

# Climate Change and Food Price: A Systematic Review and Meta-Analysis of Observational Studies, 1990-2021

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## Abstract

Climate extreme events have threatened food security and the second Sustainable development goals (SDGs) “zero hunger” both directly via agricultural food loss and indirectly through rising food prices. We systematically searched and used a combination of results from various models, which play a crucial role in predicting the potential impact of climate change on agricultural production and food price. Therefore, we searched online databases including EMBASE, Web of Science, Scopus, Google Scholar, and grey literature. Then observational studies were included from January 1990 to August 2021, which reported food price proportion under climate disturbances. Results showed that 22 out of 26 studies from 615 articles, identified in the meta-analysis predicted the food price ratio would be fluctuated up to 28% before 2020, while the ratio will be marked up at 31% from 2020 to 2049 and then will scale down during 2050-2100. The compiled ratio was estimated at 26% in the long period between 2000 until 2100 under climatic weather events. Drought was a significant weather disturbance with a 32% increase in food prices. Consequently, the Food price increase will significantly affect food accessibility in lower-income countries, primarily until 2050. Policymakers should prioritize and act through redesigning food security policies according to climatic extremes in their settings.

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## Keywords

Climate Change, Food Security, Food Price, Extreme Weather Events, Systematic Review

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## 1. Introduction

Climate change has broad implications for agricultural food production through temperature-related and precipitation-related drivers. Climate drivers are classified as modal climate changes, seasonal changes, for instance, warming trends extending growing seasons, extreme events, and atmospheric conditions, e.g., Co<sub>2</sub> concentration (Mbow et al., 2019). Climate change refers to long-term changes usually over 30 years and has different impacts on human life (Dell et al., 2014). Therefore, Researchers apply the combination of Representative Concentration Pathways (RCPs) to Socio-economic Pathways (SSPs) conditions for focusing on a specific part of the future socioeconomic condition to estimate climate change impacts (Hasegawa et al., 2015a). The Special Report of (Intergovernmental Panel on Climate Change) IPCC on global warming presented that climate-related risks to food security are projected to increase with global warming of 1.5°C and rise more with 2°C (Mbow et al., 2019). During the last decades, much evidence has corroborated the relationship between extreme climate events such as drought, flood, storms, etc., and the direct and indirect adverse impacts on the food security dimension (availability, accessibility, utilization, sustainability). Conceptually, climate change might have direct and indirect primary effects on agriculture, leading to declined crop production. In other words, local weather disturbances inevitably affect food markets, resulting in increased food prices. The indirect impact will be diminished food accessibility. This phenomenon is a growing menace of food utilization by reducing both quantity and quality of food consumption as well as health sanitation and safe water access (Nelson et al., 2010; Wheeler & Von Braun, 2013; Hallegatte, 2016). Overwhelming evidence shows an upward exposure of low- and middle-income countries to climate disturbances rising from 83 percent of the countries in 1996-2000 to 96 percent in 2011-2016. Findings indicate that the agricultural sector comprising an average of 25% of the economy, has been adversely affected by extensive and medium-degree climate hazards, particularly in low and middle-income countries (LMICs) (WHO, 2020). A well-known example is the food price crisis in 2008 that led to the dramatic increase of food prices up to 130 percent for traded wheat and 70 percent for rice compared to 2007 (Conceição & Mendoza, 2009). In 2006 and 2007, when the primary producers of some grains and oilseeds in the European Union (EU), Australia and Ukraine experienced the harmful impact of climate variability and declined products. Consequently, such food price spikes pushed 40 million people worldwide to an undernourished condition and aggravated the numbers from 923 million in 2007 to 963

million in 2008 (Mittal, 2008). Recently the estimation of relative to median-level climate change shows additional hunger exposure of 20% - 36% and 11% - 33% population by 2050 under high and low emission scenarios, respectively (Hasegawa et al., 2021). Several studies attempted to explore the relationship between climate change and food price using different approaches, i.e., parameter choice harmonization or model structure (Green et al., 2013; Wheeler & Von Braun, 2013; Delincé et al., 2015). The typical method is combining different economic, agricultural and climatic models to estimate the impacts of climate change on the economy and the behavioral prediction of scenarios.

Researchers have used four distinguished models, each with its own merits and limits, to understand the future effects of climate change on food security and economic features: 1) Agro-economic simulation and partial equilibrium (PE), 2) Statistical cross-sectional or intertemporal analysis, 3) Computable general equilibrium models (CGE), and 4) Crop simulation models (Delincé et al., 2015). However, there are several limitations for each one. Consequently, an excellent review of the results of food prices through different models will be more comprehensive. This article aims to overview the global food price resulting from climate change effects by synthesizing the outcomes from observational evidence taken from all continents. According to our search, no systematic review or meta-analysis has compiled the food price prediction for a long future horizon with different models. We conducted a meta-analysis to determine the magnitude of the impact of climate change and the relative influence of other economic and agricultural uncertainties on food prices. Our findings will provide an evidence-informed perspective, which we envisage for policymakers and scientists in designing efficient policies to attain zero hunger along the pathway towards sustainable development goals (SDGs).

## 2. Methods

This is a systematic review and a meta-analysis designed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page & Moher, 2017) and the Meta-analysis of Observational Studies in Epidemiology (MOOSE) guideline statements (Stroup et al., 2000). In this study, PICOTS stands for the following:

Population: People in all regions of the globe;

Intervention: None;

Comparator: None;

Outcome: The percent change in food price under climate change;

Time: From January 1990 to August 2021;

Type of studies: Observational studies.

### 2.1. Search Strategy

We systematically searched PubMed, Web of Science, SCOPUS, Google Scholar, Magiran and Iranian Scientific Information Database for observational studies

published from 1990 to August 2021. The searched keywords were “climate change”, “global warming”, “climate variability”, “greenhouse gas emissions”, “GHGE”, “food price”, “food price change”, “food price elasticity”, “food cost”, “food price index”. No limitation was imposed on language and geographic region. In addition, we manually searched relevant studies by screening the reference lists of the retrieved studies, reference lists of review articles, and the grey literature. We screened all articles by importing them into EndNote (version X7, for Windows, Thomson Reuters, Philadelphia, PA, USA). **Table 1** presents the search strategy.

## 2.2. Study Selection

We selected relevant studies according to the following criteria: 1) Observational studies designed with case-control, cohort or cross-sectional, and 2) all studies that reported the percentage of food price under climate change. No restriction imposed on model estimation, geographical region, time period, and extreme weather events. Initially, two investigators (AK and RAB) independently checked the titles and abstracts and excluded articles that did not meet the eligibility criteria, according to a hierarchical approach based on the study design, population, exposure, and outcome. We retrieved the full texts of all eligible articles and screened them through the second evaluation. Any disagreement was resolved through researchers’ discussion until consensus was obtained.

## 2.3. Exclusion Criteria

We excluded review articles, animal studies, short communications, letters, books, grey literature (congress abstracts, dissertations, and patents), and those not published in English or were irrelevant to the subject of our review, as well as all studies that reported food price under different reasons, e.g., conflicts or wars combined with weather extreme events.

## 2.4. Data Extraction

Two researchers (AK and RAB) independently extracted data from each eligible study based on a predefined structure and resolved any disagreement by discussion. We extracted the first author’s name, publication date, country, area, and Continent; study design, study period and time horizon, the season of data gathering, and effect sizes that reported the percentage of food price with 95% CI

**Table 1.** Search strategy used in Scopus database.

Scopus
(TITLE-ABS-KEY (“climate change”) OR TITLE-ABS-KEY (“global warming”) OR TITLE-ABS-KEY (“green house effect”) OR TITLE-ABS-KEY (“climate variability”) OR TITLE-ABS-KEY (“GHGE”) AND TITLE-ABS-KEY (“food price strategy”) OR TITLE-ABS-KEY (“food costs”) OR TITLE-ABS-KEY (food AND price AND elasticity) OR TITLE-ABS-KEY (“food price”) OR TITLE-ABS-KEY (“food price change”) OR TITLE-ABS-KEY (“food price index”))

under climate change with any method. All economic, agricultural, or climatic variables, including GDP, type of weather extreme events, climatic variables, food consumption, type of crop or other agricultural food products, agricultural situation, food import, food inflation and subsidies, and the economic situation of countries were extracted. To obtain the missing data, the first author (RAB) sent E-mails to the corresponding authors of selected studies; if there was no response after 3 - 4 weeks, the study was excluded.

## 2.5. Quality Assessment and Assessment of the Risk of Bias

We assessed the quality of observational studies according to the indicators introduced by the Joanna Briggs Institute's (JBI), the critical appraisal tool (Checklist for Proportion Studies). In this tool, the quality characteristics are categorized in 9 items, the items which answered by Yes, took one point and if answered by No, took zero points. Items: 1) Was the sample frame appropriate to address the target population? 2) Were study participants sampled in an appropriate way? 3) Was the sample size adequate? 4) Were the study subjects and the setting described in detail? 5) Was the data analysis conducted with sufficient coverage of the identified sample? 6) Were valid methods used for the identification of the condition? 7) Was the condition measured in a standard, reliable way for all participants? 8) Was there appropriate statistical analysis? 9) Was the response rate adequate, and if not, was the low response rate managed appropriately? The total points will be 9 that would be allocated to the highest quality of studies (Joanna Briggs Institute, 2017). Accordingly, we categorized the studies into three quality groups and labeled them as "high quality" (7 - 9 points), "medium quality" (4 - 6 points), and "low quality" (below 3 points). Finally, fourteen studies were classified as high quality between (7 - 9 points) according to our categorization of JBI tool scores and 12 studies as medium qualities between (4 - 6 points). We excluded low-quality studies that took (below 3 points) points which were explained above. All discrepancies were resolved through discussion with the corresponding authors (AT, HP) and were reported in supplemental **Table S1**.

## 2.6. Data Analysis

### *Statistical analysis*

We applied the fixed-effects model to calculate pooled percentage (proportion) estimation with 95% Confidence Intervals CIs for food price. When between-study heterogeneity was significant, DerSimonian-Laird random-effects model was used to take between-study variation into account. Some studies had a proportion under 5%; therefore, we used CI Method (exact) or the binominal method according to the metaprop commands (Nyaga et al., 2014).

We conducted the Cochran Q test and  $I^2$  statistics to evaluate heterogeneity among the studies (Higgins et al., 2019). If the Q statistic had  $P < 0.1$  or  $I^2 > 50\%$ , the heterogeneity was perceived as significant (DerSimonian & Laird, 1986).

In the analyses, where  $I^2 > 50\%$  was observed, we explored possible sources of heterogeneity by subgroup analyses based on pre-defined criteria. Those criteria include; the type of extreme weather events (droughts, floods, RCP scenarios, temperature-precipitation varieties), the type of study design (cross-sectional, cohort), the geographical region (in 5 continents), and multiple continents if conducted in two or more continents, time horizon classified into three groups to predict food price (before 2020, 2020-2049, and 2050-2100), the agricultural crop production set at three levels (decreased production, increased production, no report as to increase or decrease), the GDP (decreased, increased, no-report), and the economic position of countries (high, middle and low-income). Many studies reported food prices for a couple of agricultural food products during the time zone, for which we estimated the mean of food price ratio. Other studies reported food prices for the baseline year and a long-term future. Hence, we calculated the food price change and included it in the meta-analysis.

Outputs are presented in tables and forest plots, where the proportion and 95% (CI) are figured out for every study inserted in the model and for the overall estimate.

We conducted sensitivity analyses to evaluate the considerable influence of an individual study or a group of studies on the results. In all subgroup analyses, the fixed-effects model was applied. When this was the case, the data were re-analyzed by excluding that study. In addition, Egger's test was conducted to visualize the inspection of asymmetry in funnel plots to assess the potential publication bias.

To avoid systematic bias, studies were entered into the model of each cumulative meta-analysis successively according to the data collection time and not the publication time. All statistical analyses for the current meta-analysis were performed using STATA version 14.0 (Stata Corporation, College Station, TX).  $P$  values  $< 0.05$  were considered statistically significant.

### 3. Results

We identified 615 studies in the primary systematic search and 23 grey literature. After removing 86 duplicates and 385 irrelevant articles, 167 full-text articles were assessed for eligibility. Finally, 26 articles, including eight cross-sectional and 18 prospective cohort articles, met the inclusion criteria for the systematic review, of which 22 studies with 23 effect sizes that reported food price in percentage were selected for analysis in the qualitative part for meta-analysis. Four studies did not report the outcome by percentage and described the food price situation with "increase" or "decrease" included in the systematic review. The included articles were published between 2009 to 2021. According to the model administration or measurement approach, different research areas were chosen: 13 studies were conducted in a single country.

In contrast, data for other 13 studies were gathered from 4 to 133 countries and regions in five continents. We categorized research areas according to data

gathering; therefore, studies in which the countries were selected from two continents were clustered as a multiple continent level, while others were classified according to one Continent's source. The study period was chosen before 2020 in 9 articles, whereas most of the remaining 17 studies used the time horizon to estimate food prices between 2021-2100. It was necessary to report data gathering for extreme climatic events, but in 8 studies, only the situation of (precipitation or temperature) was illustrated. Seven studies did not report any extreme weather events, but such conditions were directly mentioned in 12 studies.

Studies in which food price was reported in more than two countries from different economic situations were categorized in one level. The characteristics of data extraction are presented in **Tables 2-4**.

**Table 2.** Descriptive summary of 26 studies included on the effects of climate change on food price for systematic review and meta-analysis, during 1990-2021.

Author/ Country	Year of publication	Research Area/Continent	Study Design	Model/Measurement approach	Study period/ Time Horizon	food consumption
Batisani, N. Botswana	2012	Botswana AFRICA	Cross Sectional	Spatial-Temporal Agricultural drought Dynamics, SPI McKee	2008-2009 Rainfall data (1975-2005)	NR
Bandara, J. S. Australia	2014	Bangladesh, India, Nepal, Pakistan, Sri Lanka, ASIA	Prospective- cohort	Dynamic GTAP (Global Trade Analysis Project) Model known as Gdyn	2007-2010 2007-2030	overall to 2030 = 0.5% - 5% decline
Brizmohun, R. USA	2019	Mauritius AFRICA	Cross Sectional	Equilibrium Displacement Model	2007-2014	5% increase
Brown, M. E. USA	2015	51 countries, Afghanistan, Kenya, Senegal, Mali	Cross Sectional	State Space Models	2008-2012	NR
Cai, Y. Australia	2016	Bangladesh, India, Nepal, Pakistan, Sri Lanka, South Asia (Bhutan, Maldives and Afghanistan) ASIA	Prospective- cohort	Integrated Assessment Modelling (IAM), Computable General Equilibrium (CGE) Model GTEM-C, the GTEM-C model is calibrated to the GTAP 9 economic database. RCP8.5 Coupled Model Inter-comparison Project Phase 5 (CMIP5) database	2015-2040 1961-2010, 2000-2008,	Baseline = 2015 RICE = 2040 = -1.1 wheat = 2040 = -1.04 average = -1.07%
Calzadilla, A. Germany, UK Netherlands	2013	The United States, the Middle East, North Africa and South Asia (Multiple Continents)	Prospective- cohort	GTAP-W model, multi-region world CGE model, IPCC SRES A1B and A2 Scenarios, Hadley Centre Global Environmental Model version 1 (HadGEM1)	1961-1990 2006-2030 = mean 2020, 2036-2065 = mean 2050	NR
Chen, B. USA	2019	27 countries, Africa, Asia, and Latin America (Multiple Continents)	Prospective- cohort	Models included in the GGCMi-AgMIP archive, panel structure with 76 sub-national markets (denoted by k) in 27 countries (denoted by i) observed during the 2000-2015 marketing years, estimate regression	2006-2050 2000-2015	NR
Calzadilla, A. Germany, UK Netherlands, USA	2013	Sub-Saharan Africa AFRICA	Prospective- cohort	Partial Equilibrium Model (IMPACT MODEL), GTAP-W General Equilibrium Model. Model has 16 regions, 22 sectors, 7 FOOD. agriculture SRES B2 scenario	1961-2014 2011-2015 2000-2050	malnutrition (<5 years' child) increase 32%
Chung, U. Mexico, USA, KENYA, South Korea	2014	USA, developing country	Prospective- cohort	Geo-Spatial Crop Modeling, crop model (DSSAT CSM-CERES-Maize v4.5). Trend Analysis. CSIRO-Mk3.0 and MIROC 3.2 global climate models. Emission scenari- os (A1B and B1)	2000-2050	5% decrease consumption maize in USA2012



## Continued

Delince, J. Spain, Germany	2015	73 countries, EU-27 Norway, Turkey, China, Western Balkans, Canada, USA, Brazil, South and Central America, former Soviet Union, Middle-East, North Africa, sub-Saharan Africa, India, South-East Asia, Australia, New Zealand (Multiple Continents)	Prospective-cohort	AgMIP approach, horizontal model inter comparison from 11 economic models (six are CGE models (AIM, ENVISAGE, EPPA, FARM, GTEM, MAGNET), whereas the rest (GCAM, GLOBIOM, IMPACT, MAgPIE), including CAPRI, are PE multimarket models	2000-2050, (1980-2012) climate data	lower consumption levels dropping on average between 0.6% and 2.8% in China.
Gohar, A. A. Barbados	2016	island of Barbados NORTH AMERICA	Cross Sectional	Mathematical Programming Techniques, Nonlinear Dynamic Framework	1989-2012	Sugarcane consumption drop 5%
Gohar, A. A. Barbados	2018	island of Barbados NORTH AMERICA	Prospective-cohort	Representative Concentration	2018-2100 (1995-2100)	NR
Lee, H. L. Taiwan, China	2009	18 agro-ecological zones of all countries/regions in the world-OECD countries, China, Africa, Middle-east, North Latin America, the Caribbean, REF = Central, Eastern Europe, Newly independent states of the former Soviet Union Sub-Saharan Africa (Multiple Continents)	Prospective-cohort	GTAP Model, Land use change Modeling, Multi-sector CGE Model, SRES scenario A2 using the above-introduced model	2005-2020	NR
Lee, H. L. Taiwan, China	2018	133 countries in 5 continents (Multiple Continents)	Prospective-cohort	Multi-Regional CGE Model, GTAP Land use (GTAP-LU) Model	2000-2030 2011-2030	NR
Sassi, M. Italy, Sudan	2013	Sudan AFRICA	Prospective-cohort	Stochastic Model, Parametric Model	2010-2060 2002-2010	53% Kilocalorie Per capita Per day
Skjeflo, S. Norway	2013	Malawi AFRICA	Prospective-cohort	Computable General Equilibrium Model	2000-2030	NR
Sulser, T. B. USA	2011	14 countries, Arab region, Egypt, Syria, Mauritania, Qatar, Morocco, Bahrain, Djibouti, Jordan, Libya, Saudi Arabia, Yemen, United Arab Emirates (Multiple Continents)	Prospective-cohort	IMPACT Simulation Model. Partial Equilibrium Model, General Circulation Model (GCM) The SRES A2 scenario foresees moderate climate change 2 scenarios (2025, 2050)	2000—2025-2050	Per capita food 2025 = 18.2%, 2050 = 27% Food demand cereal 2025 = 33.2%, 2050 = 49.5%
Tigchelaar, M. USA	2018	Argentina, Brazil, China, France, Ukraine, and United States (Multiple Continents)	Prospective-cohort	Empirical Crop Models, Regression Models to the future climate data, temperature projections for all CMIP5 models in three emission scenarios (RCP4.5, RCP6.0, and RCP8.5). For all time-varying quantities 9 variables are calculated, Global maize production (GMP), 2008 = maize production	Crop (190I-2061) Climate (1901-2014) (1989-2008) GMP (2012-2017)	NR
Wiebelt, M. Germany, USA	2013	Yemen ASIA	Prospective-cohort	IMPACT Model, Dynamic Computable General Equilibrium (DCGE) Model, Global Climate Models, Crop Simulation Model, Decision Support System for Agrotechnology Transfer (DSSAT) Crop Modeling Framework	2000 and 2050. 2010, 2050	Calorie deficiency = 32.1% of people
Wong, K. K.S. Malaysia	2019	Malaysia ASIA	Cross Sectional	Engle-Granger Co-integration test (hereafter EG) and Error Correction Mechanism (ECM) Regression-Time Series Data	2010-2017, 1980-2017	NR
Wossen, T. Nigeria, Germany	2018	Ethiopia, Ghana AFRICA	Cross Sectional	Agent-Based Decision Modelling (ABM) Historical CPIs	E (1980-2010) G (1989-2009) CPIs (2000-2014)	Household food expenditure = Ethiopia = 35% Ghana = 70%
Yaffa, S. Gambia	2013	Gambia AFRICA	Cross Sectional	Qualitative Methods, Quantitative Method-Questionnaire Survey, FGD, Interview Annual rainfall in Banjul (1886) & Kerewan (1931)	2003-2012, B (1886-2003) K (1931-2011)	64% decrease food



## Continued

Zidouemba, P. R. Burkina Fao	2017	Burkina Faso AFRICA	Prospective-cohort	CGE Model identifies 66 production sectors, 27 of which are in agriculture and 25 in industry	2013-2050	Rural poor = -8.9, Nonpoor = -9.2, Urban Poor = -9.2, Non-poor = -8.3
Alvi, Sh.	2021	South Asia (Bangladesh, India, Pakistan, and Sri-Lanka)	Prospective-cohort	Integrated assessment model (IAM), climate models (CMIP5), (GTAP) model, empirical model, CGE modeling for future	1991 to 2015 climatic and non-climatic variables 2011-2050	Decrease = India = -5%, Pakistan = -19%, Bangladesh = -31%, Sri Lanka = -11%
Sam, A.G.	2021	Swaziland	Prospective-cohort	Almost Ideal Demand System (AIDS) model, Household and Income Survey data	2000-2001 survey, 2009-2010 survey/ 2010-2050	decrease
Putra, A.W.	2021	Indonesian	Cross Sectional	Volatility model, augmented Dickey-Fuller (ADF) test, ARCH-GARCH model, (autoregressive conditional heteroscedasticity ARCH or generalized autoregressive conditional heteroscedasticity (GARCH), Box-Jenkins model. ARIMA forecasting method	2009-2018	food shortage increase

**Table 3.** Descriptive summary of 26 studies included on the effects of climate change on food price for systematic review and meta-analysis, during 1990-2021.

Author	Season	Extreme Events	Climatic Variable	Setting/ Location	crop type	Agriculture+/-
Batisani, N.	4	Drought	Precipitation	cities/villages	Maize, Sorghum	Decrease (cultivation area)
Bandara, J. S.	4	Temperature	Temperature, precipitation	farm land	Rice, Wheat, Cereal Grains	2030 = rice = -4%-wheat = -11, cereal = -7%
Brizmohun R.	4	sea level rise, flooding	Temperature	urban/rural	Basmati Rice, Ration Rice	decrease
Brown, M. E.	winter	NR	Precipitation	urban/rural	Maize, Wheat, Rice	20% of local market prices were affected by domestic weather disturbances in the short run, 9% by international price changes and 4% by both domestic weather disturbances and international price changes
Cai Y.	4	Flood	Precipitation, Temperature, CRP8.5	NR	Rice, Wheat	decrease
Calzadilla, A.	NR	NR	Temperature Precipitation river flow, CO <sub>2</sub>	NR	Rice, Wheat, Cereal grains, Sugarcane, Oil seeds, irrigated Vegetables-Fruits	2020s = increasing global rain fed production 2050s = rain fed crop production declines due to heat stress, irrigated production declines in both periods. 2.3% decrease food production globally in 2050 scenario
Chen, B.	NR	NR	temperature, precipitation	76 retail wholesale markets	Maize	NR
Calzadilla, A.	4	NR	temperature, precipitation, CO <sub>2</sub> fertilization, surface water	Rural	Rice, Wheat, Sugarcane	-1.55% Decline
Chung, U.	May-August	heat wave, Drought	Precipitation, temperature	NR	Maize	Corn 2012 = 29% decrease Simulated scenarios 2050 = B1 = -38% A1B = -57%

## Continued

<b>Delince, J.</b>	NR	NR	Precipitation, Temperature	NR	Wheat Grains, Coarse Grains, Rice	climate change will cause a decrease in the agricultural productivity between -2% and -15% by 2050. Mean = -8.5%
<b>Gohar, A. A</b>	4	flood, Drought	Precipitation	farm land	pumpkin, sweet potato, sweet pepper, pigeon peas, cabbage, sugar cane	Decrease 4% in rainfed production
<b>Gohar, A. A</b>	4	3 RCP scenario CO <sub>2</sub> , CH <sub>4</sub>	seasonal, spatial, temporal Precipitation, Temperature RCP 2.6, RCP 4.5, RCP 8.5	farm land	pumpkin, sweet potato, sweet pepper, pigeon peas, cabbage, sugarcane, Onion Cassava, Cucumber, Squash	decrease-8%, 9%, and 13% for climate scenarios RCP 2.6, RCP 4.5, and RCP 8.5 respectively = Average for 3 scenarios = -10%
<b>Lee, H. L.</b>	NR	Increase temperature scenario RCP8.5	Precipitation, Temperature	Rural	Rice, Wheat, Other cereal grains, Vegetable and fruits, Oilseeds, Sugar cane and beets, Other crops	Average for crop production in all regions under scenario A2 by 2020 = -1.92%
<b>Lee, H. L</b>	NR	temperature anomalies	Precipitation, Temperature, RCP.6	NR	Crop	6.4% increase world
<b>Sassi, M.</b>	4	extreme rainfall events	Precipitation	Rural	Sorghum	NR
<b>Skjeflo, S.</b>	4	flood, drought	NR	Rural/Urban	Maize	3 scenario, high productivity = 2% increase, medium productivity = 10% decrease, low productivity = 22% decrease
<b>Sulser, T. B.</b>	4	NR	Temperature, Precipitation, CO <sub>2</sub>	NR	Maize-rice-wheat	Cereal production 2025 = 40.5%, 2050 = 40.3%
<b>Tigchelaar, M.</b>	NR	Increase temperature scenario RCP, 2, 4	2C scenario-4C scenario	NR	Maize	United States, China, Brazil, Argentina (the top four producing countries), mean total production is projected to decline by 18% (17.4 - 18.3), 10% (10.1 - 10.7), 8% (7.6 - 8.1), 12% (11.3 - 11.9), respectively, under 2°C of global warming and by 46% (45.4 - 47.5), 27% (26.7 - 28.0), 19% (19.0 - 19.9), and 29% (27.9 - 29.0) with 4°C of warming (mean and 90% confidence intervals)
<b>Wiebelt, M.</b>	Spring summer march July	Drought Flood	Precipitation, Temperature	Rural	Maize, Millet, Sorghum, Wheat, Potatoes, Tomatoes	The annual agricultural growth rates across zones under the MIROC and CSIRO scenario vary between (-0.06) percentage points and 1.2 percentage.
<b>Wong, K. K.S.</b>	NR	NR	Co <sub>2</sub> , Temperature	NR	Crop	Decrease
<b>Wossen, T.</b>	October, January February, May June, September	Rainfall events	Precipitation	NR	Maize, Wheat	average agent income declined by about 5% in Ethiopia and 20% in Ghana = most of farmers are buyer because food insecurity increase and income decline after production decrease
<b>Yaffa, S.</b>	June-July	Drought	NR	Rural	Millet, Maize	production decrease from 2010 in millet (64.2%), maize (44.8%) and groundnut (39.1%), Rice paddy (48.8%)

## Continued

<b>Zidouemba, PR</b>	NR	Extreme weather events	NR	Urban/Rural	Rice-Corn, Sorghum, Millet	NR
<b>Alvi Sh.</b>	NR	RCP6	RCP6	NR	Cereal	Cereals production can be decreased up to 31.49 (Bangladesh) 24.19 (Pakistan), 25.74 (Sri-Lanka), 6.4 (India) percent in the mid of this century-2050
<b>Sam A.G.</b>	4	Temperature, precipitation	Temperature, precipitation	rural	Rice, Wheat, Maize	decrease
<b>Putra, A.W.</b>	4	Indian Ocean dipole, Nino 3.4	Rainfall	urban/rural	Rice	decrease

**Table 4.** Descriptive summary of 26 studies included on the effects of climate change on food price for systematic review and meta-analysis, during 1990-2021.

Author	Food Inflation/ Subsidies	GDP	Food Import	Food Price %	Country Income Classification	Study Quality Score (max: 9 points)
<b>Batisani, N.</b>	25%increase	22%decrease	90%	increase 25%	middle income	8
<b>Bandara, J. S.</b>	2030 Bangladesh = 6%, India = 5.5%, Nepal = 29%, Pakistan = 4%, Sri Lanka = %	2030 = -0.5% - -3%	NR	overall increase price 2030 = rice = 10%, wheat = 25%, cereal = 45%, Mean crop = 26.6%	low income	7
<b>Brizmohun R.</b>	28.8% increase/ 25% total cost	decrease	92%	<b>35% increase</b>	low income	6
<b>Brown, M. E.</b>	NR	NR	NR	Asia = Afghanistan = 12% increase in local rice prices Africa = Senegal = 6% decrease in price for millet in Kaolack Kenya = 9% decrease in price of maize, mean = 7.5%	world	5
<b>Cai Y.</b>	NR	losing 0.15% - 0.6% of GDP = 2040	increase	Baseline = 2015 RICE = 2040 = 5.6%, Wheat = 2040 = 4.4%, Mean = 5%	low or middle-income	6
<b>Calzadilla, A.</b>	NR	0.29% decrease global	increase	6 food prices % increase global Mean = 34.5%	world	4
<b>Chen, B.</b>	NR	NR	10% of total consumption	increases to 10%	Low or middle income	6
<b>Calzadilla, A.</b>	NR	decrease 0.20%	NR	increase 7%	low income	7
<b>Chung, U.</b>	NR	NR	NR	USA maize price 2012 = 25%	world	8
<b>Delince, J.</b>	NR	NR	NR	Increase 1.3% & 56% = mean = 29%	world	9
<b>Gohar, A. A</b>	increase	decrease	NR	Increase Sugarcane = 22.8%, Cabbage = 10.4%, Cassava = 6.4%, Cucumber = 6.4%, Okra = 2.8%, Onion = 4.3%, Pigeon peas = 12.9%, Pumpkin = 22.8%, Squash = 5%, Sweet pepper = 5.8, Sweet potato = 8%, Tomato = 4%, average = 9.3%	high income	5
<b>Gohar, A. A</b>	Increase/50% of the total cost	NR	average annual increases 47%, 57%, 82% for RCP2.6, RCP 4.5, RCP 8.5, base climate scenario = average = 62%	Increase-average total food prices will increase by 8%, 9%, and 12% for climate scenario RCP 2.6, RCP 4.5, and RCP 8.5 respectively Average 3 Scenario = 10%	high income	5
<b>Lee, H. L.</b>	NR	GDP 2020 = OECD = 20.8 REF = 4.2 ASIA = 14.3 ALM = 11.2 base = 2000 y	Average = 9.21% increase	2.3% increase	world	9

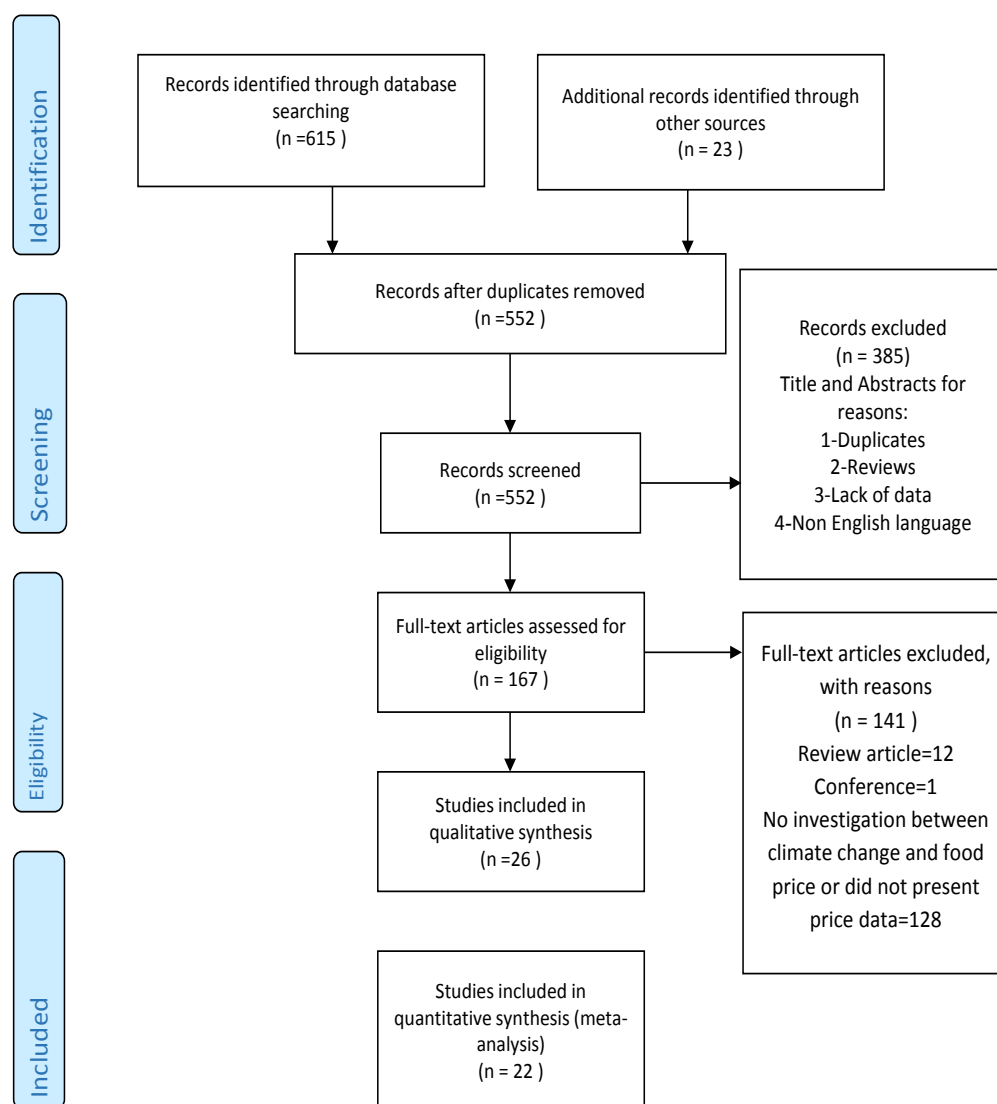
## Continued

Lee, H. L.	NR	NR	NR	4.9% world	world	8
Sassi, M.	NR	NR	NR	Model 2 wet scenario = 12.35% increase	low income	7
Skjeflo, S.	NR	Low productivity scenario = -2.8%	-1%	54% increase	low income	5
Sulser, T. B.	NR	Max = 18%, Min = 3%, Average = 10.5%	2000 baseline Import cereal 2025 = 16.3%, 2050 = 49%	2025 = Maize = 40%, wheat = 45%, Rice = 33% 2050 = maize = 59%, wheat = 63%, Rice = 48%	high income	9
Tigchelaar, M.	NR	NR	virtually zero today but jumps to 69% under 4 °C warming	increase	high income	8
Wiebelt, M.	increase	Agriculture 10% GDP. MIROC scenario (Scenario 1a), GDP growth 0.3%/year, CSIRO scenario higher 0.2%/year	increase	From IFPRI report of this research 2000-2050 = price increase 63% for maize & 39% for wheat = average = 51%	low income	8
Wong, K. K.S.	increase	1% increase in real GDP = 0.78 increase food price	NR	28.6% increase compare to 2010	upper-middle income	5
Wossen, T.	NR/25% fertilizer subsidy (only in Ethiopia)	NR	NR	Household food expenditure = Ethiopia = 35%, Ghana = 70%. household income decreases about 5% in Ethiopia and 20% in Ghana	low income	6
Yaffa, S.	Increased in 48% of households	NR	NR	increase	low income	5
Zidouemba, P. R.	NR	share of agriculture in the total GDP decreases from 35.8% in 2013 to 31.1% in 2050., decrease = -12.3% Rainfed corn = -12.2, Rainfed rice = -13.8	NR	NR	low income	4
Author	Food Inflation/ Subsidies	GDP	Food Import	Food Price%	Country Income Classification	Study Quality Score (max: 9 points)
Alvi Sh.	NR	loss GDP is 6.4, 24.19, 31.49, and 25.74 percent in India, Pakistan, Bangladesh, and Sri-Lanka respectively.	increase = India = 49%, Pakistan = 151%, Bangladesh = 230%, Sri Lanka = 90%	prices will increase due to climate change and the highest increase is in Bangladesh and Pakistan which are 97.19, and 60.25 percent, respectively. While this increase in India is 21.64, and 47.33 in Sri-Lanka. MEAN = 57%	Lower middle income	9
Sam A.G.	NR	NR	NR	cereal prices (wheat-maize-rice) are expected to rise by 70.14%, 53.85%, and 82.1%, respectively in the baseline (most likely), optimistic and pessimistic cases by 2050, relative to 2010 baseline prices = 68% mean of optimist-pessimist	low income	8
Putra, A.W.	8 provinces affected by inflation, /energy subsidies	NR	don not have considerable effect in price during this period	increase from 5800 rupiah per kg in 2009 to 11,800 rupiah in 2018 averagely = 100%	Lower middle income	6

Reviewers came to a consensus for including the final eligible articles. Detailed reasons for excluding and including the papers are addressed in the PRISMA flow diagram (Moher et al., 2009) in **Figure 1**.

### 3.1. Findings of the Systematic Review

The systematic search found 18 different models and techniques for food price estimation. Food consumption situation, which was investigated in 16 studies



**Figure 1.** Prisma flow diagram of: The effect of climate change on food pricing. A systematic review and meta-analysis.

(Calzadilla et al., 2013; Sassi, 2013; Wiebelt et al., 2013; Yaffa, 2013; Bandara & Cai, 2014; Chung et al., 2014; Delincé et al., 2015; Cai et al., 2016; Gohar & Cashman, 2016; Zidouemba, 2017; Wossen et al., 2018; Brizmohun, 2019; Alvi et al., 2021; Putra et al., 2021; Sam et al., 2021). Results demonstrated the reduction in this variable in 15 studies (10, 19 - 32). In one study (Sulser et al., 2011), food consumption was intensified despite the increased food price. Some general characteristics included in all studies are presented in **Table 2**. Weather extreme events, climatic variables, agricultural crop production, and crop types in each study are provided in **Table 3**. Findings from agricultural crop production show that three studies (Sassi, 2013; Brown & Kshirsagar, 2015; Chen & Villoria, 2019) did not report the amount of crop production. In contrast, crop production was decreased in most of the 17 studies (Lee, 2009; Sulser et al., 2011; Batisani, 2012; Calzadilla et al., 2013; Calzadilla et al., 2013; Wiebelt et al., 2013; Bandara & Cai,

2014; Chung et al., 2014; Brown & Kshirsagar, 2015; Delincé et al., 2015; Cai et al., 2016; Gohar & Cashman, 2016; Brizmohun, 2019; Chen & Villoria, 2019; Alvi et al., 2021; Putra et al., 2021; Sam et al., 2021). Crop production showed an increase under climate change only in two studies (Sulser et al., 2011; Lee et al., 2018). Food price situation in different seasons under climate change and other economic indicators consists of food import, GDP, food inflation, subsidies, and income classification of countries in each study, presented in **Table 4**. Finally, the results reported on food prices from 22 studies were included in the meta-analysis.

### 3.2. Findings of the Meta-Analysis

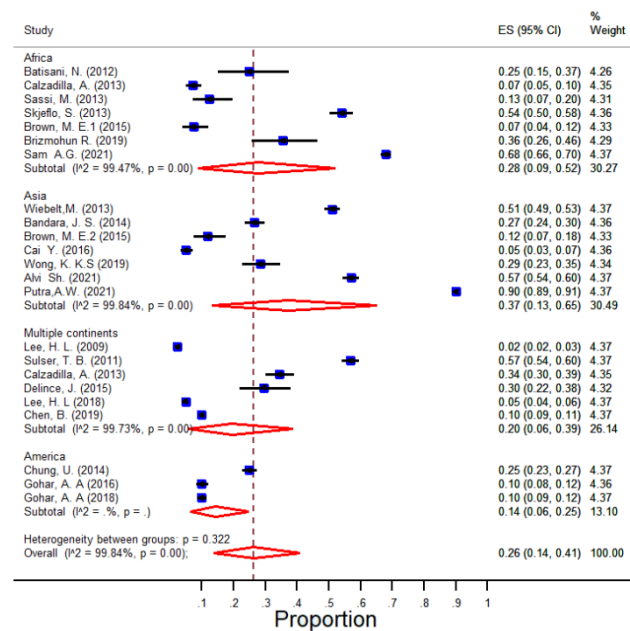
The analysis of 23 effect sizes from 22 observational studies (Lee, 2009; Sulser et al., 2011; Batisani, 2012; Calzadilla et al., 2013; Calzadilla et al., 2013; Sassi, 2013; Skjeflo, 2013; Wiebelt et al., 2013; Bandara & Cai, 2014; Chung et al., 2014; Brown & Kshirsagar, 2015; Delincé et al., 2015; Cai et al., 2016; Gohar & Cashman, 2016; Gohar & Cashman, 2018; Lee et al., 2018; Brizmohun, 2019; Chen & Villoria, 2019; Wong et al., 2019; Alvi et al., 2021; Putra et al., 2021; Sam et al., 2021), ranked as medium to high quality. It estimated that the pooled proportion of food prices was 26% (95% CI: 14, 41). According to the heterogeneity of included studies, further sub-group analysis was conducted using the study characteristics, which was presented in **Table 5**. The subgroup analysis indicated that heterogeneity between groups was significant in studies at extreme weather events and agricultural crop productions. However, our estimate did not show any evidence of statistical heterogeneity between groups of studies at the level of Continent **Figure 2**, weather extreme events **Figure 3**, agricultural crop production **Figure 4**, economic situation of countries (country income) **Figure 5**, study design **Figure S1**, study period /time horizon **Figure S2**, GDP **Figure S3**, and quality scores of the studies (high and medium) **Figure S4**. The results of each analysis are presented below in forest plots in **Figures 2-5**, **Supplemental Figures S1-S4**, and Subgroup Analysis of 22 Studies on the effect of climate change on food pricing from 1990 to 2021 **Table 5**.

#### 3.2.1. Extreme Weather Events

The forest plot of food price proportion according to the classification of extreme events is shown in **Figure 3**. Significant heterogeneity was observed among groups ( $p = 0.001$ ). Weighted pool proportion of food price showed that Drought was the frequent event, which was responsible for food price ratio of 32% [95% CI: 15% - 52%] as reported in 5 studies (Batisani, 2012; Skjeflo, 2013; Wiebelt et al., 2013; Chung et al., 2014; Gohar & Cashman, 2016); the ratio of 8% [95% CI: 6% - 10%] was due to flood as presented in 2 studies (Cai et al., 2016; Brizmohun, 2019); different RCP scenarios with a ratio of 17% [95% CI: 6% - 30%] as reported in 8 studies (Lee, 2009; Sassi, 2013; Bandara & Cai, 2014; Delincé et al., 2015; Gohar & Cashman, 2018; Lee et al., 2018; Chen &

## Meta-analysis of the Global Food Price Variation under Climate Change

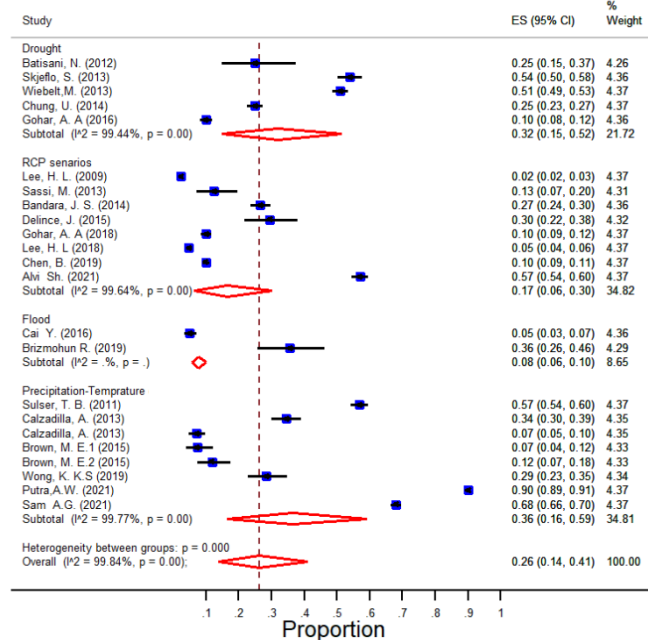
Stratified according to Continent



**Figure 2.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change., stratified according to Continent. The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.

## Meta-analysis of the Global Food Price Variation under Climate Change

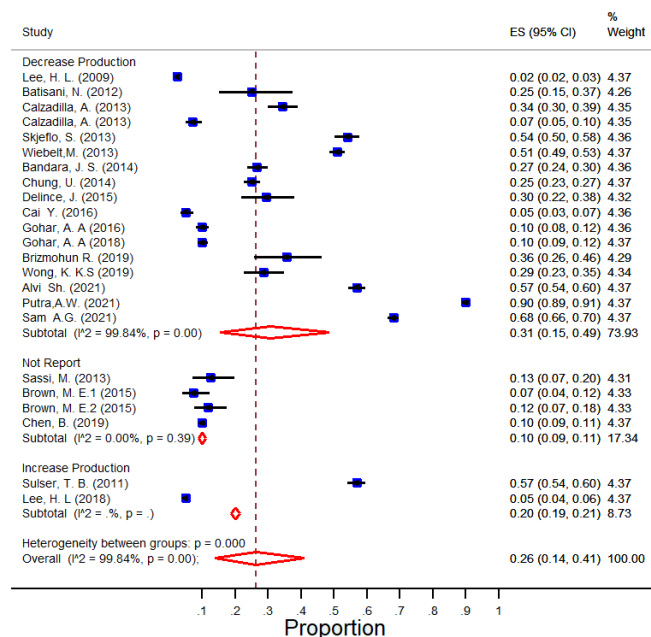
Stratified according to ExtremeEvents



**Figure 3.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change, stratified according to Weather extreme events. The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.

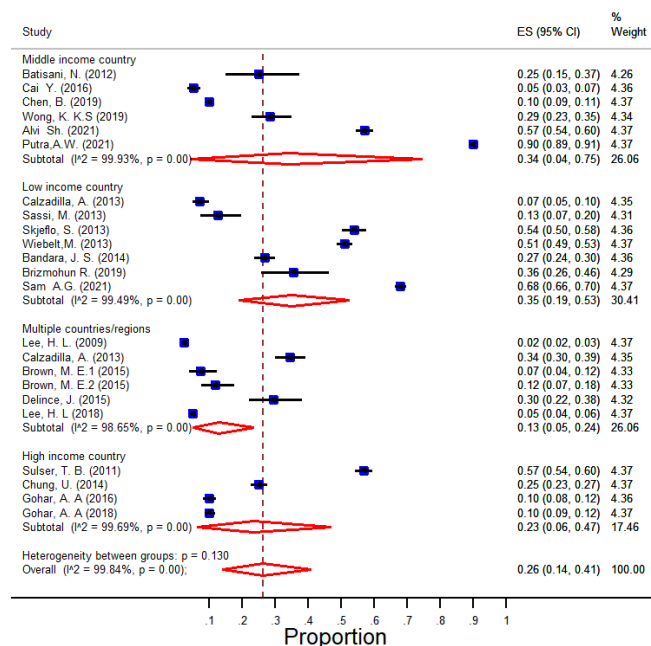


### Meta-analysis of the Global Food Price Variation under Climate Change Stratified according to Agricultural crop production



**Figure 4.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change, stratified according to Agricultural crop production. The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.

### Meta-analysis of the Global Food Price Variation under Climate Change Stratified according to CountryIncome



**Figure 5.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change, stratified according to Economic situation of countries (country income). The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.

**Table 5.** Subgroup analysis of 22 Studies according to subgroups of main variables that shows the effect of climate change on food pricing from 1990 to 2021.

Variable	Subgroup	Studies (effect size) (n)	Food Price proportion (95% CI)	I <sup>2</sup> (%)	Heterogeneity between Groups P-value
Continent	Asia	7	23 (13 - 65)	99.84	0.322
	Africa	7	28 (9 - 52)	99.47	
	America	3	14 (6 - 25)	0.0	
	Multiple Countries	6	20 (6 - 39)	99.73	
Country level classification by Income	High Income Country	4	23 (6 - 47)	99.69	0.130
	Middle Income Country	6	34 (4 - 75)	99.93	
	Low Income Country	7	35 (19 - 53)	99.49	
	Multiple Countries/Regions	6	13 (5 - 24)	98.65	
Time Horizon of studies	Before 2020	8	28 (4 - 63)	99.85	0.811
	2020-2049	6	31 (8 - 62)	99.89	
	2050-2100	9	22 (9 - 38)	99.63	
Study Design	Cross sectional (before 2020)	6	35 (5 - 76)	99.88	0.553
	Prospective Cohort (2020-2100)	17	23 (12 - 37)	99.78	
Weather Extreme Events	Drought	5	32 (15 - 52)	99.44	0.001
	Flood	2	8 (6 - 10)	0.0	
	RCP scenario	8	17 (6 - 30)	99.64	
	Precipitation-Temperature	8	36 (16 - 59)	99.77	
Agricultural Crop Production	Increase Production	2	20 (19 - 21)	0.00	0.001
	Decrease Production	17	31 (15 - 49)	99.84	
	Not Report	4	10 (9 - 11)	0.00	
GDP	Decrease GDP	7	28 (12 - 47)	99.40	0.933
	Increase GDP	4	31 (5 - 66)	99.83	
	Non report GDP	12	24 (6 - 48)	99.90	
Quality score of Studies (JBI Checklist)	Medium Quality	12	27 (8 - 52)	99.88	0.897
	High quality	11	25 (10 - 44)	99.80	

Villoria, 2019; Alvi et al., 2021), and the remaining 8 effect sizes showed fluctuation in temperature and precipitation with 36% [95% CI: 16% - 59%], which was reported in 7 studies (Sulser et al., 2011; Calzadilla et al., 2013; Calzadilla et al., 2013; Brown & Kshirsagar, 2015; Wong et al., 2019; Putra et al., 2021; Sam et al., 2021).

### 3.2.2. Agricultural Crop Production

There was high and significant ( $p < 0.001$ ) heterogeneity among groups in agricultural crop production subgroup analysis, as shown in forest plots in **Figure 4**. Weighted pooled proportion (percentage) of food price was higher in studies (Lee, 2009; Batisani, 2012; Calzadilla et al., 2013; Calzadilla et al., 2013; Skjeflo, 2013; Wiebelt et al., 2013; Bandara & Cai, 2014; Chung et al., 2014; Delincé et al.,

2015; Cai et al., 2016; Gohar & Cashman, 2016; Gohar & Cashman, 2018; Briz-mohun, 2019; Wong et al., 2019; Alvi et al., 2021; Putra et al., 2021; Sam et al., 2021) in which crop production showed reduction under climate change (31% [95% CI: 15% - 49%]) compared to studies (Sulser et al., 2011; Lee et al., 2018) which accounted crop production increment (20% [95% CI: 19% - 21%]).

### 3.3. Publication Bias and Sensitivity Analysis

The funnel plot revealed no existence of asymmetry and publication bias (**Supplemental Figure S5**), and the Egger's test ( $p = 0.161$ ) suggested no small-study effects (**Supplemental Figure S6**). Besides, we conducted trim-and-fill analysis and observed no publication bias (**Supplemental Figure S7**) (Egger et al., 2008).

The leave-one-out sensitivity analysis found no outlier study significantly shifted the primary pooled estimate. Based on the JBI scale, nine criteria were used to assess the quality of the included studies. All studies accounted for significant for subgroups. The results are summarized in **Supplemental Table S1**.

## 4. Discussion

We included 26 observational studies in this systematic review and meta-analysis. First hand, this is a research of its type to feature food accessibility under climate change by comparing critical drivers and over 18 economic, agricultural and climatic models using advanced analyses to enhance food policy insights. Our results revealed the following: 1) the meta-analysis predicted the global pooled food price growth will be 26% under climate extreme events in the time horizon until 2100 with substantial heterogeneity between the studies, 2) the sub-group analysis indicated that climate anomalies and agricultural crop production had significant heterogeneity between groups. Hence, drought was responsible for an increase of 32% in food prices compared to other weather disturbances. Therefore, a decline in agricultural crop production was another remarkable reason for some 31% increase in food price compared to other crop production categories, 3) another considerable effect size was presented by GDP status. Despite a decrease in some areas and an increase in other regions, it shows a 28% rise in food price due to decreased GDP in some countries and 31% through gained GDP in other areas, 4) findings of countries' economic situation pooled analysis revealed the highest food price increased 35% in low-income countries compared to 23% in high-income countries, and 5) our pooled analysis has revealed the higher food price increase in Africa (28%) and Asia (37%) as compared to North America (14%). There is some scientific evidence that might explain this situation, and the current study is an attempt in this regard.

Consequently, all four components of food security will be threatened by climate change. Eventually, regular access to safe, nutritious, and sufficient food in 2019 was in danger for two billion people globally. Cost estimates show that the international poverty line (established at USD 1.90 purchasing power parity (PPP) per person per day is not enough to provide a healthy diet at all. The increased

food expenditure for 57 percent of the population in the LMICs has made a healthy diet for their households unaffordable (WHO, 2020).

The general coping mechanism is that people will cut down on the consumption of these crops and may change their dietary patterns to scale down their foods both in quantity and quality. This meta-analysis discovered the global 26% increase in food price under climate change. The included studies showed a decrease in crop production that increased food prices by around 31% in some areas. As expected, food consumption showed a reduction in these regions and countries. Another systematic review (Green et al., 2013) is in line with our findings in predicting that an increase of all foods prices in developing countries would result in more significant reductions in food consumption. Every 1% increase in the price of cereals results in a diminishing of 0.61% and 0.43% in food consumption in low and high-income countries, respectively. A similar study (Haile et al., 2017) estimated the future climate effects on global crop production for maize, wheat, rice, and soybeans by general circulation models (GCMs) which is a type of climate model provided by the Coupled Model Inter-comparison Project Phase 5 (CIMP5). Projections showed that climate change could reduce global crop production by 9% in the 2030s and 23% in the 2050s, leading to increased food prices and adversely impacting production and intake, particularly among poor consumers. Others compared nine economic models that captured the general effects of climate change on food price and showed that the producer's increase of 20% in food price would slightly affect the consumption responses (Nelson et al., 2014). This percentage of food price is the same as our result.

Nevertheless, our review displayed that food consumption will be decreased in most countries that experience weather extremes events and inevitable agricultural production loss. The meta-analysis indicated that food prices would be increased one and a half-fold in low-income countries as much as about 35% compared to high-income countries, where a 23% rise is predicted. This feature of food prices is a normal response to the dramatic decrease in agricultural production. The analysis results in most of these countries showed that their GDP would be reduced, and they will suffer from a 28% increase in food prices. The research also predicted a 32% growth in food price as a continuous impact of Drought for many years starting from 2006 and a 36% increase in food price due to precipitation and temperature anomalies in many settings.

Our meta-analysis revealed that Africa and Asia might experience a higher food price of around 28% and 23%, respectively, as compared to North America, with a 14% increase during the years to come. Several reasons might contribute to this diversity. First, the review showed that some countries with increased production are located in North America; therefore, the harmful impact of climate change on agricultural production in this part of the world is lower than in other countries. The less detrimental effect in North America might be due to better fundamental conditions and adaptation policies against extreme climatic events there. Consequently, these producers will increase the amount of produc-

tion and the price of these crops. Our meta-analysis also revealed a 31% future growth in food prices in the countries that experience GDP growth.

One study that simulated food price under climate change scenario through IMPACT model in the Arab region revealed that from 2050, the population and income would grow due to demand for high nutritional value food, e.g., meat and fruits. Moreover, the other consequence was the need for livestock feed and calorie per capita (Sulser et al., 2011). Agricultural production will increase but not sufficiently provide food needs; therefore, food prices will rise to around 57%. Another study applied 12 climate models and one economic and demographic scenario to predict the period leading to 2050 and reported that the impact of climate change on food consumption depends more strongly on income than on food price (Hasegawa et al., 2015b).

Food prices intensification warns us against inequality between supply and demand. It also signals the lack of resources due to demand drivers consisting of population growth and income, including reducing agricultural productivity due to climate change on the supply side (WHO, 2018).

#### 4.1. Strengths and Limitations of the Study

Our study has some strengths. First, we could show the association between climate change's power threatening food accessibility through food price fluctuations by estimating all climatic, economic, and agricultural different models in over 170 regions and countries. Second, our findings displayed potential economic drivers such as GDP, food import, subsidies, food inflation, countries' financial and food consumption, food production details, and climatic conditions, including the seasons and extreme events. Third, we could show the percentage changes of food price under climate change for the five upcoming decades, with a cumulative ratio of high-quality studies conducted during the last two decades to alarm this risk for food security through prediction.

Our review had some limitations. Due to the low number of researches that reported food consumption, import, inflation, and subsidies, an appropriate description of various combinations of these variables and the impact on food price under climate change were complex.

#### 4.2. Suggestions for the Future Direction

It may be helpful to leave room for future research by identifying and applying economic variables which are substantial to draw comprehensive features of food price under climate change. As well as put these variables into models simultaneously, e.g., GDP, food consumption, household food purchasing, food inflation, and subsidies either to farmers or households. Researchers analyze only one or two of these economic drivers in most articles. However, this is a more precise method to evaluate food prices and accessibility in different parts of the food system. Subgroup analysis according to those economic variables would create a broader perspective. In addition, research conducted in other countries and

compared food price policies under the same climatic extreme events were rarely designed despite their helpful resolution to raise food affordability.

## 5. Conclusion

This paper has assessed the impact of extreme climatic events on food price prediction by applying meta-analysis and compiling food price results from different climatic or economic models with disparate drivers. Moreover, our estimates presented the remarkable role of some climatic anomalies, e.g., Drought, which threatened food affordability by multiplying food prices in vulnerable regions. This research has three crucial implications: first, Food prices rise under climate change in low-income countries much more than in high-income countries and threaten food accessibility in the 2050-2100 period.

Second, Drought is the most common climatic anomaly, 32%, responsible for higher global food prices until 2100.

Third: GDP growth will happen in LMICs simultaneously with the food price increase, but it is not guaranteed food accessibility in the future because other factors play a significant role in this situation like population growth, economic drivers, and climatic adaptation policies.

Finally, decision-makers should redesign food policies towards improving the fundamental macro and microeconomic elements of such policies to support the main stakeholders of the food system. Indeed, decision-makers should pay more attention to a successful experience for food security policy formulation, e.g., farmer subsidies support, food inflation control, and tax incentives under global warming and climate change shocks. These different experiences are crucial steps to increase adaptation strategies of food production on the supply-side and food accessibility on the demand side in the future.

## Author Contributions

Ramesh Allipour Birgani: Conceptualization, Investigation, Writing Original-Draft preparation, Visualization, Formal analysis Ali Kianirad: Investigation, Data Curation Hamed Pouraram: Conceptualization, Writing-Reviewing and editing Sakineh Shab-Bidar: Data Curation, Methodology, Validation Abolghasem Djazayeri: Reviewing and editing Amirhossein Takian: Project Administration, Writing-Reviewing and editing, Supervision.

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## Ethical Statement

This study was approved by the ethics committee of Tehran University of Medical Sciences on June 8, 2019 (Approval ID: IR. TUMS. VCR.REC.1398.216).

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## Consent for Publication

All authors of the manuscript have read and agreed to its content and are accountable for all aspects of the accuracy and integrity of the manuscript.

## Conflicts of Interest

The authors have no relevant financial or non-financial interests to disclose.

## References

- Alvi, S., Roson, R., Sartori, M., & Jamil, F. (2021). An Integrated Assessment Model for Food Security under Climate Change for South Asia. *Heliyon*, 7, Article ID: e06707. <https://doi.org/10.1016/j.heliyon.2021.e06707>
- Bandara, J. S., & Cai, Y. (2014). The Impact of Climate Change on Food Crop Productivity, Food Prices and Food Security in South Asia. *Economic Analysis and Policy*, 44, 451-465. <https://doi.org/10.1016/j.eap.2014.09.005>
- Batisani, N. (2012). Climate Variability, Yield Instability and Global Recession: The Multi-Stressor to Food Security in Botswana. *Climate and Development*, 4, 129-140. <https://doi.org/10.1080/17565529.2012.728129>
- Brizmohun, R. (2019). *Impact of Climate Change on Food Security of Small Islands: The Case of Mauritius*. *Natural Resources Forum*, 43, 154-163. <https://doi.org/10.1111/1477-8947.12172>
- Brown, M. E., & Kshirsagar, V. (2015). Weather and International Price Shocks on Food Prices in the Developing World. *Global Environmental Change*, 35, 31-40. <https://doi.org/10.1016/j.gloenvcha.2015.08.003>
- Cai, Y., Bandara, J. S., & Newth, D. (2016). A Framework for Integrated Assessment of Food Production Economics in South Asia under Climate Change. *Environmental Modelling & Software*, 75, 459-497. <https://doi.org/10.1016/j.envsoft.2015.10.024>
- Calzadilla, A., Rehdanz, K., Betts, R., Falloon, P., Wiltshire, A., & Tol, R. S. (2013). Climate Change Impacts on Global Agriculture. *Climatic change*, 120, 357-374. <https://doi.org/10.1007/s10584-013-0822-4>
- Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R. S., & Ringler, C. (2013). Economywide Impacts of Climate Change on Agriculture in Sub-Saharan Africa. *Ecological Economics*, 93, 150-165. <https://doi.org/10.1016/j.ecolecon.2013.05.006>
- Chen, B., & Villoria, N. B. (2019). Climate Shocks, Food Price Stability, and International Trade: Evidence from 76 Maize Markets in 27 Net-Importing Countries. *Environmental Research Letters*, 14, Article ID: 014007. <https://doi.org/10.1088/1748-9326/aaf07f>
- Chung, U., Gbegbelegbe, S., Shiferaw, B., Robertson, R., Yun, J. I., Tesfaye, K., Hoogenboom, G., & Sonder, K. (2014). Modeling the Effect of a Heatwave on Maize Production in the USA and Its Implications on Food Security in the Developing World. *Weather and Climate Extremes*, 5-6, 67-77. <https://doi.org/10.1016/j.wace.2014.07.002>
- Conceição, P., & Mendoza, R. U. (2009). Anatomy of the Global Food Crisis. *Third World Quarterly*, 30, 1159-1182. <https://doi.org/10.1080/01436590903037473>



- Delincé, J., Ciaian, P., & Witzke, H.-P. (2015). Economic Impacts of Climate Change on Agriculture: The AgMIP Approach. *Journal of Applied Remote Sensing*, 9, Article ID: 097099. <https://doi.org/10.1117/1.JRS.9.097099>
- Dell, M., Jones, B. F., & Olken, B. A. (2014). What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature*, 52, 740-798. <https://doi.org/10.1257/jel.52.3.740>
- DerSimonian, R., & Laird, N. (1986). Meta-Analysis in Clinical Trials. *Controlled clinical trials*, 7, 177-188. [https://doi.org/10.1016/0197-2456\(86\)90046-2](https://doi.org/10.1016/0197-2456(86)90046-2)
- Egger, M., Davey-Smith, G., & Altman, D. (2008). *Systematic Reviews in Health Care: Meta-Analysis in Context*. John Wiley & Sons.
- Gohar, A. A., & Cashman, A. (2016). A Methodology to Assess the Impact of Climate Variability and Change on Water Resources, Food Security, and Economic Welfare. *Agricultural Systems*, 147, 51-64. <https://doi.org/10.1016/j.agsy.2016.05.008>
- Gohar, A. A., & Cashman, A. (2018). The Economic Value of Groundwater Irrigation for Food Security under Climate Change: Implication of Representative Concentration Pathway Climate Scenarios. *Water Resources Management*, 32, 3903-3918. <https://doi.org/10.1007/s11269-018-2026-1>
- Green, R., Cornelsen, L., Dangour, A. D., Turner, R., Shankar, B., Mazzocchi, M., & Smith, R. D. (2013). The Effect of Rising Food Prices on Food Consumption: A Systematic Review with Meta-Regression. *BMJ*, 346, Article No. f3703. <https://doi.org/10.1136/bmj.f3703>
- Haile, M. G., Wossen, T., Tesfaye, K., & von Braun, J. (2017). Impact of Climate Change, Weather Extremes, and Price Risk on Global Food Supply. *Economics of Disasters and Climate Change*, 1, 55-75. <https://doi.org/10.1007/s41885-017-0005-2>
- Hallegatte, S. (2016). *Shock Waves: Managing the Impacts of Climate Change on Poverty*. World Bank Publications. <https://doi.org/10.1596/978-1-4648-0673-5>
- Hasegawa, T., Fujimori, S., Takahashi, K., & Masui, T. (2015a). Scenarios for the Risk of Hunger in the Twenty-First Century Using Shared Socioeconomic Pathways. *Environmental Research Letters*, 10, Article ID: 014010. <https://doi.org/10.1088/1748-9326/10/1/014010>
- Hasegawa, T., Fujimori, S., Shin, Y., Tanaka, A., Takahashi, K., & Masui, T. (2015b). Consequence of Climate Mitigation on the Risk of Hunger. *Environmental Science & Technology*, 49, 7245-7253. <https://doi.org/10.1021/es5051748>
- Hasegawa, T., Sakurai, G., Fujimori, S., Takahashi, K., Hijioka, Y., & Masui, T. (2021). Extreme Climate Events Increase Risk of Global Food Insecurity and Adaptation Needs. *Nature Food*, 2, 587-595. <https://doi.org/10.1038/s43016-021-00335-4>
- Higgins, J. P., Thomas, J., Chandler, J., Cumpston, M., Li, T., Page, M. J., & Welch, V. A. (2019). *Cochrane Handbook for Systematic Reviews of Interventions*. John Wiley & Sons. <https://doi.org/10.1002/9781119536604>
- Joanna Briggs Institute (2017). The Joanna Briggs Institute Critical Appraisal Tools for Use in JBI Systematic Reviews: Checklist for Prevalence Studies. The University of Adelaide: The Joanna Briggs Institute. [https://joannabriggs.org/assets/docs/sumari/ReviewersManual\\_2017-The-Systematic-Review-of-Prevalence-and-Incidence-Data\\_v2.pdf](https://joannabriggs.org/assets/docs/sumari/ReviewersManual_2017-The-Systematic-Review-of-Prevalence-and-Incidence-Data_v2.pdf)
- Lee, H.-L. (2009). The Impact of Climate Change on Global Food Supply and Demand, Food Prices, and Land Use. *Paddy and Water Environment*, 7, Article No. 321. <https://doi.org/10.1007/s10333-009-0181-y>
- Lee, H.-L., Lin, Y.-P., & Petway, J. R. (2018). Global Agricultural Trade Pattern in a Warm-

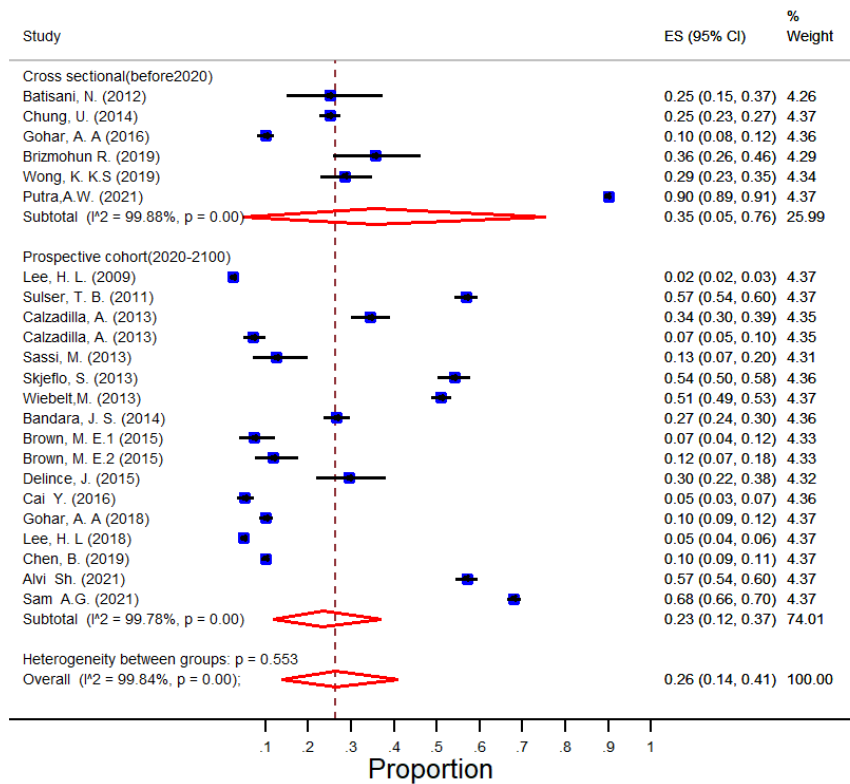
- ing World: Regional Realities. *Sustainability*, 10, Article No. 2763. <https://doi.org/10.3390/su10082763>
- Mbow, C., Rosenzweig, C., Barioni, L., Benton, T., Herrero, M., Krishnapillai, M., Liwenga, E., Pradhan, P., Rivera-Ferre, M., Sapkota, T. et al. (2019). Food Security. In P. R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner (Eds.), *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems* (pp. 437-550). Intergovernmental Panel on Climate Change (IPCC). [https://www.IPCC.ch/site/assets/uploads/sites/4/2019/11/08\\_Chapter-5.pdf](https://www.IPCC.ch/site/assets/uploads/sites/4/2019/11/08_Chapter-5.pdf)
- Mittal, A. (2008). *The 2008 Food Price Crisis: Rethinking Food Security Policies*. G24 Technical Group Meeting, United Nations.
- Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Group, P. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLOS Medicine*, 6, Article ID: e1000097. <https://doi.org/10.1371/journal.pmed.1000097>
- Nelson, G. C., Bereuter, D., & Glickman, D. (2014). *Advancing Global Food Security in the Face of a Changing Climate*. Chicago Council on Global Affairs.
- Nelson, G. C., Rosegrant, M. W., Palazzo, A., Gray, I., Ingersoll, C., Robertson, R., Tokgoz, S., Zhu, T., Sulser, T. B., & Ringler, C. (2010). *Food Security, Farming, and Climate Change to 2050: Scenarios, Results, Policy Options*. International Food Policy Research Institute.
- Nyaga, V. N., Arbyn, M., & Aerts, M. (2014). Metaprop: A Stata Command to Perform a Meta-Analysis of Binomial Data. *Archives of Public Health*, 72, Article No. 39. <https://doi.org/10.1186/2049-3258-72-39>
- Page, M. J., & Moher, D. (2017). Evaluations of the Uptake and Impact of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Statement and Extensions: A Scoping Review. *Systematic Reviews*, 6, Article No. 263. <https://doi.org/10.1186/s13643-017-0663-8>
- Putra, A. W., Supriatna, J., Koestoer, R. H., & Soesilo, T. E. B. (2021). Differences in Local Rice Price Volatility, Climate, and Macroeconomic Determinants in the Indonesian Market. *Sustainability*, 13, Article No. 4465. <https://doi.org/10.3390/su13084465>
- Sam, A. G., Abidoye, B. O., & Mashaba, S. (2021). Climate Change and Household Welfare in Sub-Saharan Africa: Empirical Evidence from Swaziland. *Food Security*, 13, 439-455. <https://doi.org/10.1007/s12571-020-01113-z>
- Sassi, M. (2013). Impact of Climate Change and International Prices Uncertainty on the Sudanese Sorghum Market: A Stochastic Approach. *International Advances in Economic Research*, 19, 19-32. <https://doi.org/10.1007/s11294-012-9380-1>
- Skjeflo, S. (2013). Measuring Household Vulnerability to Climate Change—Why Markets Matter. *Global Environmental Change*, 23, 1694-1701. <https://doi.org/10.1016/j.gloenvcha.2013.08.011>
- Stroup, D. F., Berlin, J. A., Morton, S. C., Olkin, I., Williamson, G. D., Rennie, D., Moher, D., Becker, B. J., Sipe, T. A., & Thacker, S. B. (2000). Meta-Analysis of Observational Studies in Epidemiology: A Proposal for Reporting. *JAMA*, 283, 2008-2012. <https://doi.org/10.1001/jama.283.15.2008>
- Sulser, T. B., Nestorova, B., Rosegrant, M. W., & van Rheenen, T. (2011). The Future Role of Agriculture in the Arab Region's Food Security. *Food Security*, 3, 23-48. <https://doi.org/10.1007/s12571-010-0100-5>
- Wheeler, T., & Von Braun J. (2013). Climate Change Impacts on Global Food Security. *Science*, 341, 508-513. <https://doi.org/10.1126/science.1239402>

- WHO (World Health Organization) (2018). *The State of Food Security and Nutrition in the World 2018: Building Climate Resilience for Food Security and Nutrition*. Food & Agriculture Organization.
- WHO (World Health Organization) (2020). *The State of Food Security and Nutrition in the World 2020: Transforming Food Systems for Affordable Healthy Diets*. Food & Agriculture Organization.
- Wiebelt, M., Breisinger, C., Ecker, O., Al-Riffai, P., Robertson, R., & Thiele, R. (2013). Compounding Food and Income Insecurity in Yemen: Challenges from Climate Change. *Food Policy*, 43, 77-89. <https://doi.org/10.1016/j.foodpol.2013.08.009>
- Wong, K. K. S., Lee, C., & Wong, W. L. (2019). Impact of Climate Change and Economic Factors on Malaysian Food Price. *Journal of the International Society for Southeast Asian Agricultural Sciences*, 25, 32-42.
- Wossen, T., Berger, T., Haile, M. G., & Troost, C. (2018). Impacts of Climate Variability and Food Price Volatility on Household Income and Food Security of Farm Households in East and West Africa. *Agricultural Systems*, 163, 7-15. <https://doi.org/10.1016/j.agsy.2017.02.006>
- Yaffa, S. (2013). Coping Measures Not Enough to Avoid Loss and Damage from Drought in the North Bank Region of the Gambia. *International Journal of Global Warming*, 5, 467-482. <https://doi.org/10.1504/IJGW.2013.057286>
- Zidouemba, P. R. (2017). Economywide Implications of Climate Change in Burkina Faso. *Economics Bulletin*, 37, 2797-2808.

Appendix A. Supplementary Data

Supplementary material related to this article: [Table S1](#), [Figures S1-S7](#).

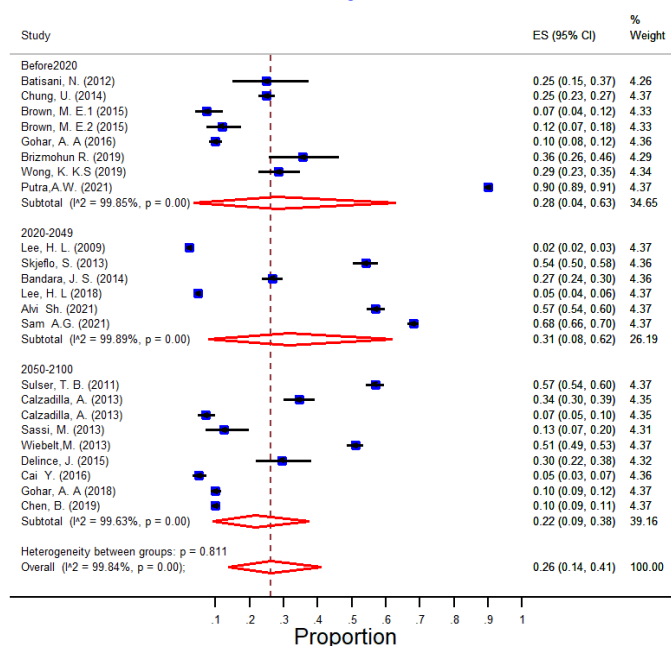
Meta-analysis of the Global Food Price Variation under Climate Change  
Stratified according to StudyDesign



**Figure S1.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change, stratified according to Study Design. The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.

## Meta-analysis of the Global Food Price Variation under Climate Change

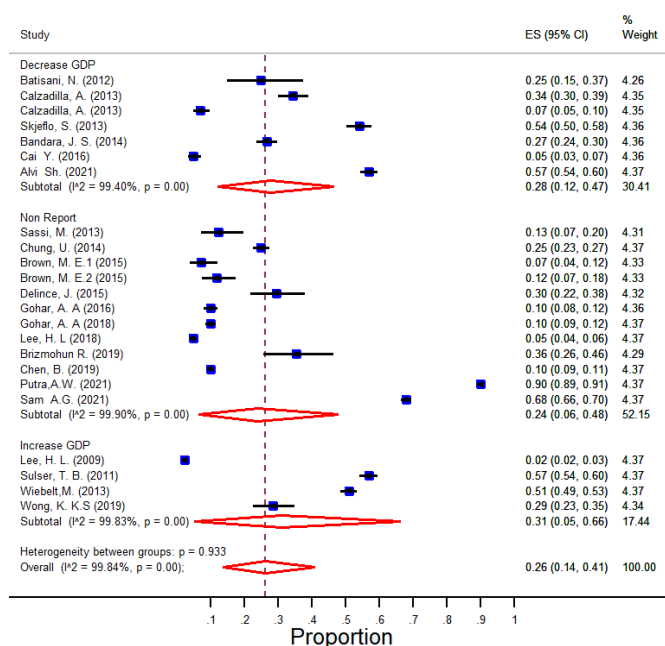
Stratified according to TimeHorizon



**Figure S2.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change, stratified according to Time Horizon. The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.

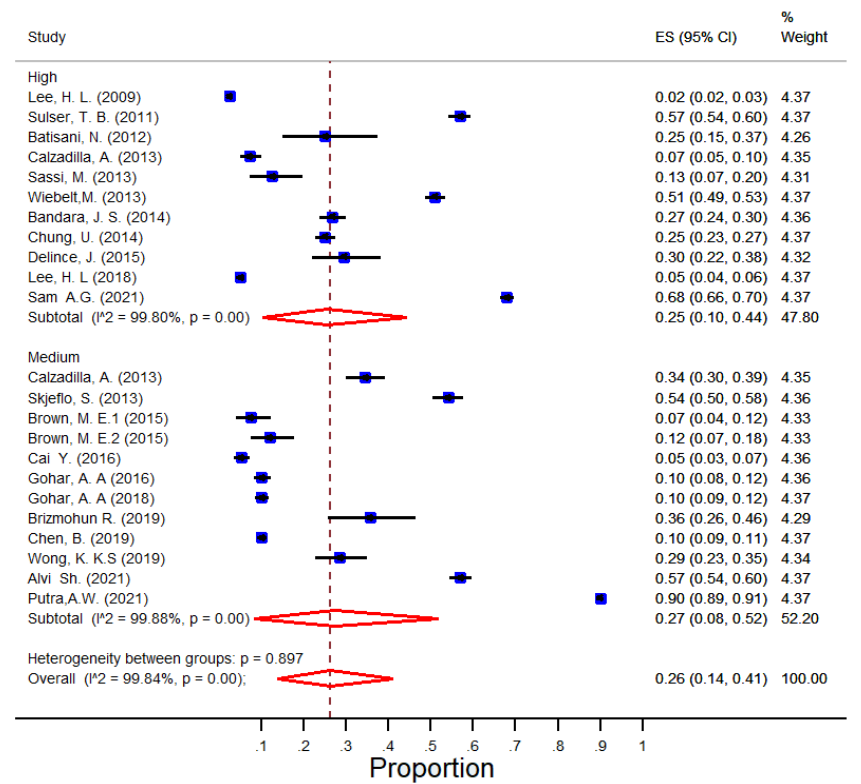
## Meta-analysis of the Global Food Price Variation under Climate Change

Stratified according to GDP

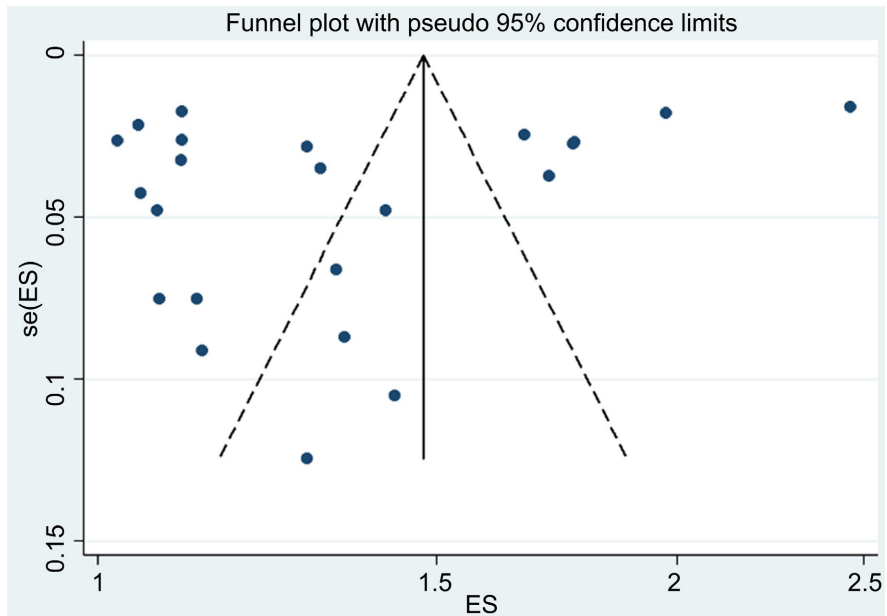


**Figure S3.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change, stratified according to GDP. The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.

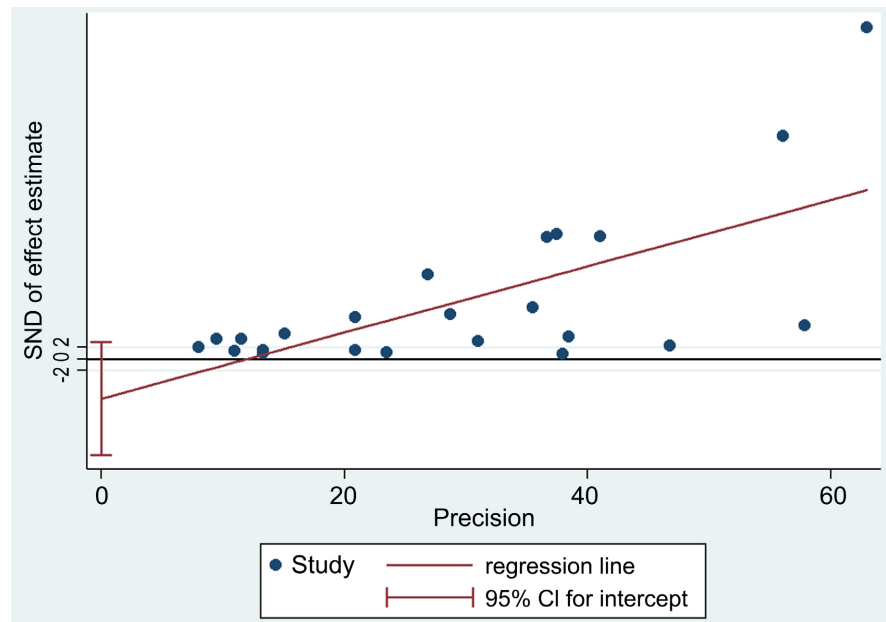
Meta-analysis of the Global Food Price Variation under Climate Change  
Stratified according to qualityscore



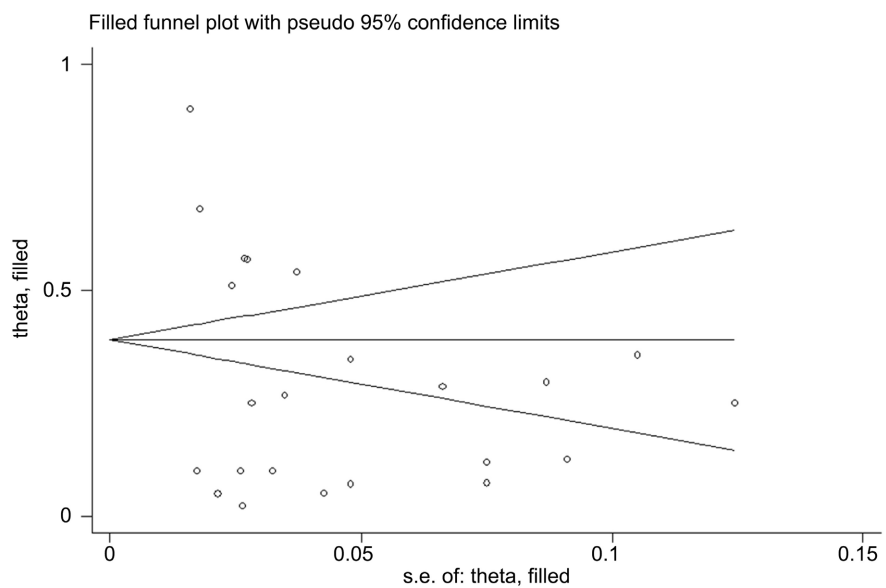
**Figure S4.** Forest plot of proportion, with 95% confidence intervals (CIs) of global food price variation under climate change, stratified according to Quality score of studies. The midpoint of each line illustrates the proportion estimated in each study. The diamond design shows the proportion throughout the studies.



**Figure S5.** Funnel plot for the publication bias of the studies that evaluated the prevalence of global food price variation under climate change.



**Figure S6.** Egger plot presented the visual inspection of publication bias for systematic review and meta-analysis the prevalence of global food price variation under climate change.



**Figure S7.** Filled funnel plot with the visual inspection of publication bias for systematic review and meta-analysis the prevalence of global food price variation under climate change.



**Table S1.** The quality score of each study using JBI critical appraisal tool (Checklist for Proportion Studies).

Author	Was the sample frame appropriate to address the target population?	Were study participants sampled in an appropriate way?	Was the sample size adequate?	Were the study subjects and the setting described in detail?	Was the data analysis conducted with sufficient coverage of the identified sample?	Were valid methods used for the identification of the condition?	Was the condition measured in a standard, reliable way for all participants?	Was there appropriate statistical analysis?	Was the response rate adequate, and if not, was the low response rate managed appropriately?	Total Quality score	Quality Level category
Bandara, J. S.	yes	yes	yes	yes	yes	yes	un clear	yes	unclear	7	high
Batisani, N.	yes	yes	yes	yes	yes	yes	yes	yes	unclear	8	high
Brizmohun, R.	yes	unclear	unclear	yes	unclear	yes	yes	yes	yes	6	medium
Brown, M. E.	yes	yes	yes	no	yes	yes	yes	yes	unclear	7	high
Cai, Y.	yes	no	unclear	no	yes	yes	yes	yes	yes	6	medium
Calzadilla, A.	unclear	yes	unclear	no	yes	yes	no	yes	unclear	4	medium
Chen, B.	yes	yes	unclear	no	no	yes	yes	yes	yes	6	medium
Calzadilla, A.	yes	yes	unclear	no	yes	yes	yes	yes	yes	7	high
Delince, J.	yes	yes	yes	yes	yes	yes	yes	yes	yes	9	high
Gohar, A. A.	yes	yes	unclear	yes	unclear	yes	un clear	yes	unclear	5	medium
Gohar, A. A.	yes	yes	unclear	yes	unclear	yes	un clear	yes	unclear	5	medium
Chung, U.	yes	unclear	yes	yes	yes	yes	yes	yes	yes	8	high
Lee, H. I.	Yes	yes	yes	yes	yes	yes	yes	yes	yes	9	high
Lee, H. L.	yes	yes	yes	no	yes	yes	yes	yes	yes	8	high
Sassi, M.	yes	yes	unclear	no	yes	yes	yes	yes	yes	7	high
Skjeflo, S.	unclear	unclear	yes	no	yes	yes	yes	yes	unclear	5	medium
Sulser, T. B.	yes	yes	yes	yes	yes	yes	yes	yes	yes	9	high
Tigchelaar, M.	yes	yes	yes	yes	yes	yes	yes	yes	unclear	8	high
Wiebelt, M.	yes	yes	yes	yes	yes	yes	yes	yes	unclear	8	high
Wong, K. K. S.	not applicable	not applicable	unclear	yes	yes	yes	not applicable	yes	yes	5	medium
Wossen, T.	unclear	yes	unclear	yes	yes	yes	yes	yes	unclear	6	medium
Yaffa, S.	yes	yes	unclear	yes	yes	unclear	yes	no	unclear	5	medium
Zidouemba, P. R.	unclear	unclear	unclear	yes	unclear	yes	yes	yes	unclear	4	medium
Alvi, Sh.	Yes	yes	yes	Yes	Yes	Yes	Yes	Yes	Yes	9	high
Sam, A. G.	Yes	yes	unclear	Yes	Yes	Yes	yes	Yes	unclear	8	high
Putra, A. W.	yes	unclear	unclear	yes	yes	yes	unclear	yes	yes	6	medium