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Are Egypt’s Elderly Prepared for A Warmer Future?

Studying the Nexus Between Climate Change and the Wellbeing of Elderly in Egypt

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Are Egypt's Elderly prepared for a warmer future? Studying the nexus between climate change and the wellbeing of elderly in Egypt.

Amira Elayouty[1] and Hala Abou-Ali[2]

Abstract

Egypt is warming rapidly, raising concerns about the vulnerability of its growing elderly population. This study examines how short- and long-term climate exposures shape the wellbeing of older adults by linking district-level temperature, humidity, and precipitation data with individual responses from the 2023 Egypt Labour Market Panel Survey (ELMPS). The results show that short-term increases in maximum temperature and humidity significantly reduce mental wellbeing, with an amplified adverse effect when both rise concurrently. Long-term exposure to persistently high temperatures and humidity also imposes a chronic burden, while precipitation has no measurable influence. Spatial modelling reveals minimal residual geographic clustering once climate, demographic, and health factors are accounted for, indicating that remaining contextual influences are highly localized. The findings underscore the need for climate-sensitive public health measures, including heat warnings, improved indoor cooling, and pollution reduction, to protect older Egyptians as climate variability intensifies.

Keywords: climate change; elderly; wellbeing

1. Introduction

Over the past two decades, Egypt has experienced a pace of warming that surpasses the global average. Between 2000 and 2020, national average annual temperatures increased by about 0.38 degrees Celsius per decade, exceeding the world average (IEA, 2023). This warming trend places Egypt among the most climate vulnerable countries in the Middle East and North Africa (MENA) region, facing more frequent and intense heatwaves, coastal storms along the Mediterranean, dust storms and extreme weather events. These changes put further stress on the limited water resources and threaten food security, exacerbated by Egypt's large population and heavy reliance on the Nile River waters. Many previous studies have explored the environmental, economic and health impacts of climate change, with a particular focus on children (Elayouty, Abou-Ali and Hawash, 2022), money metric poverty (Abou-Ali, Elayouty and Ramadan, 2025) and the labour force

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(Abou-Ali et al., 2022), less is known about the social and health impacts of climate change, on elderly as one of the fastest growing and most vulnerable demographic groups in Egypt.

This research gap is striking given Egypt's current demographic transition. The share of individuals aged 60 years and above is projected to nearly triple, rising from 6.6% in 2022 to 17.9% in 2052 (CAPMAS, 2022). The ageing population coupled with challenges in terms of social protection policies and public health care systems, where only one third of older adults are covered by pensions, and health services, especially in rural areas, remain unevenly distributed and under-resourced (UNFPA, 2024). These features heighten the vulnerability of older population group and reduce their adaptive capacity to climate related stressors.

A growing body of international literature underscores the augmented vulnerability of elderly to climate hazards such as heatwaves, air pollution, disease outbreaks and disruptions of food systems and essential public services like electricity and healthcare (Singer, Shoreman-ouimet and Graham, 2022). Physiological factors such as reduced thermoregulatory capacity, chronic illness, immunosenescence and neurocognitve decline, compound the risks facing older adults (Kalaiyarasi and Rajumar, 2020; Sonia and Ismail, 2023). At the same time, psychosocial and environmental determinants, including social isolation, limited mobility, inadequate housing, and financial insecurity, shape the ability of older adults to anticipate, respond to, and recover from climate shocks.

Recent interdisciplinary reviews emphasise that the climate health relationship for elderly individuals is not limited to mortality but extends to cognitive, psychological, and social dimensions of wellbeing (Print et al., 2024; Cremonini and Georgiadis, 2025). However, these insights remain fragmented across disciplinary silos, with limited integration of environmental science, public health, gerontology and social policy. Climate hazards such as drought, wildlife, sea-level rise, and extreme weather events, though widely studied in high income countries, are unevenly examined in low- and middle-income countries (LMICs), where vulnerabilities are often more severe. In high income settings, such as Canada, studies highlight the importance of early warning systems, resilient infrastructure, and community-based support in reducing climate related risks for older adults (Ostapchuk et al., 2015; Madani Hosseini, Zargoush and Ghazalbash, 2024). These studies call for vulnerability mapping and improved metrics to identify high risk elderly populations. Still the evidence predominantly reflects contexts where institutional safety nets are strong. Far less is known about how older adults in LMICs cope with climatic stressors in environments with limited healthcare access, weaker social protection, and substantial socioeconomic disparities.

Research on how residential settings, housing conditions, neighbourhood infrastructure and urban versus rural environments shape older adults' climate vulnerability is also emerging but remains limited (Molinsky and Forsyth, 2023). These studies highlight that vulnerabilities vary widely across local contexts, suggesting that place of residence matters for exposure, sensitivity, and adaptive capacity. This insight is highly relevant for Egypt, where inequalities across districts, especially between urban and rural areas are substantial.

Studies examining mental wellbeing among the elderly in Egypt pint an inconclusive picture of place-based vulnerabilities. El-Gilany, Elkhawaga and Sarraf (2018), reported higher levels of depression among urban elderly in the Mansoura District of Lower Egypt, whereas Ali et al. (2018), studying older individuals in Sohag, Upper Egypt, identified rural residence as a risk factor for depression. Research from Fayoum found no statistically significant differences between rural and urban elderly (El-Sherbiny, Younis and Masoud, 2016). This mixed evidence suggests the need for finer spatial analysis and suggests that local socioeconomic conditions, environmental stressors, and access to services may jointly define wellbeing outcomes.

Empirical evidence on climate and elderly wellbeing linkages in Egypt is sparse. While several studies examined social integration, living arrangements and support systems among older Egyptians (Khader, 1997 and Khader, 2011), these works do not explicitly link climate exposure to health or wellbeing outcomes. Only a cross-sectional study by Abdullah, Esmat and Hasaneen (2022) on adults aged 60 above in Cairo and Al-Fayoum governorates showed that 56.8% of the total health status of older adults related to climate change was good and 43.2% was poor. The study also concluded that about 16.8% of the sample has good knowledge about climate change, 40% had moderate knowledge, and 43.2% had poor knowledge. The study found a highly significant statistical correlation between knowledge and adaptive practices of older adults, suggesting that awareness and behavioural adjustments play a critical role in shaping resilience. However, the pathways through which climate variability affects elderly wellbeing in Egypt remain poorly understood.

This paper addresses these critical gaps by analysing how climate change influences the physical and mental wellbeing of elderly in Egypt. It draws on data from the 2023 wave of Egypt Labour Market Panel Survey (ELMPS), combined with gridded satellite climate data, including temperature, humidity, and precipitation. The analysis aims to identify the pathways through which changes in climate affect the quality of life among the older population and the dimensions of elderly wellbeing that are most sensitive to climate stressors. Th study also test for inequalities across the country and examine geographic and socio-economic disparities, by urban-rural, gender and education, to assess whether and how climate change impacts the wellbeing among older Egyptians.

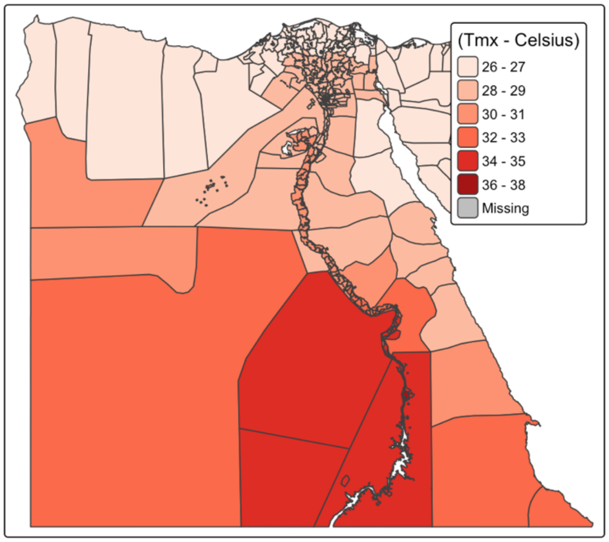
By linking climate exposure to micro-level wellbeing outcomes and embedding the analysis within Egypt's evolving democratic, socio-economic and environmental context, this study offers the first nationwide empirical assessment of whether older Egyptian are prepared for an increasingly warmer and more volatile climate. The remainder of this paper is organised as follows. Section 2 describes the data available for the analysis. Section 3 outlines the methodological framework. Then, the results are presented in Section 4, and finally, Section 5 concludes.

2. Data

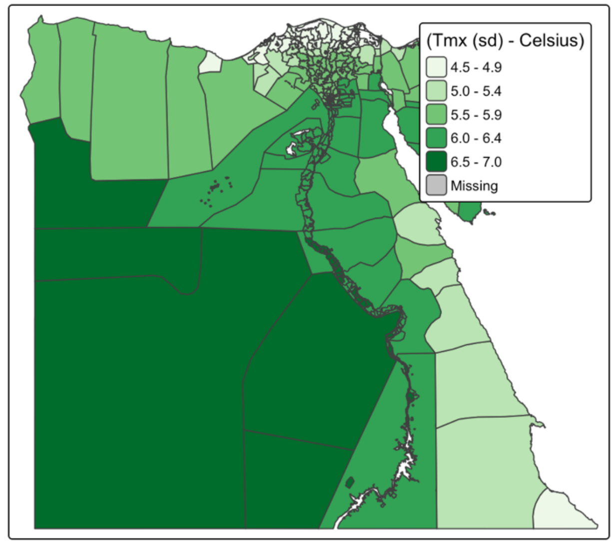
This paper relies on data from the 2023 wave of ELMPS, which captures 70,636 individuals and 17,784 households. The ELMPS is considered the main source of publicly available labour market and human development microdata in Egypt. The nationally representative ELMPS dataset was collected as a joint effort of the Economic Research Forum (ERF) and the Central Agency for Public Mobilization & Statistics (CAPMAS) in Egypt (OAMDI, 2024). The dataset provides rich information on employment, income sources, earnings and pensions; yet it also includes other various modules encompassing questions and indicators for physical and mental health, housing conditions, food security, residential mobility, and access to healthcare and social safety net programs. In this research, we will focus on individuals aged 50 and above, which makes up a total of 11284 elderly adults across 22 governorates in Egypt, excluding the frontier governorates. After removing observations with missing values for the relevant variables, the sample is reduced to 11224 individuals of interest. Mental wellbeing indicators are extracted as response variables, complemented by a set of control variables capturing general health status and the socio-economic and demographic characteristics of individuals. To ensure that the findings of our study accurately reflect the broader Egyptian population, we accounted for the survey's complex sampling design, including stratification, clustering, and non-response/attrition, using the individual expansion sampling weights available within the ELMPS dataset throughout the whole steps of analysis.

To measure climate exposure, the ELMPS data are integrated with high-resolution, geocoded satellite data on maximum temperature (in degree Celsiuis - ^{o}C), precipitation (in millimetres - mm), and vapour pressure (in hectopascals - hPa) from the Climate Research Unit (CRU) at University of East Anglia. The vapour pressure is a proxy for humidity level. Relative humidity is defined as the ratio of vapour pressure (in hPa) to the saturation vapour pressure at a given temperature, typically expressed as a percentage. These data are monthly observations available at $0.5^{o}\times0.5^{o}$ resolution. Thus, they permit the calculation of 10-year averages of monthly climate variables as well as the temperature variability over the decade past the survey year as a proxy for the long-term climate conditions across Egypt districts. To assess the short-term climate conditions that may immediately influence the mental wellbeing of elderly, we extract the climate variables for the visiting month of the interview date and the month before for each respondent. These data are matched to the second administrative level identifiers (Markaz/Kism) of the ELMPS respondents. Climate exposure is then assigned based on the interview date. For interviews conducted within the first 10 days of the months, the respondent is assigned the climate variables from the preceding month. For an interview between the 11^{th} and 20^{th} of the month, short-term climate variables are calculated as the average of the past and current month. Finally, for a respondent taking an interview starting from the 21^{st} onward, respondents are assigned the climate variables of the current month.

Figure 1 displays the long-term climate variables across the different areas in Egypt which do not vary between households/individuals in the same district, but they do vary across districts capturing the geographic differences in climate across Egypt. As expected, the major direction of



(a)



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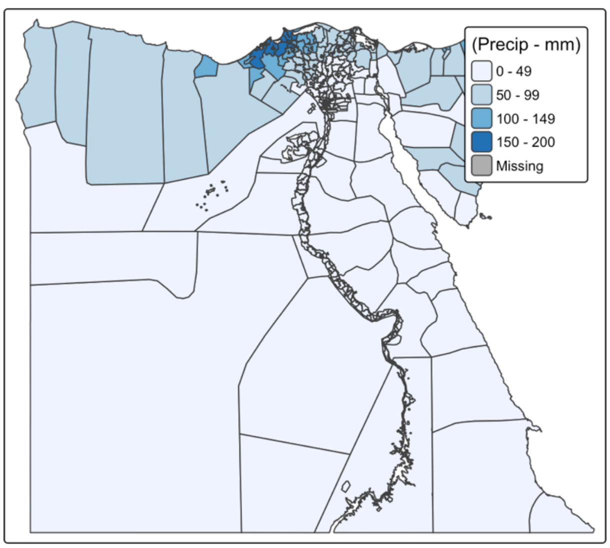
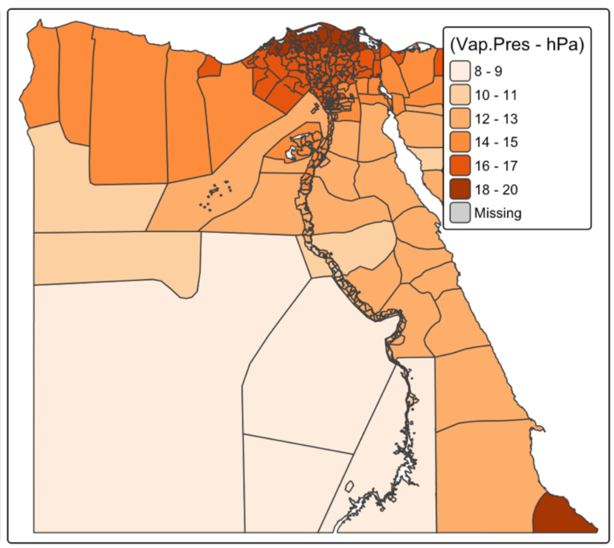


(c)



(d)

Figure 1: Maps for the spatial distribution of key climate indicators - (a) the mean of the monthly maximum temperature, (b) the standard deviation of the monthly maximum temperature, (c) the mean of the yearly precipitation, and (d) the mean of the monthly vapour pressure - across Egypt's second administrative level.

variability in climate across Egypt is from south to north. The south of Egypt is generally hotter than its north, yet the north coast of Egypt has significantly more rainfall than the rest of the country. The annual average rainfall in the northern coastal region in the past decade is typically between 50 and 150 millimeters (mm) and can be up to 200 mm/year in cities like Alexandria. In contrast, areas south of Cairo often receive nearly 0 mm of rain annually. As for humidity, it reaches its highest levels at the north of the Delta. Humidity also varies and increases from west to east of the country as we move far from the western desert. It is evident from the figure that the variability in maximum temperature over the past decade is higher in Upper Egypt relative to Lower Egypt; see Figure 1 - panel (b). Given these discrepancies in climate across the country, alongside the demographic and socio-economic disparities, individuals and especially vulnerable groups such as the elderly people are likely to experience more difficulties in adapting to changes in climate. These considerations underscore the importance of assessing the relationship between the mental wellbeing of elderly in Egypt and both the long-term climate conditions and short-term climate exposures.

To achieve the above research objectives, first an indicator for elderly wellbeing in Egypt is constructed. Second, the impacts of climate variability on the wellbeing of older Egyptians across Egypt is investigated using a mixed effects statistical model framework, accounting for both individual level characteristics and regional variation. Up to our knowledge, this is the first study that investigates the impacts of climate on elderly in Egypt using ELMPS.

3. Methodology

The study examines how long-term and short-term climate exposures influence the wellbeing of elderly in Egypt, controlling for the socio-economic, demographic, and health heterogeneities. It also identifies climate-sensitive areas and maps the geographic disparities in elderly wellbeing that remain after controlling for climate and other confounding variables.

Our response variable is the mental wellbeing of elderly measured in the ELMPS using 5 item-questions: (1) “I have felt cheerful and in good spirits,” (2) “I have felt calm and relaxed,” (3) “I have felt active and vigorous,” (4) “I woke up feeling fresh and rested,” and (5) “My daily life has been filled with things that interest me”. Respondents answer these questions on a six-points scale ranging from 1 ``All of the time” to 6 ``At no time”. To construct an overall indicator of mental wellbeing, the scores for all 5 questions are reverse coded then summed for each individual, where a small value indicates a poor mental wellbeing, and a high score implies a better mental wellbeing. To validate the consistency of the scale, we calculated Cronbach’s alpha, which is found equal to 0.9 highlighting a strong consistency.

To achieve the study objectives, three models are fitted. The first model is an Ordinary Least Squares (OLS) regression which models the relationship between mental wellbeing and short- and long- term climate exposures, controlling for the general health of the respondents as well as their socio-economic and demographic characteristics. The second model is a multilevel model which models the relationship between climate and mental wellbeing at the individual level as nested in districts by allowing for a random intercept for each district to capture systematic differences between districts. The third model is a multilevel model too, yet it considers the possible spatial dependence between districts across Egypt. The last model is better fitted within a Bayesian framework as shown later in the next section. Therefore, the goodness of fit of the three models is compared with the aid of Deviance Information Criteria (DIC) and Widely Applicable Information Criteria (WAIC) for fairness. The two criteria are Bayesian model comparison balancing the model's goodness of fit with its complexity such that a lower DIC or WAIC indicates a better performing model. Both criteria indicated the overperformance of the third model above the first and second models in fitting the mental wellbeing of elderly across Egypt; see Table 1. This result highlights the persisting spatial structure in the data after accounting for the effect of climate on elderly mental wellbeing.

Table 1. Goodness of fit Criteria of the OLS model, multilevel (mixed effects) model and multilevel spatial model.

Model	Deviance Information Criteria (DIC)	Widely Applicable Information Criteria (WAIC)
OLS (fixed effects model)	69376	69375
Multilevel (mixed effects model)	69339	69339
Multilevel spatial (spatial mixed effects model)	67666	67663

Following from this result, the paper will focus on describing the formulation and estimation of the multilevel spatial model. Let y_{ij} be the mental wellbeing overall score for individual i in district j at the second administrative level. The response y_{ij} can be assumed to be normally distributed with mean η_{ij} and variance σ^2, that is $y_{ij} \sim N(\eta_{ij}, \sigma^2)$, where η_{ij} is a linear predictor that can be expressed as follows:

$$\eta_{ij} = \boldsymbol{x}_{ij}^{\top}\beta + \boldsymbol{z}_j^{\top}\gamma + \omega_j, \quad (1)$$

where $\boldsymbol{x}_{ij}^{\top}$ is the vector of individual-level covariates including the short-term climate variables e.g. maximum temperature, precipitation and vapour pressure (as a proxy for humidity) of the month past the interview date, general health score, in addition to the demographic and socio-economic characteristics, e.g. age, gender, education level, wealth quintile, urban/rural residence. $\boldsymbol{z}_j^{\top}$ denotes the vector of long-term climate variables common to the individuals within the same district j, e.g. the monthly maximum temperature, precipitation and vapour pressure averaged over the 10-years before the survey, namely, from 2013 to 2022. In the above model, ω_j is the random effect for district j. For each district, the random effect w_j can be divided into spatially structured random effect u_j and unstructured random effect v_j according to the Besag-York-Mollié (BYM) model (Besag, York and Mollié, 1991).

The BYM model considers the possibility of data to be spatially correlated and observations in neighbouring areas to be more similar than observations far apart. This model decomposes the random effect ω_j into a spatial random effect u_j smoothing the data according to a neighbourhood structure and an unstructured random effect v_j accounting for the uncorrelated noise as independent and identically distributed errors across the different areas or districts, such that $\omega_j = u_j + v_j$. One major problem with this model is that the two components are not independent, which makes it difficult to separate them and interpret the relative contribution of spatial versus unstructured variation. Therefore, a reparameterization of this model was proposed by Riebler et al. (2016) such that:

$$\omega_j = \sqrt{\frac{\phi}{\tau}} u_j^* + \sqrt{\frac{1-\phi}{\tau}} v_j^*, \quad (2)$$

where u_j^* and v_j^* are scaled versions of the spatially-structured and unstructured random effects, respectively; $\phi \in [0,1]$ is the mixing parameter controlling the proportion of variance attributed to the spatial component, such that a value of ϕ close to 1 implies that almost all variation is spatially structured and a value close to zero implies independence; and τ is the overall precision (inverse of the variance) of the district effects.

As mentioned above, the unstructured component v_j^* is usually modelled as independent and identically distributed random Gaussian noise to account for local heterogeneity; that is:

$$v_j^* \sim N(0, \xi^2). \quad (3)$$

In contrast, the spatially structured component u_j^* is modelled using an Intrinsic Conditional Auto-Regressive (ICAR) prior. This model implies that the conditional distribution of a district's random effect, given all effects in all other districts, depends only on the random effects of its neighbours as follows:

$$u_j^* | u_{-j}^*, \sigma_u^2 \sim N\left(\frac{\sum_{k \sim j} u_k^*}{d_j}, \frac{\sigma_u^2}{d_j}\right), \quad (4)$$

where u_{-j}^* are the spatially structured random effects in all districts except district j, σ_u^2 is the variance of the random effect u controlling the smoothness of the spatial structure, and d_j is the number of neighbours for district j. Accordingly, the mean effect of u_j^* is equal to the average effect of its neighbours and its variance decreases as the number of neighbours increases.

Defining the above ICAR model for spatially structured component u_j^* requires the definition of a neighbourhood structure encoded as an adjacency matrix $\boldsymbol{W}$ with elements w_{jk} defined as follows:

$$w_{jk} = \begin{cases} 1 & if\ district\ j\ and\ k\ share\ a\ boundary, \\ 0 & otherwise. \end{cases}$$

Thus, the number of neighbours for district j denoted by d_j can be calculated as $\sum_k w_{jk}$.

The above model specification is often estimated under a Bayesian framework using the Integrated Nested Laplace Approximations (INLA), introduced by Rue, Martino and Chopin (2009), by initially specifying prior distributions for σ^2, ξ^2, ϕ and τ. By reviewing the literature, we found that the prior distributions for these parameters are often determined by the penalized complexity priors (Simpson et al. 2017). For more details on the estimation procedure and the choice of priors see Blangiardot and Cameletti (2015).

4. Results

The mental wellbeing score of the elderly respondents aged 50 and above in the ELMPS dataset, excluding those from the Frontier governorates, averages 18 points on a scale ranging from 5 for poor mental wellbeing to 30 for good mental wellbeing. Figure 2 displays the spatial distribution of the mental wellbeing of elderly across Egypt districts, revealing substantial geographic variation. Also, Moran's I statistic (a measure of spatial dependence) is found equal to 0.3 with a p-value < 0.05, indicating a potential global spatial structure in the data and supporting the use of spatial mixed effects model. The selected sample of elderly has an average age of 62 years old, and an approximately equal gender distribution with 49% being males and 51% are females. Urban and rural residents are also represented in nearly equal portions. Education attainment is generally low, with 44% of the older adults being illiterate, and only 14% are university graduates. Additionally, 55% report having a chronic illness, and of these, 41% identify cardiovascular or respiratory conditions.

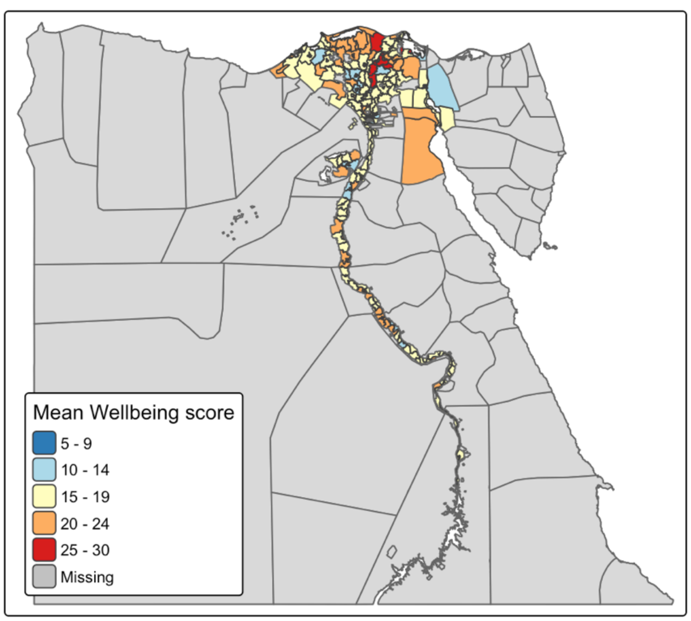


Figure 2: Map of the average mental wellbeing score of elderly across Egypt second level administrative areas, excluding the Frontier governorates and districts without observations (coloured in grey).

The climate variables also exhibit substantial spatial trends and variability across Egypt. The average long term maximum temperature over the decade preceding the survey ranges between 26ºC to 36ºC and is clearly trending upwards. Over the same period (2013-2022), the average 10-year precipitation is highly variable across the country and ranges between 0 and 184 mm, while the average vapour pressure (a measure for humidity) ranges between 10 and 18 hPa. More details on the spatial variability of these climate variables across Egypt districts can be inferred from Figure 1. Short-term climate exposure displays even greater spatial variability. The mean short term maximum temperature exposure is 32ºC, spanning from 20ºC to 42ºC, while the average short-term precipitation level is 1.55 mm, ranging between a minimum of 0 and a maximum of 55mm. The summary statistics for all variables in the study are summarized in Table 1.

Table 1: Summary statistics of the mental wellbeing among elderly in Egypt and its determinants.

Variable	n. Obs.	Mean	Std. Dev.	Min.	Max.
Mental Wellbeing	11224	17.8	6.14	5	30
Sex: Female	11224	0.51	--	0	1
Education: Illiterate	11214	0.44	--	0	1
Education: Less than intermediate	11214	0.19	--	0	1
Education: Less than University	11214	0.23	--	0	1
Education: University or above	11214	0.14	--	0	1
Residence: Urban	11224	0.49	--	0	1
Wealth Score	11217	-0.10	0.92	-1.96	3.92
Age	11224	62.7	9.4	50	99
General Health	11224	3.74	0.90	1	5
Chronic Illness: NO	11224	0.45	--	0	1
Long-term mean max temperature	11224	29.41	2.43	26.09	36.27
Long-term mean humidity	11224	15.40	2.38	9.65	18.17
Long-term mean precipitation	11224	46.65	53.42	0.36	183.85
Long-term max temperature std. dev	11224	5.86	0.62	4.62	6.62
Short-term max temperature exposure	11224	32.3	3.57	19.99	42.25
Short-term precipitation exposure	11224	1.55	3.45	0	54.53
Short-term humidity exposure	11224	19.4	3.43	7.282	26.95

As mentioned above, a spatial multi-level model is fitted for the mental wellbeing overall score accounting for the spatial dependence between districts across Egypt. Note that all continuous predictors in the model are standardized before fitting the model to ensure better interpretability, numerical stability, and comparability of regression coefficients. The results of the fitted model are presented in Table 2. The table displays the mean of the posterior distribution of the estimated coefficients along with 95% credible interval. A coefficient is considered significant at 5% significance level if the zero is not included within the 95% credible interval limits.

Table 2. Estimated coefficients of the multilevel spatial model fitted to the mental wellbeing of elderly people aged 50 or above with main effects of temperature and humidity only.

Variable	Mean	St. Dev	0.025 quantile	0.975 quantile	Sig at α =10%
Intercept	17.562	0.135	17.298	17.826	YES
Sex: Female	-0.047	0.002	-0.052	-0.043	YES
Education: Less than intermediate	0.207	0.003	0.201	0.214	YES
Education: Less than University	0.126	0.003	0.119	0.132	YES
Education: University or above	0.236	0.004	0.227	0.244	YES
Residence: Urban	-0.061	0.005	-0.071	-0.051	YES
Wealth Score	0.752	0.001	0.749	0.755	YES
Age	-0.238	0.001	-0.240	-0.235	YES
General Health	2.367	0.001	2.364	2.370	YES
Chronic Illness: NO	0.422	0.002	0.417	0.427	YES
Long-term mean max temperature	-1.247	0.408	-2.014	-0.414	YES
Long-term mean humidity	-1.390	0.462	-2.293	-0.481	YES
Long-term mean precipitation	0.859	0.462	-0.103	1.708	NO
Long-term max temperature std. dev	-0.089	0.617	-1.395	1.024	NO
Short-term max temperature exposure	0.008	0.005	-0.003	0.018	NO
Short-term humidity exposure	-0.595	0.007	-0.609	-0.580	YES
Short-term precipitation exposure	-0.005	0.002	-0.010	-0.001	YES

The table indicates that the long-term mean maximum temperature and humidity over the decade past the survey are negatively related with the mental wellbeing of elderly, in the sense that an increase in the average long-term maximum temperature or humidity is associated with a poor mental wellbeing of the studied group. This can be attributed to the reduced thermoregulation among older adults, making chronic heat stressful for them (Blatteis, 2012). This finding aligns with global evidence showing that higher temperature and humidity levels are potentially linked with higher depression and anxiety levels (Rony and Alamgir, 2023), lower quality of sleep (Zheng, Li and Wang, 2019), lower life satisfaction due to reduced outdoor activities and socialization (Kim, Sung and Park, 2022; Chen and Delina, 2025) and lower energy and environment-driven fatigue (Chen and Delina, 2025) among older adults.

As for the long-term mean precipitation over the period 2013-2022, it seems to be insignificantly correlated with the mental wellbeing of older adults in Egypt. This can be attributed to the very low precipitation levels in most areas and the low variability between its values across the country, as shown in Figure 1 - panel (c), which reduce the statistical power of its effect. Also, the variability in the monthly maximum temperature over the 10-year period from 2013 to 2022 does not seem to have a great effect on the mental wellbeing.

Regarding the short-term climate exposure effects on mental wellbeing, we found that both short-term precipitation and humidity are significantly and negatively associated with mental wellbeing. This suggests that recent weather conditions characterised by increased rainfall and humidity reduce daily comfort and contribute to poor mental states among older adults by conceivably reducing sleep quality, physical energy, cognitive function, and the ability to go outside. In contrast, short-term maximum temperature, shows a non-significant association, although the long-term mean maximum temperature exhibited a negative relationship as highlighted above. This finding perhaps suggests that living in persistently hot districts imposes a chronic climate burden on mental wellbeing than short-term elevated temperatures.

The above model assumes that each climatic variable operates independently, which may not reflect the true environmental processes through which weather affects wellbeing. However, studies consistently indicate that the interaction between high temperature and high humidity significantly impacts people's health (Wu et al., 2025, Tobaldini et al., 2020, Guillien et al., 2021) and mental wellbeing (Florido Ngu et al., 2021). To capture this joint mechanism, a second model is fitted with an interaction term between short-term maximum temperature and short-term humidity exposures.

Once the interaction term is added to the model, the results reveal several important patterns; see Table 3. The main effect of the short-term maximum temperature becomes evident in the sense that periods with above-average maximum temperature are linked to significantly lower wellbeing among older adults in Egypt. The short-term humidity exposure continues to exhibit a significantly negative association with mental wellbeing. The interaction between short-term maximum temperature and humidity exposures is negative and statistically significant. This demonstrates that simultaneous increases in maximum temperature and humidity short-term exposures are associated with a substantial reduction in the wellbeing of elderly. Figure 3 illustrates how the adverse effect of humidity intensifies as temperature increases, and how higher humidity amplifies the negative influence of heat resulting in reduced wellbeing under very hot and humid conditions. This pattern aligns with previous evidence that humidity causes heat to accumulate more rapidly in the body amplifying discomfort during hot conditions (Sobolewski et al., 2021). After explicitly modelling the interaction term between humidity and temperature, the short-term precipitation effect shows a positive and significant association with wellbeing. This suggests that rainfall episodes ease environmental conditions, such as reducing heat, dust, and air pollution, thereby enhancing mental wellbeing. This result is also justified by the fact that Egypt does not experience heavy rainfall that can disrupt or pose risk to the life of elderly.

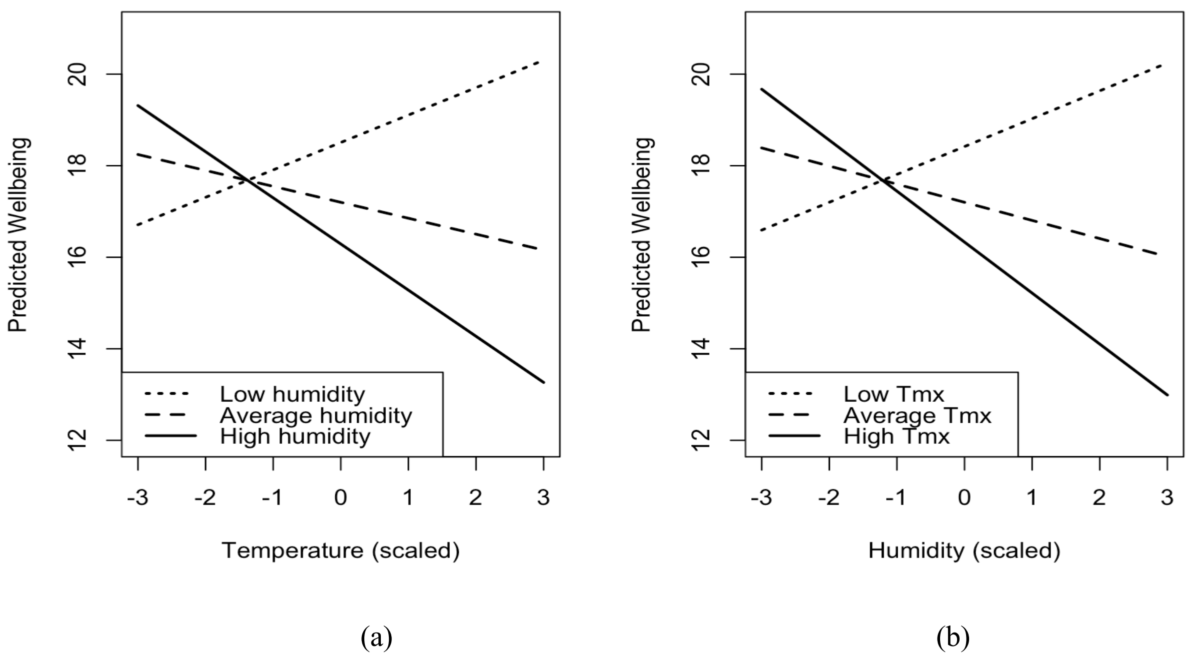


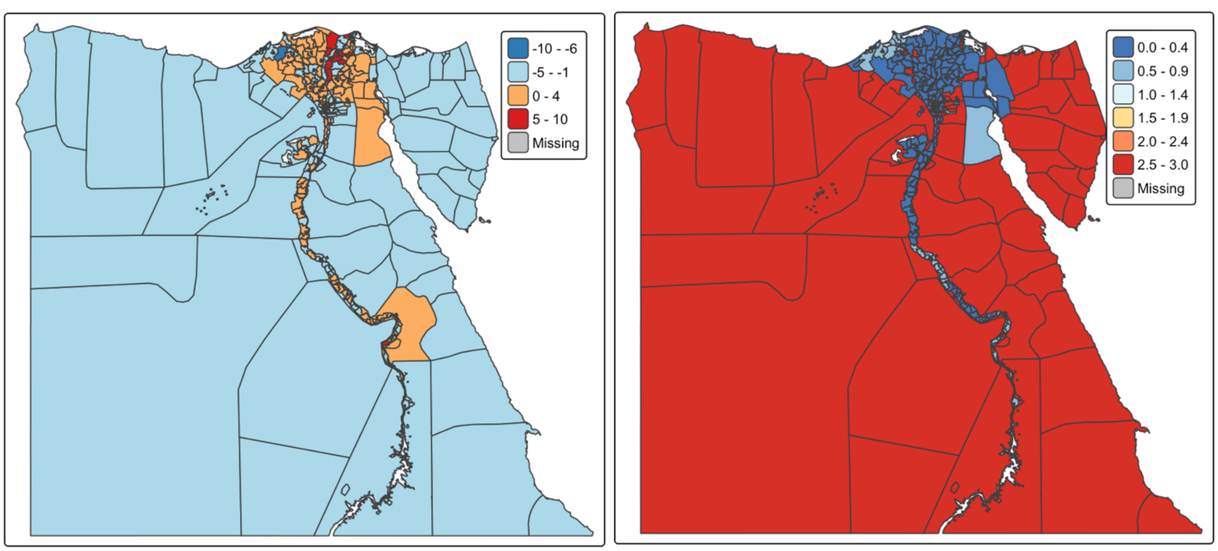
Figure 3: The estimated marginal effects of (a) maximum temperature and (b) humidity (measured by vapour pressure) on the mental wellbeing of elderly in Egypt, by holding the other variables at low, medium and high levels.

Table 3. Estimated coefficients of the multilevel spatial model fitted to the mental wellbeing of elderly people aged 50 or above with interaction term between short-term temperature and humidity term.

Variable	Mean	St. Dev	0.025 quantile	0.975 quantile	Sig at α =10%
Intercept	17.579	0.142	17.243	17.938	YES
Sex: Female	-0.051	0.002	-0.056	-0.047	YES
Education: Less than intermediate	0.213	0.003	0.207	0.220	YES
Education: Less than University	0.140	0.003	0.134	0.147	YES
Education: University or above	0.234	0.004	0.226	0.242	YES
Residence: Urban	-0.073	0.005	-0.082	-0.063	YES
Wealth Score	0.747	0.001	0.744	0.750	YES
Age	-0.241	0.001	-0.243	-0.239	YES
General Health	2.356	0.001	2.354	2.359	YES
Chronic Illness: NO	0.415	0.002	0.410	0.420	YES
Long-term mean max temperature	-1.320	0.435	-2.334	-0.239	YES
Long-term mean humidity	-1.492	0.502	-2.659	-0.303	YES
Long-term mean precipitation	0.796	0.509	-0.418	1.923	NO
Long-term max temperature std. dev	-0.114	0.674	-1.527	1.610	NO
Short-term max temperature exposure	-0.348	0.006	-0.360	-0.337	YES
Short-term humidity exposure	-0.396	0.007	-0.411	-0.381	YES
Short-term precipitation exposure	0.046	0.002	0.042	0.050	YES
Short-term max temperature * humidity	-0.287	0.002	-0.291	-0.283	YES

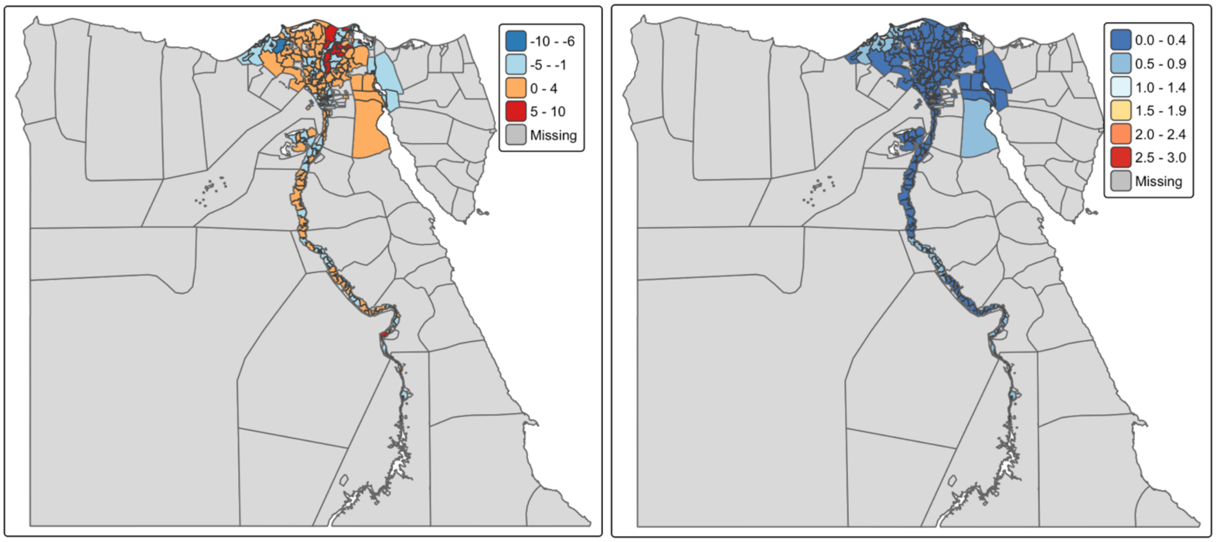
In addition to the short-term and long-term climate variables, several demographic and health control variables are found correlated with the mental wellbeing of elderly. For example, male respondents exhibit significantly better mental wellbeing scores than females. This pattern is consistent with the findings of Alsayyad et al. (2020), who reported that Egyptian women aged 60 and above experience significantly poorer physical and mental health, sleep quality and nutritional status. This disparity can reflect long standing differences in income, resources, and overall poorer quality of life. In addition, older people living in urban areas tend to have significantly lower wellbeing score than those living in rural areas, suggesting that urban environments may expose elderly individuals to additional stressors. This finding that urban elderly exhibit poorer mental wellbeing is partly supported by existing evidence. El-Gilany, Elkhawaga and Sarraf (2018), studying elderly from rural and urban areas of Mansoura District in Al-Dakahleya governorate in Lower Egypt, reported significantly higher levels of depression among urban residents compared to their rural counterparts. However, the literature is not fully consistent. Ali et al. (2018) using data from a group of elderly in Souhag in Upper Egypt found that rural residence is a risk factor for depression. Beyond place of residence, mental wellbeing of elderly is found positively correlated with people's wealth and higher education attainment. In contrast, age is negatively associated with wellbeing in the sense that older people suffer from poorer wellbeing. It is also evident that as the general health score of the subject increases, the mental wellbeing score increases and that elderly without chronic illness enjoy a significantly better wellbeing relative to those suffering from chronic illness.

For the random effects, the posterior mean for the observation-level precision is 0.042. This corresponds to a large residual standard deviation ($\hat{\sigma} = \sqrt{\frac{1}{0.046}} = 4.66$) at the individual level, consistent with the large individual-level heterogeneity in the mental wellbeing scores. In contrast, the precision of the spatially structured random effect is $\hat{\tau} = 0.128$, indicating a moderate amount of district-level variability and that a spatial clustering among the second-level administrative areas across Egypt exists. The estimated mixing parameter ($\hat{\phi} = 0.033$) suggests that a very small proportion of the district-level variation is spatially structured. This pattern implies negligible spatial dependence is remaining between the districts across Egypt, after accounting for the long-term climatic conditions of the districts, short-term climate exposures and the demographic and health individual characteristics.



(a) (b)

Figure 4: The estimated posterior (a) means and (b) standard deviations (uncertainty) of the spatially structured random effects across Egypt, including districts with and without data.



(a) (b)

Figure 5: The estimated posterior (a) means and (b) standard deviations (uncertainty) of the spatially structured random effects across Egypt, excluding districts without data.

Figure 4 displays the map of the spatially structured random effects across the second-level administrative level areas (districts) in Egypt after adjusting for the short-term and long-term climate exposures and the demographic and health variables. Note that the model can predict the spatial effects at districts in the Frontier governorates where no observations are available by applying spatial smoothing and borrowing strength from neighbouring areas. As expected, the uncertainty (standard errors) associated with the estimated spatial effects at those districts is larger relative to districts with observed data. To provide a clearer description of the spatial variability across areas with actual data, the same map is produced after removing the Frontier governorates and other districts without observations; see Figure 5.

A district (Kism/markaz) with a positive spatial random effect indicates an area where wellbeing is higher than expected after accounting for climate exposure and demographic characteristics. Conversely, districts with negative spatial random effects show lower wellbeing, reflecting localized disadvantages and vulnerabilities that are not captured by the model. The figure shows no remaining spatial clustering in the mental wellbeing status, after accommodating for the climate variables and the socio-economic and general health conditions of the elderly in Egypt. This implies that, in addition to the socio-economic characteristics, short-term and long-term climate stressors, rather than geographical clustering, account for the majority of the observed regional differences in mental wellbeing. That is, the climate conditions and weather variability across districts in Egypt have a potentially significant and immediate influence on the wellbeing of the ageing population.

5. Conclusion and Policy Implications

Climate change disproportionately affects vulnerable groups, including older adults. Understanding how climate variability impacts the elderly, the pathways involved, and how these effects may differ across different areas and socio-economic characteristics in Egypt significantly contributes to the decision-making process of policymakers. This paper is among the first studies to examine the relationship between climate exposure and the wellbeing of elderly in Egypt using empirical microdata, by integrating individual-level survey data with district-level climatic and spatial information.

The results indicate that short-term exposure to elevated maximum temperature and humidity is associated with lower mental wellbeing; and that the interaction between temperature and humidity exerted an additional adverse effect. This finding suggests that heat and humidity jointly amplify physical discomfort and psychological stress. Regarding the long-term climate indicators, persistently high temperatures and humidity appear to impose a chronic climate burden on the mental wellbeing of older adults. In contrast, the long-term precipitation does not appear to affect the mental wellbeing. Likely, this might be attributed to the arid climate in Egypt and minimal rainfall levels.

After adjusting for climate exposures and demographic and health characteristics, the fitted model reveals negligible remaining spatially structured variations in mental wellbeing across Egypt. This implies that most contextual influences including socio-economic, environmental quality, housing and access to services conditions are localized rather than being geographically clustered. Overall, the study demonstrates that both climate exposures and contextual factors are essential determinants for the mental wellbeing of older Egyptians. Yet, systematic geographic variation or spatially structured influences appear limited once climatic stress and other covariates are taken into consideration.

The results underscore the need for targeted climate-sensitive public health strategies that protect elderly from short-term heat and humidity stress. Such strategies may include the reinforcement of early-warning systems for extreme heat and humid weather events, the support of households in maintaining cool indoor environments by promoting affordable household cooling options and improving the ventilation in residential buildings, and the enhancement of public awareness on heat-related risks. The study indicated that older adults experiencing rises in the short-term precipitation tend to have an improved mental wellbeing score. Also, elderly living in rural areas seem to have a better wellbeing than those living in urban areas. These two associations suggest that controlling for the dust and urban pollutants may further enhance the resilience of elderly against climate changes.

Given the minimal spatial clustering remaining in mental wellbeing, after accommodating for the different climate and socio-economic covariates, these policy interventions and efforts should focus less on geographic targeting and more on population-wide measures designed for reducing the environmental stress attributed to changes in climate. These measures will become increasingly essential as Egypt continues to experience greater climate variability and rising temperatures.

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