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Club convergence in cereal exports: Is climate change an important dynamic?

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Abstract: In view of the increasing negative impacts of climate change, international cereal trade has become a growing concern. This study examines the impact of climate change on cereal exports. The analysis consists of two stages. In the first stage, we investigate convergence in cereal exports across countries and identify potential clusters of similar export behaviour. To this end, club convergence analysis was conducted using export data from 95 countries for the period 2000–2022. The results reveal that countries are grouped into seven distinct clubs, indicating shared convergence paths. In the second stage, the impact of climate change on the formation of these clubs is analysed using the ordered logit model. This model assesses how climatic factors influence a country's likelihood of belonging to a particular convergence club. The findings show that precipitation and carbon emissions significantly increase the likelihood of being in the top two clubs with high cereal trade. This suggests that climate change is a critical dynamic in shaping convergence clubs.

Keywords: agricultural trade; food security; club convergence analysis; ordered logit model

Cereal crops such as wheat, maize, and paddy are considered essential staples as they serve as primary food sources for a large share of the global population. As of 2024, the global population is estimated at 8.2 billion, and according to projections, it is expected to reach 9.7 billion by 2050 and 10.4 billion by 2100 (UN 2024). While this growth is expected to drive up food demand, the initial response has been to increase agricultural production (Godfray et al. 2010). However, this strategy, often seen as a conventional solution, has proven inadequate given current productivity levels, as demonstrated by historical data (Ray et al. 2013; Kornhuber et al. 2023). Climate change is considered a fundamental factor in the failure to meet these targets (Wheeler and Von Braun 2013; Kogo et al. 2021; Pinke et al. 2022; Yin et al. 2024; Khmeleva et al. 2025). Climate change-through short-term disasters (hurricanes, floods, heatwaves) and long-term trends (temperature rise, altered rainfall) significantly affects cereal production (Ahsan et al. 2020; IPCC 2023).

Climate change poses a significant challenge to sustainability in countries where agriculture serves as a primary source of livelihood and plays a vital role in maintaining food security (Kogo et al. 2021). An analysis of research in this context reveals that the literature predominantly focuses on the impacts of climate change on agricultural production and related economic activities (Ruane et al. 2013; Chandio et al. 2020; Xiang and Solaymani 2022; Artık et al. 2024). Indeed, numerous studies have examined the impacts of climate change on cereal crop production and productivity (Thompson and Scoones 2009; Schlenker and Lobell 2010;

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Lobell et al. 2013; Wang et al. 2018; Arora 2019; Chandio et al. 2020; Pickson et al. 2020; Abbas and Mayo 2021; Kumar et al. 2021; Asfew and Bedemo 2022; Abdi et al. 2023; Chandio et al. 2023; Farooq et al. 2023; Sarwary et al. 2023; Alimagham et al. 2024). Studies emphasise that low- and middle-income countries suffer most from climate change. Protecting these vulnerable groups and strengthening their sustainable production capacity are essential for global food security and equity. Therefore, international technical and financial support is necessary to strengthen climate adaptation policies.

The literature generally acknowledges that climate change significantly impacts the supply of agricultural products. Rising global temperatures are expected to impact the availability of food crops, particularly rice, wheat, and maize (Lobell et al. 2011; Calzadilla et al. 2014; Ali et al. 2017). In this regard, the Notre Dame Global Adaptation Initiative (ND-GAIN) computes the average Food Climate Vulnerability Score for these three crops to assess the impacts of climate change on the agricultural sector and food supply. The index combines variables on cereal output, population projections, import dependence, rural population share, agricultural capacity, and child malnutrition (ND-GAIN 2023). Figure 1 illustrates the relationship between ND-GAIN's Food Climate Vulnerability Score and national cereal exports.

As illustrated in Figure 1, the countries most vulnerable to climate change-induced food insecurity are in Africa (Niger, Ethiopia, and Madagascar), with notably low cereal export values. Conversely, the countries least vulnerable to climate change-induced food insecurity are the Netherlands (0.11) and Ireland (0.14), yet they account for nearly 5% of global cereal exports. Therefore, the relationship between climate change and cereal exports presents an intriguing dynamic.

This study focuses on the impacts of climate change on cereal exports and examines the linkages between the two under three key assumptions. First, countries may gradually limit cereal exports to meet domestic demand, as climate change increasingly shapes social welfare sustainability. Second, climate change is expected to transform cereal producers' production and export structures over time. Third, the effect of climate change on cereal exports may differ by income level. This assumption is grounded in the prediction that as countries' income levels increase, their exposure to the negative impacts of climate change will decrease, allowing them to diversify their exports and reduce their reliance on agricultural products (or *vice versa*).

Considering these three assumptions together, the analysis of this study consists of two stages. In the first stage, the aim is to determine whether countries converge in terms of cereal exports. To achieve this, a club

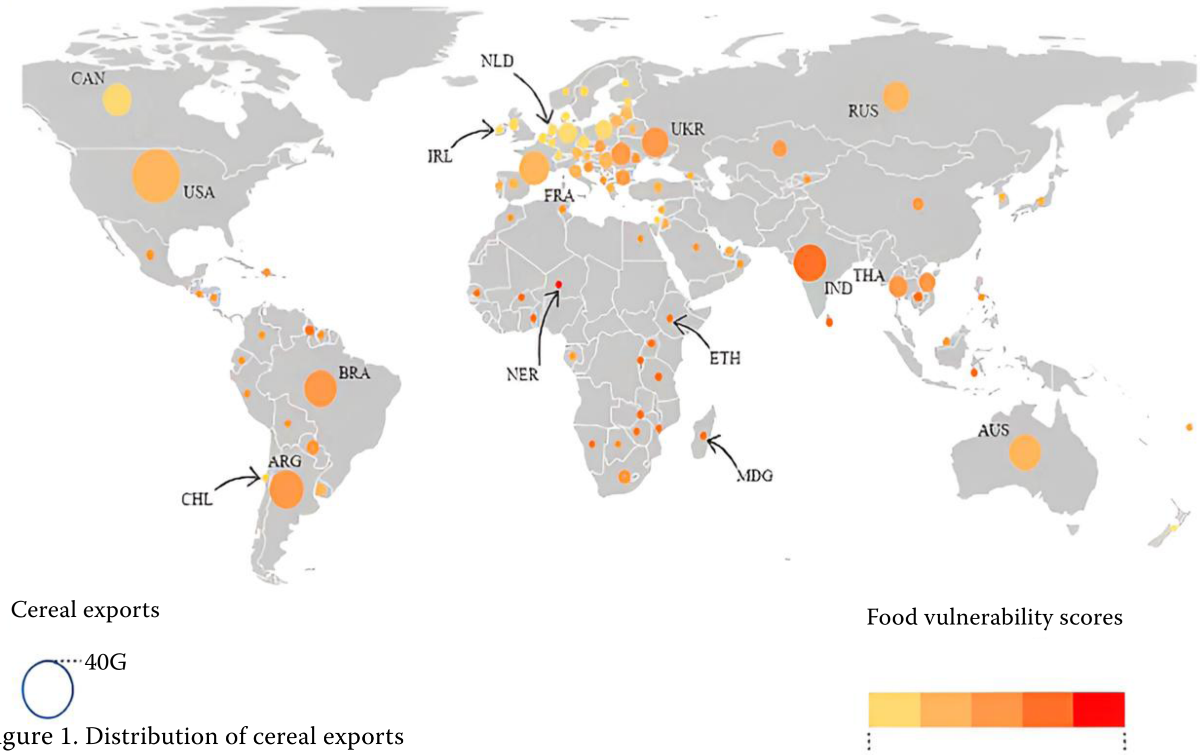

Figure 1. Distribution of cereal exports

Source: Visualisation of authors based on ND-GAIN and UN Comtrade

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convergence analysis is conducted using export data from 95 countries for the period 2000–2022. In the second stage, the impacts of climate change are analysed within the convergence clubs identified based on cereal exports. The purpose of this stage is to determine the influence of climate change factors on a country's membership in a particular club. The ordered logit model is employed at this stage. This study is expected to contribute to the literature in two key aspects. The first contribution is its focus on the convergence of countries in cereal exports. To our knowledge, the convergence of cereal exports has not yet been empirically examined in the literature. The second contribution is its examination of which climate change factors influence a country's convergence to a particular club, in line with the club convergence results.

Current debate on cereal exports, convergence and climate change. The literature on the convergence hypothesis has primarily focused on agricultural productivity rather than cereal exports. Lusigi et al. (1998) argued that education and investment are crucial for convergence in agricultural value added across African countries. Rezitis (2010) observed long-run convergence in agricultural productivity across the US and nine EU countries, though the effect vanishes in the short run. Alexiadis (2010) analysed EU-26 agricultural productivity using absolute and club convergence methods and found convergence mainly among older EU-15 members. Baráth and Fertő (2017) found significant productivity gaps between old and new EU members, but β-conditional convergence suggests a gradual move towards equilibrium. Kijek et al. (2019) reported a faster convergence rate in agricultural productivity among new EU-10 members compared to the old EU-15. Zhan et al. (2017) showed declining productivity gaps across 29 Chinese provinces, signalling convergence. Gong (2020) highlighted the presence of conditional β-convergence but not σ-convergence in China. Yuan et al. (2021) identified both σ- and unconditional β-convergence in sub-Saharan and other low-income agricultural economies. Mukhopadhyay (2021) found σ-convergence for wheat and β-convergence for other major cereals such as rice and maize. Hu (2023) examined agricultural total factor productivity in 306 Chinese cities using σ- and β-convergence analyses, finding β-convergence only among eastern cities.

To our knowledge, Kaplan et al. (2024) is the only study that investigates the link between climate change and cereal exports using a club convergence approach. They analysed exports of nine plant-based products, including cereals, and identified five convergence clubs, along with a group of countries (Canada, Barbados, Austria, Denmark) that did not converge to any club. Thus, the following hypothesis is proposed:

H_1: Countries that are more capable of combating climate change are more likely to be members of higher-level cereal export clubs.

Climate variables-temperature, precipitation, humidity, and drought-directly influence cereal productivity and trade. Recent studies in the literature have demonstrated that climate change affects cereal crop production. Kumar et al. (2021) found that an increase in average temperature reduces cereal production in lower-middle-income countries. Xiang and Solaymani (2022), in their study on Malaysia, used the autoregressive distributed lag (ARDL) model and found that climate change negatively affects cereal yields. In another study using the ARDL model, Asfew and Bedemo (2022) emphasised that precipitation has a positive and significant impact on cereal crop production in Ethiopia in both the long and short run, while temperature change has a negative and significant impact. Chandio et al. (2023) emphasised that climate risks-both short and long term-threaten food security in Southeast Asia. Abdi et al. (2023) obtained similar evidence for East African economies.

Pickson et al. (2024) showed that rainfall boosts agricultural output, whereas higher temperatures have adverse effects in Africa. Similarly, Singh et al. (2024) found that rainfall benefits long-term cereal yields, while higher temperatures harm them in both the short and long run. Ahmed et al. (2015) concluded that temperature increases have negative short- and long-term effects, while precipitation positively affects only short-term output. In contrast, Baig et al. (2024) found that increased temperature and carbon emissions positively affect wheat output in India. Bambi and Pea-Assounga (2024), examining 15 US states, emphasised that low levels of carbon emissions harm cereal production. Łącka et al. (2024), using the 'Feasible Generalized Least Squares (FGLS)' method, found that increased temperature and precipitation positively impact agricultural output in the EU. On the other hand, Chandio et al. (2025), in an ARDL-based study for China, found that precipitation negatively affects food production. Focusing specifically on agricultural exports, Abdi et al. (2024) used the ARDL model to analyse climate variables' effects on agriculture and livestock exports in Somalia. The study revealed that increased precipitation enhances exports in both the short and long run, while temperature increases have a long-term negative effect on exports.

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Based on these findings, the following hypothesis is put forward:

H_2: Climate change-related factors significantly affect the composition of cereal export convergence clubs.

H_{2a}: Increased precipitation raises the likelihood of countries being in higher-level cereal export clubs.

H_{2b}: Increased average temperatures reduce the likelihood of countries being in higher-level cereal export clubs.

H_{2c}: Increased carbon emissions raise the likelihood of countries being in higher-level cereal export clubs.

MATERIAL AND METHODS

Data sources. The study analysed used UN Comtrade data on cereal exports from 95 countries covering the period 2000–2022. Production volumes and the island status of countries were considered when selecting the sample countries. Island nations (e.g. Barbados, Cyprus) and countries with low cereal output (e.g. Eswatini, Malawi) were excluded from the dataset.

The club convergence algorithm developed by Phillips and Sul (2007) was preferred over traditional panel unit root tests in the analysis of cereal export convergence. An ordered logit model was then used to identify which climate change factors increase or decrease the probability of a country belonging to a particular club. Climate change indicators include average temperature (*tas*), total precipitation (*lpr*), and carbon emissions (*lco*2). In addition to climate change factors, the share of the rural population in the total population (*rural*) and land under cereal production (*land*) were used as control variables. All variables were sourced from the World Bank database. Table 1 provides information on these variables.

Club convergence model. Panel unit root tests, time series approaches, or dynamic panel data methods are commonly used as traditional tests in convergence analysis. Panel unit root tests assume that the variable under study is equally affected by other influencing factors, which may lead to non-converging regions appearing as if they have converged (Ulucak and Apergis 2018). Yet, time series analyses are often inadequate in detecting heterogeneity across regions. Unlike traditional tests, the Phillips-Sul (PS) approach identifies individual clubs within the panel that share similar convergence patterns, even when the entire panel does not converge. This process reveals the existence of clubs and allows some countries to diverge (Barrios et al. 2019). Furthermore, unlike a priori assumptions, the clustering approach is based on the individual characteristics of the data and accommodates heterogeneity among time series within the panel. Moreover, the PS approach yields robust results regardless of whether the series are trend-stationary or not (Ivanovski et al. 2018). Phillips and Sul (2007) used a nonlinear transition factor model to examine cross-country convergence behaviour.

$$Y_{it} = \partial_{it}\mu_t \tag{1}$$

where: Y_{it} – cereal exports; ∂_{it} – a time-varying idiosyncratic element that captures the deviation of state i from the common path; ì $_t$ – a single common trend.

Next, the relative pass-through coefficient needs to be constructed for hypothesis testing:

$$h_{it} = \frac{Y_{it}}{\frac{1}{N}\sum_{i=1}^{N} Y_{it}} = \frac{\partial_{it}}{\frac{1}{N}\sum_{i=1}^{N} \partial_{it}} \tag{2}$$

where: h_{it} – the transition path with respect to the panel mean.

This approach takes into account its semiparametric form ∂_{it}, which provides an empirical algorithm

Table 1. Definitions and sources of the variables used in the study

Variable	Indicator	Source
Lexp	logarithm of cereal export	UN Comtrade
Lat	logarithm of average temperature over period (°C)	Climate Change Knowledge Portal of World Bank
Lpr	logarithm of aggregated accumulated precipitation (mm)	Climate Change Knowledge Portal of World Bank
*Lco*2	logarithm of CO_2 emissions (kt)	World Bank, World Development Indicators (WDI)
Lrural	logarithm of rural population (% of total population)	World Bank, World Development Indicators (WDI)
Lland	logarithm of land under cereal production (hectares)	World Bank, World Development Indicators (WDI)
Lgdp	GDP *per capita* (USD)	World Bank, World Development Indicators (WDI)

Source: Authors' own elaboration

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for identifying clubs and hence an econometric test of convergence given in Equation (3):

$$\partial_{it} = \partial_i + \sigma_{it}\xi_{it} \tag{3}$$

where: ∂_i – the constant parameter; $\acute{o}_{it} = \dfrac{\acute{o}_i}{L(t)t^a}$, $\acute{o}_i > 0$, $t \geq 0$ and $\hat{\imath}_{it}$, *iid* (0,1) is weakly dependent on t along i; $L(t)$ – equal to log(t), diverges as t goes to infinity.

In the panel, we test the H_0 ($H_0 = \partial_\mathrm{i} = \partial$ and $a \geq 0$) which shows whether there is convergence in the panel against the alternative hypothesis H_1 ($H_1 = \partial_\mathrm{i} \neq \partial$ and $a < 0$). Equation (4) is used to test H_0:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{a} + \hat{b}\log(t) + \hat{\varepsilon}_t, for\ t. = \\ = [rT],[rT]+1\ , \ \ldots, with\, r > 0 \tag{4}$$

where: $H_t = \dfrac{1}{N}\sum_{i=1}^{N}(h_{it}-1)^2$ – the variance of the relative transition coefficient (h_{it}); $\hat{b} = 2\hat{a}$ – the speed of convergence parameter; $-2\log L(t)$ – the penalty function that improves the performance of the test; r – the parameter that removes a certain number of initial observations [Phillips and Sul (2007, 2009) suggest setting it to 0.33 for a small or medium sample ($T \leq 50$) and 0.22 for a large sample ($T \geq 100$). However, Kwak (2022) states that r should be 0.1 when the time series is short as a result of Monte-Carlo simulations. In this respect, r = 0.1 is used in this study]. In Equation (4), if $t_{\hat{b}} < -1.65$, the hypothesis of convergence is rejected at 5% significance level.

Ordered logit model. Phillips and Sul's (2007) approach clusters regions according to the transition paths that result from factoring the logarithm of income. Thus, this method alone is insufficient to verify the club convergence hypothesis. Therefore, we follow Bartkowska and Riedl (2012) and Von Lyncker and Thoennessen (2017), who suggest a two-step procedure. The first step involves the PS clustering approach, and the second involves investigating the marginal impacts of the factors that drive club formation with an ordered logit model. Marginal impacts assess how the probability of belonging to a club changes when one of the independent variables changes by one unit, while all other variables are held constant at their sample means (Arogundade et al. 2023). Countries in the convergence clubs for cereal exports are assigned values ranging from 1 to n and ranked from highest to lowest. In general, the ordered logit model is constructed as follows:

$$y^* = \beta X + e_i, u \mid X \sim Logit(0,1) \tag{5}$$

$$y = \begin{cases} 1,\ if\ y^* \leq r_0 \\ 2,\ if\ r_0 < y^* \leq r_1 \\ \quad . \\ \quad . \\ \quad . \\ n,\ if\ y^* > r_{n-1} \end{cases} \tag{6}$$

where: y^* – an unobservable latent variable corresponding to the value assigned to the country-specific convergence club (i.e. Club 1 member countries = 1); $r_0 < r_1 < \ldots < r_{n-1}$ – the threshold value obtained from the regression estimation; – the estimated coefficient for each explanatory variable in Equation (5); X – a set of explanatory variables; u – the error term. The explanatory variables considered in the study are average surface temperature, precipitation, carbon emissions, the rural population-to-total population ratio, and the total land devoted to cereal production. Variable selection follows prior studies such as Yu et al. (2020), Asfew and Bedemo (2022), Abdi et al. (2023), and Lee et al. (2024).

RESULTS AND DISCUSSION

Club convergence results. Table 2 presents the convergence results for cereal exports of 95 countries for the period 2000–2022. For the club convergence test, a one-sided t-statistic is used, and the hypothesis H_0 is rejected at the 5% significance level when the t-statistic is less than –1.65. Table 2 shows the results of the 95-country club convergence analysis.

The first row of Table 2 presents the convergence analysis for the entire panel. The t-statistic for the entire panel is smaller than the critical value of –1.65, and the hypothesis of general convergence in cereal exports among the countries in the sample is rejected. The absence of convergence suggests that these countries have different transition paths. The club convergence results show that 13 initial clubs converge. The t-statistics for these clubs are 1.041, 0.340, 0.539, –0.952, 1.111, 0.030, 0.337, 0.126, –0.776, –0.627, 1.569, –0.215, and –1.30, and the t-statistics for these 13 clubs exceed the critical value of –1.65, supporting the hypothesis of converging clubs. Next, we analyse whether neighbouring clubs converge with each other. The club convergence approach might overestimate the true number of clubs. Hence, we apply the club merger test proposed by Phillips and Sul (2009). The t-statistics for the merged clubs, Club 1+2, Club 10+11, and Club 12+13, are –2.456, –2.525, and –5.324, which are below –1.65. Thus, the

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Table 2. Club convergence analysis results

log (t)	Convergence Speed ($\hat{b}$)	StErr	t-Statistic ($t_{\hat{b}}$)				
	–0.889**	0.045	–19.718				
Initial classification	Club1	Club2	Club3	Club4	Club5	Club6	Club7
B	0.167	0.044	0.140	–0.405	0.218	0.013	0.141
T	1.041	0.340	0.539	–0.952	1.111	0.030	0.337
	Club8	Club9	Club10	Club11	Club12	Club13	
B	0.156	–0.457	–0.756	0.643	–0.280	–0.556	
T	0.126	–0.776	–0.627	1.569	–0.215	–1.303	
Club merger	Club 1+2	Club 2+3	Club 3+4	Club 4+5	Club 5+6	Club 6+7	Club 7+8
B	–0.222**	–0.128	0.099	–0.039	0.140	–0.183	–0.155
T	–2.456	–1.054	0.376	–0.252	0.786	–0.557	–0.395
	Club 8+9	Club 9+10	Club 10+11	Club 11+12	Club 12+13		
B	–0.537	–0.651	–0.684**	–0.302	–0.929**		
T	–1.082	–1.531	–2.525	–1.055	–5.324		

**indicates statistical significance at the 5% level

Source: Authors' own calculations

merger of these neighbouring clubs is not statistically significant. Finally, the final club convergence results are shown in Table 3.

As a result, 95 countries are divided into 7 clubs in the final classification, and the t-values exceed –1.65. Thus, the initial panel of 13 clubs is consolidated into seven clubs in the final classification. Based on the final classification, Club One comprises 22 countries, Club Two comprises 33 countries, Club Three comprises 21 countries, Club Four comprises 8 countries, Club Five comprises 2 countries, Club Six comprises 5 countries, and Club Seven comprises 4 countries. To continue the analysis, relative transition path curves for each club are plotted to visually illustrate the trend and path of each club's cereal exports relative to the steady-state average. The relative transition curves are shown in Figure 2.

Table 3. Final club convergence results

Clubs	$\hat{b}$	$t_{\hat{b}}$	Countries
Club1	0.167	1.041	Argentina, Australia, Brazil, Bulgaria, Cambodia, Canada, France, Germany, Hungary, India, Kazakhstan, Latvia, Lithuania, Paraguay, Poland, Romania, Russian Federation, Rwanda, Thailand, USA, Ukraine, Vietnam
Club2	–0.128	–1.054	Austria, Belgium, Bolivia, Chile, China, Croatia, Czechia, Denmark, Estonia, Greece, Guyana, Italy, Japan, Jordan, Malaysia, Mexico, Netherlands, Peru, Portugal, South Korea, Moldova, Slovakia, Slovenia, South Africa, Spain, Sweden, Türkiye, Uganda, United Arab Emirates, United Kingdom, Tanzania, Uruguay, Zambia
Club3	–0.170	–1.016	Belarus, Colombia, Ecuador, Egypt, Ethiopia, Finland, Indonesia, Ireland, Israel, Lebanon, Luxembourg, Mozambique, Nicaragua, Oman, Philippines, Senegal, Singapore, Sri Lanka, Suriname, Switzerland, Zimbabwe
Club4	–0.537	–1.082	Albania, El Salvador, Fiji, Gabon, Georgia, Kyrgyzstan, New Zealand, Saudi Arabia
Club5	–0.756	–0.627	Dominican Rep., Niger
Club6	–0.302	–1.055	Botswana, Burkina Faso, Morocco, Norway, Tunisia
Club7	–0.556	–1.303	Iceland, Madagascar, Namibia, Togo

$\hat{b}$ – convergence speed; $t_{\hat{b}}$ – t-statistic

Source: Authors' own calculations

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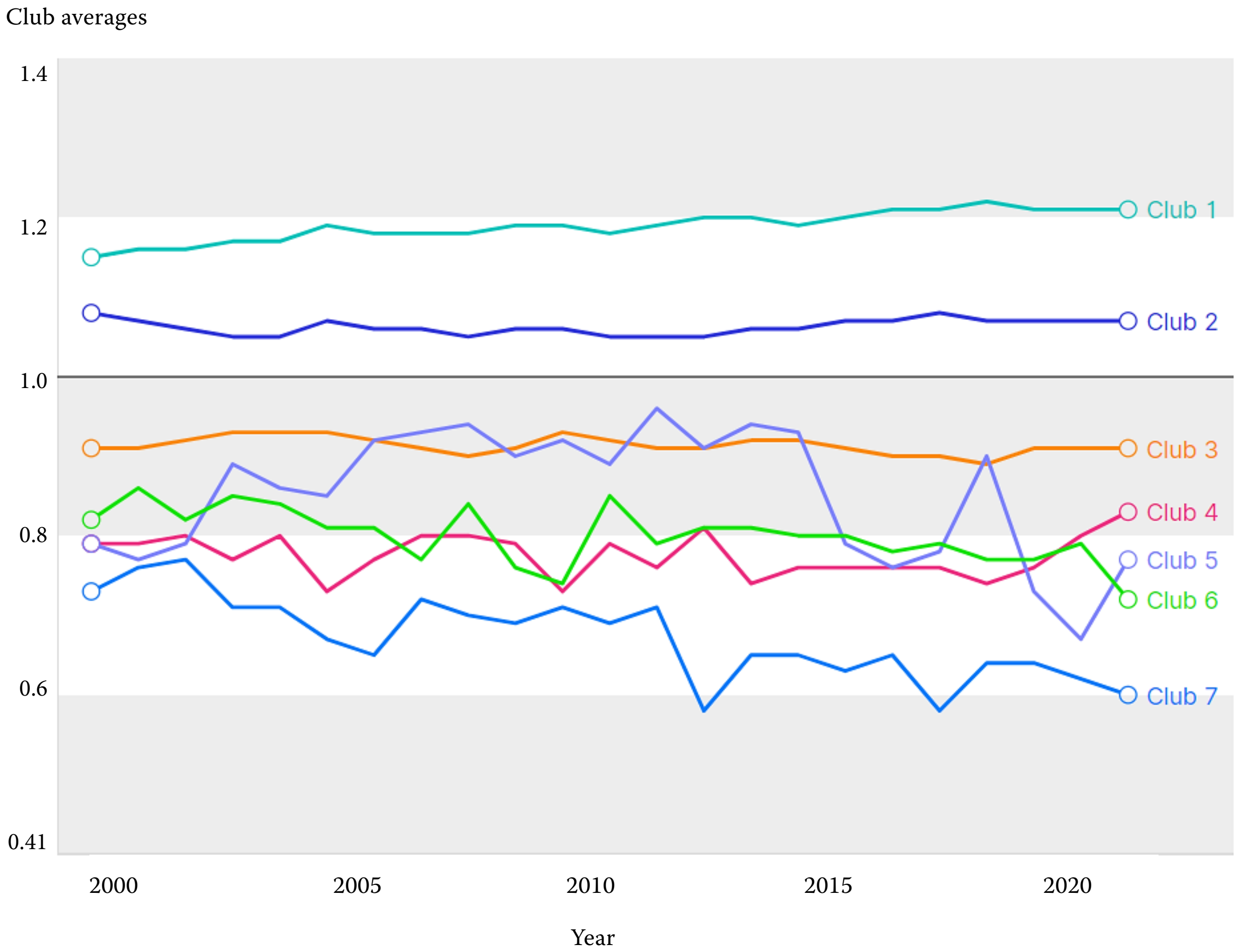

Figure 2. Club averages

Source: Visualisation of authors

Phillips and Sul (2007, 2009) state that if the relative transition parameter of a convergence club exceeds 1, the cereal exports of that club are higher than the steady-state average of the sample. In contrast, a transition path below 1 indicates that the club's level is below the panel average. As shown in Figure 2, the relative transition paths of the countries in Clubs 1 and 2 follow a stable path above the average value of 1. The leading role of developed and developing countries such as the US, Argentina, India, Brazil, France, and Russia in global cereal exports causes their values to be much larger than the steady-state average and prevents a decreasing trend. The relative transition paths for the other clubs are below 1, and particularly the members of Clubs 6 and 7 are gradually diverging from the average.

The top three clubs meet nearly 99.7% of global cereal demand. The relationship between the average export distances of these countries and their share of world cereal exports is shown in Figure 3, highlighting the global export dynamics and competition among countries.

The size of the circles in Figure 3 shows the share of cereals in world exports as of 2022. The distance, denoted by 'k', represents 1 000 km. Based on the final club convergence results, all members in Club 1 [USA (14.4), Brazil (9.2), Australia (8.0), Russian Federation (7.0), Canada (6.9), India (6.9), France (5.1), Ukraine (5.1), Argentina (4.7), Thailand (3.2), Romania (2.7), Poland (2.4), Viet Nam (2.4), Germany (2.0), Bulgaria (1.4), Kazakhstan (1.3), Cambodia (1.2), Hungary (1.1), Paraguay (0.8), Lithuania (0.7), Latvia (0.5), and Rwanda (0.1)] account for approximately 87% of world exports of cereals. Among these countries, the average export distances of Brazil (13 158), Argentina (10 900), Australia (7 914), Canada (7 534), and the United States (6 494) are notably

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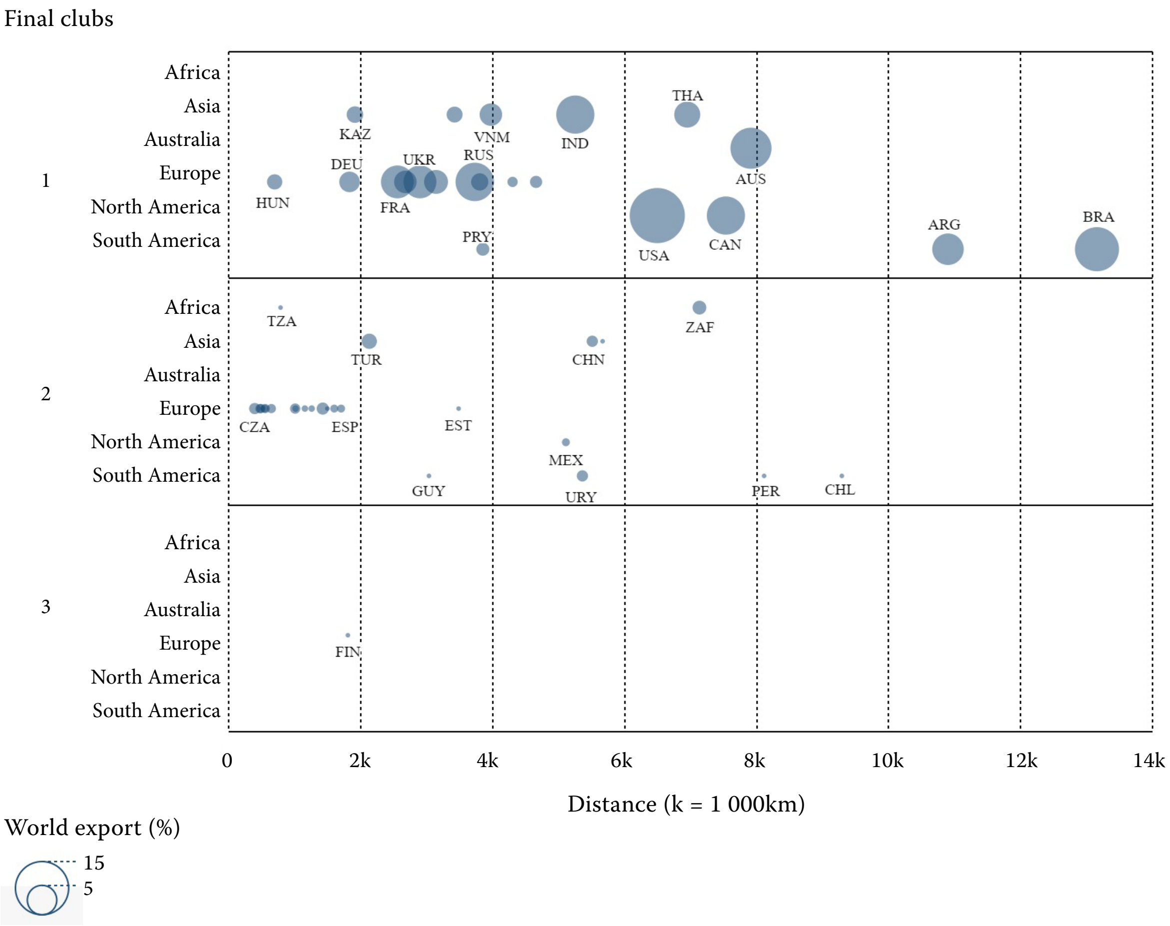

Figure 3. Distribution of final clubs

Source: Visualisation of authors based on Trade Map

high (Trademap 2024). This highlights the importance of cereal exports, considering both its share in world exports and the average export distances.

Analysis of influencing factors of convergence clubs. The club convergence analysis reveals that the cereal exports of 95 countries are divided into seven final convergence clubs. Therefore, the following question arises as an extension of the club convergence hypothesis: Which climate change factors influence a country's membership in a particular club? Based on the existing literature, this study primarily considers three climate change factors: precipitation (mm), average mean temperature over the period (°C), and CO_2 emissions (kt). Descriptive statistics of the variables that may influence club formation in the study are presented in Table 4.

Table 4 shows the descriptive statistics of the variables used in the determinants of club convergence across 95 countries. From 2000 to 2022, the average value of cereal exports among the 95 countries was 7.47. Gabon has the lowest cereal export value at 0.39, while USA have the highest at 10.50. The average surface temperature ranges from –0.97 °C to 3.40 °C, with a mean of 2.69 °C. The average precipitation is 2.90, with a minimum of 1.04 and a maximum of 3.61. The average CO_2 value is 4.57. The Dominican Republic has the lowest CO_2 level of 2.02, while China has the highest level of 7.04. The rural population and land under cereal production have mean values of 3.41 and 5.60, respectively. The GDP *per capita* values in the sample range between 4.70 and 11.8. Among the countries in the dataset, Luxembourg has the highest *per capita* income, while Ethiopia records the lowest.

To assess the relative importance of the explanatory variables affecting club membership in cereal exports, an ordered logit model was employed. The sign of the coefficients derived from the ordered logit model indicates whether the explanatory variable increases or decreases the likelihood of belonging to a higher-numbered club, which in this study refers to clubs with lower cereal export performance. For instance,

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Table 4. Descriptive statistics

Variable	Mean	SD	Min	Max
Lexp	7.567	1.445	0.387	10.500
Lat	2.690	0.614	–0.968	3.402
Lpr	2.903	0.384	1.035	3.615
Lco2	4.574	0.910	2.024	7.039
Lrural	3.410	0.696	0.614	4.446
Lland	5.600	1.033	1.322	8.014
Lgdp	8.851	1.520	4.697	11.813

Source: Authors' own calculations; variables are explained in Table 1

a positive coefficient implies a greater probability of being a member of lower-performing export clubs (i.e. Clubs 3, 4, 5, 6, and 7). Conversely, a negative coefficient suggests a higher likelihood of belonging to better-performing clubs (i.e. Clubs 1 and 2). However, because the interpretation of coefficients in ordered logit models is not straightforward or intuitively clear, marginal effects were calculated to better understand the impact of each explanatory variable on club membership. Marginal effects measure how a one-unit change in an explanatory variable, holding all other variables constant at their sample means, alters the probability of a country belonging to each convergence club. This approach provides a more accurate representation of the practical significance of each variable (Von Lyncker and Thoennessen 2017). The detailed results of the marginal effects analysis are presented in Table 5.

Table 5 presents the regression results for the climate change variables. The coefficient for annual precipitation is negative (–0.132), indicating that increases in precipitation raise the probability of being in lower-numbered clubs, which correspond to countries with higher levels of cereal exports. This result

Table 5. Marginal effects of factors on different club probabilities

	Marginal effects							
	β	Club 1	Club 2	Club 3	Club 4	Club 5	Club 6	Club 7
Lgdp	–0.254***	0.036***	0.026***	–0.027***	–0.016***	–0.004***	–0.009***	–0.006***
	(0.050)	(0.007)	(0.005)	(0.006)	(0.003)	(0.001)	(0.002)	(0.001)
Lrural	–0.012	0.002	0.001	–0.001	–0.001	–0.001	–0.001	–0.001
	(0.082)	(0.012)	(0.008)	(0.009)	(0.005)	(0.001)	(0.003)	(0.002)
Lland	–0.243***	0.035***	0.025***	–0.026***	–0.016***	–0.004***	–0.009***	–0.006***
	(0.032)	(0.005)	(0.004)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
Lpr	–0.132**	0.019**	0.013**	–0.014**	–0.008**	–0.002**	–0.005**	–0.003**
	(0.050)	(0.007)	(0.005)	(0.005)	(0.003)	(0.001)	(0.002)	(0.001)
Lat	–0.292***	0.042***	0.030***	–0.031***	–0.019***	–0.004***	–0.010***	–0.007***
	(0.082)	(0.012)	(0.009)	(0.009)	(0.005)	(0.001)	(0.003)	(0.002)
Lco2	–0.211***	0.030***	0.021***	–0.022***	–0.014***	–0.003***	–0.007***	–0.005***
	(0.039)	(0.006)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)
Log likelihood	–2 845.118 9							
LR chi^2	478.37***							
Pseudo R^2	0.08							

*** and **significance at 0.01 and 0.05 levels, respectively; standard errors in parentheses; variables as explained in Table 1

LR – Likelihood Ratio Chi-Square

Source: Authors' own calculations

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is further supported by the marginal effects analysis, which shows positive marginal effects for Club 1 and Club 2, while the marginal effects for other clubs are negative. In other words, as precipitation increases, the likelihood of belonging to Club 1 or Club 2 rises, while the probability of being in other, less export-intensive clubs decreases. This finding suggests that precipitation has a more substantial impact on countries that receive above-average precipitation. The result is intuitive, as cereal production is highly dependent on precipitation. Indeed, high-yield harvests during rainy seasons lead to production surpluses, thereby enhancing the capacity for agricultural exports. Numerous studies in the literature confirm that increased precipitation boosts cereal production and exports (e.g. Pickson et al. 2020; Yu et al. 2020; Kumar et al. 2021; Asfew and Bedemo 2022; Abdi et al. 2023; Miah et al. 2025). Turning to surface temperature, its regression coefficient is negative (–0.292). This result implies that rising temperatures are associated with a greater likelihood of belonging to the top cereal-exporting clubs. Dumrul and Kilicarslan (2017), in their study on Turkey, found that increases in temperature had a positive effect on agricultural output. However, more recent studies suggest that rising temperatures generally exert a negative influence on agricultural production (Chandio et al. 2020, 2025; Pickson et al. 2020; Xiang and Solaymani 2022; Asfew and Bedemo 2022; Abdi et al. 2023; Miah et al. 2025).

Finally, the regression coefficient for annual CO_2 emissions is negative (–0.211), indicating that countries with higher carbon emissions are more likely to be members of the top cereal-exporting clubs. The marginal effects analysis supports this conclusion, showing positive effects for Club 1 and Club 2, and negative effects for the remaining clubs. This result suggests that increased carbon emissions are associated with greater cereal export performance, thereby placing countries into the higher-performing convergence groups. Thus, carbon emissions show a positive correlation with cereal exports. In some cases, the negative consequences of climate change may inadvertently support agricultural output. For example, higher CO_2 levels may reduce transpiration rates and enhance crop growth, thereby improving yield potential (Kumar et al. 2021). This finding aligns with prior research on the relationship between carbon emissions and agricultural productivity (Onour 2019; Ahsan et al. 2020; Kumar et al. 2021).

In addition to climate-related variables, Table 5 also reports the results for control variables, specifically land under cereal cultivation and GDP *per capita*, both of which offer meaningful insights into the determinants of convergence club membership. The regression coefficient for land under cereal production is negative (–0.243), indicating that increases in the size of cultivated agricultural land raise the likelihood of a country being in a higher-performing export club. This is further supported by the marginal effects, which are positive for Club 1 and Club 2, while negative for the remaining clubs. These findings imply that countries with more extensive agricultural land are more likely to generate production surpluses, which in turn enhance their capacity to export cereals. This result is consistent with previous studies by Kumar et al. (2021), Koondhar et al. (2021), Abdi et al. (2023), Chandio et al. (2023), Bambi and Pea-Assounga (2024), which highlight the critical role of land availability in boosting agricultural export potential. As for GDP *per capita*, the ordered logit model yields a negative coefficient (–0.254), suggesting that higher income levels increase the probability of belonging to the top cereal-exporting clubs. Marginal effect estimates reinforce this finding, showing positive effects for Club 1 and Club 2, and negative effects for the lower-ranked clubs. In other words, as a country's economy grows, its likelihood of being in Club 1 or Club 2 increases. This result aligns with Chandio et al. (2025), who emphasise that economic growth not only supports domestic food security but also strengthens agricultural trade performance. Increased income levels may also facilitate investments in infrastructure, technology, and logistics-further supporting export competitiveness.

Robustness analysis. To assess the validity and robustness of the main findings, additional analyses were conducted. In this context, countries were grouped based on their geographical regions, and interaction terms between climate variables and regional classifications were introduced into the model. This accounts for regional differences in environmental and structural conditions. In the first step, the effect of precipitation was examined separately for different geographic areas by incorporating region–precipitation interaction terms into the ordered logit model. This allows us to evaluate whether the relationship between precipitation and cereal export club membership is region-specific. The results of the ordered logit model with precipitation–region interaction terms are reported in Table 6.

According to the results presented in Table 6, the coefficients for GDP *per capita*, land under cereal cultivation, CO_2 emissions, and average temperature are all negative. This implies that increases in these variables enhance the likelihood of a country belonging

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Table 6. Ordered logit results with regional interactions for precipitation (coefficient estimates)

	(1)	(2)	(3)	(4)	(5)
Lgdp	–0.179*** (0.050)	–0.285*** (0.054)	0.073 (0.059)	–0.283*** (0.049)	–0.297*** (0.050)
Lrural	0.004 (0.088)	–0.026 (0.088)	0.262*** (0.093)	–0.018 (0.088)	–0.268*** (0.093)
Lland	–0.392*** (0.033)	–0.261*** (0.034)	–0.183*** (0.032)	–0.253*** (0.031)	–0.213** (0.031)
*Lco*2	–0.036 (0.040)	–0.178*** (0.045)	–0.319*** (0.041)	–0.182*** (0.038)	–0.259*** (0.039)
Lat	–0.640*** (0.085)	–0.322*** (0.081)	–0.766*** (0.090)	–0.380*** (0.082)	–0.162* (0.084)
Lpr×Africa	0.349*** (0.023)				
Lpr×Asia		–0.004 (0.017)			
Lpr×Europe			–0.212*** (0.020)		
Lpr×N_America				0.102*** (0.023)	
Lpr×S_America					–0.155*** (0.019)
Log likelihood	–2 722.151	–2 848.539	–2 787.920	–2 838.9578	–2 815.059
LR chi^2	724.30***	471.53***	592.76***	490.69***	538.49***
Pseudo R^2	0.12	0.08	0.10	0.08	0.09

*** and *significance at 0.01 and 0.10 levels, respectively; standard errors in parentheses; variables as explained in Table 1
LR – Likelihood Ratio Chi-Square
Source: Authors' own calculations

to higher-level export clubs. In other words, countries with greater income levels, more cultivated land, higher emissions, and warmer average temperatures tend to be part of convergence clubs with stronger cereal export performance. When examining the coefficient for rural population, it is found to be statistically significant in only two of the models, indicating a limited and inconsistent influence on club membership. With regard to regional effects, the analysis reveals that precipitation exhibits heterogeneous impacts across regions. Specifically:

i) In Africa and North America, more rainfall links to lower-performing clubs, suggesting that extra precipitation does not boost cereal exports.

ii) In Europe and South America, more rainfall raises the odds of joining top export clubs, showing a positive effect on cereal trade.

iii) For Asia, precipitation–region interaction is insignificant, showing no clear effect on export club membership.

Following the ordered logit estimations, marginal effects were also calculated to better interpret the regional precipitation interactions. These average marginal effects are reported in Table 7.

According to the results presented in Table 7, increases in GDP *per capita*, land under cereal cultivation, carbon emissions, and average surface temperature all raise the likelihood of a country belonging to Club 1, which represents the group of countries with the highest levels of cereal exports. Simultaneously, these increases reduce the probability of belonging to Club 3, which includes countries with lower export levels. When examining regional effects, we observe that for countries in Africa and North America, increased precipitation lowers the probability of being in Club 1. However, it also decreases the likelihood of being in Club 3, which suggests that precipitation in these regions does not clearly push countries toward either extreme of the export performance spectrum. In contrast, for Europe and South America, precipitation increases are associated with a higher probability of membership in Club 1 and a lower probability of being in Club 3. This indicates a strong positive impact of precipitation on cereal export performance in these regions.

The results presented in Table 8 indicate that an increase in GDP *per capita* generally raises the probability of countries belonging to higher cereal export clubs. However, in the third specification [Column (3)], this relationship reverses direction. This suggests that when regional precipitation interactions are included in the model, the impact of income may operate through a different channel, highlighting the context-dependent nature of its effect. The influence of rural population on club membership does not exhibit a consistent pattern. In the Europe-interacted model [Column (3)], an increase in rural population reduces the likelihood of belonging to high-export clubs, whereas in the South America-interacted model, the opposite effect is observed. Regarding the effect of land under cereal

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Table 7. Ordered logit results with precipitation and regional interaction (avg. marginal effect)

	(1)		(2)		(3)		(4)		(5)	
	Clubs1	Clubs 3	Clubs1	Clubs 3	Clubs1	Clubs 3	Clubs1	Clubs 3	Clubs1	Clubs 3
Lgdp	0.023*** (0.006)	–0.020*** (0.006)	0.041*** (0.008)	–0.030*** (0.006)	–0.010 (0.008)	0.008 (0.007)	0.041*** (0.007)	–0.031*** (0.006)	0.041*** (0.007)	–0.033*** (0.006)
Lrural	–0.001 (0.011)	0.005 (0.010)	0.004 (0.003)	–0.003 (0.009)	–0.036*** (0.013)	0.030*** (0.011)	0.003 (0.013)	–0.002 (0.010)	0.037*** (0.013)	–0.029*** (0.010)
Lland	0.050*** (0.004)	–0.045*** (0.005)	0.038*** (0.005)	–0.028*** (0.004)	0.025*** (0.004)	–0.021*** (0.004)	0.036*** (0.004)	–0.027*** (0.004)	0.030*** (0.004)	–0.023*** (0.004)
*Lco*2	0.005 (0.005)	–0.004 (0.005)	0.026*** (0.006)	–0.019*** (0.005)	0.043*** (0.006)	–0.036*** (0.005)	0.026*** (0.005)	–0.020*** (0.004)	0.036*** (0.005)	–0.028*** (0.005)
Lat	0.082*** (0.011)	–0.073*** (0.011)	0.046*** (0.012)	–0.034*** (0.009)	0.105*** (0.013)	–0.087*** (0.011)	0.055*** (0.012)	–0.041*** (0.009)	0.022* (0.012)	–0.018* (0.009)
Lpr× Africa	–0.045*** (0.003)	0.040*** (0.003)								
Lpr× Asia			–0.001 (0.003)	–0.001 (0.002)						
Lpr× Europe					0.029*** (0.003)	–0.024*** (0.003)				
Lpr×N_ America							–0.015*** (0.003)	0.011*** (0.003)		
Lpr×S_ America									0.022*** (0.003)	–0.017*** (0.002)

*** and *significance at 0.01 and 0.10 levels, respectively; standard errors in parentheses; variables as explained in Table 1
Source: Authors' own calculations

cultivation, the results show that an increase in cultivated area reduces the probability of belonging to low-export clubs, thereby increasing the likelihood of being part of high-exporting groups. As for precipitation interactions, the effects vary significantly across regions. In the Africa-interacted model [Column (1)], an increase in precipitation raises the probability of belonging to low-export clubs. In contrast, in all other regional interactions (except South America), increased precipitation lowers the probability of being in low-export clubs and enhances the likelihood of being in high-export clubs. A similar trend is observed for carbon emissions: rising emissions generally decrease the probability of belonging to low-export groups, reinforcing their positive association with agricultural export performance. With respect to average temperature, regional heterogeneity is also evident. In Africa and North America, higher temperatures increase the likelihood of countries being in low-export clubs. Conversely, in Asia, Europe, and South America, temperature increases raise the probability of belonging to high-export clubs. The average marginal effects associated with these findings are presented in Table 9.

According to the marginal effect results reported in Table 9, increases in GDP *per capita* raise the probability of countries being in Club 1 – the high cereal export group – in Models 2, 4, and 5, while decreasing the probability of being in Club 3, the low-export group. However, in Model 3, this relationship is reversed; income growth reduces the probability of being in Club 1 and increases the likelihood of being in Club 3, suggesting regional variation in the income–export relationship. The effect of rural population also varies by model specification. In Model 5, an increase in rural population raises the probability of being in Club 1 and lowers the likelihood of being in Club 3. In contrast, in Model 3, the effect is reversed.

The expansion of land under cereal cultivation consistently improves export performance across all models. An increase in cultivated area raises the probability of being in Club 1 and reduces the probability of being in Club 3, supporting the idea that land availability enhances export capacity. The findings related to precipitation differ depending on model structure. In Model 1, increased precipitation reduces

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Table 8. Ordered logit results with regional interactions for temperature (coefficient estimates)

	(1)	(2)	(3)	(4)	(5)
Lgdp	–0.017 (0.047)	–0.231*** (0.051)	0.210*** (0.058)	–0.166*** (0.047)	–0.255*** (0.047)
Lrural	–0.045 (0.089)	–0.006 (0.088)	0.258*** (0.094)	–0.006 (0.088)	–0.275*** (0.093)
Lland	–0.368*** (0.033)	–0.255*** (0.035)	–0.126*** (0.032)	–0.204*** (0.031)	–0.193*** (0.031)
Lpr	0.167*** (0.053)	–0.147*** (0.049)	–0.215*** (0.049)	–0.183*** (0.050)	–0.034 (0.052)
*Lco*2	–0.044 (0.041)	–0.172*** (0.047)	–0.372*** (0.041)	–0.240*** (0.039)	–0.281*** (0.039)
Lat×Africa	0.790*** (0.049)				
Lat×Asia		–0.099** (0.043)			
Lat×Europa			–0.568*** (0.050)		
Lat×N_America				0.213*** (0.054)	
Lat×S_America					–0.405*** (0.047)
Log likelihood	–2 708.822	–2 848.722	–2 783.287	–2 843.766	–2 813.371
LR chi^2	750.96***	471.16***	602.03***	481.07***	541.86***
Pseudo R^2	0.12	0.08	0.10	0.08	0.09

*** and **significance at 0.01 and 0.05 levels, respectively; standard errors in parentheses; variables as explained in Table 1
LR – Likelihood Ratio Chi-Square
Source: Authors' own calculations

the probability of being in Club 1 and increases the likelihood of belonging to Club 3. In other models, however, this effect is reversed-higher precipitation increases the chance of being in Club 1 while reducing that of Club 3. For carbon emissions, a consistent trend is observed: across all models, increases in CO_2 emissions raise the likelihood of being in Club 1 and reduce the probability of membership in Club 3, indicating a strong positive link between emissions and export performance. Regarding regional temperature effects, rising temperatures in Africa and North America reduce the probability of being in Club 1, but they also lower the probability of being in Club 3, indicating a contraction of export performance extremes. Conversely, in Asia, Europe, and South America, higher temperatures increase the likelihood of belonging to Club 1 and decrease the likelihood of being in Club 3.

Finally, the effects of carbon emissions across regions were tested using region-specific interaction terms. The ordered logit model results incorporating these interactions are presented in Table 10.

The results presented in Table 10 show that increases in GDP per capita, land under cereal cultivation, and average temperature significantly increase the probability of countries belonging to higher cereal export clubs. The effect of rural population on club membership does not follow a consistent pattern. In the Europe-interacted model, an increase in rural population is associated with a lower likelihood of being in high-export clubs, whereas in the South America-interacted model, the opposite relationship is observed-rural population growth is linked to enhanced export performance. In terms of precipitation, the effects appear to be more limited. In the Africa-interacted model, increased precipitation reduces the likelihood of countries being in high-export clubs, while in the North America-interacted model, it increases that likelihood. These findings highlight the region-specific sensitivity of precipitation effects on agricultural trade performance. The results for carbon emissions also vary by region. In Africa and North America, higher emissions are associated with an increased probability of belonging to low-export clubs, suggesting that emissions in these regions may be more closely tied to domestic production and consumption rather than export-oriented agriculture. By contrast, in Asia, Europe, and South America, increases in temperature correlate with a higher probability of being in high-export clubs. This suggests that in these regions, warming may – at least in part – be associated with agricultural practices that support or even enhance cereal export potential. The average marginal effects corresponding to these results are presented in Table 11.

According to the marginal effect results presented in Table 11, increases in GDP *per capita*, land under cereal cultivation, and average temperature significantly raise the probability of a country being in Club 1 – the group of countries with the highest cereal export performance – while reducing the likelihood of being

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Table 9. Ordered logit results with temperature and regional interaction (avg. marginal effect)

	(1)		(2)		(3)		(4)		(5)	
	Clubs1	Clubs 3	Clubs1	Clubs 3	Clubs1	Clubs 3	Clubs1	Clubs 3	Clubs1	Clubs 3
Lgdp	0.002 (0.006)	−0.002 (0.005)	0.033*** (0.007)	−0.024*** (0.005)	−0.028*** (0.007)	0.023*** (0.007)	0.024*** (0.007)	−0.018*** (0.005)	0.035*** (0.007)	−0.028*** (0.005)
Lrural	0.006 (0.011)	−0.005 (0.010)	0.001 (0.013)	−0.001 (0.009)	−0.034** (0.012)	0.029*** (0.011)	0.001 (0.013)	−0.001 (0.009)	0.038*** (0.013)	−0.030*** (0.010)
Lland	0.047*** (0.004)	−0.042*** (0.005)	0.036*** (0.005)	−0.027*** (0.004)	0.017*** (0.004)	−0.014*** (0.004)	0.029*** (0.005)	−0.022*** (0.004)	0.027*** (0.004)	−0.021*** (0.004)
Lpr	−0.021*** (0.007)	0.019*** (0.006)	0.021*** (0.007)	−0.015*** (0.005)	0.029*** (0.006)	−0.024*** (0.006)	0.026*** (0.007)	−0.020*** (0.005)	0.005 (0.007)	−0.004 (0.006)
*Lco*2	0.006 (0.005)	−0.005 (0.005)	0.025*** (0.007)	−0.018*** (0.005)	0.049*** (0.006)	−0.042*** (0.005)	0.034*** (0.006)	−0.026*** (0.004)	0.039*** (0.006)	−0.031*** (0.005)
Lat×Africa	−0.101*** (0.007)	0.091*** (0.008)								
Lat×Asia			0.014** (0.006)	−0.010** (0.004)						
Lat× Europe					0.075*** (0.007)	−0.063*** (0.007)				
Lat×N_ America							−0.031*** (0.008)	0.023*** (0.006)		
Lat×S_ America									0.056*** (0.007)	−0.044*** (0.006)

*** and ** significance at 0.01 and 0.05 levels, respectively; standard errors in parentheses; variables as explained in Table 1
Source: Authors' own calculations

Table 10. Ordered logit results with carbon emissions and regional interaction (coefficient estimates)

	(1)	(2)	(3)	(4)	(5)
Lgdp	−0.227*** (0.044)	−0.411*** (0.042)	−0.197*** (0.047)	−0.420*** (0.042)	−0.475*** (0.044)
Lrural	−0.084 (0.088)	0.035 (0.087)	0.286*** (0.091)	0.069 (0.087)	−0.189** (0.093)
Lland	−0.434*** (0.021)	−0.371*** (0.020)	−0.376*** (0.020)	−0.393*** (0.021)	−0.370*** (0.020)
Lpr	0.309*** (0.053)	−0.072 (0.048)	−0.061 (0.048)	−0.082* (0.049)	0.040 (0.051)
Ltas	−0.779*** (0.086)	−0.349*** (0.081)	−0.734*** (0.089)	−0.428*** (0.082)	−0.257*** (0.082)
*Lco*2×Africa	0.288*** (0.017)				
*Lco*2×Asia		−0.027*** (0.008)			
*Lco*2×Europe			−0.104*** (0.011)		
*Lco*2×N_America				0.090*** (0.015)	
*Lco*2×S_America					−0.100*** (0.014)
Log likelihood	−2 689.178	−2 854.304	−2 813.428	−2 842.1939	−2 833.8452
LR chi^2	790.25***	460.00***	541.75***	484.22***	500.91***
Pseudo R^2	0.13	0.07	0.09	0.08	0.08

*** and **significance at 0.01 and 0.05 levels, respectively; standard errors in parentheses, variables as explained in Table 1
LR – Likelihood Ratio Chi-Square
Source: Authors' own calculations

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Table 11. Ordinary logit results with carbon emissions and regional interaction (avg. marginal effect)

	(1)		(2)		(3)		(4)		(5)	
	Clubs 1	Clubs 3	Clubs 1	Clubs 3	Clubs 1	Clubs 3	Clubs 1	Clubs 3	Clubs 1	Clubs 3
Lgdp	0.029*** (0.006)	–0.027*** (0.005)	0.060*** (0.006)	–0.044*** (0.005)	0.028*** (0.007)	–0.023*** (0.005)	0.061*** (0.006)	–0.046*** (0.005)	0.068*** (0.006)	–0.052*** (0.006)
Lrural	0.011 (0.011)	–0.010 (0.010)	–0.005 (0.013)	0.004 (0.009)	–0.040*** (0.013)	0.032*** (0.010)	–0.010 (0.012)	0.008 (0.009)	0.027** (0.013)	–0.021** (0.010)
Lland	0.055*** (0.003)	–0.051*** (0.004)	0.054*** (0.003)	–0.039*** (0.003)	0.053*** (0.003)	–0.042*** (0.003)	0.060*** (0.003)	–0.043*** (0.003)	0.053*** (0.003)	–0.040*** (0.003)
Lpr	–0.039*** (0.007)	0.036*** (0.007)	0.010 (0.007)	–0.008 (0.005)	0.009 (0.007)	–0.007 (0.005)	0.012* (0.007)	–0.009* (0.005)	–0.006 (0.007)	0.004 (0.006)
Ltas	0.099*** (0.011)	–0.092*** (0.011)	0.051*** (0.012)	–0.037*** (0.009)	0.103*** (0.013)	–0.082*** (0.011)	0.062*** (0.012)	–0.047*** (0.009)	0.037*** (0.012)	–0.028*** (0.009)
*Lco*2× Africa	–0.037*** (0.002)	0.034*** (0.003)								
*Lco*2×Asia			0.004*** (0.001)	–0.003*** (0.001)						
*Lco*2× Europe					0.015*** (0.002)	–0.011*** (0.001)				
*Lco*2×N_ America							–0.013*** (0.002)	0.010*** (0.002)		
*Lco*2×S_ America									0.014*** (0.002)	–0.011*** (0.002)

***, **, *significance at 0.01, 0.05 and 0.10 levels, respectively; standard errors in parentheses; variables as explained in Table 1

Source: Authors' own calculations

in Club 3, which includes countries with low export levels. The effect of rural population varies across models. In Model 5, an increase in rural population is associated with a higher probability of being in Club 1 and a lower probability of being in Club 3. In contrast, Model 3 shows the opposite effect, indicating regional variation in how rural population dynamics relate to export capacity. The findings regarding precipitation also differ by model specification. In Model 1, increased precipitation lowers the probability of being in Club 1 while increasing the likelihood of being in Club 3. However, in Model 4, the effect is reversed: precipitation increases the probability of being in Club 1 and reduces the probability of being in Club 3. Regional differences in the effect of average temperature are also noteworthy. In Africa and North America, rising temperatures reduce the probability of being in both Club 1 and Club 3, suggesting that extreme temperatures may have a broadly negative impact on agricultural output, limiting both high and low export performance. Conversely, in Asia, Europe, and South America, higher average temperatures increase the probability of being in Club 1 and decrease the probability of being in Club 3, indicating that moderate warming in these regions may be associated with enhanced agricultural productivity and export potential.

CONCLUSION

This study examines the convergence of cereal exports among 95 countries from 2000 to 2022 and investigates the role of climate change in the formation of export convergence clubs. The results provide no evidence of full convergence across the entire panel. Instead, the findings indicate that countries are divided into seven distinct convergence clubs. Among these, Clubs 1 and 2 clearly stand out, and the divergence between these and the lower-performing clubs is expected to widen over time, primarily due to the evolving impacts of climate change. Developed and emerging economies – like USA, Argentina, India, Brazil, France, and Russia – dominate the top two clubs and global

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cereal trade. As such, these countries are key contributors to meeting international food demand, particularly for staple grains. The use of the ordered logit model further supports the club convergence hypothesis by confirming that climate change factors significantly influence club membership. Increases in average temperature, precipitation, and carbon emissions all raise the likelihood of countries being members of the top two clubs with the highest cereal export performance. Accounting for geographic variation shows that climate effects vary by region. In Africa and North America, rising climate indicators correlate with weaker export clubs, reflecting regional vulnerability. Conversely, in Asia, Europe, and South America, the same increases enhance the probability of membership in high-performing clubs, indicating that climate shifts may be leveraged more effectively in these regions to support export growth. These results underscore the importance of region-specific climate adaptation strategies and suggest that policymakers should consider both environmental conditions and economic structures when designing trade and sustainability policies.

The main results of the study demonstrate which countries act in unison when exporting cereal crops and how climate change influences these export patterns. As expected, countries that are major cereal producers also dominate cereal exports and tend to act together over the long term. Temperature changes have little effect on convergence, while precipitation and carbon emissions play stronger roles in shaping club membership. Based on these findings, several policy recommendations can be proposed. In regions such as Africa and North America, which are more negatively affected by climate change, there is a pressing need to strengthen climate adaptation strategies and climate-smart agricultural practices through education programmes, incentives, and subsidies. For instance, Okoronkwo et al. (2024) suggest improving farmers' access to credit and financial services to support investments in climate-resilient infrastructure, such as irrigation systems, drought-tolerant seeds, and storage facilities. Tailored financial support, as noted by Mbanasor et al. (2024), can boost farmers' adoption of climate-smart technologies. Additionally, policymakers should promote and incentivise smart irrigation systems, rainwater harvesting, and groundwater management in regions with irregular precipitation. Gradually replacing fossil-fuelled machinery with electric or biofuel alternatives can lower agricultural emissions. These climate-resilient interventions are expected to improve cereal productivity, which in turn can positively influence export capacity. In contrast to countries in Africa and North America, where climate change tends to adversely affect agricultural exports, countries in Europe, Asia, and South America appear to benefit from a positive influence of climate shifts on cereal exports. This suggests the need to preserve and enhance existing comparative advantages in these regions through sustainable strategies. These regions should pursue low-carbon export policies aligned with green transformation and reinforce competitiveness via climate-smart trade agreements.

Finally, this study does not directly explain the theoretical or empirical link between climate change and cereal production. Rather, the focus is placed on export convergence dynamics and the influence of climate-related variables on trade-based groupings. Nonetheless, the findings of this study offer both a foundation and motivation for future research. As climate change continues to reshape global agricultural systems, a natural next step in this emerging literature would be to directly investigate the impact of climate variables on cereal crop production at the country or regional level. Such studies could help determine whether the observed export patterns are driven primarily by production changes, trade policy, supply chains, or a combination thereof.

Future research could extend this work by analysing net cereal trade, incorporating both exports and imports. This would allow for a more comprehensive understanding of how countries' domestic food security priorities interact with their role in global food supply chains, especially under varying climate stressors. Integrating production, trade, and adaptation data into a unified framework would meaningfully advance climate economics and food systems research.

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