Temperature in the first data wave
25. Wind speed in the first data wave
26. Total sun radiation in the second data wave
27. Atmospheric pressure in the second data wave

28. Precipitation in the second data wave
29. Relative humidity in the second data wave
30. Temperature in the second data wave
31. Wind speed in the second data wave
32. Total sun radiation in the third data wave
33. Atmospheric pressure in the third data wave
34. Precipitation in the third data wave
35. Relative humidity in the third data wave
36. Temperature in the third data wave
37. Wind speed in the third data wave
38. Vegetation height in 500-meter buffer zone
39. Tree cover in 500-meter buffer zone
40. Open areas in 500-meter buffer zone
41. Area of lake in 500-meter buffer zone
42. Length of river in 500-meter buffer zone
43. Distance from sea
44. Distance from inland waterbody

8.2. Appendix B. Tabel 2. Correlation analysis of person-specific, environmental, and weather variables, Pearson R. First Part

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	-																						
2	.81**	-																					
3	.75**	.78**	-																				
4	.07**	.09**	.08**	-																			
5	-.02	-.03	-.01	.23**	-																		
6	-.13**	-.09**	-.13**	.06**	-.12**	-																	
7	-.15**	-.13**	-.16**	-.11**	-.17**	.44**	-																
8	.05*	.05*	.05	.07**	.00	.04	.02	-															
9	-.42**	-.42**	-.50**	-.02	-.08**	.13**	.21**	-.05*	-														
10	.55**	.56**	.63**	.22**	-.02	-.10**	-.14**	.04	-.32**	-													
11	-.31**	-.30**	-.32**	.03	.00	.24**	-.17**	-.02	.63**	-.23**	-												
12	-.29**	-.29**	-.33**	.08**	-.05*	.13**	.20**	-.01	.58**	-.18**	.55**	-											
13	-.24**	-.23**	-.25**	.14**	.03	.14**	.09**	-.02	-.58**	-.- .15**	.59**	.48**	-										
14	.67**	.59**	.56**	.09**	-.05*	-.09**	-.14**	.05*	-.33**	.49**	-.26**	-.26**	-.21**	-									

15	.53**	.68**	.49**	.20**	.06	-.13*	-.20**	-.01	-.18**	.49**	-.15*	-.15**	-.10	.40**	-								
16	.38**	.34**	.34**	-.10**	-.05*	-.01	.00	.03	-.35**	.21**	-.25**	-.24**	-.32**	-.28**	.24**	-							
17	.31**	.28**	.25**	.09**	-.02	-.03	-.01	.05*	-.10**	.20**	-.07**	-.05*	-.04	.25**	.25**	.14**	-						
18	.28**	.32**	.27**	.09**	-.01	-.04*	-.04	.03	-.13**	.19**	-.08**	-.06**	-.06*	.26**	.24**	.13**	.37**	-					
19	.25**	.28**	.32**	.05*	-.01	-.06**	-.06**	-.00	-.13**	.21**	-.09**	-.10**	-.09**	.25**	.33**	.06**	.34**	.38**	-				
20	-.00	.00	.02	.03	.06*	-.02	-.07*	-.03	.02	.01	.02	.01	.00	.02	-.05	.00	-.00	-.00	-.03	-			
21	.02	.00	-.03	-.05	-.04	.01**	.08**	-.06	.00	-.05	.05	.01	-.01	.01	.05	.00	-.01	-.00	-.02	-.05	-		
22	-.00	.03	.05	.02	.01	.01	-.02	.00	-.07*	.01	-.05	-.04	-.01	.03	.01	.02	.04	.07*	.05	-.02	-.23**	-	
23	-.05	-.04	-.03	.02	.02	-.00	.01	-.00	-.01	-.03	.00	-.01	.03	-.03	.05	-.02	-.03	-.00	-.01	-.25**	--.14**	.23**	-
24	-.05	-.06	-.04	-.04	.04	.09**	.06	-.08*	-.00	-.04	.03	.01	.02	-.02	-.06	-.05	-.04	-.04	-.02	-.13**	-.03	.12**	.27**
25	.01	.01	.02	.02	.02	.01	-.01	-.04	.01	.01	-.04	-.02	-.01	.00	-.11	-.05	-.00	.03	.03	.02	-.13**	.03	-.21**
26	-.06*	-.07*	-.10**	.04	-.02	.10**	.05	-.07*	.10**	-.08**	.11**	.05	.07*	-.06	.07	-.09**	-.00	-.00	-.01	.09**	.07*	-.03	-.07*
27	.01	.04	.03	-.03	-.05	-.01	.02	-.06	--.01	.01	.03	-.04	.01	-.02	-.05	-.01	.03	.02	.02	.02	.10**	.00	-.09**
28	.06*	.06*	.06*	.02	.00	.03	..01	.02	-.07**	.04	-.10**	-.06*	-.07*	.06*	-.01	.08**	-.02	-.00	.00	-.02	.01	-.00	-.01
29	.07*	.05	.04	-.02	.06*	-.04	-.01	.06	-.06*	.02	-.06*	-.04	-.04	.08**	-.04	.07*	.01	-.01	.01	-.05	-.02	.,04	-.00
30	-.01	.01	.02	.03	-.06*	-.03	-.00	.01	.02	.02	.01	-.01	.02	-.02	-.06	-.02	.01	.03	.02	.06*	-.09**	-.01	-.04
31	-.03	-.02	-.05	.07*	-.01	.06*	.01	-.07*	.08**	-.01	.02	.07**	.04	-.04	-.03	-.06*	.00	.06*	-.01	.05	.05	-.04	-.03

32	-.04	-.03	-.00	-01	.02	.05	.06*	-.01	.04	-.02	07*	.02	.01	-.01	.02	-.04	-.01	-.03	.01	09**	-.08**	-.01	-.03
33	-.04	-.03	-.03	-.08**	-.03	.04	.06*	.01	.01	-.08**	-.01	-.04	-.06	-.04	-.01	-.00	-.03	.01	-.01	,01	.09**	.08**	-.05
34	-.03	-.01	.01	-.00	-.02	-.02	-.01	.03	-.00	.02	-.02	-.04	.03	-.01	-.09	.00	-.01	.01	-.02	00	-.02	.01	.02
35	.02	.03	.03	-.02	-.01	.01	-.01	.03	-.07*	.04	-.04	.01	-.04	.00	-.10	.06*	.01	.00	.02	-.05	11**	.00	.03
36	.01	.00	.01	.01	-.03	.00	.00	-.04	-.01	.04	.04	.01	.05	.00	.02	-.02	.06*	.00	.02	.02	.10**	.00	-.04
37	.01	.01	.02	.07*	.01	.00	.02	-.06	.01	.02	-.01	-.02	.02	.01	.02	-.03	.01	.07*	.02	.05	-.02	-.01	-.01
38	-.02	-.02	-.02	-.04	-.00	.08**	.08**	-.07**	.01	-.03	.02	-.02	.02	-.02	.06	.02	-.01	-.04	.00	.01	.05	.02	.04
39	-.05*	-.05*	-.04	-.09**	-.00	.01	.04	-.35**	.02	-.05*	.01	-.00	.01	-.04*	-.03	-.02	-.05*	-.07**	-.00	.00	.00	-.00	.05
40	-.03	-.04	-.03	-.07**	.00	-.11**	-.07**	-.62**	.05*	-.05*	.01	-.05*	.02	-.03	-.07	-.06*	-.03	-.01	.02	-.00	-.04	-0.04	.02
41	.03	.03	.02	-.02	.02	-.01	-.06*	.10**	-.04	.00	-.00	-.04*	.00	.02	.10	04*	.03	-,01	-.02	.01	.04	-.02	-.05
42	.04	-.01	.02	-.04	-.01	-.02	-.00	-.10**	-.04	.00	-.01	-.03	-.04	.03	.02	.03	.01	,00	-.01	.01	.02	-.00	-.01
43	.03	.02	.04	-.02	-.03	.02	-.04	-.20**	-.01	.01	-.00	.01	.02	.01	.08	-.01	.00	-,00	.02	.02	.00	-.01	-.03
44	-.03	-.02	-.05*	.03	.00	-.01	.06**	.01	.03	-.03	.01	-.01	.01	-.02	-.11	-.04	-.01	,00	-.01	-.03	.02	-.02	.07*

8.3 Appendix C. Tabel 3. Correlation analysis of person-specific, environmental, and weather variables, Pearson R. Second Part

	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43
25	-																			
26	.19**	-																		
27	.05	.01	-																	
28	.01	.11**	.09**	-																
29	-.05	-.04	-.09**	-.17**	-															
30	-.01	.07*	-.48**	-.47**	-.24**	-														
31	-.09**	-.02	.25**	.63**	-.12**	-.58**	-													
32	.06*	.20**	.40**	.11**	-.05	-.27**	.15**	-												
33	.01	-.00	.08**	.01	-.01	-.01	.04	.01	-											

34	.04	.09**	.00	.22**	-.04	.02	.06*	.01	.19**	-										
	-.04	-.03	-.06	-.03	.03	.03	-.03	-.04	-.06*	-.19**	-									
35	-.01	-.07*	.01	-.07*	.02	-.01	-.09**	-.02	-,.30**	-.27**	.20**	-								
36	.05	.01	.05	.05	-.01	-.02	-.01	.03	-.01	-35**	.05	-.07*	-							
37	.03	.22**	-.02	.10**	-.01	.04	.04	.16**	.08**	-.01	-.00	-.53**	.30**	-						
38	.04	-.03	-0,03	.05	.03	.01	.02	-.00	.00	.08**	-.03	-.00	-.01	.01	-					
39	.03	.01	.01	.01	-.01	-.01	.01	.03	.00	.04	.00	.02	-.00	.03	.80**	-				
40	.01	.03	.06*	-.01	-.05	-.06*	-.00	.06	.03	-.02	.02	.01	-.02	-.00	-.37**	.05*	-			
41	-.01	.03	.02	.02	-.00	.02	-.01	-.06	.01	-.02	.05	.03	.01	-.03	-.03	-.07**	-.12**	-		
42	-.01	-.00	-.02	.01	-.00	.00	-.02	-.01	-.01	-.03	-.00	.03	.01	-.05	.05*	.03	.08**	-.06**	-	
43	-.01	-.05	.05	.02	.01	-.06*	.02	-.04	-.00	.01	.00	-.01	.01	-.02	-.03	-.01	.20**	.14**	.08**	-
44	.02	.09**	-.03	.02	-.01	.04	-.02	.07*	-.02	.01	-.02	.02	.04	.08**	.10**	.13**	-.13**	-.05*	-.08**	-.69**

8.4 Appendix D. Lihtlitsents lõputöö salvestamiseks ja üldsusele kättesaadavaks tegemiseks ning juhendaja(te) kinnitus lõputöö kaitsmisele lubamise kohta

Mina, Katarina Kliit, sünniaeg 24.11.1996.,

1. annan Eesti Maaülikoolile tasuta loa (lihtlitsentsi) enda koostatud lõputöö Inimesekohased muutujad ennustavad depressiooni sümptomeid keskkonna- ja ilmamuutujatest edukamalt,

mille juhendaja(d) on Kadri Leetmaa ja Kairi Kreegipuu,

1.1. salvestamiseks säilitamise eesmärgil,
1.2. digiarhiivi DSpace lisamiseks ja
1.3. veebikeskkonnas üldsusele kättesaadavaks tegemiseks kuni autoriõiguse kehtivuse tähtaja lõppemiseni;

2. olen teadlik, et punktis 1 nimetatud õigused jäävad alles ka autorile;

3. kinnitan, et lihtlitsentsi andmisega ei rikuta teiste isikute intellektuaalomandi ega isikuandmete kaitse seadusest tulenevaid õigusi.

Lõputöö autor Katarina Kliit
Tartu, 24.05.2023

Juhendaja(te) kinnitus lõputöö kaitsmisele lubamise kohta

Luban lõputöö kaitsmisele.

Kadri Leetmaa /digitaalne allkiri/

Kairi Kreegipuu /digitaalne allkiri/

24.05.2023