Climate Anxiety among Middle-Aged and Older City Dwellers: Multi-City Quantification and Stratification by Demographic, Socioeconomic, and Contextual Factors

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Abstract

Studies in climate psychology have quantified climate anxiety, but none of them has focused on older adults. Research has explored demographic and socioeconomic predictors of climate anxiety; nonetheless, no study has considered environmental or contextual factors that may explain climate anxiety in older adults. This study, therefore, quantified climate anxiety, stratified it by demographic, socioeconomic, and contextual factors, and explored its predictors. A cross-sectional design with sensitivity analyses was employed, and data were collected from 3994 older residents of seven Ghanaian cities: Accra, Kumasi, Cape Coast, Tamale, Ho, Koforidua, and Wa. Climate anxiety was quantified using the Climate Anxiety Scale (CAS) and stratified using the Analysis of Variance, Analysis of Covariance, and *t*-test. Multiple linear regression was utilised to assess demographic predictors of climate anxiety. Climate anxiety was higher than previous levels found in the general population with the CAS and differed between cities. The highest climate anxiety was in Tamale and the Savanna. Predictors of climate anxiety include climate change awareness, not having a chronic disease, older age, climate change awareness, and full-time work. Climate anxiety differed between demographic, socioeconomic, and environmental categorisations. Research investigating whether climate anxiety changes with time is needed.

Keywords: Climate anxiety, older adults, demographic factors, socioeconomic factors, environment, Ghana

1. Introduction

Research in climate psychology has recently gained momentum in its quantification of climate anxiety. Climate anxiety is people's heightened emotional, somatic, or mental distress in response to life-threatening alterations in climatic conditions (Whitmarsh et al., 2022a). It refers to a chronic fear of environmental or ecological destruction and is a type of eco-anxiety (Ogunbode et al., 2022). Eco-anxiety is the individual's sense that the ecological basis of life is about to collapse (Hajek & Konig, 2022). This view underscores the lethality of negative emotions about climate change and corroborates evidence on the inverse relationship between climate anxiety and health. A survey has found that climate anxiety is negatively associated with mental health in 31 out of 32 countries (Ogunbode et al., 2022). A meta-analysis found a negative association between climate anxiety and mental well-being (Gago et al., 2024), and researchers agree that climate anxiety is associated with poorer physical health (Clayton, 2020; Gago et al., 2024; Hajek & Konig, 2022; Ogunbode et al., 2022).

Complementing the above evidence are results from research aimed at quantifying climate anxiety. Quantification is about estimating climate anxiety levels in a population (Hajek & Konig, 2022; Ogunbode et al., 2022), and this procedure has been performed with samples from Germany (Hajek & Konig, 2022), the United Kingdom (Whitmarsh et al., 2022a), and 32 other countries (Ogunbode et al., 2022), including four African countries (i.e., Egypt, Nigeria, Tanzania, and Uganda). Research quantifying climate anxiety has been based on the general population or younger people (Hajek & Konig, 2022), and no study has quantified climate anxiety in only older adults.

Older adults are generally people aged 60 years or over (Borelli et al., 2018), but the minimum old age differs across countries. The minimum old ages in the United Kingdom and Ghana are 65 and 60, respectively (Borelli et al., 2018; Hillsdon et al., 2005; Kpessa-Whyte, 2018). In this study, 50 is chosen as the minimum old age based on the concept of “early old age” (Grundy & Holt, 2000). Early old age refers to a middle age less than 60, at which a person experiences biological, social, emotional, or physiological problems associated with ageing (Grundy & Holt, 2000; Hillsdon et al., 2005). Our definition of old age allows for the determination of a more inclusive sample of people experiencing ageing.

Older adults are among the most vulnerable to climate change events (Jones & Mays, 2016) and live with unique physiological limitations and health problems (Borelli et al., 2018; Kpessa-Whyte, 2018) that may explain climate anxiety differently. The Strengths and Vulnerabilities Integration (SAVI) model (Charles, 2010) and the Socioemotional Selectivity Theory (SST) (Carstensen, 2006; Laura L Carstensen & Barbara L Fredrickson, 1998) offer opposite views on the relationship between negative emotions (e.g., climate anxiety) and age. The SAVI implies that climate anxiety is higher in older age, but the SST upholds the opposite of this relationship. As explained later, these opposing views are supported by mixed results from studies based on children, the general population, and adolescents. Thus, no previous study focused on middle-aged or older adults. Quantifying climate anxiety in only older adults may offer unique evidence for practice and theory development, especially in an African context where welfare support for older adults is inadequate (Kpessa-Whyte, 2018).

The literature shows stark inconsistency in climate anxiety within and across countries. Ogunbode et al. (2022) observed varied climate anxiety levels across 32 countries. Based on the same scale and population, two studies in Germany estimated different climate anxiety levels (Hajek & Konig, 2022; Wullenkord et al., 2021). This evidence suggests climate anxiety varies between subgroups and cities in a country, but no study has quantified climate change across multiple cities of a country. Quantifying climate anxiety by city can identify areas where mental health is more likely to decline, informing mental healthcare planning. Most previous studies (Cameron & Kagee, 2025; Hajek & Konig, 2022; Swahn et al., 2025; Whitmarsh et al., 2022b) focused on urban populations in quantifying climate anxiety, but the only previous studies carried out in Ghana (Abunyewah et al., 2023a; Boafo & Yeboah, 2025) utilised data from rural communities. To complement the evidence, this study focused on urban or semi-urban communities, which are experiencing higher climate change worry and more urgently need evidence for policy interventions (Tenbrink & Willcock, 2023).

Studies (Asgarizadeh et al., 2023a; Hajek & Konig, 2022; Whitmarsh et al., 2022a, 2022b) have also recently explored potential demographic and socioeconomic predictors or correlates of climate anxiety. Assessing these predictors complements the quantification of climate anxiety to unfold subgroups experiencing higher climate anxiety (Hajek & Konig, 2022). Yet, research exploring these predictors has not considered contextual or environmental factors. Some contexts (e.g., coastal cities and the Savanna) experience more extreme climate change events than others (Chen et al., 2023; Yankson et al., 2017), and negative emotions such as climate anxiety can be stronger in such environments (Nestor Asiamah, Mohammad Javad Koohsari, et al., 2023). For this reason, climate anxiety may vary between contexts. This study, therefore, quantified climate anxiety, stratified its level by demographic, socioeconomic, and contextual factors, and explored its predictors in older city dwellers in Ghana.

"Older city dwellers" in this study refer to city residents aged 50 years or older. This group is frequently referred to as older adults in this study for reasons explained later. The focus of this study was on cities because, compared to rural areas, cities experience a more significant impact from climate change events such as heatwaves (Gough et al., 2019; Hallegatte & Corfee-Morlot, 2010) and are in a higher need of evidence-based interventions against climate change (Gough et al., 2019; Hallegatte & Corfee-Morlot, 2010). Ghanaian cities are in low- and middle-income settings where climate change has the worst impact (Barry et al., 2018; Nangombe et al., 2019). This study would provide evidence for healthcare planning in Ghana, where the population is rapidly ageing (Kpessa-Whyte, 2018) and experiencing worsening climate change events (Abunyewah et al., 2023b; Armah et al., 2010). The study seeks to identify subgroups of older city residents needing higher social and healthcare support due to severe climate anxiety. To this end, the proportions of individuals experiencing mild, moderate, and severe climate anxiety are estimated following previous research (Whitmarsh et al., 2022b).

1.1. Quantifying Climate Anxiety

Studies that have quantified climate anxiety (Hajek & Konig, 2022; Ogunbode et al., 2022; Whitmarsh et al., 2022a) were published after 2020, suggesting that research in this field is relatively new. Climate anxiety quantification, subsequently called stratification analysis, uncovers implications for public health planning by spotlighting segments of the population most vulnerable to climate crises (Hajek & Konig, 2022). This viewpoint endorses previous stratification analysis in which researchers (Hajek & Konig, 2022; Whitmarsh et al., 2022a) estimated the average climate anxiety level in a population and stratified it by demographic and socioeconomic factors such as age, gender, income, and work status.

Most studies have quantified climate anxiety with the Climate Anxiety Scale (CAS) (Hajek & Konig, 2022; Wullenkord et al., 2021), a 13-item Likert-type tool with seven descriptive anchors [ranging from *strongly disagree (1)* to *strongly agree (7)*]. Some researchers (Whitmarsh et al., 2022a) used five instead of seven anchors on this tool, although scales with more anchors produce better psychometric properties (Lozano et al., 2008; Weijters et al., 2010). Other scales (e.g., the seven-item State-Trait Anxiety Inventory) have been acknowledged (Ogunbode et al., 2022), but the CAS is the most widely used tool. Most studies (Hajek & Konig, 2022; Ogunbode et al., 2022; Whitmarsh et al., 2022a) quantified climate anxiety by averaging the 13 items of CAS and computing the average and Standard Deviation (SD) of the resulting variable. This approach is the *items averaging method*. Only one study (Abunyewah et al., 2023b) utilised a different method (i.e., *the items summation method*) by adding the 13 items into a composite variable. The highest levels of climate anxiety based on the seven- and five-point CAS and the *items averaging method* are 7 and 5, respectively, and the highest level based on the seven-point CAS and the *items summation method* is 91. Higher scores on these scales indicate higher climate anxiety (Abunyewah et al., 2023b; Hajek & Konig, 2022).

Based on the items averaging method and CAS, Hajek and König (2022) found a climate anxiety level of 2 (Mean = 2.1; SD = 1.2) with a German sample. Another study utilising the same method and scale in Germany (Wullenkord et al., 2021) reported an average of 1.8 (Mean = 1.81; SD = 0.81). The level of climate anxiety estimated with the five-point CAS and the items averaging method for the UK was 1.2 (Mean = 1.25; SD = 0.46). On a seven-item scale, the items averaging method yielded an average score of 3.2 based on data from 32 countries (Mean = 3.21; SD = 0.82) (Ogunbode et al., 2022). Among the 32 countries, Brazil produced the highest climate anxiety (Mean = 3.76; SD = 0.96), and Uganda had the highest climate anxiety among four African countries (Mean = 3.18; SD = 0.87). Only one study (Abunyewah et al., 2023b) estimated the climate anxiety level in Ghana with the CAS and items summation method (Mean = 39.41; SD = 4.2). Inconsistent measurement in the literature makes most of the estimates incomparable.

A more advanced quantification stage is stratifying climate anxiety between groups in a population. Researchers stratified climate anxiety by estimating averages for groups of categorical variables to visualize potential differences in the groups (Hajek & Konig, 2022; Whitmarsh et al., 2022a). Hajek and König performed this procedure and found that younger people, full-time workers, individuals without a chronic disease, and migrants reported higher climate anxiety. In another study in the UK, stratification revealed higher climate anxiety for younger people and those concerned about climate change (Whitmarsh et al., 2022a). However, stratification across subgroups does not control for potential covariates, so this has been complemented with multiple regression analysis, in which confounding could be checked (Abunyewah et al., 2023b; Asgarizadeh et al., 2023a, 2023b; Hajek & Konig, 2022; Whitmarsh et al., 2022a). Thus, the exploration of correlates of climate anxiety with multiple regression analysis or related methods adds value to a stratification analysis.

1.2. Predictors of Climate Anxiety

Studies utilising data from the general population have considered two categories of variables (i.e., demographic and socioeconomic variables) as potential correlates of climate anxiety. Demographic variables considered are age, gender, educational level, and marital status. In studies conducted in Germany and the UK (Hajek & Konig, 2022; Whitmarsh et al., 2022a), age was negatively associated with climate anxiety, suggesting that climate anxiety is higher among younger people. Another study in Germany did not confirm the association of climate anxiety with age and educational level (Wullenkord et al., 2021). No association between climate anxiety and gender was found in Germany and the UK (Hajek & Konig, 2022; Whitmarsh et al., 2022a), but Wullenkord and colleagues confirmed gender as a correlate of climate anxiety in Germany (i.e., climate anxiety was higher in women, compared with men). Hajek and König found no association between marital status and climate anxiety.

Income, employment status, whether one lived with children or dependants, climate change knowledge, pro-environmental behaviours (e.g., visits to green places), fear of war, vaccination against coronavirus, coronavirus anxiety, generalised anxiety, and migration status are the socioeconomic predictors considered (Asgarizadeh et al., 2023a, 2023b; Hajek & Konig, 2022; Whitmarsh et al., 2022a; Wullenkord et al., 2021). Climate anxiety was higher among those with full-time employment (compared with retired individuals), individuals vaccinated against coronavirus, individuals with a higher level of coronavirus anxiety, and individuals with a greater fear of war (Hajek & Konig, 2022). Concern for the environment, pro-environmental behaviour, climate change information seeking, climate information exposure, knowledge of climate change, environmental values, and experience with climate change events (e.g., flood) are also confirmed correlates of climate anxiety (Asgarizadeh et al., 2023b; Whitmarsh et al., 2022a).

Chronic disease status, mental well-being, and generalised anxiety were considered health-related socioeconomic factors (Hajek & Konig, 2022; Ogunbode et al., 2022; Whitmarsh et al., 2022a; Wullenkord et al., 2021). The evidence on these variables is mixed or varies across contexts, and variations can be attributed to inconsistent measurement methods. Notably, a negative bi-directional association between climate anxiety and mental well-being has been confirmed in 31 countries (Ogunbode et al., 2022), implying that mental well-being can be a correlate in most contexts. Each previous study included a unique set of potential predictors, contributing to an increasing scope of correlates reported in the literature. It might not have been possible for studies to consider all potential predictors in their contexts, but the inclusion of topical social issues (e.g., fear of a conventional war) in some studies (Hajek & Konig, 2022; Whitmarsh et al., 2022a) advanced the evidence. Yet, the failure of research to incorporate contextual factors in their analyses is a significant shortcoming.

1.3. The Current Study

Climate anxiety has been framed by researchers (Chan et al., 2024; Ogunbode et al., 2023) as a negative emotion. It is associated with other measures of *negative affect* such as maladaptive behaviours (e.g., drug use), climate change worry, and suicide (Hajek & Konig, 2022; Kõlves et al., 2025). As a negative emotion, climate anxiety drives negative self-concept and causes sadness, leading to both physical and mental health problems (Kõlves et al., 2025; Watson & Clark, 1984; Whitmarsh et al., 2022b). It is worth noting, however, that moderate climate anxiety can spur pro-environmental action (Hajek & Konig, 2022; Whitmarsh et al., 2022b) and prompt the utilisation of psychological capital (e.g., resilience and self-efficacy) in ways that sustain life engagement (Asiamah et al., 2025). Individuals with moderate climate anxiety are more likely to perform behaviours (e.g., walking instead of driving a carbon-dependent car) that protect the environment (Hajek & Konig, 2022). The mixed impacts of climate anxiety on behaviour may be explained by its contradictory negative feelings (e.g., anger and guilt) about climate change action or inaction.

There is an ongoing debate about whether negative emotion is associated with age. Researchers (Barbeau et al., 2022; Jiang & Fung, 2019; Ross & Mirowsky, 2008) argue that older adults express less negative emotions, such as climate anxiety, than younger people. They insinuate that age is positively associated with positive emotion but negatively associated with negative emotion. This relationship has been explained by the SST, which avers that people's time horizon shrinks as they age (L.L. Carstensen & B.L. Fredrickson, 1998; Jiang & Fung, 2019). Shortening people's time perspective accompanies a change in life goals, which impels older adults to invest resources in only emotionally meaningful pursuits and worry less about social and environmental problems (Jiang & Fung, 2019). If so, older adults, compared with younger people, would report lower climate anxiety.

The SAVI model (Charles, 2010) opposes the SST and provides a framework for stratifying climate anxiety across age groups. According to the model, older adults are more vulnerable to disorienting life events (e.g., climate change events) than younger adults. Consequently, well-being is more likely to be adversely impacted by climate crises in older adults than in younger adults. This viewpoint is opposed by the SST, which assumes that negative emotions are fewer in older age. As stated earlier, the evidence on the relationship between negative emotions and age is mixed, implying that the SAVI can be supported in some contexts. If so, older age groups may report higher climate anxiety, especially in an African context, where older adults receive limited welfare support from the government (Kpessa-Whyte, 2018). In places where there is limited welfare support, older groups may be more worried and anxious about problems that adversely affect their lives, including climate change.

Some studies (Barbeau et al., 2022; Ross & Mirowsky, 2008) have reached results supporting the foregoing relationship, but others have yielded mixed results, including a positive association between age and negative emotions (Jiang & Fung, 2019; Lallement & Lemaire, 2024). Similarly, studies (Hajek & Konig, 2022; Whitmarsh et al., 2022a; Wullenkord et al., 2021) have reported mixed evidence about the association of age with climate anxiety. Jiang and Fung concluded, based on the mixed results, that negative emotional expression depends on contextual factors, which were not incorporated into previous quantifications of climate anxiety. Their conclusion is supported by the Context Dynamics in Ageing (CODA) (Wahl & Gerstorf, 2018) and the Socially Active Neighbourhood (SAN) (Nestor Asiamah, Andrew Bateman, et al., 2023) frameworks. These models argue that the social environment, built environment, and personal factors influence behaviours and health. Some researchers (Nestor Asiamah, Mohammad Javad Koohsari, et al., 2023) recently drew on them to reason that emotions depend on environmental conditions such as safety.

The influence of the environment on emotions can stem from differences in the socioeconomic, geographic, and spatial profiles of cities and communities. Cities with different socioeconomic profiles would offer various levels of protection from climate crises and could experience environmental problems differently. Cities within rainforest zones, for example, would less frequently experience heatwaves than those in the Savanna. Larger cities are getting warmer due to climate change (Gough et al., 2019; Hallegatte & Corfee-Morlot, 2010), so their residents may report higher climate anxiety. A city's population density can influence a sense of safety from environmental problems since it determines whether social support and services are reachable during a crisis. Population density is the number of people living in a specific area, measured as the number of people per square kilometre (Cramer et al., 2004). In a city with a high population density, residents would feel protected by proximally located neighbours and services within the dense social environment and feel less anxious about the climate crisis.

Both the CODA and SAN models recognize the importance of equity in the distribution of psychosocial and built environmental factors between cities and communities. They imply that safety (a psychosocial factor), parks, recreational grounds, interconnected streets, and essential services (healthcare) fairly protect residents if they are equitably distributed across cities and communities. A fair distribution of such environmental attributes maximises equity in access to environmental resources expected to protect residents from climate change events. Yet, there are disparities in built environmental design across cities in Ghana, where some cities, such as Accra and Kumasi, are more vulnerable to flooding than others . Both models also emphasize the role of social support in physical and mental health. Unfortunately, social support may not be readily available in larger, sprawling, or more urbanized cities where people need to constantly work to meet the cost of living (Aboderin, 2004; Adei et al., 2026). This situation contrasts the high population density of cities, which rather worsens competition for scarce resources.

Drawing on the CODA and SAN frameworks, therefore, this study stratifies climate anxiety across cities and ascertains whether city-level differences in climate anxiety are affected (confounded) by demographic and socioeconomic factors. The contextual factors considered are city population density, population size, urban status (i.e., whether one lives in a city with a complete or partial urban status), and ecosystem type (i.e., whether one lives in a coastal city, rainforest, or Savanna). These variables were considered at our convenience, but their analysis would set the foundation for incorporating related variables in future research. Their inclusion in this study would clarify how demographic and socioeconomic factors and topical issues in Ghana (e.g., worry about the increasing cost of living) may be associated with climate anxiety.

Worry about the increasing cost of living in Ghana has been acknowledged as an entrenched social problem following the coronavirus pandemic (Aduhene & Osei-Assibey, 2021). Since a high cost of living makes caring for dependants more daunting, older city residents with dependants can be more anxious about climate change. Similarly, residents may be more worried about their dependents getting hurt or killed by a climate change event. People who rate their health as poor can feel more vulnerable to climate change events and would, therefore, report higher climate anxiety. Hence, we deemed it necessary to consider self-reported health, “having dependants”, and “worry about the increasing cost of living in Ghana” as novel potential predictors of climate anxiety.

Climate Change Awareness (CCA) encompasses knowledge about the adverse impacts of climate change on the environment and humans (Asiamah et al., 2024; Baiardi & Morana, 2021). People with higher CCA may be better informed about the dangers of climate change, and some groups (e.g., people without formal education) may only worry about climate change if they are aware of it. If so, CCA may influence or confound the relationship of climate anxiety with demographic and socioeconomic factors. Therefore, a sensitivity analysis is used to control for CCA in assessing the association of climate anxiety with demographic and socioeconomic factors. CCA in this study is a unique measure of climate change knowledge, comprising a higher number of questions than a previously used measure (Asgarizadeh et al., 2023a, 2023b). It is included in this study as a potential correlate of climate anxiety based on previous research (Asgarizadeh et al., 2023a). Drawing on the CODA and SAN models, CCA is also treated as a potential confounder of the association of climate anxiety with demographic and socioeconomic variables, providing evidence for future hypothesis generation and testing.

2. Methods

2.1 Design

This study adopted a cross-sectional design with sensitivity analyses and procedures against Common Methods Bias (CMB) and confounding.

2.2 Study context

Ghana is a West African country adjacent to the Gulf of Guinea and shares borders with Togo, the Ivory Coast, and Burkina Faso. According to the Population and Housing Census, Ghana's population was 30,832,019 as of 2021 (GSS, 2021). Ghana has sixteen regional capitals recognised as cities, located in the northern Savanna (i.e., northern region), the middle belt (i.e., rainforest area), and the southern belt (i.e., coastal area). Like most African countries, Ghana is experiencing climate change events such as flooding, heat waves, and drought. Heatwaves and flooding have been more intense and frequent in cities, coastal areas, and the Savanna, and atmospheric temperatures have risen across the country over the last two decades (Abunyewah et al., 2023b; Codjoe et al., 2020). Heatwaves are more frequently experienced in cities, especially in the northern Savanna (Codjoe et al., 2020; Yankson et al., 2017).

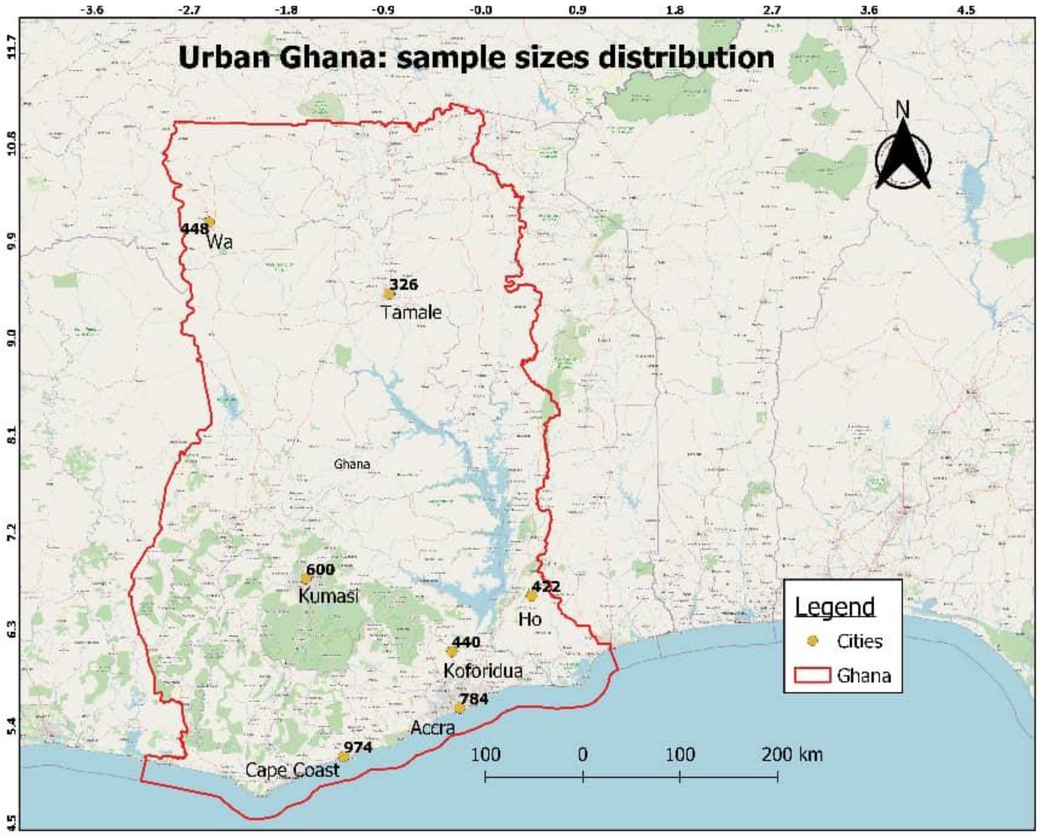


Fig 1. A map of Ghana showing selected cities and their samples

2.3 Participants, sample size, and selection

The participants were middle-aged and older adults aged 50 years or older who permanently resided in seven of Ghana's sixteen regional capitals: Accra, Ho, Koforidua, Kumasi, Tamale, Wa, and Cape Coast. Although older adults in Ghana are individuals aged 60 years or older (Kpessa-Whyte, 2018), the current study included middle-aged adults aged 50 or older in view of potential "early old age" (Grundy & Holt, 2000; Hillsdon et al., 2005) in Ghana. Early old age is caused by several factors, including lifestyle (e.g., diet and physical inactivity), poverty, and living in a low socioeconomic context. This study included adults aged below 60 years to ensure that middle-aged adults who were probably experiencing old age were included in the sample. Although no policy document or framework recognises 50 years as the minimum old age in Ghana, landmark studies such as the World Health Organization's Study on global AGEing and adult health (Kowal et al., 2012), set the minimum old age at 50 years. Many other studies (Dzando et al., 2025; Gatimu et al., 2016; Gyasi et al., 2020) assessing the prevalence of diseases in Ghana set the minimum old age at 50 years based on the principle of early old age. We adopted the "early ageing" framework in this study to maximise the inclusivity of the sample.

A multi-stage sampling method was utilised to select the participants. Cities were randomly selected in each of three national blocks: northern Savanna, middle (rainforest) zone, and southern (coastal) area. Tamale and Wa were selected from the northern Savanna; Kumasi, Ho, and Koforidua were selected from the middle or rainforest zone; and Accra and Cape Coast were selected from the southern or coastal area. Figure 1 shows a map of Ghana, and the seven cities selected. Each selected city was then divided into subblocks (i.e., north, east, west, and south) using Google Maps, and the participants were chosen from each subblock. Potential participants in their homes, workplaces, and community centres were recruited through reconnaissance fieldwork. Through a structured interview, research assistants identified and selected participants from each block's neighbourhoods.

We calculated two sample sizes and used the one with higher statistical power. The first sample size was for stratifying climate anxiety across a maximum of seven groups (cities) with one-way Analysis of Variance (ANOVA), and the second sample size was for identifying up to 24 predictors with multiple linear regression. We used the G*Power software, an effect size of 0.25, and other recommended statistics (i.e., power = 0.8 and $\alpha = 0.05$) to calculate a sample size of 231 for one-way ANOVA (Kang, 2021). The minimum sample size for identifying predictors with multiple linear regression based on these statistics was 110. Thus, 231 was the ideal minimum sample needed for this study, but we aimed to collect data on a larger sample to maximise the power of our tests.

2.4 Data collection

This study received ethics clearance from the University of Essex, School of Health and Social Care Research Ethics Committee (reference TH2425-0021) following ethics review and clearance from the Social Sciences and Humanities Ethics Committee at Kwame Nkrumah University of Science and Technology in Ghana (reference HuSSREC/AP/52/VOL. 3). All the participants provided written informed consent and participated in the study voluntarily. Fourteen trained research assistants supported data collection in the seven cities from 2nd July to 23rd August 2024. The participants completed and returned the questionnaire at their homes or agreed locations, and the average time for completing a questionnaire was 11 minutes. A total of 3994 questionnaires were completed and analysed. Figure 1 shows the sample size for each city.

2.5 Measures

2.5.1 Climate anxiety

The 13-item CAS (Susan Clayton & Bryan T. Karazsia, 2020) was used as a whole to measure climate anxiety. This tool was preferred to other measures because it produced satisfactory psychometric properties (e.g., internal consistency) on a Ghanaian sample (Abunyewah et al., 2023b) and is the most frequently used scale. Some of the scale's items are "thinking about climate change makes it difficult for me to concentrate" and "I have nightmares about climate change". It yielded Cronbach's $\alpha \geq 0.7$ (i.e., consolidated = 0.96; Accra = 0.98; Ho = 0.88; Koforidua = 0.90; Kumasi = 0.79; Tamale = 0.96; Wa = 0.96, and Cape Coast = 0.96). The item summation method was used to generate the climate anxiety score. We followed previous research (Whitmarsh et al., 2022b) to group the sample into groups of mild, moderate, and severe climate anxiety. The grouping was based on the following three score thresholds: 1.00-2.33 (mild), 2.34-3.66 (moderate), and 3.67-5.00 (severe). We rescaled the composite score into a 5-item scale on which this grouping was originally based (Asiamah et al., 2025).

2.5.2 Climate change awareness

CCA was measured with a 17-item tool adopted in whole with its five descriptive anchors (i.e., strongly disagree – 1, disagree – 2, somewhat agree – 3, agree – 4, and strongly agree – 5) from Gönen and colleagues (Gönen et al., 2022). This tool produced satisfactory psychometric properties on a Ghanaian sample (Asiamah et al., 2024) and in the current study (i.e., consolidated = 0.88; Accra = 0.88; Ho = 0.76; Koforidua = 0.74; Kumasi = 0.74; Tamale = 0.94; Wa = 0.88, and Cape Coast = 0.91). Some of its items are "I am aware that human activities cause global warming" and "I am amazed by people who are unaware of how dangerous climate change is". Scores on CCA were generated with the item summation method. Appendix A1 and Appendix A2 are the climate anxiety and CCA scales, respectively.

2.5.3 Demographic and socioeconomic variables

The demographic and socioeconomic variables were measured as categorical variables. Chronic disease status was measured by asking participants to name specific chronic diseases they had, and their responses were coded into two groups: individuals with no chronic disease (coded 1) and those with one or more chronic diseases (coded 2). Worry about the increasing cost of living was measured by asking participants to indicate (based on a 'yes' or 'no' response) whether they were worried about the increasing cost of living in Ghana. "Having a dependant" was measured by asking participants to indicate (based on a 'yes' or 'no' response) whether the participants had at least one dependant. 'No' and 'yes' were coded 1 and 2, respectively. Appendix A3 shows how other demographic and socioeconomic variables were defined, operationalised, and coded.

2.5.4 Contextual factors

The seven cities were coded as shown in Appendix A3, and the other contextual factors were created by classifying them according to their ecosystem type, population size, population density, and urban status. The 2021 Population and Housing Census was the data source used to classify the cities (GSS, 2021). Ecosystem type measured whether the city where the participant lived permanently was in the northern Savanna (i.e., Savanna coded 1), in a rainforest zone in the middle belt (i.e., rainforest zone coded 2), or was by the sea in the south (i.e., coastal area coded 3). This classification followed previous research and was consistent with the traditional grouping of ecological zones in Ghana (Amekudzi et al., 2015; Owusu et al., 2021). Although Accra is in the Savanna, it is classified as a coastal city in this study because of its location near the sea and the fact that it differs from the northern Savanna with respect to weather conditions (Amekudzi et al., 2015). Appendix A3 shows the other contextual factors' definition, operationalisation, and coding.

2.6 Instrumentation

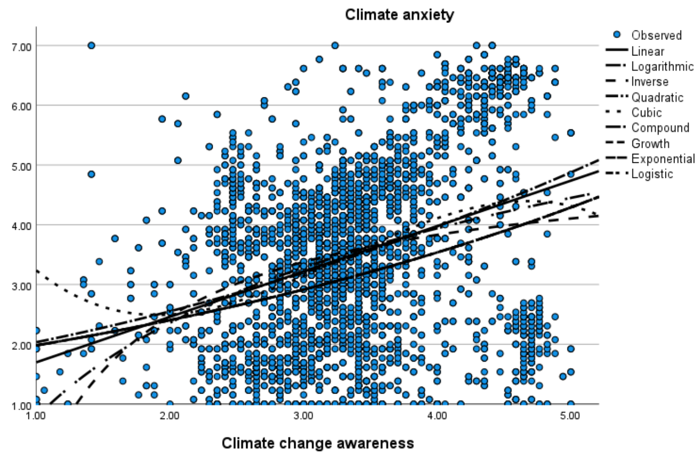
Data were collected with a self-reported questionnaire containing three blocks of information. The first block introduced the study aim, ethical statements, and survey completion instructions. The second block presented scales for measuring climate anxiety and CCA, whereas the third block contained questions for measuring the demographic and socioeconomic variables.

Procedural and statistical processes recommended in the literature (Fuller et al., 2016; Kock et al., 2021) were followed to avoid CMB. We ensured that all measurement methods were validated or reliably used in previous research. Scales and questions were presented separately in unique blocks or subblocks, ensuring responses were based on the right context. The researchers and three experts in psychometrics reviewed and approved the contents of the questionnaire. Harman's one-factor statistical procedure was utilised to confirm the absence of CMB in the data. Based on the consolidated data, Exploratory Factor Analysis (EFA) through maximum likelihood was employed to assess the factor structures of the scales. As recommended in the literature (Fuller et al., 2016; Kock et al., 2021), climate anxiety produced two factors (i.e., the variance of factor 1 = 37.4%, and factor 2 = 23.9%), whereas CCA produced three factors (i.e., the variance of factor 1 = 34.2%; factor 2 = 19.2%, and factor 3 = 7.0%) in their factor structures. The variance of each factor was less than 40%, and the factor loadings of items were ≥0.5.

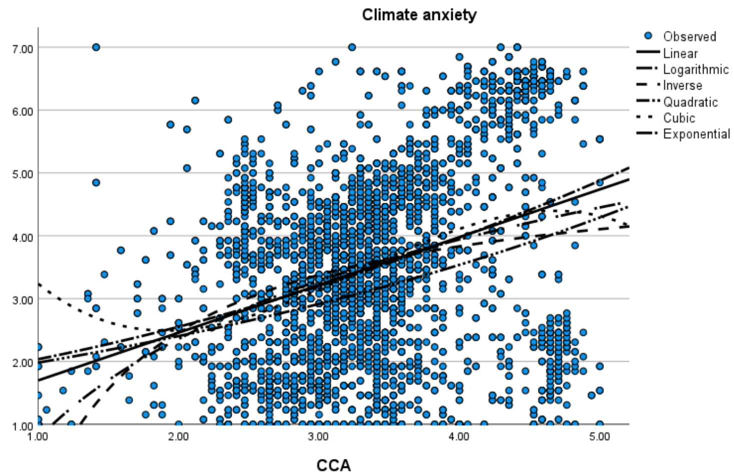
Since climate anxiety was the dependent variable and the focus of the study, we further performed a Confirmatory Factor Analysis (CFA) on its scale to ascertain whether our data fitted the original factor solution from Clayton and Karazsia (2020). According to the CFA, the original two-factor solution (comprising two domains: *cognitive-emotional impairment* and *functional impairment*) fitted our data. The average variances extracted (AVEs) were 0.65 for *cognitive-emotional impairment* and 0.64 for *functional impairment*. The AVEs were greater than 0.5, signifying convergent validity (Cheung et al., 2024). They were also greater than the Shared Variance (SV) of the two extracted factors, suggesting that the scale had discriminant validity under the "AVE-SV approach" (Cheung et al., 2024). Thus, the reliability and construct validity of the scale were confirmed with our data. Appendix A4 shows the factor loadings ≥0.5 and AVEs ≥0.5 from the CFA, as well as the Cronbach's alpha ≥ 0.7 for each factor. Following previous research (Cheung et al., 2024; Susan Clayton & Bryan T Karazsia, 2020), we assessed the fit of the CFA model with the chi-square (χ^2) value and its significance, Adjusted Goodness of Fit (AGFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). The model yielded satisfactory indexes at χ^2 = 1.130 (p >0.05), AGFI = 0.998, TLI = 0.000, and RMSEA = 0.000.

2.7 Statistical analyses

Two stages of data analysis were performed with Amos 28 and SPSS 28 (IBM Inc., New York, USA). Amos was used for CFA, whereas SPSS was used for the other analyses. In the first stage, exploratory data analysis was performed to summarise the data, deal with missing data, and test relevant assumptions.



A.



B

Figure 2. Curve estimated relationship between climate change anxiety and climate change awareness

Missing data were associated with only the categorical variables and constituted up to 6% of the data per variable. An MCAR (i.e., Missing Completely at Random) test yielded non-significant results at $p>0.05$, suggesting that the missing data were randomly distributed. “Multiple imputation” (Woods et al., 2023) for categorical variables was, therefore, utilised to replace missing data. We investigated the impact of missing data by comparing the results between the complete data and the original data with missing observations. The specific multiple imputation method used was the "multivariate imputation by chained equations", which is the most flexible and widely used approach (Woods et al., 2024). We included all variables in the analysis in harmony with best practice. The results from the quantification and linear regression analyses were consistent between datasets. However, the normal distribution of the data stratified by city was not confirmed. Even so, the data were analysed without transforming them since the normal distribution of the data on the dependent variable (i.e., univariate normal distribution) was confirmed with the Kolmogorov-Smirnov test at a p>0.05. Deviation from the normal distribution at the group level does not affect the results when the sample size is as large as ours (Gaerson, 2012). Assumptions governing the use of our statistical tools were assessed following recommendations in the literature (Garson, 2012; Hickey et al., 2019). The linearity of the regression relationships was examined and confirmed with curve estimation in SPSS. The linear model among all possible non-linear models in curve estimation yielded the largest variance and a p-value <0.001 for each of the relationships. Figure 2a and Figure 2b show sample graphs from curve estimation.

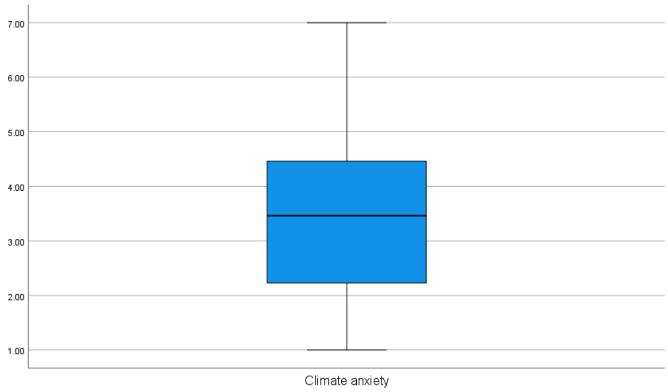


Fig 3a. A boxplot on climate anxiety

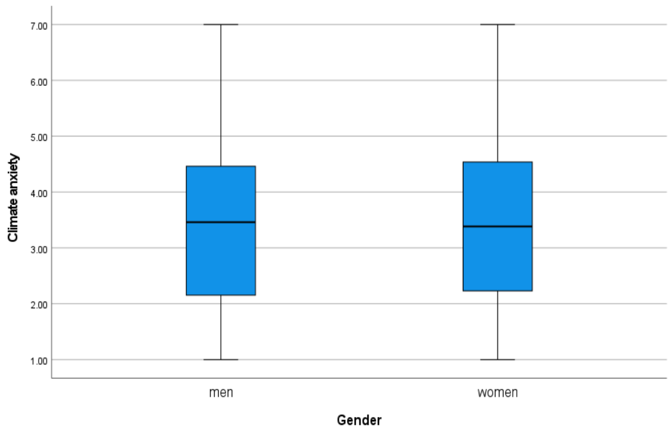


Fig 3b. A gender-stratified boxplot on climate anxiety

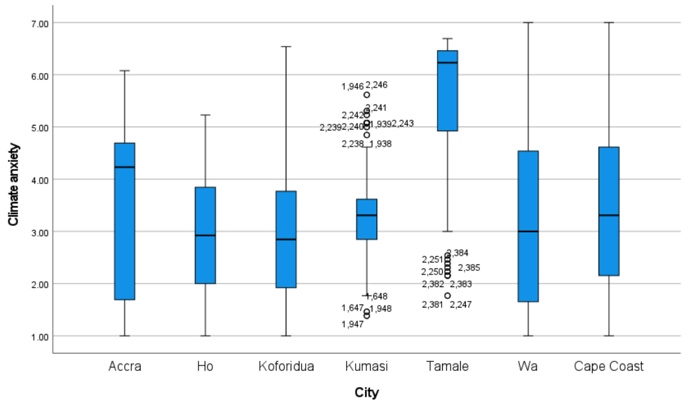


Fig 3c. A boxplot on climate anxiety stratified by city

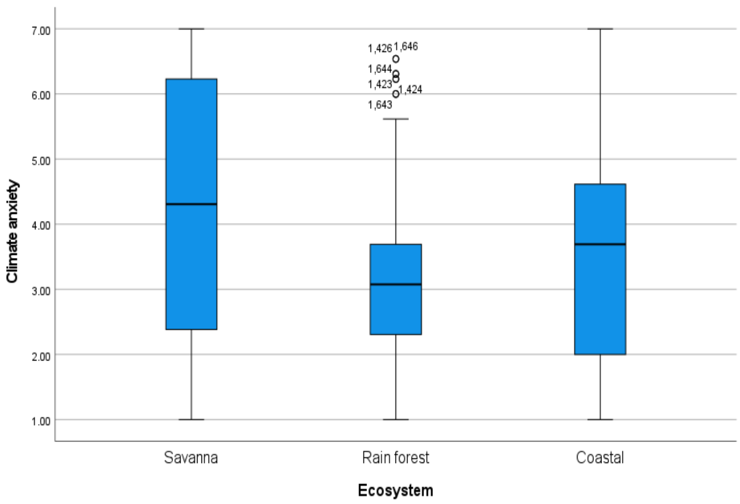


Fig 3d. An ecosystem-stratified boxplot on climate anxiety

We created box plots to identify potential outliers in climate anxiety and sampled groups. The first two plots (i.e., Figure 3a and Figure 3b) showed no outliers in the whole data and in two groups (i.e., men and women), whereas the other two plots (i.e., Figure 3c and Figure 3d) showed mild and “interesting outliers” (Aguinis et al., 2013) in two cities (i.e., Kumasi and Tamale) and the rainforest zone. “Interesting outliers” are extreme but unbiased values from respondents that often accompany new knowledge (Aguinis et al., 2013). They are not outcomes of data entry errors, so we did not remove them from the data. Univariate normality of the data and the results were similar between the data with and without the “interesting outliers”. Multicollinearity in multiple regression was confirmed with a "tolerance" value ≥0.5 for each predictor(Garson, 2012). Finally, a graph of residuals against predicted values depicted the homogeneity of variances around the regression line.

In the stratification analysis, the independent samples *t*-test and one-way ANOVA were used to compare climate anxiety between groups, following previous research (Hajek & Konig, 2022). The Bonferroni post-hoc test was used if the homogeneity of variances assumption was met, and the Tamhane's T2 test was used if this assumption was not met. A one-way Analysis of Covariance (ANCOVA) was then performed to control for individual factors in the ANOVA. This analysis involved stratifying climate anxiety across the seven cities while controlling for individual factors (i.e., work status, education, income, age, and CCA) that may explain variations in climate anxiety across cities. Due to individuals being nested within cities, we first used a one-way ANCOVA (in which city is made a fixed factor) to ascertain whether differences between cities remained significant after accounting for individual factors. When exploring predictors at the individual level with multiple linear regression analysis, we excluded the city-level factors.

In a sensitivity analysis, two multiple linear regression models were fitted to assess the association of demographic and socioeconomic variables with climate anxiety. Model 1 (i.e., crude model) examined the relationship of climate anxiety with the demographic and socioeconomic variables. Models 2, the CCA-controlled or adjusted model, built on model 1 by incorporating CCA as a covariate. We compared both models to ascertain whether CCA changed the regression weights of demographic and socioeconomic variables on climate anxiety. The statistical significance of the results was set at a minimum of $p<0.05$.

Table 1. Summary statistics (N = 3994)

Variable	Group	n/M	%/SD
	Categorical variables		
Gender	men	2118	53.03
	women	1834	45.92
	Missing	42	1.05
Work status	full-time	2169	54.31
	part-time	921	23.06
	retired	801	20.06
	Missing	103	2.58
Educational level	none	169	4.23
	basic school	489	12.24
	secondary	1460	36.55
	tertiary	1763	44.14
	Missing	113	2.83
Income (₵)	<500	407	10.19
	500-1000	1291	32.32
	1500-2000	1008	25.24
	>2000	1145	28.67
	Missing	143	3.58
Age group (yrs)	50-59	2551	63.87
	60-69	890	22.28
	70-79	397	9.94

	80+	90	2.25
	Missing	66	1.65
Chronic disease status	none	2411	60.37
	one or more	1353	33.88
	Missing	230	5.76
Marital status	not married	1052	26.34
	married	2683	67.18
	Missing	259	6.48
Self-reported health	poor	647	16.20
	good	3219	80.60
	Missing	128	3.20
Worried about increasing cost of living	no	207	5.18
	yes	3752	93.94
	Missing	35	0.88
Having dependants	no	662	16.57
	yes	3288	82.32
	Missing	44	1.10
City	Accra	784	19.63
	Ho	422	10.57
	Koforidua	440	11.02
	Kumasi	600	15.02
	Tamale	326	8.16
	Wa	448	11.22
	Cape Coast	974	24.39
Urban status	urban	2684	67.20
	urban-rural	1310	32.80
City population size	Small (<200000 people)	1836	45.97
	Large (≥ 200000 people)	2158	54.03
City population density	Low (<1000 people/sq kms)	1196	29.94
	Moderate (1000-5000 people/sq kms)	1414	35.40
	High (Above 5000 people/sq kms)	1384	34.65
Ecosystem type	Savanna (North)	774	19.38
	Rain forest zone (Middle belt)	1462	36.60
	Coastal zone (South)	1758	44.02
Climate anxiety severity	Mild	1844	46.2
	Moderate	1594	39.9
	Severe	556	13.9
	Discrete variables		
Climate anxiety (average)	---	3.48	1.53
Climate anxiety (sum)	---	45.23	19.85
Climate change awareness	---	3.36	0.68

Note: N – total sample analysed; n – frequency; M – mean; SD – standard deviation; the frequency and per cent (%) apply to only categorical variables, whereas the mean and standard deviation apply only to discrete variables

3. Results

Table 1 shows a summary of all variables. About 53% (n = 2118) of the participants were men, whereas 34% (n = 1353) had at least one chronic disease. About 94% (n = 3752) of the participants were worried about the increasing cost of living in Ghana, and 82% (n = 3288) had dependants. About 67% (n = 2684) of the participants lived in cities with a complete urban status, whereas 33% (n = 1310) lived in cities with urban-rural status. The average climate anxiety in the consolidated sample was 3.5 (Mean = 3.48; SD = 1.53). About 14% (n = 556) of the participants experienced severe climate anxiety, 40% (n = 1594) experienced moderate climate anxiety, and 46% (n = 1844) experienced mild climate anxiety (see Table 1).

Table 2. Level of climate change anxiety stratified by demographic, contextual, and socioeconomic factors

Variable	*n*	*M*	*SD*	*95% CI*	*F/t statistic*	*p*
Total	3994	3.48	1.53	±0.10		
Sex						
men	2118	3.49	1.53	±0.13	0.15	0.696
women	1834	3.47	1.53	±0.14		
Work status						
full-time	2169	3.62	1.52	±0.13	38.03	<0.001
part-time	921	3.43	1.55	±0.20		
retired	801	3.08	1.44	±0.20		
Educational level						
none	169	3.70	1.58	±0.48	3.89	0.009
basic school	489	3.27	1.53	±0.27		
secondary	1460	3.47	1.63	±0.17		
tertiary	1763	3.47	1.44	±0.13		
Income (₵)						
<500	407	3.36	1.38	±0.27	2.57	0.053
500-1000	1291	3.50	1.18	±0.13		
1500-2000	1008	3.57	1.63	±0.20		
>2000	1145	3.43	1.81	±0.21		
Age group (yrs)						
50-59	2551	3.43	1.47	±0.11	2.69	0.045
60-69	890	3.59	1.59	±0.21		
70-79	397	3.54	1.68	±0.33		
80+	90	3.55	1.81	±0.76		
Chronic disease status						
none	2411	3.58	1.56	±0.13	41.35	<0.001
one or more	1353	3.24	1.49	±0.16		
Marital status						
not married	1052	3.39	1.47	±0.18	0.30	0.584
married	2683	3.42	1.56	±0.12		
Self-reported health						
poor	647	3.74	1.45	±0.22	25.66	<0.001
good	3219	3.40	1.54	±0.11		
Worry about increasing cost of living						
no	207	3.14	1.51	±0.42	10.14	<0.001
yes	3752	3.49	1.52	±0.10		
Having dependants						
no	662	3.16	1.41	±0.21	32.60	<0.001
yes	3288	3.53	1.54	±0.11		
City						
Accra	784	3.49	1.53	±0.21	165.09	<0.001
Ho	422	2.94	1.07	±0.21		
Koforidua	440	2.88	1.21	±0.23		
Kumasi	600	3.26	0.66	±0.11		
Tamale	326	5.63	1.26	±0.27		
Wa	448	3.21	1.72	±0.32		

Cape Coast	974	3.51	1.57	±0.20		
Urban status						
urban	2684	3.71	1.55	±0.12	190.733	<0.001
urban-rural	1310	3.01	1.37	±0.15		
City population size						
Small (<200000 people)	1836	3.23	1.42	±0.13	93.62	<0.001
Large (≥ 200000 people)	2158	3.69	1.58	±0.13		
City population density						
Low (<1000 people/sq kms)	1196	3.77	1.80	±0.20	33.48	<0.001
Moderate (1000-5000 people/sq kms)	1414	3.31	1.50	±0.16		
High (Above 5000 people/sq kms)	1384	3.39	1.24	±0.13		
Ecosystem type						
Savanna (North)	774	4.23	1.95	±0.28	162.44	<0.001
Rain forest zone (Middle belt)	1462	3.05	0.99	±0.10		
Coastal zone (South)	1758	3.50	1.55	±0.15		

Note: n – sample; M – mean; SD – standard deviation (of M), CI – confidence interval (of M); p – statistical significance or probability value; F-statistic applies to variables involving three or more groups whereas t-statistic applies to variables involving two groups.

Table 2 shows the average climate anxiety stratified by demographic, socioeconomic, and contextual characteristics. Appendix B shows Tamhane's post-hoc tests performed following ANOVA. There was no difference between men and women regarding their climate anxiety (t = 0.15; p = 0.696), but full-time, part-time, and retired participants reported different climate anxiety scores (F = 38.03; p <0.001). The post-hoc test suggests that full-time workers reported higher climate anxiety scores than part-time and retired workers (see Appendix B). Part-time employees, compared with retired workers, reported higher climate anxiety (p<0.001). Individuals with no chronic disease, compared with those with at least one chronic disease, reported higher climate anxiety (t = 41.35; p<0.001). Participants who were worried about the increasing cost of living in Ghana reported higher climate anxiety (t = 10.14; p<0.001).

Climate anxiety differed across the seven cities (F = 165.09; p<0.001). The post-hot test suggests the largest score of climate anxiety was reported in Tamale (M = 5.63), and Accra had the second-largest climate anxiety score. Urban cities, compared to urban-rural cities, produced higher climate anxiety (t = 190.73; p<0.001), and climate anxiety was higher in larger cities (t = 93.62; p<0.001). The climate anxiety score for the low population density was higher compared to moderate and high densities (p<0.001), but there was no difference between moderate and high densities. The climate anxiety reported for the Savanna was higher than the rainforest and coastal zones (F = 162.44; p<0.001). The coastal zone had a larger climate anxiety than the rainforest zone (p<0.001).

Table 3. Tests of between-subject effects from ANCOVA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	2560.223[a]	21	121.915	64.064	<.001	0.294	1345.345	1.000
Intercept	226.1	1	226.1	118.811	<.001	0.035	118.811	1.000
Work status								
full-time	9.307	1	9.307	4.891	0.027	0.002	4.891	0.599
part-time	17.572	1	17.572	9.234	0.002	0.003	9.234	0.859
retired	71.354	1	71.354	37.495	<.001	0.011	37.495	1.000
Education								
none	38.906	1	38.906	20.444	<.001	0.006	20.444	0.995
basic education	107.6	1	107.6	56.542	<.001	0.017	56.542	1.000
secondary education	95.238	1	95.238	50.045	<.001	0.015	50.045	1.000
tertiary education	48.243	1	48.243	25.351	<.001	0.008	25.351	0.999
Income (GhC)								
< 500	2.993	1	2.993	1.573	0.210	0.000	1.573	0.241
500-1000	21.761	1	21.761	11.435	<.001	0.004	11.435	0.922
1001-1500	1.771	1	1.771	0.931	0.335	0.000	0.931	0.161
>2000	0.702	1	0.702	0.369	0.544	0.000	0.369	0.093
Age (yrs)								
50_59	5.962	1	5.962	3.133	0.077	0.001	3.133	0.425
60_69	0.026	1	0.026	0.013	0.908	0.000	0.013	0.052
70_79	0.883	1	0.883	0.464	0.496	0.000	0.464	0.105
>80	2.352	1	2.352	1.236	0.266	0.000	1.236	0.199
CCA	344.657	1	344.657	181.11	<.001	0.053	181.11	1.000
City	1053.634	5	210.727	110.733	<.001	0.146	553.663	1.000
Error	6146.766	3230	1.903					
Total	49349.79	3252						
Corrected Total	8706.99	3251						

Note: R square = 29.4%; Adjusted R-square = 28.9%; α = 0.05; CCC – climate change awareness

Table 4. Association of climate anxiety with demographic, contextual, and work characteristics (n = 3994)

Predictor	Model 1 (Crude model)				Model 2 (CCA-controlled model)				Model 3 (Contextual factors controlled)				Model 4 (Fully adjusted)			
	B	*SE*	β(t)	95% CI	B	*SE*	β(t)	95% CI	B	*SE*	β(t)	95% CI	B	*SE*	β(t)	95% CI
(Constant)	3.66	0.38	(9.60)**	±1.50	1.48	0.39	(3.83)**	±1.52	6.45	0.42	(15.43)**	±1.02	4.51	0.44	(10.26)**	±1.72
Gender																
Men (ref – women)	-0.02	0.06	-0.01(-0.38)	±0.24	0.00	0.06	0.00(0.00)	±0.23	0.06	0.05	0.02(1.20)	±1.54	0.06	0.05	0.02(1.16)	±0.21
Chronic disease status																
One or more (ref – none)	-0.66	0.07	-0.19(-9.30)**	±0.28	-0.55	0.07	-0.16(-8.12)**	±0.27	-0.31	0.07	-0.09(-4.52)**	±1.27	-0.27	0.07	-0.08(-3.99)**	±0.26
Marital status																
Married (ref – not married)	-0.02	0.07	-0.01(-0.24)	±0.28	0.00	0.07	0.00(0.03)	±0.27	-0.1	0.07	-0.03(-1.56)	±1.32	-0.12	0.07	-0.03(-1.89)	±0.25
Self-reported health																
Good (ref – poor)	-0.68	0.09	-0.15(-7.46)**	±0.36	-0.62	0.09	-0.14(-7.06)**	±0.35	-0.51	0.08	-0.11(-6.21)**	±1.13	-0.48	0.08	-0.11(-5.95)**	±0.32
Worry about increasing cost of living																
Yes (ref – no)	0.4	0.14	0.06(2.98)*	±0.53	0.43	0.13	0.06(3.24)**	±0.52	0.18	0.12	0.03(1.48)	±1.31	0.18	0.12	0.02(1.45)	±0.49
Having dependants																
Yes (ref – no)	0.35	0.08	0.08(4.37)**	±0.32	0.17	0.08	0.04(2.10)*	±0.31	0.19	0.08	0.04(2.43)*	±2.25	0.14	0.08	0.03(1.79)	±0.30
Work status																
Full-time (ref – retired)	0.76	0.09	0.23(8.59)**	±0.35	0.70	0.09	0.21(8.09)**	±0.34	0.51	0.08	0.15(6.40)**	±1.74	0.5	0.08	0.15(6.29)**	±0.31
Part-time (ref – retired)	0.36	0.09	0.09(4.00)**	±0.35	0.35	0.09	0.09(3.99)**	±0.34	0.35	0.08	0.09(4.31)**	±2.62	0.37	0.08	0.10(4.62)**	±0.31
Educational level																
Basic (ref – none)	-0.41	0.14	-0.09(-3.00)*	±0.53	-0.46	0.13	-0.10(-3.54)**	±0.51	-0.47	0.12	-0.10(-3.82)**	±4.25	-0.56	0.12	-0.12(-4.68)**	±0.47
Secondary (ref – none)	-0.19	0.12	-0.06(-1.56)	±0.48	-0.38	0.12	-0.11(-3.27)**	±0.46	-0.32	0.11	-0.10(-2.94)**	±4.57	-0.49	0.11	-0.14(-4.45)**	±0.43
Tertiary (ref – none)	-0.19	0.13	-0.05(-1.51)	±0.49	-0.30	0.12	-0.09(-2.51)*	±0.47	-0.16	0.12	-0.05(-1.33)	±2.01	-0.34	0.12	-0.10(-2.87)**	±0.46
Income (₵)																
500_1000 (ref - <500)	0.21	0.1	0.05(2.21)*	±0.38	0.27	0.09	0.07(2.91)*	±0.37	0.14	0.09	0.03(1.48)	±2.50	0.25	0.09	0.06(2.65)*	±0.37
1500_2000 (ref - <500)	0.1	0.09	0.03(1.07)	±0.36	-0.03	0.09	-0.01(-0.36)	±0.35	-0.06	0.1	-0.02(-0.61)	±2.88	-0.01	0.1	0.00(-0.11)	±0.37
above_2000 (ref - <500)	0.03	0.09	0.01(0.29)	±0.35	-0.04	0.09	-0.01(-0.45)	±0.34	-0.19	0.1	-0.05(-1.95)	±1.33	-0.14	0.1	-0.04(-1.40)	±0.38
Age group (yrs)																
60_69 (ref – 50-59)	0.44	0.08	0.12(5.67)**	±0.31	0.47	0.08	0.12(6.15)**	±0.30	0.29	0.07	0.08(4.13)**	±1.46	0.33	0.07	0.08(4.65)**	±0.28
70_79 (ref – 50-59)	0.77	0.11	0.15(7.14)**	±0.42	0.73	0.11	0.14(7.01)**	±0.41	0.51	0.1	0.10(5.18)**	±1.18	0.5	0.1	0.10(5.10)**	±0.39
Above_80 (ref – 50-59)	1.03	0.2	0.10(5.03)**	±0.80	0.94	0.20	0.09(4.77)**	±0.77	0.66	0.18	0.06(3.65)**	±4.03	0.66	0.18	0.06(3.68)**	±0.71
Urban status																
Urban-rural (ref – urban)	---	---	---	---	---	---	---	---	-2.35	0.11	-0.70(-21.87)**	±6.13	-1.92	0.11	-0.56(-17.40)**	±0.43
City population size																
Large (ref – small)	---	---	---	---	---	---	---	---	-0.1	0.13	-0.03(-0.72)	±5.37	-0.18	0.14	-0.05(-1.29)	±0.54
City population density																
Moderate (ref – low)	---	---	---	---	---	---	---	---	-0.57	0.17	-0.13(-3.45)**	±8.04	-0.64	0.17	-0.14(-3.80)**	±0.66
Ecosystem type																
Savanna (ref – Rainforest zone)	---	---	---	---	---	---	---	---	1.81	0.17	0.48(10.85)**	±1.02	1.74	0.17	0.47(10.04)**	±0.68
Coastal (ref – Rainforest zone)	---	---	---	---	---	---	---	---	2.01	0.17	0.54(11.94)**	±7.71	1.63	0.17	0.42(9.54)**	±0.67
Climate change awareness	---	---	---	---	0.7	0.04	0.32(17.81)**	±0.15	---	---	---	---	0.48	0.04	0.22(12.22)**	±0.15

**p<0.001; *p<0.05; --- not applicable; *SE* – standard error (of B); CI – confidence interval (of B); B – unstandardised regression weight, β – standardised regression weight; variance inflation factor for predictors ≥0.1; Durbin Watson statistic ranged between 1.98 and 2.21; F-tests for all models were significant at p<0.001; Adjusted R^2 ranged between 9% and 35%; the group “high” population density was automatically removed; individual cities were classified into the contextual factors.

Table 3 shows the tests of between-subject effects from ANCOVA. After controlling for the measured individual factors, climate anxiety still differed across the cities ($F = 110.733$; $p < .001$, and partial eta-squared = 0.146). Although "city" as a variable had the largest effect size in the model, there was a reduction in the corresponding F-statistic from 165.09 (in ANOVA) to 110.73 (in the ANCOVA). This reduction translated into differences in the results from the ANCOVA post hoc test (see Appendix B2). In both ANOVA and ANCOVA, Tamale yielded the highest climate anxiety among the cities. In ANOVA, the climate anxiety in Accra is higher than the climate anxiety in the three cities in the rainforest zone (i.e., Kumasi, Ho, and Koforidua). After adjusting for the personal factors through ANCOVA, there is no difference in climate anxiety between Accra and the three cities in the rainforest zone. Thus, the difference in climate anxiety between Accra and each of the cities in the rainforest zone was lost after adjusting for the personal factors. Deductively, Accra yielded a higher climate anxiety than the three cities in the rainforest zone because of personal factors such as age, gender, and income level.

In the CCA-adjusted model (see Table 4), chronic disease status, self-reported health, work status, educational level, income, and age group were significantly associated with climate anxiety. Compared with retirees, full-time ($\beta = 0.21$, $t = 8.09$; $p<0.001$) and part-time ($\beta = 0.09$, $t = 3.99$; $p<0.001$) workers reported larger climate anxiety. Individuals with basic, secondary, and tertiary education reported less climate anxiety than those without formal education. Adults in older age groups reported larger scores of climate anxiety than those aged 50-59 years. Participants with "good health" reported lower climate anxiety than adults with "poor health", and participants with at least one chronic disease reported lower climate anxiety than those living without a chronic disease. Finally, adults with higher climate change awareness reported higher climate anxiety ($\beta = 0.22$; $t = 12.22$; $p<0.001$).

4. Discussion

This study quantified climate anxiety, stratified it according to demographic, socioeconomic, and contextual factors, and explored its predictors.

4.1 Quantification of climate anxiety

The estimated level of climate anxiety in the consolidated sample was higher (Mean = 3.5; SD = 1.5) compared to levels found with the CAS in two studies conducted in Germany on the general population (Hajek & Konig, 2022). In Ghana, the climate anxiety level estimated on middle-aged adults using the items summation method was 39.4 (SD = 4.2) (Abunyewah et al., 2023b), which was higher in this study (Mean = 45.2; SD = 19.9). A higher climate anxiety level in this study, compared to estimates from Germany, may be attributed to socioeconomic problems unique to low- and middle-income countries. Welfare support for older adults in Ghana is poor, and Ghana has an unstable economic environment where older adults are left unprotected from social and environmental problems (Kpessa-Whyte, 2018). In such an environment, older people would be less capable of avoiding negative emotions such as climate anxiety.

Alternatively, higher climate anxiety in this study may be due to this study's focus on city residents. Climate change events are more frequent and impactful in cities (Gough et al., 2019; Hallegatte & Corfee-Morlot, 2010), and Ghanaian cities have experienced disorientating climate crises (e.g., floods and heatwaves) in the past decade (Abunyewah et al., 2023b). These anomalies, coupled with economic instability and the vulnerabilities faced by older city residents in Ghana, might have resulted in higher climate anxiety. Finally, climate change outcomes such as extreme weather are worsening over time (Abunyewah et al., 2023b; Hajek & Konig, 2022), so climate anxiety can increase with time. Thus, higher climate anxiety in this study is possibly due to a time-driven increase in the frequency and intensity of climate change events, given that climate anxiety levels in the literature were estimated at least two years ago. We call for longitudinal studies investigating potential changes in climate anxiety over time.

Climate anxiety differed between the seven cities, with Tamale accounting for the highest levels. This result was consistent between the ANOVA and ANCOVA, implying that climate anxiety was still highest after controlling for individual factors such as age, gender, and work status. This outcome supports the view that the intensity of negative emotions can vary between contexts (Jiang & Fung, 2019) and that neighbourhoods influence emotions or feelings differently in crises (Nestor Asiamah, Mohammad Javad Koohsari, et al., 2023). Climate anxiety would be stronger in environments where war and other crises may complement climate change events (Nestor Asiamah, Mohammad Javad Koohsari, et al., 2023). Tamale poses a higher risk of climate anxiety, possibly because climate change events are more frequent and extreme in these cities. Without controlling for the individual factors, climate anxiety in Cape Coast and Accra was higher than in the other cities, except Tamale. In the ANCOVA, nevertheless, climate anxiety in these two cities was not higher than in any other city. Thus, the ANCOVA reduced the city-level variance attributable to individual factors and yielded more unbiased estimates of climate anxiety.

Like the survey of Hajek and Konig (2023), this study found that full-time workers had higher climate anxiety than retired workers. Those with no chronic disease reported higher climate anxiety, compared with those with at least one of such diseases, and this result supports previous research (Hajek & Konig, 2022). Older age groups reported lower climate anxiety in the literature (Hajek & Konig, 2022; Whitmarsh et al., 2022a), but no difference in climate anxiety was found between age groups in the stratification analysis.

Climate anxiety differed between categories of contextual factors. Older residents in more urban cities reported higher climate anxiety, possibly because these cities are experiencing a higher impact of climate change as noted by earlier researchers (Gough et al., 2019; Hallegatte & Corfee-Morlot, 2010). The highest climate anxiety was reported in the Savanna, which was possibly because this area of Ghana is experiencing more extreme heatwaves (Armah et al., 2010), compared to coastal and rainforest zones. Unlike the stratification analysis, regression shows no association between city size and climate anxiety, an outcome influenced by covariates not considered in the stratification analysis. This result suggests that the association of contextual factors with climate anxiety can depend on covariates.

Climate anxiety was higher at lower population density because cities with the lowest population densities (i.e., Tamale = 825 persons/ sq kms, and Wa = 343.5) were in the Savanna, where climate anxiety was highest. We infer that cities with a low population density would yield higher climate anxiety if sited in an ecosystem more vulnerable to climate change. Increased climate change is associated with higher population density (McClelland et al., 2018), but cities in spaces experiencing extreme climate change events may have a low and stable population density, especially if their settlements are dispersed, as is the case in the northern part of Ghana. Low population density signifies long proximity to neighbours and social services (e.g., police stations and hospitals), which can evoke fears and anxiety about environmental problems. Residents may feel anxious about climate change if social services and their neighbours are not close to them.

4.2 Predictors of climate anxiety

The study found chronic disease status, self-reported health, and work status as predictors of climate anxiety in the regression analysis. As seen in the stratification analysis, individuals with no chronic disease, with full-time employment, and with poor self-reported health reported higher climate anxiety. No previous study had considered self-reported health as a correlate of climate anxiety, but our result is analogous to the positive correlation found between mental health and climate anxiety (Gago et al., 2024; Ogunbode et al., 2022), given that self-reported health is based on people's assessment of their mental and physical health.

Unlike the stratification analysis, regression analysis reveals age as one of the predictors of climate anxiety. Older age groups, compared with those aged 50-59 years, reported higher climate anxiety, which contradicts previous studies on the general population (Hajek & Konig, 2022; Whitmarsh et al., 2022a). Supporting our result, nevertheless, are studies reporting negative or less positive emotions in older adults, compared with younger adults (Jiang & Fung, 2019; Lallement & Lemaire, 2024). Researchers (Nestor Asiamah, Mohammad Javad Koohsari, et al., 2023; Jiang & Fung, 2019) have implied in harmony with our result that older adults would express higher negative emotions, including climate anxiety, depending on where they live. Low and middle-income cities are less resilient to climate change (Barry et al., 2018; Nangombe et al., 2019) and middle-aged and older adults in Ghana receive limited welfare support (Kpessa-Whyte, 2018). The SAVI model argues that older adults are more vulnerable to climate change than younger adults. Hence, crises are more likely to predict health problems such as climate anxiety in older adults than in younger adults. A higher climate anxiety in older adults, thus, is consistent with the argument of the SAVI model.

Notably, age predicted climate anxiety in the regression analysis owing to covariates not incorporated into the stratification analysis. It can, thus, be deduced that the relationship between age and climate anxiety is better understood with a linear regression model that incorporates demographic and socio-contextual covariates. Studies conducted in high-income European countries (Hajek & Konig, 2022; Whitmarsh et al., 2022b) reported a negative relationship between age and climate anxiety, but this study confirmed the opposite of this relationship. Ghana offers a different cultural environment where adults receive care from their less-equipped family members (Kpessa-Whyte, 2018), not from nursing and residential care homes where older adults usually receive care in European countries. Pensions and social welfare systems in Ghana are not as effective as those in Europe (Kpessa-Whyte, 2018). In a context where older people feel less protected by their families, pensions, and the social welfare system, climate anxiety would be associated with older age.

CCA, a form of climate change knowledge, was significantly associated with climate anxiety, which supports previous research (Asgarizadeh et al., 2023b; Ramírez-López et al., 2023) confirming a positive association between climate change knowledge and climate anxiety. People without CCA would know little or nothing about the adverse impacts of climate change and may, therefore, be less anxious about the climate crisis. Compared to a previously used measure of climate change knowledge (Asgarizadeh et al., 2023b), CCA comprises many differently worded questions. The confirmed relationship between CCA and climate anxiety, thus, implies the possibility of different measures of climate change knowledge predicting climate anxiety.

CCA was included in the study as a potential predictor of climate anxiety following previous studies’ recognition of similar constructs (e.g., climate change knowledge) (Asgarizadeh et al., 2023a; Ramírez-López et al., 2023) as correlates of climate anxiety. Yet, the standardised regression weights between the demographic variables (e.g., educational level) and climate anxiety significantly changed after CCA was incorporated into models 2 and 4, suggesting that CCA confounded the relationship between some of the demographic factors and climate anxiety. Only basic education was negatively associated with climate anxiety in the model without CCA (i.e., model 1). In the CCA-adjusted model, all levels of education were negatively associated with climate anxiety. Thus, our sensitivity analyses identified CCA as both a predictor and a potential cofounder, an outcome that future researchers must consider when designing their studies.

Compared with older adults without formal education, older adults with basic, secondary, and tertiary education reported lower climate anxiety. More educated people may have reported lower climate anxiety because they felt more confident and knowledgeable about navigating climate change events such as floods and extreme weather. They might have felt better prepared financially since more educated older adults in Ghana have a higher physical quality of life linked to access to health and social services (Alaazi et al., 2021). This result contrasts with evidence from studies that found no association between educational level and climate anxiety in the general population (Hajek & Konig, 2022; Wullenkord et al., 2021). Although Hajek and König found a difference in climate anxiety between educational levels, the difference became non-significant after considering covariates. In this study, the regression weights between levels of education and climate anxiety became more significant in the adjusted models, suggesting that the relationship between education and climate anxiety depended on contextual factors and CCA. Since the relationship between age and climate anxiety is consistent between the crude and adjusted regression models (see Table 4), the contextual factors and CCA did not influence it.

Climate anxiety may be explained by psychological, emotional, and physiological adaptations to climate change (Ogunbode et al., 2022; Taylor, 2020), especially among older adults who – compared with younger adults – have a higher level of positive affect (Löckenhoff & Carstensen, 2004; Strough et al., 2024). Yet, older adults with higher income and with more social support may be more resilient to climate change than others. In contexts where there are ongoing interventions against climate change, older adults would be more optimistic about the future. Such adults would look forward to a future without climate crises and may, therefore, be less anxious about climate change. Suffice it to say that the individual's level of climate anxiety could depend on positive affect or psychological factors (e.g., resilience, optimism, and self-efficacy) not considered in this study. To advance our evidence, future researchers should assess how such factors interact with demographic, contextual, and socioeconomic factors on climate anxiety.

Observed differences in climate anxiety between cities and ecosystem types were supported by our analysis of the CODA and SAN models. The differences observed were probably due to disparities in the distribution of psychosocial and built environmental factors expected to protect residents from climate change events. Owing poverty in the Northen part of Ghana, residents are highly exposed to extreme heat and perennial floods (Dovie et al., 2026; Nastar & Armah, 2026). A similar situation is experienced in Accra, where rising temperatures, perennial floods, and declining social support coexist (Adei et al., 2026; Nastar & Armah, 2026) and may be associated with climate anxiety.

4.3 Implications for practice and policy

This study unfolds the need for climate anxiety to be reduced through policy-driven initiatives. Ghana has a policy against climate change (Adu-Boateng, 2015; Lawson, 2016), but this policy undermines specific public health threats such as climate anxiety. As such, the government of Ghana should revise its climate change policy by, in part, enacting laws that mandate and equip institutions [e.g., Ghana Health Service, and Ministry of Health (MoH)] to monitor and reduce climate anxiety. Such laws would increase citizens' confidence in the repertoire of actions taken by the government against climate change. The revised climate change policy ought to advocate a reduction in health risks (e.g., climate anxiety) directly caused by climate change. It should also mandate institutions to provide specialist and diagnostic health services, communicate government actions against climate change, and build social infrastructure to protect livelihoods and foster social security.

Building social infrastructure is about developing community-level social and physical infrastructure to reduce climate anxiety. This pathway involves creating a system of social security that maximises the safety of residents from climate change events such as extreme weather. It may help reduce climate anxiety in the savanna and coastal communities, where climate anxiety may be exacerbated by residents' expectations of extreme weather. The government should make cooling of homes more affordable by reducing the cost of electricity and subsidising air conditioners in regions (e.g., savanna) experiencing heatwaves. An upstream (population-level) complementary strategy is building community cooling centres and providing free access to them (Dearman et al., 2024). Food production during climate change can be sustained by providing farmers with affordable implements, drought-resistant seeds, and breeds. Farmers ought to be trained to engage in eco-friendly and productive farming.

The unique results from ANCOVA have implications for research and practice. Individual-level factors (e.g., gender, age, and work status) may more strongly influence climate anxiety in some cities than in others. This evidence underscores a need for future studies to adjust for all possible individual-level confounders at the city level in quantifying climate anxiety. Without the ANCOVA, we would have wrongly concluded that the second-highest climate anxiety levels were in coastal cities. The result also implies that interventions supporting individuals with climate anxiety may not be more important or urgent in coastal cities than in forest zones (e.g., Koforidua, Kumasi, and Ho). Such interventions may be as essential in cities within the rainforest zone as in coastal cities.

Ghana's climate policy should empower the MoH to increase access to climate anxiety diagnostic services in Ghana. Clinical diagnostic services are needed to estimate and monitor climate anxiety levels, identify people needing treatment, and reduce climate anxiety through specialist care. To increase access to diagnostic services, the MoH must equip health facilities in each district with specialist clinical psychologists, medicines, and diagnostic tools. Research aimed at developing and validating climate anxiety diagnostic tools is needed. Treatment of climate anxiety disorders must be free-of-charge or should be paid for through Ghana's health insurance policy, since individuals experiencing climate anxiety may not utilise healthcare if it imposes out-of-pocket expenses on them.

Whereas mild or moderate climate anxiety may encourage individuals to take pro-environmental action, severe climate anxiety is a risk factor for a mental health decline and hospitalization (Hajek & Konig, 2022; Whitmarsh et al., 2022b). Individuals with severe climate anxiety are more likely to perform maladaptive behaviours such as harmful self-medication than those with mild climate anxiety. Our supplement analyses reveal that 14% of the sample reported severe climate anxiety, which has implications for the burden of healthcare and planning.

Enhancing healthcare infrastructure in the Savanna may be necessary for effectively managing the potentially higher burden of care in this area. This step is essential for eliminating any inequalities in mental health due to climate anxiety. More clinical psychologists and community mental healthcare providers may be needed in the future, especially in larger cities where the population of older adults can be expected to grow in the coming years. Training and recruitment of care providers and the expansion of care infrastructure should be driven by a policy, possibly developed through a national process of legislation. This policy should mandate and resource stakeholders to provide the requisite infrastructure and personnel for scaling up psychological care in the future. Improving the availability of the skilled personnel and infrastructure needed for treating diseases and disabilities caused by climate change events has been acknowledged as an apex public health strategy (Nestor Asiamah, Mohammad Javad Koohsari, et al., 2023; Braithwaite et al., 2024).

The stratification analysis has uncovered subgroups more vulnerable to climate anxiety. These subgroups – which include older adults living in the Savanna – may be more susceptible to mental disorders (Hajek & Konig, 2022). Hence, policies enabling health organisations to meet their needs sustainably are imperative. Support needed by older people in the savanna would increase as the population ages, so measures for effectively managing geriatric care in this context must be sustainable. The availability of qualified personnel and infrastructure for geriatric care in the savanna is necessary.

In 2010, Ghana introduced a healthy ageing policy that encourages interventions aimed at improving well-being in older people (Kpessa-Whyte, 2018), and the policy is in harmony with the above recommendations. For instance, the construction of cooling centres aligns with the policy's prioritization of the creation of age-friendly environments in Ghana. However, the non-availability of specific climate change adaptation policies for older adults in Ghana could make our recommendations unrealistic or unachievable. Ghana's fragile macro-economic situation and the government's low commitment to the welfare of older adults have been cited as barriers to the implementation of healthy ageing policies (Araujo de Carvalho et al., 2014; Kpessa-Whyte, 2018). It is, therefore, incumbent on the government to adopt a special climate change adaptation policy that prioritises older adults, create a special fund for supporting older adults to cope with the climate crisis, constitute a climate change adaptation commission or board to implement measures against climate change, and adopt an interdisciplinary framework for engaging stakeholders, including older adults, in rolling out climate change mitigation strategies.

4.4 Limitations and Strengths

Our cross-sectional design could not assess potential changes in climate anxiety over time and overcome possible confounding from other variables. Consequently, this study does not establish causation between the variables. We call for prospective or experimental studies that monitor climate anxiety over time and assess causation. Studies considering relevant contextual and socio-demographic variables not considered in this study as covariates or predictors (e.g., atmospheric temperature, humidity, and average annual rainfall) are also needed. Despite utilising a relatively large sample and a multistage sampling method, this study could not have reached results representative of all people aged 50 or over in Ghana. The results from participants in rural settings may differ, so studies utilising a nationally representative sample are needed. The sample was stratified only at the city level, so the representativeness of the sample in other subgroups was not achieved. The nested data structure precluded a statistical test (e.g., a multilevel regression model) that ideally accounts for the city-level variance. Future researchers may account for the city-level variance by utilizing the multilevel linear regression model to concurrently explore the demographic, socioeconomic, and contextual predictors of climate anxiety.

This study employed self-reported measures, which are vulnerable to recall and social desirability bias. Thus, we call for future studies utilising objective measures. Interactions among the demographic, socioeconomic, and contextual factors are probable and could be associated with climate anxiety. However, an assessment of these interactions was beyond the scope of this study. Future research may explore the interactions in different contexts. Although the ANCOVA helped minimise confounding bias, it did not incorporate unmeasured individual factors. Future researchers are encouraged to include as many covariates as possible in their analysis to maximise the statistical validity of their estimates. We compared our results with findings from previous research that employed different designs, measurement tools, and populations. The similarities or inconsistencies reported through such a comparison should be interpreted and accepted with caution. Our classification of climate anxiety scores (i.e., mild, moderate, and severe) based on previous research (Whitmarsh et al., 2022b) was not validated for the middle-aged and older adult population. The application of the method on a more vulnerable population could result in a higher prevalence of severe climate anxiety.

This study was the first to consider contextual factors in quantifying climate anxiety across multiple cities and subgroups in a country. Our incorporation of contextual factors as covariates yielded unique results and lessons for improving the design of future research. By utilising a multi-stage sampling method and a priori sample size calculation, this study minimises sampling bias. The sample used was representative of middle-aged and older city dwellers in Ghana; hence, the evidence could be generalised to this group. The sensitivity analysis performed to assess possible changes in regression weights between the crude and adjusted models offers nuanced evidence. Without this analysis, we would have wrongly confirmed “having dependants” and “worry about the increasing cost of living” as predictors of climate anxiety. Our research design was made robust with statistical and procedural processes against CMB.

5. Conclusion

Climate anxiety was higher than levels previously reported for the general population based on the same scale. The stratification analysis showed a difference in climate anxiety among seven cities, with Tamale accounting for the highest level. Failing to adjust for individual factors at the city level may lead to an overestimation of climate anxiety. Predictors of climate anxiety include climate change awareness, not having a chronic disease, older age, and full-time work. Groups and individuals who reported higher climate anxiety may need more clinical and social support to cope with the climate crisis. Future research into changes in climate anxiety levels over time is needed.

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Appendices

Appendix A1 – Items used to measure climate anxiety

No	Item	1	2	3	4	5	6	7
1	Thinking about climate change makes it difficult for me to concentrate.							
2	Thinking about climate change makes it difficult for me to sleep.							
3	I have nightmares about climate change.							
4	I find myself crying because of climate change.							
5	I think, "why can't I handle climate change better?							
6	I go away by myself and think about why I feel this way about climate change.							
7	I write down my thoughts about climate change and analyze them.							
8	I think, "why do I react to climate change this way?"							
9	My concerns about climate change make it hard for me to have fun with my family or friends.							
10	I have problems balancing my concerns about sustainability with the needs of my family.							
11	My concerns about climate change interfere with my ability to get work or school assignments done.							
12	My concerns about climate change undermine my ability to work to my potential.							
13	My friends say I think about climate change too much.							

Note: 1 – not at all, 2 – practically never, 3 – seldom, 4 – sometimes, 5 – most of the time, 6 – almost always, and 7 – always

Appendix A2: Items used to measure climate change awareness

SN	Statement	1	2	3	4	5
1	Permanent changes in the habitats or environments of animals are some of the consequences of global warming					
2	I am aware that global warming is caused by human activities					
3	I am aware that the warm weather nowadays lasts longer each year					
4	I am amazed by people who are unaware of how dangerous climate change is					
5	I am aware that floods will occur if the temperature of the world increases					
6	I am aware that most emissions of greenhouse gases (i.e., gases that cause global warming) are caused by people’s use of fossil fuels such as petrol					
7	I am aware that greenhouse gases such as nitrous oxide used in vehicles increase global warming					
8	It will make me happy to see the creation of new businesses that seek to produce environment-friendly energy options					
9	I am aware that methane and carbon dioxide are natural greenhouse gases					
10	I am worried about energy waste					
11	I would like to improve my knowledge on combating climate change					
12	I am aware that less consumption of energy from fossil fuels slows down global warming					
13	I am not worried about the number of hungry people in the world due to climate change					
14	I am not concerned about problems (e.g., flooding and extreme temperatures) faced by people due to climate change					
15	I am not interested in the disappearance of animal species due to climate change					
16	I think that global climate change will not cause drought in my country					
17	I don’t think expected rises in the level of the sea is due to global warming					

Note: 1 – strongly disagree, 2 – disagree, 3 – somewhat agree, 4 – agree, and 5 – strongly agree

Appendix A3. Operational definitions and coding scheme of categorical variables

Variable	Definition	Categories	Codes
Gender	Whether the participant identified as a man or a woman	men, and women	Men – 1; women – 2
Work status	Whether the participant was a full-time, part-time, or retired employee	Full-time, part-time, and retired	Full-time – 1; part-time – 2; retired – 3
Educational level	The highest formal educational level achieved by the participant	None, primary, secondary, and tertiary	None – 1; primary – 2; secondary – 3; tertiary – 4
Income (₵)	The individual’s net monthly income	<500, 500-1000, 1001-1500, 1501-2000, above 2000	less than 500 – 1; 500-1000 – 2; 1001-1500 – 3; 1501-2000 – 4; above 2000 – 5
Age group (yrs)	The age group to which the individual belonged	50-59, 60-69, 70-79, 80+	50-59 – 1; 60-69 – 2; 70-79 – 3; 80+ – 4
Chronic disease status	Whether the individual had at least one clinically diagnosed chronic disease	None, one or more	None – 1; one or more – 2
Marital status	Whether the individual was married or not	Not married, married	Not married – 1; married – 2
Self-reported health	Whether the individual perceived their health to be good or poor	Poor, good	Poor (1); good – 2

Worry about the increasing cost of living	Whether the individual was worried about the increasing cost of living in Ghana	No, yes	No – 1; yes – 2
Having dependants	Whether the individual had at least one dependant or not	No, yes	No – 1, yes – 2
City	The city where the participant permanently resided	Accra, Ho, Koforidua, Kumasi, Tamale, Wa, Cape Coast	Accra – 1; Ho – 2; Koforidua – 3; Kumasi – 4; Tamale – 5; Wa – 6; Cape Coast – 7
Urban status	Whether the city where the participant lived permanently was completely urban	Rural-urban*, urban	Rural-urban – 1; urban – 2
City population size	Whether the population of people in the city where the participant lived permanently was less than 200000 (i.e., small) or greater than 200000 (i.e., large)	Small, large	Small – 1, large – 2
City population density	Whether the population density of the city where the participant lived permanently was less than 1000 people/sq kms (i.e., low), between 1000 and 5000 people/ sq kms (i.e., moderate), or greater than 5000 people/ sq kms (i.e., high)	Low, moderate, high	Low – 1, moderate – 2, and high – 3
Ecosystem type	Whether the city where the participant lived was in the northern savanna (i.e., savanna), in a rainforest zone in the middle belt (i.e., rainforest), or was by the sea in the south (i.e., coastal)	Savanna, rainforest zone, coastal	Savanna – 1; rainforest zone – 2; coastal – 3

*a rural-urban city was predominantly urban but has some suburbs that were classified as rural areas; sq – square; kms – kilometres

Appendix A4. Table showing Cronbach's alpha coefficients as well as factor loadings and average variances extracted from the CFA

Items	Loadings	Cronbach's alpha	AVE
Cognitive-emotional impairment			
Thinking about climate change makes it difficult for me to concentrate.	0.738	0.94	0.651
Thinking about climate change makes it difficult for me to sleep.	0.798		
I have nightmares about climate change.	0.877		
I find myself crying because of climate change.	0.868		
I think, "why can't I handle climate change better?	0.792		
I go away by myself and think about why I feel this way about climate change.	0.779		
I write down my thoughts about climate change and analyse them.	0.760		
I think, "why do I react to climate change this way?"	0.715		
Functional impairment			
My concerns about climate change make it hard for me to have fun with my family or friends.	0.844	0.91	0.641
I have problems balancing my concerns about sustainability with the needs of my family.	0.820		
My concerns about climate change interfere with my ability to get work or school assignments done.	0.863		
My concerns about climate change undermine my ability to work to	0.847		

my potential.			
My friends say I think about climate change too much.	0.727		

Note: CFA – confirmatory factor analysis; AVE – average variance extracted

Appendix B1. Results of multiple comparison tests following ANOVA

Group (I)	Groups (J)	Mean Difference (I-J)	SE	p	95% CI	
					Lower Bound	Upper Bound
Work status						
full-time	part-time	.18739*	0.061	0.006	0.04	0.33
	retired	.54324*	0.061	0.000	0.40	0.69
part-time	full-time	-.18739*	0.061	0.006	-0.33	-0.04
	retired	.35585*	0.072	<.001	0.18	0.53
retired	full-time	-.54324*	0.061	0.000	-0.69	-0.40
	part-time	-.35585*	0.072	<.001	-0.53	-0.18
Educational level						
none	basic	.42815*	0.140	0.015	0.06	0.80
	secondary	0.22685	0.129	0.395	-0.12	0.57
	tertiary	0.22999	0.127	0.356	-0.11	0.57
basic	none	-.42815*	0.140	0.015	-0.80	-0.06
	secondary	-0.20129	0.081	0.078	-0.42	0.01
	tertiary	-0.19815	0.077	0.061	-0.40	0.01
secondary	none	-0.22685	0.129	0.395	-0.57	0.12
	basic	0.20129	0.081	0.078	-0.01	0.42
	tertiary	0.00314	0.055	1.000	-0.14	0.15
tertiary	none	-0.22999	0.127	0.356	-0.57	0.11
	basic	0.19815	0.077	0.061	-0.01	0.40
	secondary	-0.00314	0.055	1.000	-0.15	0.14
City						
Accra	Ho	.55166*	0.076	<.001	0.32	0.78
	Koforidua	.61291*	0.079	<.001	0.37	0.85
	Kumasi	.23384*	0.061	0.003	0.05	0.42
	Tamale	-2.13810*	0.089	0.000	-2.41	-1.87
	Wa	0.28488	0.098	0.074	-0.01	0.58
	Cape Coast	-0.01654	0.074	1.000	-0.24	0.21
Ho	Accra	-.55166*	0.076	<.001	-0.78	-0.32
	Koforidua	0.06125	0.078	1.000	-0.17	0.30
	Kumasi	-.31782*	0.059	<.001	-0.50	-0.14
	Tamale	-2.68976*	0.087	0.000	-2.95	-2.42
	Wa	-0.26678	0.096	0.115	-0.56	0.03
	Cape Coast	-.56820*	0.073	<.001	-0.79	-0.35
Koforidua	Accra	-.61291*	0.079	<.001	-0.85	-0.37
	Ho	-0.06125	0.078	1.000	-0.30	0.17
	Kumasi	-.37907*	0.063	<.001	-0.57	-0.19
	Tamale	-2.75101*	0.090	0.000	-3.03	-2.48
	Wa	-.32803*	0.099	0.021	-0.63	-0.03
	Cape Coast	-.62945*	0.076	<.001	-0.86	-0.40
Kumasi	Accra	-.23384*	0.061	0.003	-0.42	-0.05
	Ho	.31782*	0.059	<.001	0.14	0.50
	Koforidua	.37907*	0.063	<.001	0.19	0.57
	Tamale	-2.37194*	0.075	0.000	-2.60	-2.14

	Wa	0.05104	0.085	1.000	-0.21	0.31
	Cape Coast	-.25038*	0.057	<.001	-0.42	-0.08
Tamale	Accra	2.13810*	0.089	0.000	1.87	2.41
	Ho	2.68976*	0.087	0.000	2.42	2.95
	Koforidua	2.75101*	0.090	0.000	2.48	3.03
	Kumasi	2.37194*	0.075	0.000	2.14	2.60
	Wa	2.42298*	0.107	0.000	2.10	2.75
	Cape Coast	2.12156*	0.086	0.000	1.86	2.38
Wa	Accra	-0.28488	0.098	0.074	-0.58	0.01
	Ho	0.26678	0.096	0.115	-0.03	0.56
	Koforidua	.32803*	0.099	0.021	0.03	0.63
	Kumasi	-0.05104	0.085	1.000	-0.31	0.21
	Tamale	-2.42298*	0.107	0.000	-2.75	-2.10
	Cape Coast	-.30142*	0.095	0.034	-0.59	-0.01
Cape Coast	Accra	0.01654	0.074	1.000	-0.21	0.24
	Ho	.56820*	0.073	<.001	0.35	0.79
	Koforidua	.62945*	0.076	<.001	0.40	0.86
	Kumasi	.25038*	0.057	<.001	0.08	0.42
	Tamale	-2.12156*	0.086	0.000	-2.38	-1.86
	Wa	.30142*	0.095	0.034	0.01	0.59
City population density						
Low	Moderate	.46076*	0.066	<.001	0.30	0.62
	High	.38281*	0.062	<.001	0.24	0.53
Moderate	Low	-.46076*	0.066	<.001	-0.62	-0.30
	High	-0.07795	0.052	0.348	-0.20	0.05
High	Low	-.38281*	0.062	<.001	-0.53	-0.24
	Moderate	0.07795	0.052	0.348	-0.05	0.20
Ecosystem type						
Savanna	Rain forest	1.17531*	0.07	0.000	1.00	1.35
	Coastal	.72649*	0.08	0.000	0.54	0.92
Rain forest	Savanna	-1.17531*	0.07	0.000	-1.35	-1.00
	Coastal	-.44883*	0.05	0.000	-0.56	-0.34
Coastal	Savanna	-.72649*	0.08	0.000	-0.92	-0.54
	Rain forest	.44883*	0.05	0.000	0.34	0.56

*mean difference significant at p<0.05; Group (I) – the category being compared to the other categories within a variable; Groups (J) – the other categories of the variable being compared to "Group (I)"; SE – standard error; CI – confidence interval.

Appendix B3. Results of multiple comparison tests following ANCOVA

(I) City	(J) City	Mean Difference (I-J)	Std. Error	Sig. b	95% CI for Difference. b	
					Lower Bound	Upper Bound
Accra	Ho	-0.022	0.100	1.000	-0.315	0.271
	Koforidua	0.258	0.122	0.523	-0.101	0.616
	Tamale	-2.063*	0.102	<.001	-2.362	-1.764
	Wa	-0.092	0.092	1.000	-0.362	0.178
	Cape Coast	-0.216	0.076	0.066	-0.439	0.007
Ho	Accra	0.022	0.100	1.000	-0.271	0.315
	Koforidua	0.28	0.122	0.333	-0.079	0.639
	Tamale	-2.041*	0.112	<.001	-2.371	-1.711
	Wa	-0.07	0.098	1.000	-0.358	0.218

	Cape Coast	-0.194	0.091	0.489	-0.461	0.073
Koforidua	Accra	-0.258	0.122	0.523	-0.616	0.101
	Ho	-0.28	0.122	0.333	-0.639	0.079
	Tamale	-2.320*	0.130	<.001	-2.702	-1.938
	Wa	-0.349	0.122	0.061	-0.706	0.007
	Cape Coast	-.474*	0.122	0.002	-0.834	-0.114
Tamale	Accra	2.063*	0.102	<.001	1.764	2.362
	Ho	2.041*	0.112	<.001	1.711	2.371
	Koforidua	2.320*	0.130	<.001	1.938	2.702
	Wa	1.971*	0.109	<.001	1.652	2.290
	Cape Coast	1.846*	0.093	<.001	1.572	2.121
Wa	Accra	0.092	0.092	1.000	-0.178	0.362
	Ho	0.07	0.098	1.000	-0.218	0.358
	Koforidua	0.349	0.122	0.061	-0.007	0.706
	Tamale	-1.971*	0.109	<.001	-2.290	-1.652
	Cape Coast	-0.125	0.087	1.000	-0.379	0.130
Cape Coast	Accra	0.216	0.076	0.066	-0.007	0.439
	Ho	0.194	0.091	0.489	-0.073	0.461
	Koforidua	.474*	0.122	0.002	0.114	0.834
	Tamale	-1.846*	0.093	<.001	-2.121	-1.572
	Wa	0.125	0.087	1.000	-0.130	0.379

Based on estimated marginal means; * The mean difference is significant at the .05 level; b Adjustment for multiple comparisons: Bonferroni.