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Assessing the Representativeness of Irrigation Adoption Studies: A Meta-Study of Global Research

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Abstract: For decades, nations around the world have been promoting irrigation expansion as a method for improving agricultural growth, smoothing production risk, and alleviating rural poverty. Despite its apparent advantages, suboptimal adoption rates persist. According to the existing literature, determinants of irrigation adoption are often highly dependent on cultural, contextual, and/or local institutional factors. Yet, studies from diverse geographies identify a consistent set of factors. Thus, to be able to make generalizable inferences from such studies, a global geographic representativeness assessment of irrigation adoption studies was conducted to determine whether identified factors influencing irrigation were the result of geographic, epistemological, or disciplinary biases. The results indicate that multiple geographic biases exist with respect to studying farmers' irrigation adoption decision-making. More research on this topic is being conducted in regions that have little to a high percentage of irrigation (>1%), are readily accessible, receive moderate amounts of average annual rainfall, and have moderate amounts of cropland cover. The results suggest the need to expand research efforts in areas with little to no irrigation to identify constraints and help accelerate economic growth, poverty reduction, and food and livelihood security for rural communities in these regions.

Keywords: agriculture technology; diffusion and adoption; farmers; climate change adaptation; systematic review

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1. Introduction

One of the major global environmental issues confronting us today is climate change, which threatens our ability to meet the growing population demands for basic resources like food and water [1,2]. Due to its inherent link to natural resources, agriculture is highly sensitive to changing climatic conditions [3] and is among the most vulnerable sectors to climate change risks and impacts [4]. Changes in temperature and rainfall patterns will have direct and indirect impacts on our food systems, ranging from reduced crop production to volatility in markets and food prices [5,6]. Even though food production trends of the last 40 years have more or less kept pace with the rising food demands [7], pressure on our food systems will only intensify with changing consumption patterns, lifestyles, and diets in the coming years [1,8]. Additionally, in most developing countries, agriculture provides the main livelihood and employment opportunities for rural populations and contributes significantly to the national GDP [9]. Therefore, any reductions in production will impact agricultural economies and challenge the resilience of agricultural-dependent communities as well [9,10]. Hence, there is a need to strengthen local capacity to deal with forecasted and/or unexpected climatic changes [3], and this requires adaptation [11].

Adaptation is considered a vital component of any policy response to climate change in addition to mitigation [4], and often involves changes in processes, practices, or structures to reduce potential adverse impacts [3]. Sakschewski et al. (2014) in their assessment of agricultural production argued that production increases can be accomplished either by increasing land productivity or by increasing land resources, but since cropland expansion is limited, engineered or technological adaptive responses remain the most common in this sector [12]. One such adaptation strategy is to augment rainfed production with the use of irrigation [13]. Irrigation has the potential to buffer climate stress and increase production on existing agricultural lands, smooth production risks, and improve the growth of agricultural economies [9,13–15]. According to the UN Food and Agriculture Organization (FAO), the global area equipped for irrigation worldwide increased from 184 million ha in 1970 to 324 million ha in 2012 [16]. Much of this expansion has occurred in developing Asian countries [17], with China having the largest irrigated area in the world, followed by countries like India, the United States of America, Pakistan, and Iran in the top five [18,19].

Despite the multiple benefits, irrigation adoption among farming communities has been slow or the long-term investments needed delay its adoption [20]. This is because adoption of any technology, in general, is a complex sociological phenomenon [21] that involves a large number of factors affecting the adoption decision [21] and is seldom rapid [20]. Globally, many attempts from different disciplinary backgrounds have been made to identify the factors that act as barriers to irrigation technology adoption by farmers [22–27]. Studies from diverse geographies identify a consistent set of factors, with the cost of technology cited as the most common barrier to its adoption/uptake [28]. However, the existing literature also asserts that the determinants of irrigation adoption are often dependent on local culture, context, and/or policies [29]. For example, Alabama in the south-eastern U.S. receives an average of 55 inches of precipitation annually which allows for a long growing season in the state. However, the recent increase in flash drought instances within the state is a cause of worry for those practicing rainfed agriculture, especially the small farm owners, making them the most vulnerable to these changing climatic conditions (For more details see the U.S. Drought Monitor for Alabama from the year 2000–Present available at: https://www.drought.gov/states/alabama, accessed on 15 October 2022). Accordingly, this identification of factors influencing irrigation adoption across a wide range of geographic contexts will be useful when climate change necessitates adaptation in such unprecedented areas.

One explanation for this disconnect concerning the different factors affecting irrigation adoption, which we explore in this paper, is that the geographic contexts in which irrigation adoption studies are often conducted might be biased, and this bias has influenced the set of factors identified as having explanatory power. If such a bias exists, it would not be unique to irrigation adoption studies. For instance, Martin et al. (2012) found the global distribution and context of ecological field study sites to be biased toward more accessible locations with limited human influence. According to the authors, the geographical context of selected study sites greatly influenced the observations made within these locations [30]. Therefore, to better understand the reasons as to why a farmer chooses to adopt or not adopt irrigation, it is first essential to recognize the global extent and context-dependency of irrigation adoption. This can be achieved through a geographic representativeness analysis. Using this analytical approach, the representativeness of studies examining factors affecting the diffusion and adoption of irrigation by farmers from around the world will be assessed to determine whether the identified factors (influencing irrigation adoption) from a set of case studies selected through a systematic review were the result of certain geographic biases or not. Accordingly, to identify these potential biases, we test the following two hypotheses:

H_1. *The geographic context of irrigation adoption studies is biased towards locations with substantial levels of existing irrigation, relatively low annual precipitation, and greater accessibility to markets.*

H_2. *The same factors (affecting farmers' decision-making) are observed regardless of the geographic context of these studies.*

Thus, the goal of this review is to understand whether the apparent consistency of factors influencing irrigation adoption is the result of the geographic contexts in which it is studied. Given the emerging challenges presented by climate change, we suspect that there are settings in which irrigation (and the study of its adoption) is currently limited but would be beneficial (i.e., improved yields, profits). If this is the case, then the set of factors influencing the irrigation adoption process may be different than in contexts with established irrigation practices. To answer this question, we narrowed our review to articles that explicitly addressed the irrigation adoption process, rather than broader investigations of the adoption of climate-smart agriculture or best management practices, e.g., [31] or those that assessed the benefits of irrigation adoption, e.g., [32].

This paper is structured as follows. Sections 1.1–1.3 give a brief overview of the motivations behind irrigation adoption and the technological and theoretical perspectives commonly used to study the adoption process. Section 2 describes the procedure followed for this systematic review, followed by the presentation and discussion of the results of the geographic representativeness and adaptation factors' analyses in the subsequent sections and some concluding remarks.

1.1. Why Irrigation?

Irrigation refers to the systematic and artificial application of water to plants at regular intervals to assist in the growing of crops and maintenance of landscapes [33–35] and is usually classified as surface, sprinkler, and micro-irrigation [35,36]. Irrigated agriculture, which accounts for more than 70% of total global freshwater withdrawals [15,37], provides for about 40% of the world's agricultural production [38] from less than 20% of its area [39–41]. Asia continues to contribute the largest share of total irrigated area, followed by Latin America, while sub-Saharan Africa only contributes 6% of its cultivated area to irrigation [18,38].

Irrigation use increases and stabilizes crop production in areas that do not receive enough precipitation [42–44], and has helped shape the economies of many semi-arid and arid regions around the world [45,46]. It also contributes toward income stabilization of dependent communities by improving agricultural growth and smoothing production risk [47–49]. According to a study by Bhattarai et al. (2007) [50], irrigation use can provide direct benefits like increased crop production that go to individual farm owners and/or entire community(s), and indirect benefits that are accrued to the wider sectors of the economy. There can also be spillover effects, which is brought by the increased household spending in the local economy due to enhanced income and employment as a result of increased land productivity made possible by irrigation [48].

1.2. Technology Adoption and Related Theories

Adoption is the decision to use a particular technology or innovation by an individual [51,52], which then leads to its diffusion or dissemination within a social system [52,53]. There exists a plethora of literature on factors that determine the adoption of a technology. Various researchers even define 'technology' itself in different ways and based on their definitions and disciplinary backgrounds use different theories or models to study its adoption [29,54–57]. For instance, in marketing research, the purchase of a technology is often the focus rather than its actual use [53]. Within agriculture, scholars have commonly used economic models and theories to explain individual technology adoption decisions [57,58], which allow for only rational and objective decision-making behaviors of farmers, rather than their perceptions, and assume that they adopt technology only for profit or utility maximization [59,60]. Alternatively, some research has shifted analytical focus to the role of individual knowledge, perceptions, and/or attitudes in the decision-making process, which in turn are conditioned by extrinsic factors, such as characteristics of the individual (~age, gender, education levels, etc.) and their external environment [29,61]. While others have taken a relatively more macro-perspective as they focus not only on the individual but also on the characteristics of the technology in question and the infrastructure needed for its successful diffusion to comprehensively understand its spread across the entire society (or market) over time [51,62,63]. A more recent strand of literature on agricultural technology adoption has also included the role of social networks in influencing the adoption of agricultural technologies [64–68]. Another key element associated with the adoption decisions is that of uncertainty or risk, which refers to the suitability of technology with an individual's characteristics including his/her experience or skillset, and with their local conditions (~agronomic, economic, and/or climatic) [57,69].

Since there exists no single model for understanding the decision-making processes in which an individual engages before adopting a certain technology, adoption is examined through a combination of research paradigms [55,57]. Moreover, these studies mostly utilize regression models to explain the uptake of technology as a function of several independent variables [70,71] including personal characteristics, preferences, individual attitudes, economic or institutional constraints, that are gathered either through census data, surveys, or personal interviews or a combination of it [29].

1.3. Factors Affecting Irrigation Adoption

Studies suggest that uptake of a new technology is rarely rapid, particularly among small farmers in developing countries [61,72,73], and with a wide range of factors acting as possible deterrents [72,74,75]. For example, a study in Burkina Faso (West Africa) of 629 farmers highlighted the need for farmers' training and information dissemination on irrigation to increase adoption [76]. Another study investigated factors affecting the adoption and application of sprinkler irrigation technology by farmers in the county of Famenin, Iran, and showed that the adoption was influenced by both environmental factors, such as farm size, access to water, water quality, and non-environmental factors, including workforce number in the family, employment diversity, and participation in extension education and courses on agricultural water management [77]. Another study investigated the sources of variation for on-farm irrigation systems across producer fields in Nebraska (USA) [42]. Their findings showed that biophysical factors such as soil, crop type, and weather, explained about half of the observed variations in field irrigation. However, the rest of the variations remained unexplained, suggesting that both producer behavior and skills played a significant role in shaping these decisions. Another study looked at the effect of production risk on irrigation technology choice among small-scale farmers in Chile and their results indicated that more educated farmers, with credit access, receiving extension services, and living in communes with other adopters were more likely to use modern irrigation techniques [78]. Another study of 1500 farmers from Henan Province in China found that the farmers who believed in climate change adopted adaptation measures like irrigation to respond to and mitigate its negative impacts [79]. Thus, understanding the kinds of factors influencing adoption decisions is crucial not only for the propagators of these technologies to increase the likelihood of their adoption but also for identifying the overall determinants of agricultural growth and development [80].

2. Materials and Methods

2.1. Data Collection

2.1.1. Literature Search Strategy

A literature search was conducted using Science Direct and Scopus databases. The search was limited to only research articles written in the English language and published in peer-reviewed journals between 2000 and 2021. Articles prior to 2000 were excluded as the global irrigation dataset used in this analysis is based on the nationally reported statistics from around the year 2000 (more details about this dataset are presented in Table 1). Moreover, this also reflects the broader trends in irrigation adoption globally because the percentage of reported data on irrigation use from around the world is largest from the year 2000 onwards compared to the earlier years [81]. The steps taken in the search and screening process are presented in Figure 1. First, a target set of 10 articles containing both 'true positives' and 'true negatives' was assembled from a wide range of disciplines to represent the full range of publications in this research domain and assemble a set of search keywords. Target set articles are listed in Appendix A. Different keywords such as irrigation, technology adoption, agriculture, farmer decisions, water management, and climate change adaptations were combined using Boolean operators to download relevant studies. The specific search terms used were: ((“irrigation”) AND (“technology” OR “adoption”) AND ((“reasons and constraints”) OR (“attitudes”) OR (“drivers”) OR (“perception”) OR (“barriers”)) AND (“climate change adaptation” OR “climate smart agriculture” OR “climate change” OR “adaptive capacity”) AND ((“drought”) OR (“water management practices”)) AND ((“farmers”) OR (“farmer decisions”))).

Table 1. Description and sources of all the datasets used in this analysis.

Dataset Name	Description	Source
Global Administrative Areas (GADM)	A spatial database of the location of administrative areas of all countries, at all levels of sub-division.	GADM (2018–2022) [82]
GLOBE Land Units (GLUs)	GLUs are equal-area hexagonal cells that cover the Earth’s land surface and are based on the geodesic Discrete Global Grid (DGG) system of Kevin Sahr (2003).	GLOBE (2012)
Average Annual Precipitation	Average annual precipitation (mm/year) from 1950–1999. Native resolution is 30 arcminutes projected in Geographic Coordinate System WGS 1984.	Willmott & Matsuura (2001) [83]
Percent Crop Area	Percent crop land cover area per grid cell derived from HYDE (History Database of the Global Environment) land cover data. Native resolution is 0.5° projected in Geographic Coordinate System WGS 1984.	Klein Goldewijk et al. (2011) [84]
Market Access Index	Global grid of a normalized market access index based on travel time to cities with populations of at least 50,000 and 750,000.	Verburg et al. (2011) [85]
Percent Area Equipped for Irrigation	Global map of irrigation areas showing the amount of area equipped for irrigation around the year 2000 in the percentage of the total area on a raster with a resolution of 5 min.	Siebert et al. (2005) [86]

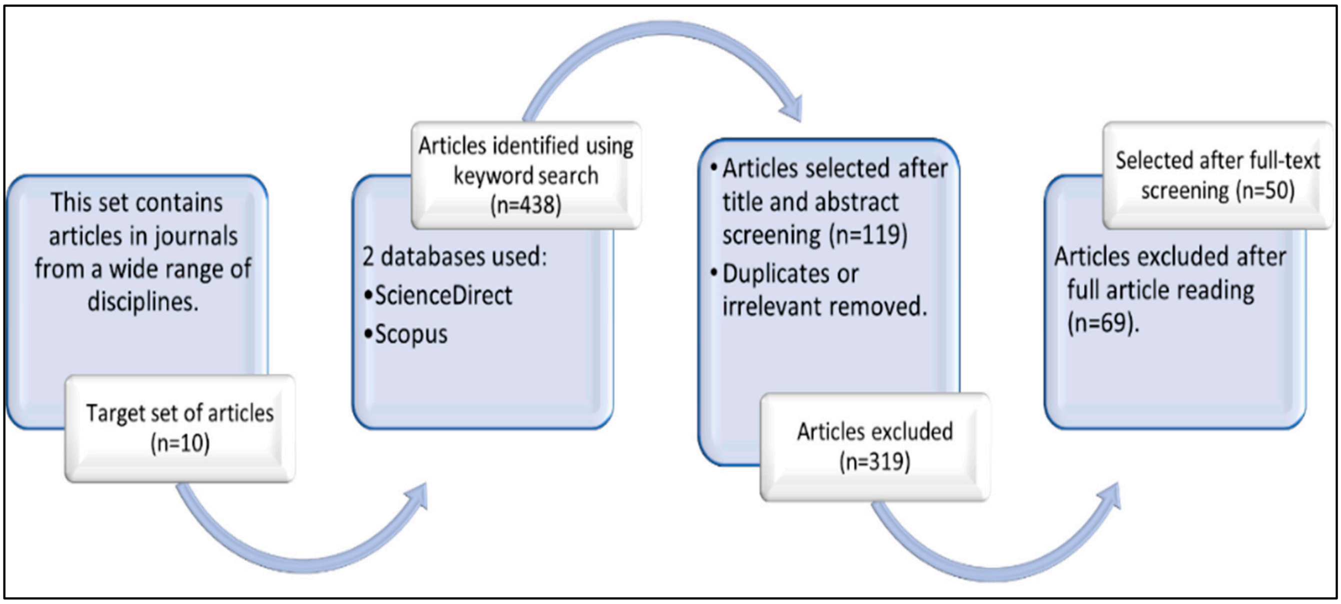


Figure 1. Steps involved to assemble research articles for this analysis.

2.1.2. Selection of Case Studies

After the literature search, the resulting dataset consisted of 438 publications. The next step was article screening to identify case studies that should be used in this meta-study. Both study titles and abstracts were checked and critically reviewed for suitability for this analysis. Articles were excluded if they did not (1) investigate the different factors/reasons affecting technology adoption within the agricultural sector, and (2) present an assessment of farmers' views or opinions. Conference proceedings, grey literature, reports, and duplicate articles were also excluded from the dataset. The initial screening reduced the number of eligible articles to 119. The second round of screening was performed using the full text of each remaining article. Articles were primarily screened to determine specifically if irrigation adoption by farmers was studied or not, irrespective of the type of irrigation system. For instance, many studies examined the adoption of several different agricultural practices together, in the form of climate change adaptation strategy, conservation agriculture, or as sustainable farming practices adopted by farmers including high-yielding crop varieties, different soil, and water management practices see, e.g., [87–89]. All the studies that did not include irrigation as one of the technologies or practices being studied were discarded. Moreover, studies that were conducted at a very large-scale and reported aggregated results (e.g., for entire U.S. mid-west region [90] or 11 African countries together [91]), were excluded to ensure comparability of results, since the goal was to examine the geographic contexts of these studies that would otherwise have been difficult to capture. Additionally, studies that investigated the benefits of irrigation adoption, assessed its impact on crop production under climate change, or estimated future adoption rates were also not considered, e.g., [92–95]. As a result, 50 case studies, which passed the inclusion and exclusion criterion were selected and used in this meta-study. A complete list of the studies included in this review is also provided in Appendix A.

2.2. Data Analysis

A representativeness analysis provides a robust statistical test to enable the user to investigate potential geographic biases within a collection of primary data observations (e.g., case studies) [96]. Using this analytical approach, for a given global variable of interest (e.g., average annual precipitation), the frequency distribution of the global variable within a user-specified geographic extent was compared with the frequency distribution of the observations in the sample collection, and the degree to which the sample collection's distribution is representative of the distribution of the global variable was quantified [96,97]. The null hypothesis for this analysis was that the frequency distributions of the global variable and sample collection are not statistically different. If the null hypothesis can be rejected with a low probability of type I error, then the sample can be declared as significantly biased. To enable comparability between values of the global variable and sample collection observations, which might include case study geographies of diverse extents, the standardized, hexagonal, and equal-area geographic units from the GLOBE system were used, known as GLOBE land units (GLUs). The degree of representedness (r) was then computed with a chi-squared ($\chi 2$) test and was characterized as follows:

$$
\begin{aligned}
r = 0 &\text{ if } f_e(g_v) = f_o(g_v) \\
-(1-p) &\text{ if } f_e(g_v) > f_o(g_v) \\
(1-p) &\text{ if } f_e(g_v) \leq f_o(g_v) \\
\text{undefined} &\text{ if } f_e(g_v) = 0 \wedge f_o \neq 0
\end{aligned}
$$

where $f_e(g_v)$ was the expected frequency of the bin to which GLU g belonged (calculated from the population set), $f_o(g_v)$ was the observed frequency of that bin (calculated from the sample set), and p was the p-value for the χ^2 test. The range of r is between [−1 to 1], with 0 indicating perfect representedness, negative numbers indicating under-representedness, and positive numbers indicating over-representedness [96].

Several data preparation steps were followed to produce the sample and global (~population) datasets. Table 1 describes all the datasets used for this analysis. After shortlisting the case studies, the locations of the study sites (total = 53) mentioned in each of the selected 50 articles were mapped using the shapefiles of administrative boundaries from the GADM dataset in ArcGIS Pro software (see Figure 2). Next, the global GLU feature layer obtained from GLOBE was filtered using several context variables (see Table 2) to restrict the global dataset to the expected geographic extent of agricultural areas. Case study locations were also intersected with the filtered GLU layer to form the sample dataset and to maintain a similar unit of analysis for both the layers. For each GLU, values of three variables—average annual precipitation (mm/year), percent crop area, and market access index were calculated. For the area equipped for irrigation (%) variable, mean values were computed using zonal statistics within each GLU for both the above feature layers. The extent/range of the selected four variables within both the global and sample layers are shown in Figures 3–6. For each of these four variables, these two datasets were divided into different intervals or bins. The binning strategy was kept the same as their source datasets (see Table 1 for dataset details) except for average annual precipitation variable for which a geometric interval was used. Finally, Pearson's χ^2 test for the independence of two datasets was conducted to compare the frequency distributions of the sample and global datasets for each of the selected four variables to determine the geographic representativeness of the assembled case studies on irrigation adoption and answer the first hypothesis.

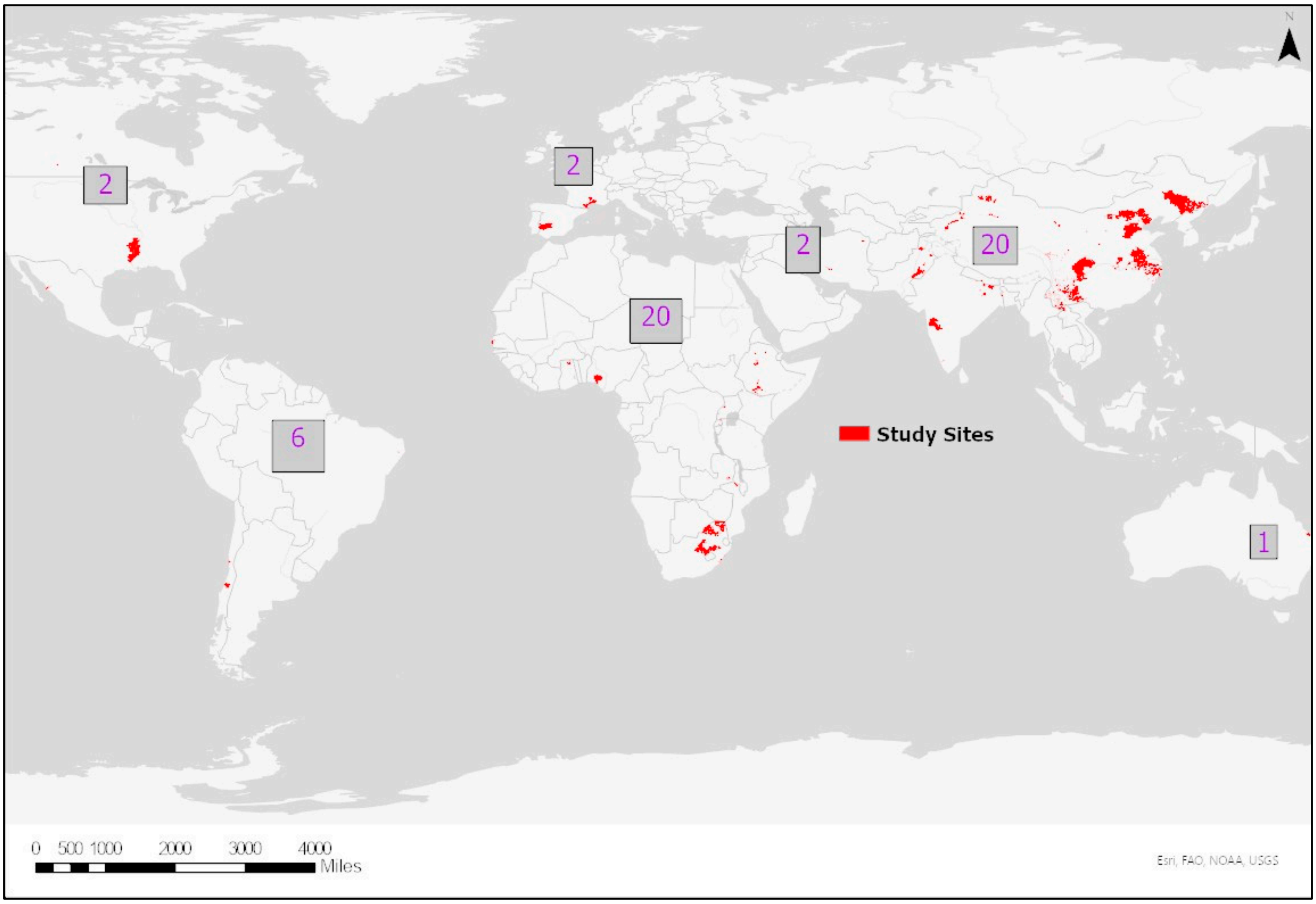
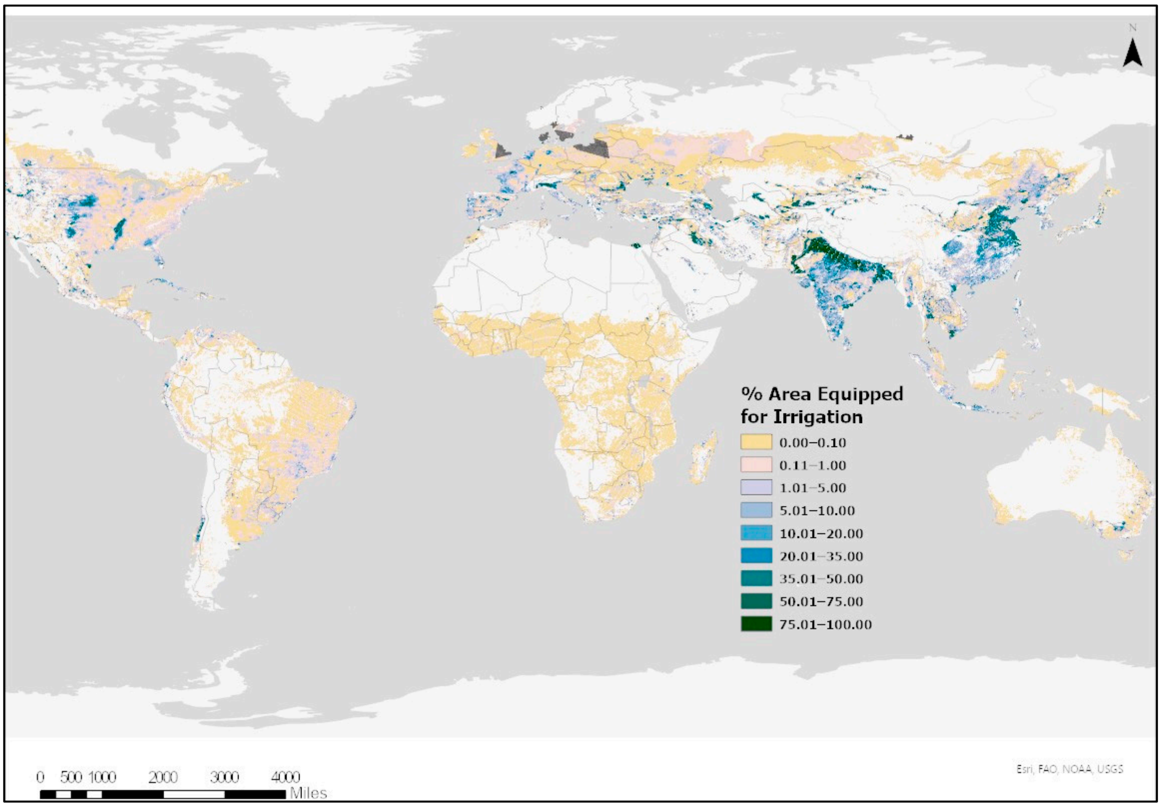
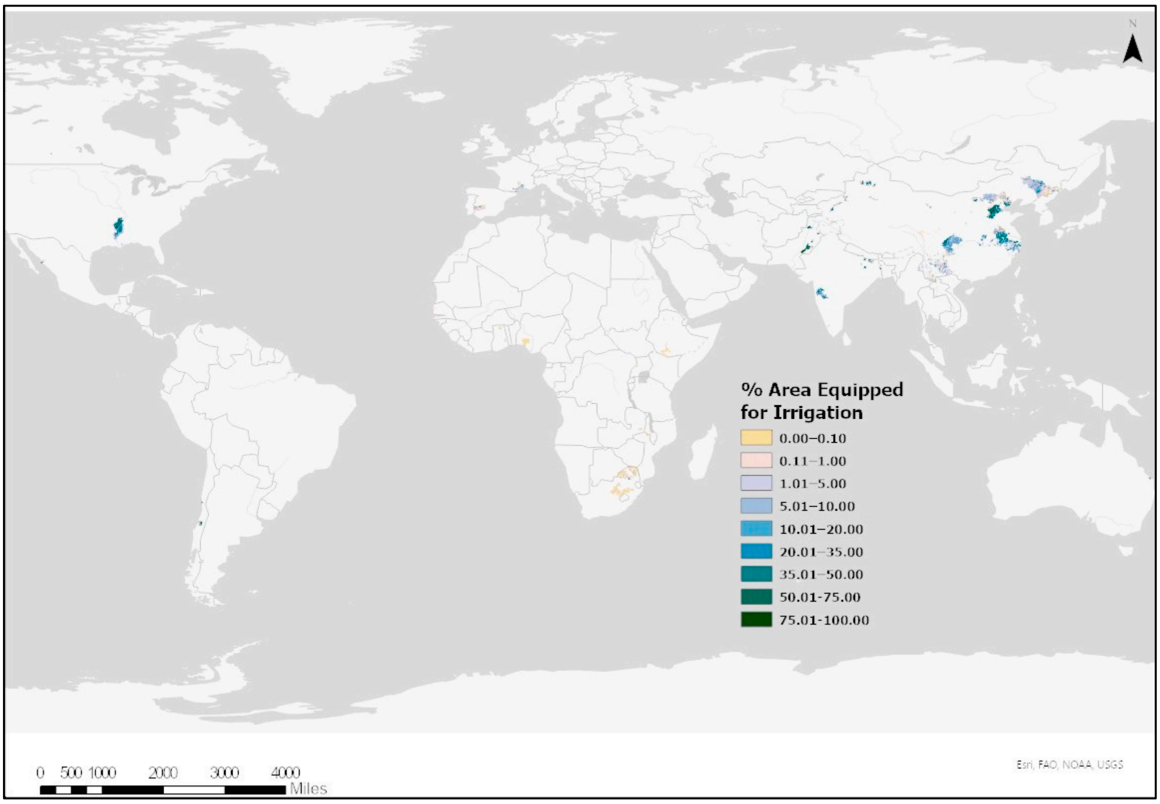


Figure 2. The map shows the location and distribution of selected cases.

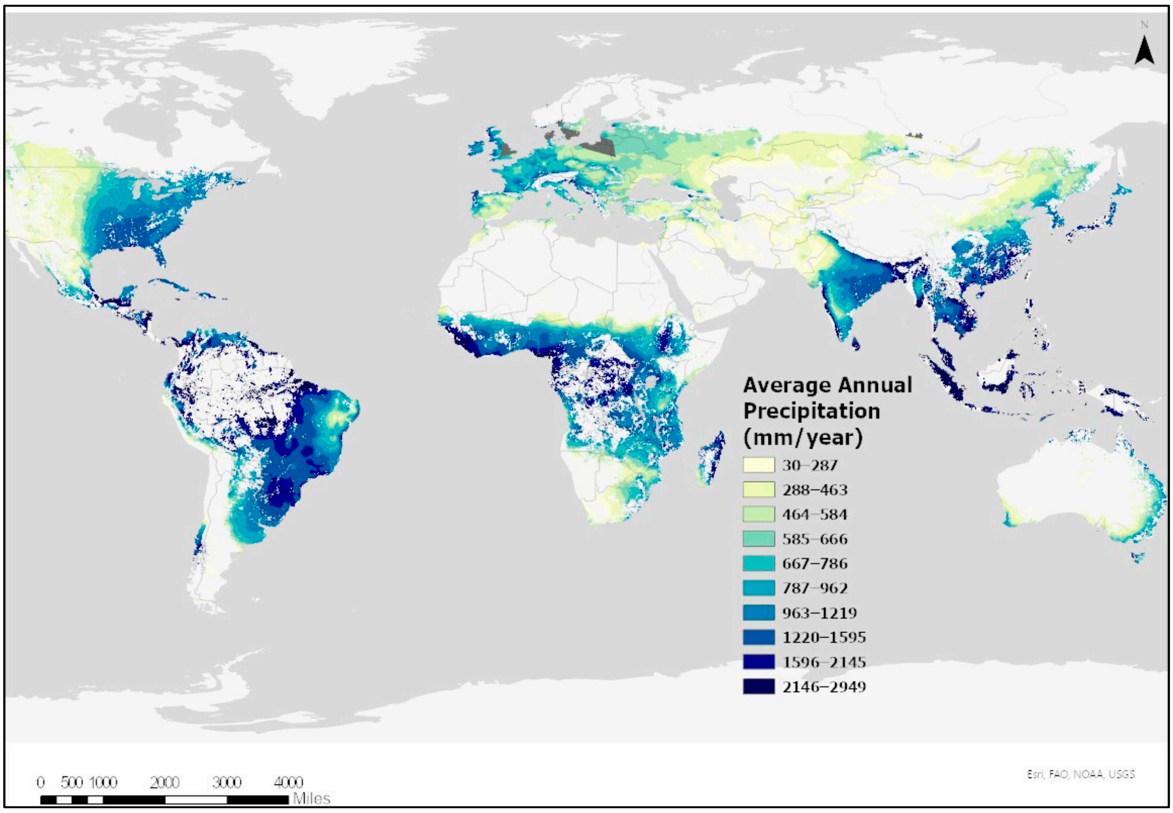


(**a**)



(**b**)

Figure 3. (**a**) Global extent for % Area Equipped for Irrigation variable. (**b**) Sample extent for % Area Equipped for Irrigation variable.



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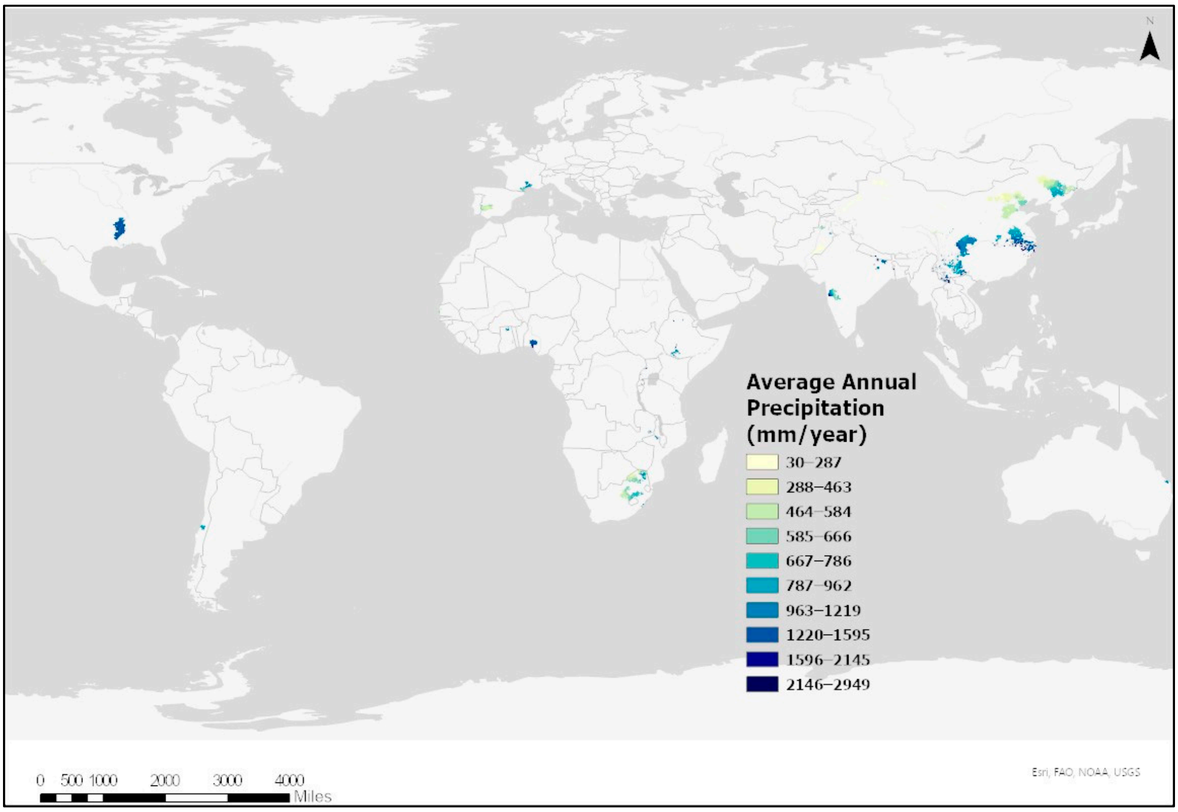

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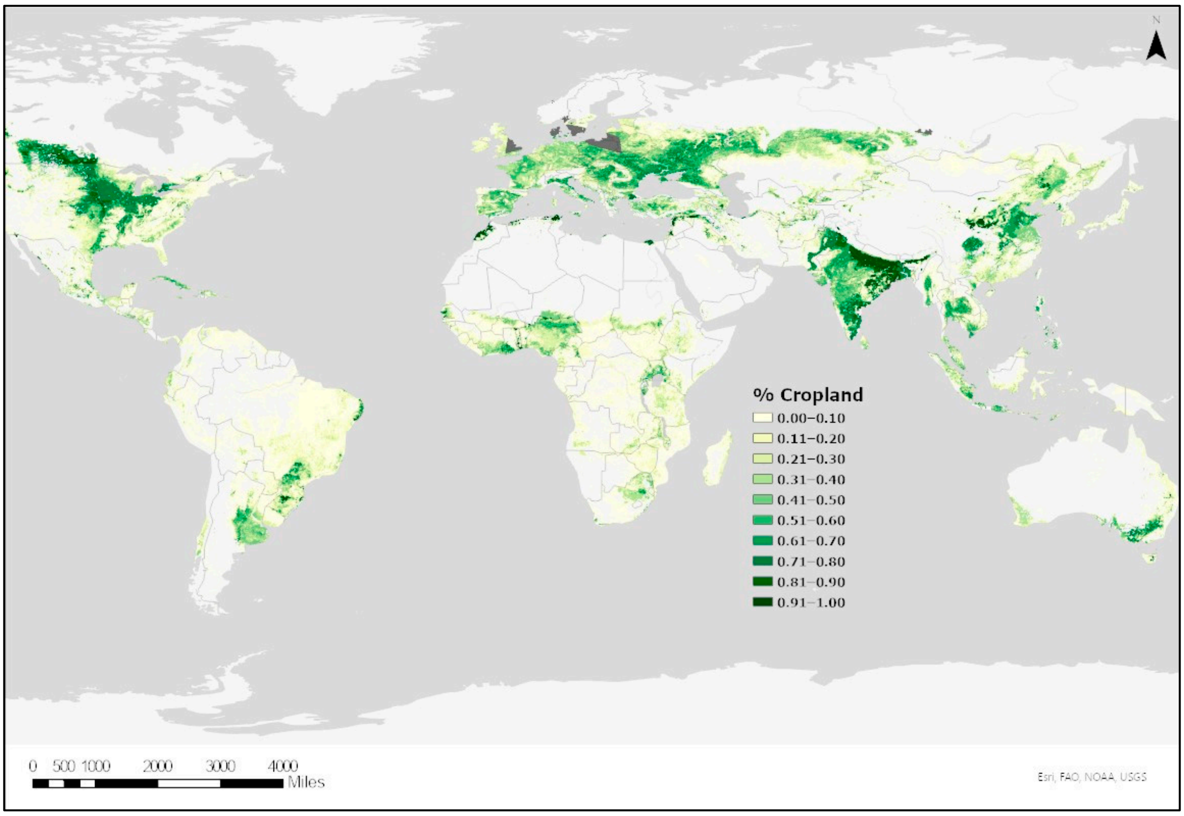
Figure 4. (**a**) Global extent for Avg Annual Precipitation variable. (**b**) Sample extent for Avg Annual Precipitation variable.



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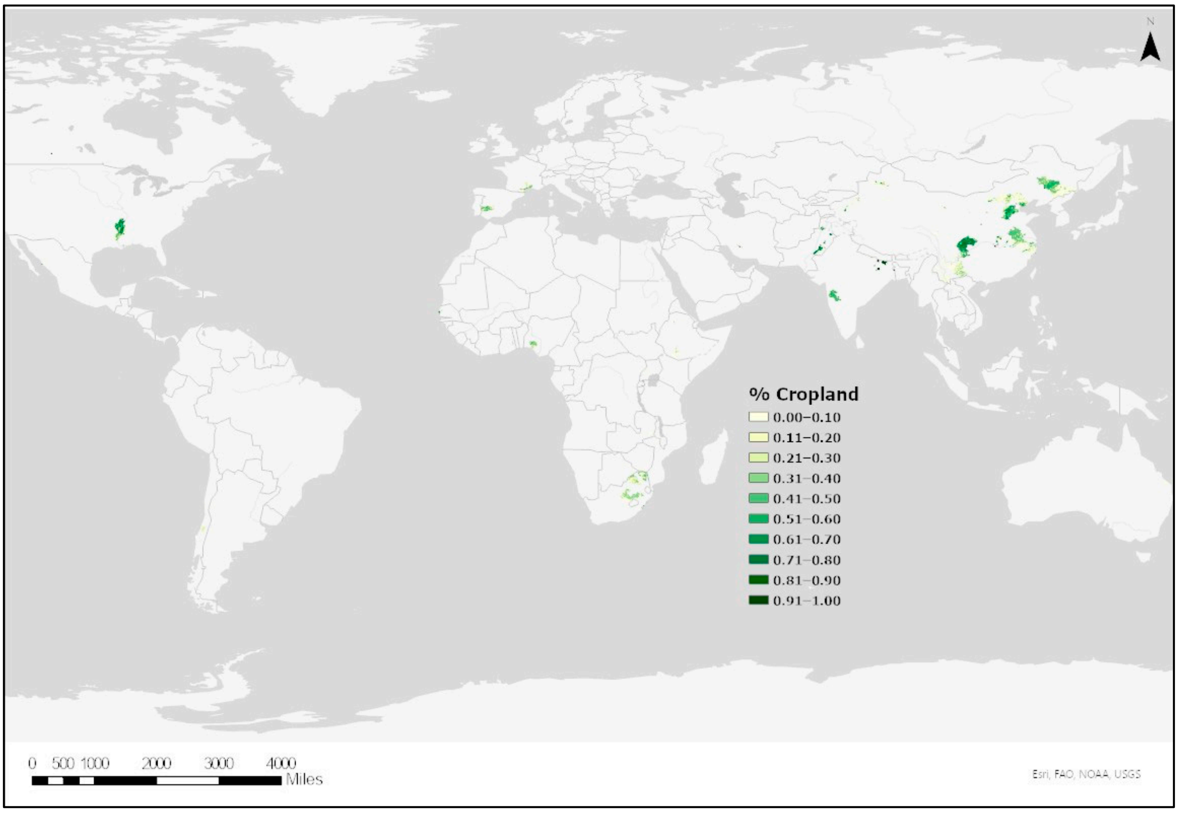
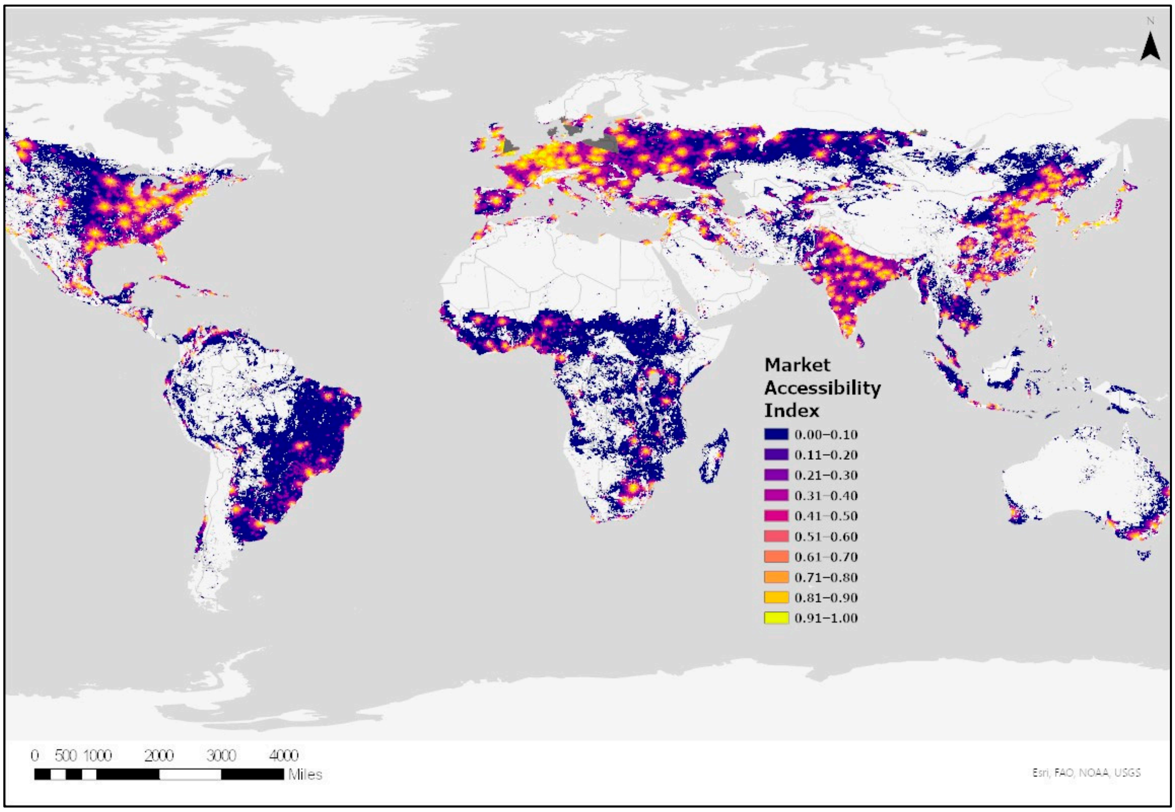


(**b**)

Figure 5. (**a**) Global extent for Percent Cropland variable. (**b**) Sample extent for Percent Cropland variable.



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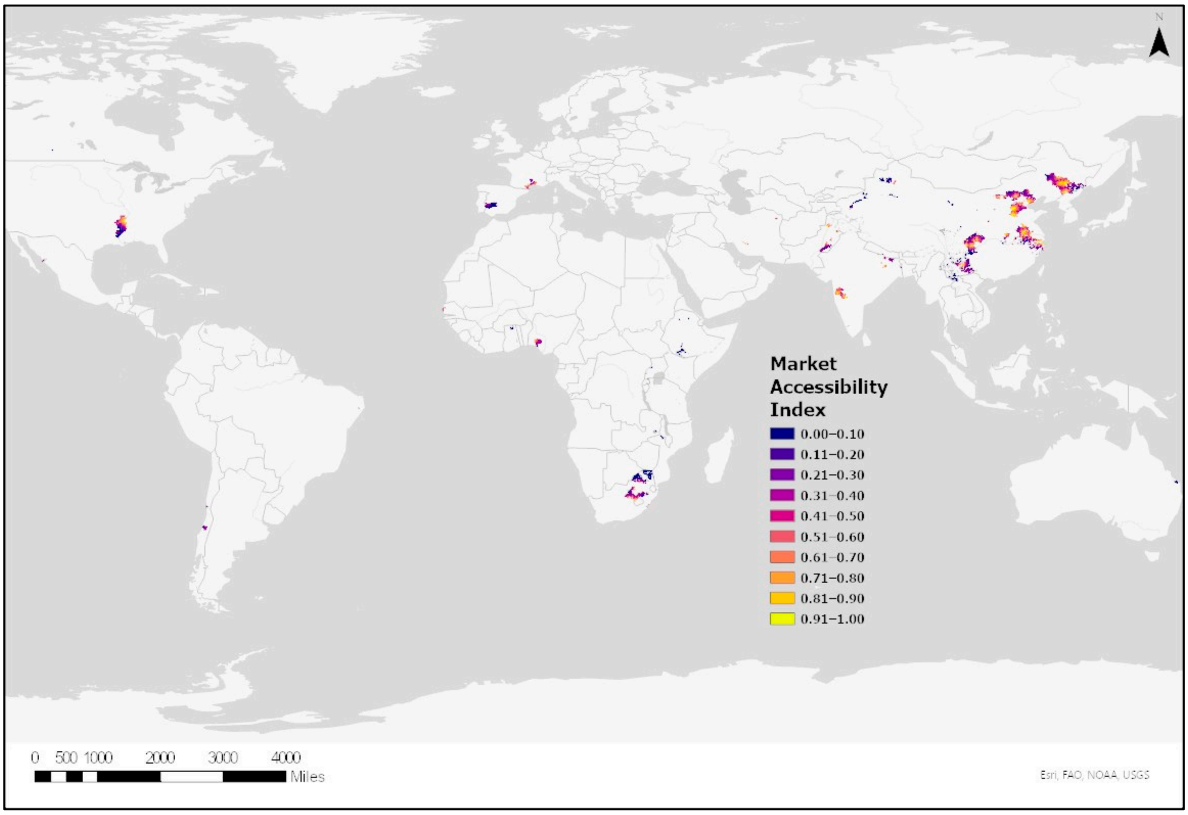

(**b**)

Figure 6. (**a**) Global extent for Market Access variable. (**b**) Sample extent for Market Access variable.

Table 2. Description of all the filters applied to the GLU layer obtained from GLOBE.

Variable Name	Description and Source	Filter(s) Applied
Olson Biomes	Terrestrial ecoregions of the world defined by climate, geology, and evolutionary history from Olson et al. (2001) [98]	Biomes—Boreal forests and Tundra removed.
Average Annual Temperature	Average annual temperature (°C) from 1951–2002. Values range from −28 °C to 31 °C. See [97] for more details.	Values greater than 28.57 °C and less than −12.2058 °C removed.
Average Annual Precipitation	Average annual precipitation (mm yr^{-1}) from 1950–1999 [83]. Values range from 0–10,572 mm/year.	Values greater than 2948.79 mm/yr and less than 30.0 mm/yr removed.
Population Density	Global model of population density from HYDE population model 2000 [84]. Values range from 0–62,018.	Values equal to '0' removed.
Percent Land Area	Percentage of land area contained within each GLU cell based on LandScan 2007 by Oak Ridge National Laboratory (2008). See [97] for details. Values range from 0–100%	Values less than 1 removed.
Percent Crop Area	Percent crop land cover area per grid cell derived from HYDE land cover data (2000) [84]. Values range from 0–100%	Values equal to '0' removed.
Slope Suitability Class	Global grid of land suitability for agriculture based on combined slope constraints [99]. Total 8 classes.	Classes 7 and 8 corresponding to 'Very Frequent Severe Constraints' and 'Unsuitable for Agriculture', respectively, removed.

To test the second hypothesis, first a list of factors reported to influence irrigation adoption decisions of farmers was compiled from the selected case studies. Factors affecting farmers' adoption decisions are often classified into broad clusters like—financial/economic, physical, institutional, and individual characteristics, but depending on the researchers' preferences and disciplinary backgrounds this categorization can vary [57,70]. For our study, based on the background literature, the different (influential) factors were clustered into seven broad categories—biophysical, demographic, geographic, technology-specific, social capital, farm enterprise, and institutional factors (Figure 7). Individual factors were coded using these broad categories for frequency analysis. Next, the relationships between these seven factor categories and their corresponding geographical contexts were examined using correspondence analysis. Correspondence analysis (CA) is a multivariate statistical technique and a useful visualization tool for summarizing, examining, and displaying the relationships between categorical data in a contingency table [100,101]. No underlying distributional assumptions are needed for this analysis and therefore, it accommodates any type of categorical variable—binary, ordinal, or nominal [102]. Moreover, the row and column points from the contingency table are shown together on a multi-dimensional map called biplot, which allows for easier visualization of the associations among variables [103,104]. CA uses the chi-square statistic to measure the distance between points on the map, but it does not reveal whether these associations are statistically significant and is therefore used only as an exploratory method [104].

All the above-mentioned statistical tests were conducted and developed in the PyCharm IDE (Integrated Development Environment) using pandas, Matplotlib, Prince, and Scipy Stats libraries.

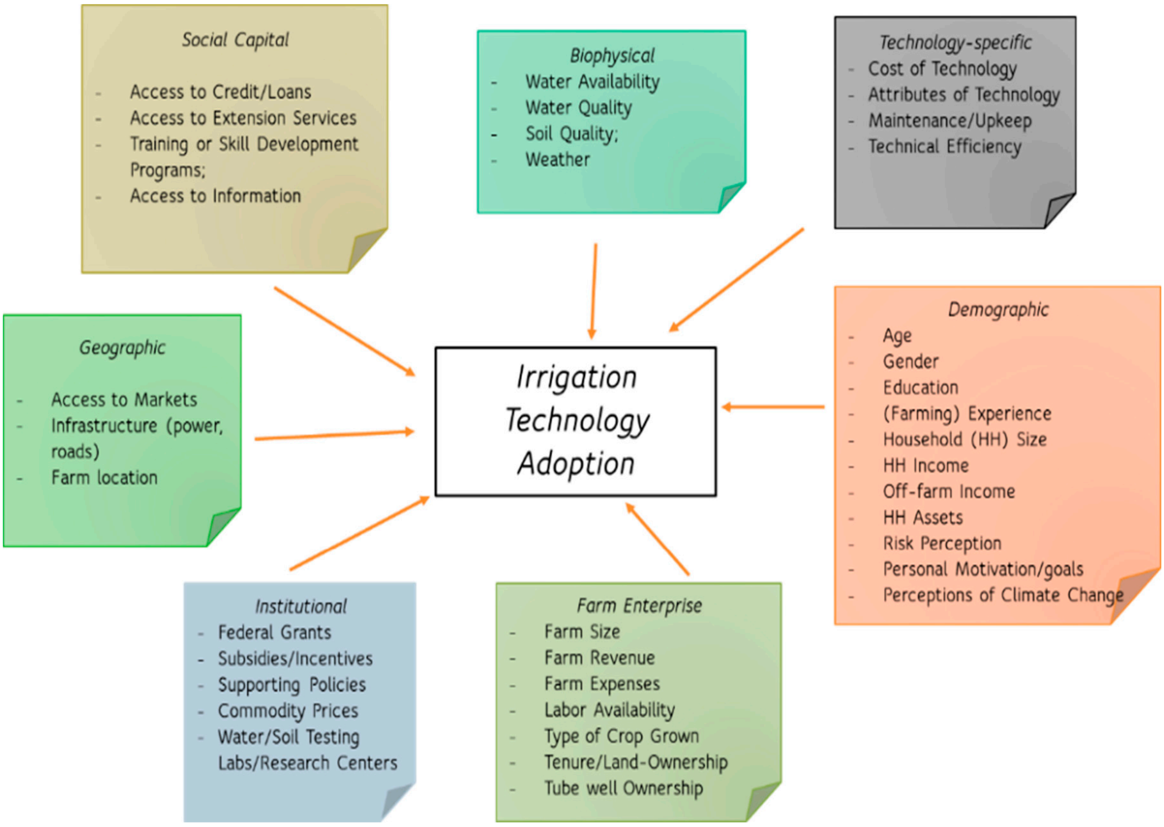

Figure 7. Categorization of different factors influencing farmers' irrigation adoption decision-making.

3. Results

3.1. Geographic Representativeness of Irrigation Adoption Studies

Geographic representativeness analyses were conducted for the percentage of GLU area equipped with irrigation, percentage of GLU area in cropland, average market accessibility, and average annual precipitation. Pearson's χ^2 tests for independence for each of the four variables (Tables 3–6) found that the observed (~sample) distributions were statistically different from the expected distributions.

Table 3. Pearson's χ^2 test results with percentage of area equipped for irrigation variable.

Bins	Frequency		χ^2 Statistic	*p*-Value *	Representedness Degree	
	Observed	Expected			r-Value **	Representedness
0.0–0.1	11469	20997	4951.870159	0.0	−1	**Highly under**
0.1–1.0	3634	5705	524.5160253	4.41×10^{-116}	−1	**Highly under**
1.0–5.0	5375	4079	203.1462568	4.30×10^{-46}	1	**Highly over**
5.0–10.0	3571	1769	654.2752213	2.63×10^{-144}	1	**Highly over**
10.0–20.0	3875	1710	906.3700068	4.05×10^{-199}	1	**Highly over**
20.0–35.0	3589	1236	1225.836112	1.48×10^{-268}	1	**Highly over**
35.0–50.0	2482	719	1013.405549	2.19×10^{-222}	1	**Highly over**
50.0–75.0	2536	694	1096.828508	1.62×10^{-240}	1	**Highly over**
75.0–100	749	369	130.4361647	3.29×10^{-30}	1	**Highly over**
Total Frequency	**37280**	**37280**	**Dist.χ^2= 24137.36522**	**Dist. *p*-value = 0.0**	**Diagnosis: Highly biased**	

* At 0.05 significance level; ** r-value calculation based on criteria defined in Section 3.2.

Table 4. Pearson's χ^2 test results with percentage of cropland variable.

Bins	Frequency		χ^2 Statistic	p-Value *	Representedness Degree	
	Observed	Expected			r-Value **	Representedness
0.0–0.1	6219	15900	5962.41	0.0	−1	**Highly under**
0.1–0.2	4595	5556	104.6993983	1.42×10^{-24}	−1	**Highly under**
0.2–0.3	5366	3863	278.0312679	2.02×10^{-62}	1	**Highly over**
0.3–0.4	6522	3245	1259.874418	5.93×10^{-276}	1	**Highly over**
0.4–0.5	6063	2856	1304.727198	1.06×10^{-285}	1	**Highly over**
0.5–0.6	3990	2551	345.7343162	3.60×10^{-77}	1	**Highly over**
0.6–0.7	2870	1954	185.2504582	3.46×10^{-42}	1	**Highly over**
0.7–0.8	2002	1319	146.4197305	1.05×10^{-33}	1	**Highly over**
0.8–0.9	203	416	73.20047746	1.17×10^{-17}	−1	**Highly under**
0.9–1.0	372	543	31.96753669	1.57×10^{-08}	−1	**Highly under**
Total Frequency	**38202**	**38202**	**Dist.χ^2= 15313.11155**	**Dist. p-value = 0.0**	**Diagnosis: Highly biased**	

* At 0.05 significance level; ** r-value calculation based on criteria defined in Section 3.2.

Table 5. Pearson's χ^2 test results with market accessibility variable.

Bins	Frequency		χ^2 Statistic	p-Value *	Representedness Degree	
	Observed	Expected			r-Value **	Representedness
0.0–0.1	10902	20736	5215.919285	0.0	−1	**Highly under**
0.1–0.2	4340	3907	25.36746844	4.74×10^{-07}	1	**Highly over**
0.2–0.3	4618	3186	292.2496414	1.61×10^{-65}	1	**Highly over**
0.3–0.4	4448	2677	484.9267588	1.81×10^{-107}	1	**Highly over**
0.4–0.5	3919	2075	614.9158442	9.54×10^{-136}	1	**Highly over**
0.5–0.6	3187	1481	663.2799333	2.89×10^{-146}	1	**Highly over**
0.6–0.7	2398	1335	317.6479106	4.71×10^{-71}	1	**Highly over**
0.7–0.8	2228	1172	342.6063765	1.73×10^{-76}	1	**Highly over**
0.8–0.9	1503	994	106.8413592	4.82×10^{-25}	1	**Highly over**
0.9–1.0	659	640	0.253736593	0.61	0.4	**Well-represented**
Total Frequency	**38202**	**38202**	**Dist.χ^2 = 12191.37033**	**Dist. p-value = 0.0**	**Diagnosis: Highly biased**	

* At 0.05 significance level; ** r-value calculation based on criteria defined in Section 3.2.

Table 6. Pearson's χ^2 test results with average annual precipitation (mm/year) variable.

Bins	Frequency		χ^2 Statistic	p-Value *	Representedness Degree	
	Observed	Expected			r-Value **	Representedness
30–287	1680	3293	558.91	1.45×10^{-123}	−1	**Highly under**
287–463	3449	5289	437.02	4.83×10^{-97}	−1	**Highly under**
463–584	6537	4397	488.33	3.28×10^{-108}	1	**Highly over**
584–666	3444	2457	178.54	1.01×10^{-40}	1	**Highly over**
666–786	3819	2999	108.02	2.66×10^{-25}	1	**Highly over**
786–962	6864	3658	1132.16	3.39×10^{-248}	1	**Highly over**
962–1219	6137	4917	157.17	4.71×10^{-36}	1	**Highly over**
1219–1595	5319	5660	12.30	4.54×10^{-04}	−1	**Highly under**
1595–2145	835	3261	1517.03	0.0	−1	**Highly under**
2145–2949	118	2270	2000.03	0.0	−1	**Highly under**
Total Frequency	**38202**	**38202**	**Dist.χ^2= 10070.33756**	**Dist. p-value = 0.0**	**Diagnosis: Highly biased**	

* At 0.05 significance level; ** r-value calculation based on criteria defined in Section 3.2.

The observed frequencies of the two lowest percent areas of irrigation were significantly lower than their expected frequencies (see Figure 8) and highly underrepresented (Table 3). Similarly, the remaining seven bins were highly over-represented in this collection as the observed frequencies of these bins were higher compared to their corresponding expected frequencies. Case studies of irrigation adoption were thus biased toward areas of existing agriculture, and studies were generally more over-represented as the area equipped for irrigation increased.

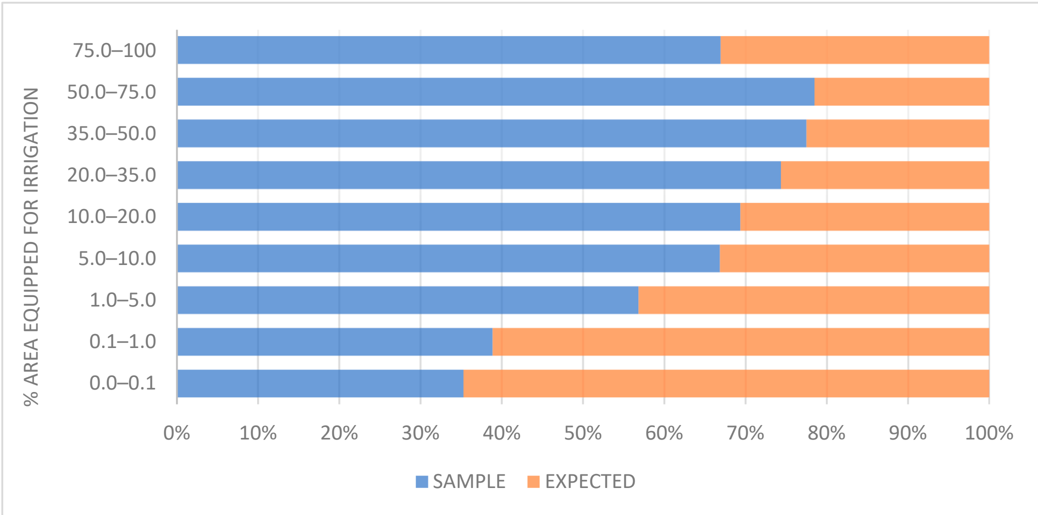

Figure 8. Percentage of Observed (~Sample) vs. Expected Counts for Irrigation Variable.

Similarly, in the case of the percent cropland variable (Table 4 and Figure 9), four out of ten bins (with very low and high cropland cover) were highly underrepresented. Irrigation adoption studies were more frequently conducted in areas with moderate extents of agricultural land use, and thus biased against areas of low or high cropland. This likely had implications for the irrigation adoption decisions studied. Locations that were dominantly or exclusively agricultural likely had better support services and infrastructure and did not compete with other land uses, which would presumably facilitate irrigation adoption. Conversely, farmers in low agricultural areas face the opposite conditions and may experience more barriers to irrigation adoption.

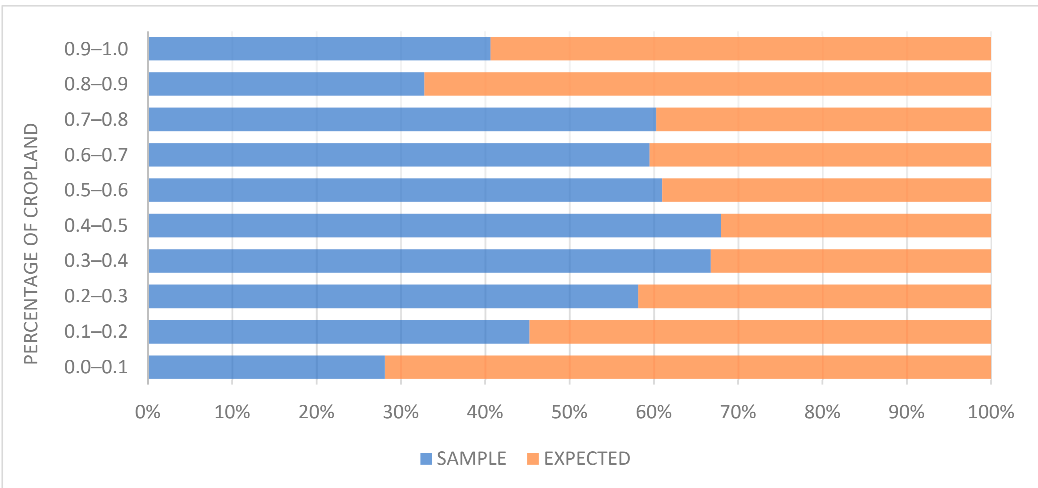

Figure 9. Percentage of Observed (~Sample) vs. Expected Counts for Cropland Variable.

In the case of the market access index, most of the bins (8 out of 10) were highly over-represented (Table 5 and Figure 10) with a bias toward areas having moderate-high market access. Market signals that might favor irrigation adoption were likely dampened in low market accessibility areas, which may not have been enough to overcome economic barriers to irrigation adoption. Additionally, remote areas are generally understudied due to access difficulties for researchers [30]. As a result, irrigation adoption studies were skewed toward locations with greater accessibility, including a well-represented sample of the most accessible locations.

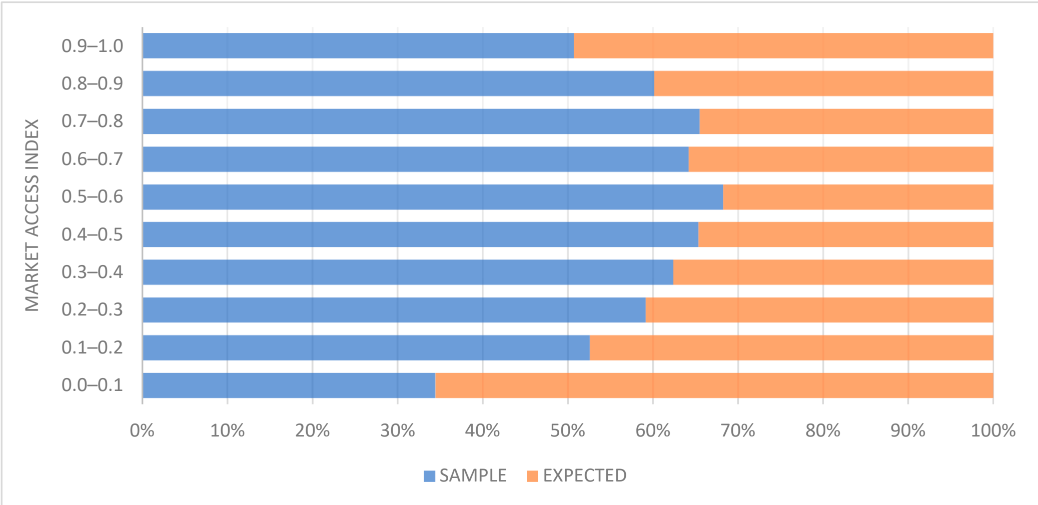

Figure 10. Percentage of Observed (~Sample) vs. Expected Counts for Market Accessibility Variable.

Finally, regions receiving moderate average annual rainfall (463–1219 mm/year) were highly over-represented, while regions with very low and high average annual rainfall were under-represented and understudied (Table 6 and Figure 11). The underrepresentation of low rainfall areas was surprising, but these may be neglected by irrigation adoption studies due to the necessity of irrigation and limited variability in decision-making. The limited sampling of high precipitation areas was not surprising, since areas receiving high average annual precipitation were more likely associated with rainfed agriculture. However, such areas may also include those in which seasonal drought is a concern despite high aggregate rainfall (e.g., humid southeast United States) and which potentially have unique sets of adoption decision factors.

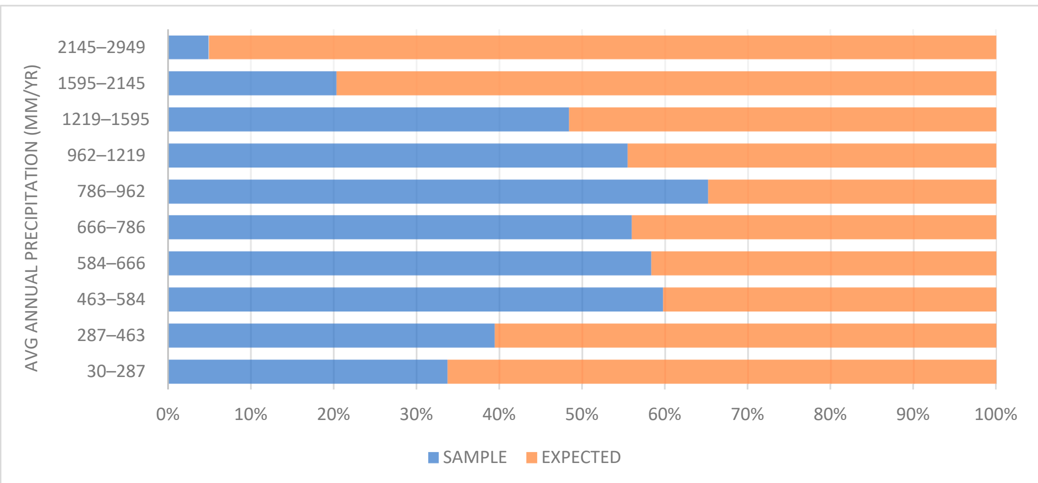

Figure 11. Percentage of Observed (~Sample) vs. Expected Counts for Average Annual Precipitation Variable.

3.2. Similarity of Irrigation Adoption Factors across Geographic Contexts

Most of the studies conducted in low irrigated regions of the world and that were highly underrepresented in this collection were from countries located in Africa and Latin America (see Table 7 and Figure 12). Further, Table 8 lists the different clusters of factors affecting irrigation adoption identified from the case studies, broken down by world regions. The frequency of each of the causal factors as reported in the case studies are provided in this table as an absolute number (this method of frequency analysis is based on the Geist & Lambin (2004) study). Only two case studies had a single variable (factor category) that explained farmers' decision-making regarding irrigation adoption, thus suggesting that the decision to adopt (or not) irrigation is best explained using a combination of factors (see Table 8). Dominating the broad clusters of factors affecting irrigation adoption decisions of farmers was the combination of—Biophysical, Demographic, Farm Enterprise, and Social Capital factors (B, D, F, S), followed by the cluster with Biophysical, Demographic, Farm Enterprise, Institutional, and Social Capital factors (B, D, F, I, S), with clear regional variations as both these clusters feature mainly in case studies from Asia and Africa. Cases from both these regions share a greater number of factors in common as compared to other regions. Demographic category that includes factors like age, gender, household size, and more (see Figure 7 for more details) featured the most, while both institutional and technology-related factor categories were least observed within these case studies. Further, demographic and social capital related factors together formed the most robust combination, although one that often occurred in combination with other clusters.

Table 7. Distribution of number of cases based on percentage of irrigation.

Percentage of Irrigation	No. of Cases	Degree of Representedness
0.0–0.1	4	Highly under
0.1–1.0	14	Highly under
1.0–5.0	7	Highly over
5.0–10.0	9	Highly over
10.0–20.0	6	Highly over
20.0–35.0	7	Highly over
35.0–50.0	2	Highly over
50.0–75.0	4	Highly over

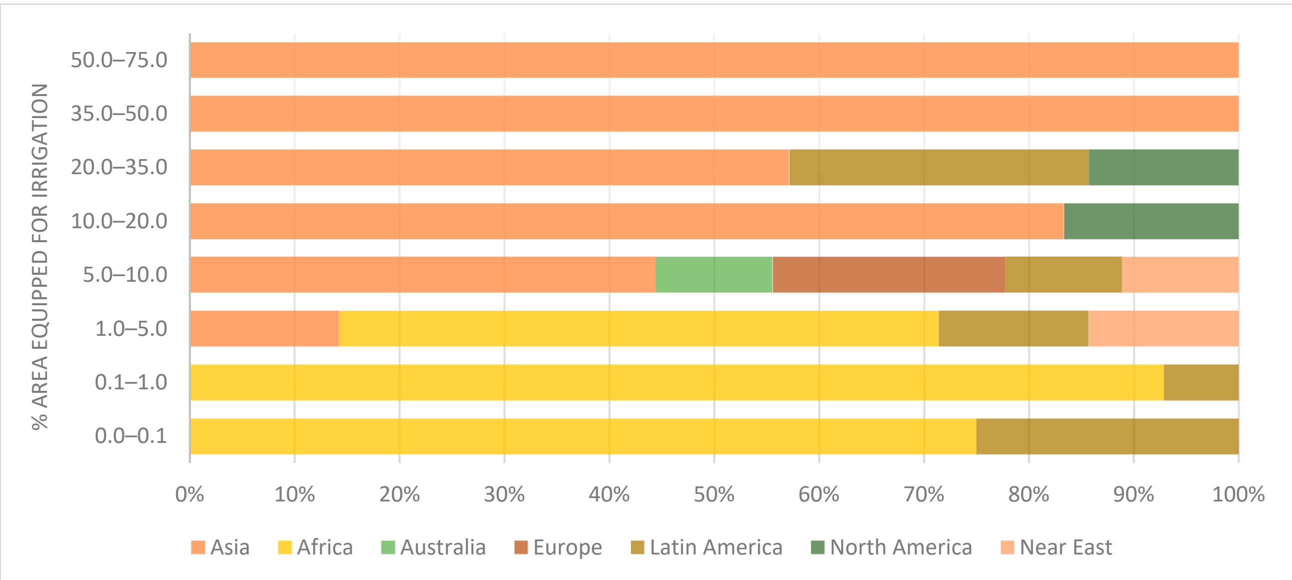

Figure 12. Distribution of study regions based on the percentage of area equipped for irrigation.

Table 8. Frequency of broad clusters of factors affecting irrigation adoption.

Factors \ Study Sites	Asia (n = 20)	Africa (n = 20)	Australia (n = 1)	Europe (n = 2)	Latin America (n = 6)	North America (n = 2)	Near East (n = 2)	All Cases (n = 53)
SINGLE-FACTOR								
B	0	1	0	0	0	0	0	**1**
D	1	0	0	0	0	0	0	**1**
TWO FACTORS								
B, I	0	1	0	0	0	0	0	**1**
D, S	2	1	0	0	0	0	0	**3**
B, D	1	0	0	0	0	0	0	**1**
THREE FACTORS								
D, S, T	0	0	0	1	0	0	0	**1**
B, D, G	0	1	0	0	0	0	0	**1**
I, S, T	0	1	0	1	0	0	0	**2**
B, D, F	0	0	0	0	1	0	0	**1**
D, F, S	1	0	0	0	0	0	1	**2**
B, D, T	0	1	0	0	1	0	0	**2**
B, S, T	0	1	0	0	0	0	0	**1**
D, G, S	1	0	0	0	0	0	0	**1**
B, D, S	1	0	0	0	1	0	0	**2**
FOUR FACTORS								
B, D, F, S	3	2	0	0	0	0	1	**6**
B, D, F, G	1	0	0	0	0	0	0	**1**
B, D, I, S	0	0	0	0	0	1	0	**1**
D, G, I, S	0	1	0	0	0	0	0	**1**
D, G, S, T	0	1	0	0	0	0	0	**1**
B, F, G, S	0	1	0	0	0	0	0	**1**
D, F, I, S	0	1	0	0	0	0	0	**1**
D, F, S, T	0	0	1	0	1	0	0	**2**
B, D, G, T	0	1	0	0	0	0	0	**1**
D, F, G, S	1	1	0	0	1	0	0	**3**
FIVE FACTORS								
B, D, G, I, S	0	1	0	0	0	0	0	**1**
B, D, F, I, S	2	2	0	0	0	1	0	**5**
B, D, F, G, S	2	0	0	0	1	0	0	**3**
B, D, G, S, T	0	1	0	0	0	0	0	**1**
B, F, G, I, S	0	1	0	0	0	0	0	**1**
B, D, F, G, T	1	0	0	0	0	0	0	**1**
SIX FACTORS								
B, D, F, G, I, S	3	0	0	0	0	0	0	**3**
TOTAL CASES	**20**	**20**	**1**	**2**	**6**	**2**	**2**	**53**

B = Biophysical; D = Demographic; F = Farm Enterprise; G = Geographic; I = Institutional; S = Social Capital; T = Technology-specific.

Additionally, the CA biplot between the study regions and set of causal factors (Figure 13) was also prepared to visually identify and understand these regional variations. In this symmetric scatterplot, component 0 was represented by the horizontal axis and component 1 by the vertical axis. Together both the components explained about 45.68% of the variance/inertia in this dataset. Europe had high positive values along component 0 (horizontal axis), while Australia had high positive values along the vertical axis. Similarly, North America had high negative values and low positive values along vertical and horizontal axis, respectively. Moreover, from just visually inspecting this biplot it was evident that the set of factors influencing irrigation adoption (of farmers) in cases from Europe, Australia and North America were very different from each other as they were placed in separate quadrants and were also far from the origin. Australia and

Latin America study regions were placed in the same quadrant and thus, shared similar profiles, i.e., within both these regions similar combination of causal factors was observed as compared to say Europe or other regions (see Table 8 for more details). Further, the map also revealed that irrigation adoption by farmers from case studies in Europe was explained by a combination of only demographic, social capital, institutional, and technology-specific attributes. Whereas in case of North America, the strongest association was seen with factors like demographic, social capital, farm enterprise, institutional and biophysical.

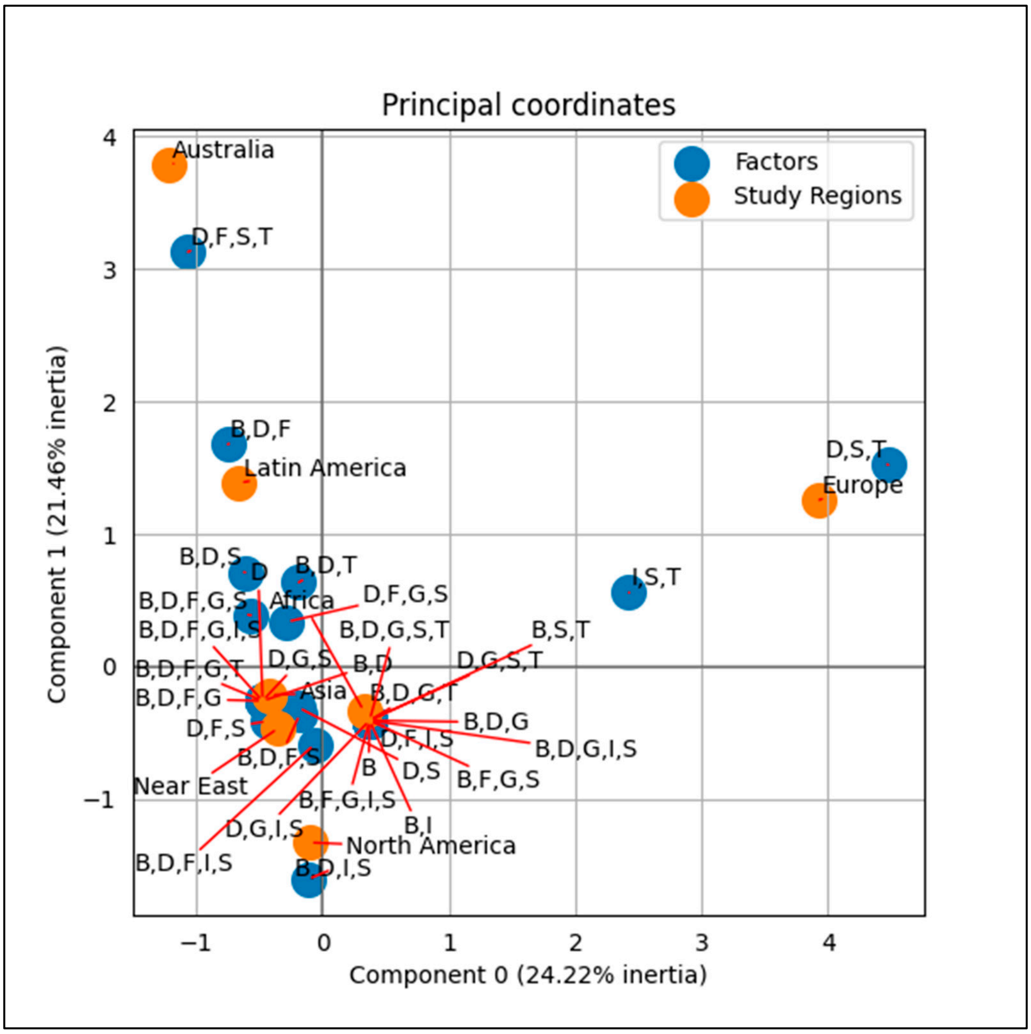

Figure 13. 2-D Correspondence Analysis biplot of Study Regions and Factors affecting Irrigation Adoption.

4. Discussion

In this paper, we explored the geographic contexts where irrigation adoption studies were conducted and the set of causal factors that were reportedly associated with irrigation adoption decisions. Based on the results of the systematic review, our first hypothesis held true. That is, the geographic contexts in which irrigation adoption studies were often conducted were biased. Geographic regions with less than 1% area equipped for irrigation, very low (less than 0.2%) and high (above 0.8%) percent of cropland, low market accessibility index (less than 0.1), and average annual precipitation with less than 463 mm/year and greater than 1219 mm/year, were highly underrepresented in this collection of case studies. In other words, these case studies were significantly biased toward areas where at least some amount of irrigation was already being practiced. An explanation for this bias towards irrigated areas could be that the research was motivated by the need to identify challenges and/or opportunities associated with further expansion. Additionally, low cropland areas were also understudied, because research might have been focused more on areas having a moderate or higher amount of cropland cover to encourage further agricultural growth and development. Usually, farmers in areas with a high percentage of cropland cover, because of the limited scope for further (land) expansion, are more likely be using intensive agricultural practices (like irrigation) to increase their crop productivity, hence the focus was towards areas with moderate amount of cropland. Further, highly accessible regions were over-represented in this collection, because research is often conducted in locations (and with communities) that are easily accessible (or reachable) as compared to remote or hard to reach locations [105]. There is also evidence that farmers with greater market access had stronger incentives to adopt irrigation for market production [106]. Hence, regions with low market accessibility were understudied and accordingly underrepresented. Similarly, regions with low and high average annual rainfall were also underrepresented and this might be due to the overall 'unsuitability' of this technology within these regions. For instance, if a region receives abundant rainfall, farmers might have a natural inclination to rely on rainfall for agricultural activities rather than investing in new technology, as irrigation is generally a substitute for rainwater [107]. For regions with low average annual rainfall, although irrigation technology can be very useful nevertheless, reliable access to water might hinder its widespread diffusion and subsequent adoption [108].

The second hypothesis that we tested in this paper held partially true as only the Demographic category of factors was observed as the most common among all the case study regions. This indicated that demographic factors such as a farmer's age, gender, household assets, income diversification options, and perceptions toward climate change (see Figure 3 for a complete list), significantly affected farmers' decisions to adopt (or not) irrigation irrespective of the geographic context. However, some distinct regional variations were also seen. For instance, studies from North America explained irrigation adoption behavior of farmers using a combination of only demographic, biophysical, social capital, farm-enterprise, and institutional factors. Factors related to place or technology did not feature in the case studies from this region. Similarly, for cases from Near East, only categories of factors such as demographic, farm enterprise, biophysical and social capital were observed. Both institutional and technology related factors were least observed among all these case studies. Further, the highest frequency was of the cluster with Biophysical, Demographic, Farm Enterprise, and Social Capital factors (B, D, F, S), followed by the cluster with Biophysical, Demographic, Farm Enterprise, Institutional, and Social Capital factors (B, D, F, I, S), suggesting that irrigation adoption decisions around the world are best explained by the combination of multiple and coupled factors instead of a single variable.

Moreover, majority of the case studies in this collection were from geographic regions of Asia and Africa and were clustered with a greater (and often similar) number of factors as compared to the rest. This suggests that some common challenges might possibly exist with regard to irrigation technology diffusion and adoption within these regions, even though the study sites within these regions (See Appendix A for more information on study locations) were different from each other in many other aspects beyond just percentage of irrigation or average annual precipitation (national wealth, population densities, etc.). A recent study on understanding sustainability challenges in three different rural landscapes, namely, Australia, central Romania, and southwestern Ethiopia, found similarities among these three different social-ecological systems, even though the systems examined appear to be very different on the surface [109], thus, highlighting the need for a comprehensive analysis to identify and better comprehend such common challenges.

Although a nearly similar set of factors were observed from case studies of Asia and Africa, many of the study sites from Africa with little to no irrigation (less than 1%) were understudied, while all those from Asia were over-studied and hence over-represented in this collection (Figure 12). One explanation for this research bias could be that the farmers in the study sites within Africa might still be in their early adoption phase. Given the low percentage of irrigated areas, one can argue that in these sites only a few individuals are taking the risk of investing in this technology. Moreover, this technology might not have been completely diffused within these sub-regions of Africa (east, west, and south), and as a result, this topic might be highly understudied within these sites because there is first a need to properly introduce this technology to the people, make them aware of its use and benefits, and only then can the adoption process be studied. Furthermore, based on the results of the frequency analysis, institutional and social capital related factors were most commonly observed in cases from this study region compared to others. These categories include factors like access to informational services, credit facilities, extension services, skill development programs, supporting policies, incentives, and subsidies. A study by Wozniak (1987) [110] highlighted the important role played by education and information on the new technology, particularly for early adoption. Another study by Diederen et al. (2003) [111] presented empirical evidence for explaining the differences in adoption behavior of innovators, early adopters, and laggards. Their findings suggested that innovators (~first or early users of technology) made more use of external sources of information. In a more recent study on the adoption of improved seed varieties by farmers in Ethiopia, the findings suggested that farmers' awareness about the available seed varieties is an important factor for the actual adoption to take place [112]. Teha & Jianjun (2021) [113] in their study on the adoption of small-scale irrigation found that 'government promotion' in the form of incentives and training positively affected a farmer's irrigation adoption decision. Thus, some kind of external support like extension and credit services are vital for farmers for enhancing the diffusion and adaptation of successful technologies and practices [114,115]. With limited information and support, a farmer's decision-making is primarily based on intuition and can be less efficient [116].

However, the results of this meta-study are limited in scope, since only peer-reviewed research articles that were available in the English language, in the two selected databases, and published on and after the year 2000 were considered for this analysis. Such a restriction on the publication date was imposed because the global irrigation dataset used in this analysis is based on the nationally reported statistics from around the year 2000. Further only articles that investigated the factors associated with irrigation adoption were selected for this analysis irrespective of the theoretical frameworks applied to examine a farmer's adoption behavior. Due to this, certain factors might be emphasized more than others. For instance, a social network analysis approach was used to assess the barriers to climate change adaptations in Spain [117]. Because of the specific framework used in this study, the barriers identified were mostly categorized within social capital and institutional categories (see Appendix A for study details). Similarly, another case study from Nepal, used risk perception and motivation theory to understand farmers preparedness to cope with the impacts of climate-change hazards [118], and as a result, only the factors characterized as demographic were identified from this case study. Moreover, conference proceedings and grey literature were also excluded from the dataset due to inconsistent methodology and results reporting. Such sources may have contained useful and unique insights, but issues of comparability with information gathered from peer-reviewed would have unduly complicated the analysis.

Despite the limitations mentioned above, the global representativeness analysis highlights the multiple (geographic) biases that exist with respect to studying farmers' irrigation adoption decision-making. More research on this topic is being conducted in regions that have little to high percentage of irrigation (>1%), are readily accessible, receive moderate amounts of average annual rainfall, and have moderate amounts of cropland cover. These results suggest the need to expand research efforts, particularly in areas with low irrigation and cropland cover to identify constraints to and help accelerate economic growth, poverty reduction, and food and livelihood security for rural communities in these regions.

5. Conclusions

Food production is still risky in many parts of the world, particularly in Sub-Saharan Africa, due to limited information about changing weather patterns, market access and demands, and unequal access to efficient technologies [116]. Additionally, this pressure on our global food systems will only intensify in the coming years with not only the changing consumption patterns but with the changing climatic conditions as well. For example, yield declines resulting from climate change (e.g., higher temperatures, increased seasonality, more frequent and severe hydroclimate events) have already occurred [119] and are expected to decrease the production of global consumable food calories by another 1% to 7% by the end of the century [120]. Irrigation currently remains one of the most critical inputs to farming today and is a key adaptation to variable precipitation and droughts resulting from changing climatic conditions [38]. New investments in irrigation infrastructure together with improved water management practices can not only minimize the impact of water scarcity but can also aid in meeting the water demands for global food production [121]. Further, managing and improving irrigation efficiency will, in turn, support global water, food, and energy goals [122]. Therefore, understanding the diverse reasons, motivations, and/or factors underlying the choices of producers regarding its adoption (or rejection), especially when climate change demands some kind of adaptation in unprecedented areas, will help better anticipate future food, energy, and water demands [123].

There is still much room left for improvements in both agricultural practices and water-use efficiency, but farmers' reluctance to adopt new technologies needs to be better understood if such sustainability targets are to be achieved [72], and societal resilience must be built to mitigate the impacts of future climatic changes [11]. In this study, we identified multiple geographic biases that exist with respect to studying farmers' irrigation adoption decision-making, thus, suggesting the need for extensive research even in areas with no irrigation and/or low cropland cover to identify opportunities for the implementation of other sustainable solutions to support agricultural development in these areas. Moreover, apart from these biases, some commonalities were observed in terms of constraints faced by farmers regarding irrigation technology adoption across different geographic landscapes. However, our findings also indicated that there may not be a 'standard set' of factors for understanding irrigation adoption, and nuances in the local context are just as important to identify as commonalities across settings. This suggests the need for more geographically comprehensive analyses that would enable comparative analysis of different landscapes, as well as studies that delve into the adoption process beyond individual technology adoption behaviors. Further, this kind of systems analysis will help unravel common challenges, drivers, and opportunities regarding agriculture development under changing climatic conditions across multiple systems, while also being attentive to local context offers the potential for co-learning [109,124].

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Institutional Review Board Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study and their description and sources have already been listed above.

Conflicts of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

A1 Target Set

1. Alcon, F., Tapsuwan, S., Martínez-Paz, J. M., Brouwer, R., & de Miguel, M. D. (2014). Forecasting deficit irrigation adoption using a mixed stakeholder assessment methodology. *Technological Forecasting and Social Change*, *83*(1), 183–193. https://doi.org/10.1016/j.techfore.2013.07.003.
2. Asfaw, A., Simane, B., Bantider, A., & Hassen, A. (2019). Determinants in the adoption of climate change adaptation strategies: evidence from rainfed-dependent smallholder farmers in north-central Ethiopia (Woleka sub-basin). *Environment, Development and Sustainability*, *21*, 2535–2565.
3. Chandran, K. M., & Surendran, U. (2016). تصصخت سروي س آموزش ی کارگا ه های تیوضع آموزشی ملف های زکرم اطلاعا ت تملع بلا گ ویژ ه سروي س های STRS همجرت کنل های دنفم درخبرنام ه Study on factors influencing the adoption of drip irrigation by farmers in humid tropical Kerala, India. In *International Journal of Plant Production* (Vol. 10, Issue 3). www.SID.ir
4. Esham, M., & Garforth, C. (2013). Agricultural adaptation to climate change_ insights from a farming community in Sri Lanka. *Mitigation and Adaptation Strategies for Global Change*, *18*, 535–549.
5. Fan, Y., & McCann, L. (2020). Adoption of pressure irrigation systems and scientific irrigation scheduling practices by U.S. farmers: An application of multilevel models. *Journal of Agricultural and Resource Economics*, *45*(2), 352–375. https://doi.org/10.22004/ag.econ.302459
6. Greenland, S., Levin, E., Dalrymple, J. F., & O'Mahony, B. (2019). Sustainable innovation adoption barriers: water sustainability, food production and drip irrigation in Australia. *Social Responsibility Journal*, *15*(6), 727–741. https://doi.org/10.1108/SRJ-07-2018-0181
7. Huang, Q., Xu, Y., Kovacs, K., & West, G. (2017). ANALYSIS OF FACTORS THAT INFLUENCE THE USE OF IRRIGATION TECHNOLOGIES AND WATER MANAGEMENT PRACTICES IN ARKANSAS. *Journal of Agricultural and Applied Economics*, *49*(2), 159–185.
8. Mase, A. S., Gramig, B. M., & Prokopy, L. S. (2017). Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern U.S. crop farmers. *Climate Risk Management*, *15*, 8–17. https://doi.org/10.1016/j.crm.2016.11.004
9. Mesfin, A. H., & Bekele, A. (2018). Farmers Perception on Climate Change and Determinants of Adaptation Strategies in Benishangul-Gumuz Regional State of Ethiopia. *International Journal on Food System Dynamics*, *9*(5), 453–469.
10. Ngigi, M. W., Mueller, U., & Birner, R. (2017). Gender Differences in Climate Change Adaptation Strategies and Participation in Group-based Approaches: An Intra-household Analysis From Rural Kenya. *Ecological Economics*, *138*, 99–108. https://doi.org/10.1016/j.ecolecon.2017.03.019.

A2 Shortlisted Case Studies

1. Abid, M., Scheffran, J., Schneider, U. A., & Ashfaq, M. (2015). Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab Province, Pakistan. *Earth System Dynamics*, *6*, 225–243.
2. Akrofi, N. A., Sarpong, D. B., Somuah, H. A. S., & Osei-Owusu, Y. (2019). Paying for privately installed irrigation services in Northern Ghana: The case of the smallholder Bhungroo Irrigation Technology. *Agricultural Water Management*, *216*, 284–293. https://doi.org/10.1016/j.agwat.2019.02.010
3. Alam, K. (2015). Farmers' adaptation to water scarcity in drought-prone environments: A case study of Rajshahi District, Bangladesh. *Agricultural Water Management*, *148*, 196–206. https://doi.org/10.1016/j.agwat.2014.10.011

4. Alauddin, M., Rashid Sarker, M. A., Islam, Z., & Tisdell, C. (2020). Adoption of alternate wetting and drying (AWD) irrigation as a water-saving technology in Bangladesh: Economic and environmental considerations. *Land Use Policy*, *91*. https://doi.org/10.1016/j.landusepol.2019.104430
5. Ali, S., Ying, L., Nazir, A., Abdullah, Ishaq, M., Shah, T., Ye, X., Ilyas, A., & Tariq, A. (2021). Rural farmers perception and coping strategies towards climate change and their determinants: Evidence from Khyber Pakhtunkhwa province, Pakistan. *Journal of Cleaner Production*, *291*. https://doi.org/10.1016/j.jclepro.2020.125250
6. Below, T. B., Mutabazi, K. D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., & Tscherning, K. (2012). Can farmers' adaptation to climate change be explained by socio-economic household-level variables? *Global Environmental Change*, *22*(1), 223–235. https://doi.org/10.1016/j.gloenvcha.2011.11.012
7. Budhathoki, N. K., Paton, D., A. Lassa, J., & Zander, K. K. (2020). Assessing farmers' preparedness to cope with the impacts of multiple climate change-related hazards in the Terai lowlands of Nepal. *International Journal of Disaster Risk Reduction*, *49*. https://doi.org/10.1016/j.ijdrr.2020.101656
8. Bukchin, S., & Kerret, D. (2020). Character strengths and sustainable technology adoption by smallholder farmers. *Heliyon*, *6*(8). https://doi.org/10.1016/j.heliyon.2020.e04694
9. Burnham, M., & Ma, Z. (2018). Multi-Scalar Pathways to Smallholder Adaptation. *World Development*, *108*, 249–262. https://doi.org/10.1016/j.worlddev.2017.08.005
10. Chen, H., Wang, J., & Huang, J. (2014). Policy support, social capital, and farmers' adaptation to drought in China. *Global Environmental Change*, *24*(1), 193–202. https://doi.org/10.1016/j.gloenvcha.2013.11.010
11. Chuchird, R., Sasaki, N., & Abe, I. (2017). Influencing factors of the adoption of agricultural irrigation technologies and the economic returns: A case study in Chaiyaphum Province, Thailand. *Sustainability (Switzerland)*, *9*(9). https://doi.org/10.3390/su9091524
12. Danso-Abbeam, G., Ojo, T. O., Baiyegunhi, L. J. S., & Ogundeji, A. A. (2021). Climate change adaptation strategies by smallholder farmers in Nigeria: does non-farm employment play any role? *Heliyon*, *7*(6). https://doi.org/10.1016/j.heliyon.2021.e07162
13. Ebi, K., Padgham, J., Doumbia, M., Kergna, A., Smith, J., Butt, T., & McCarl, B. (2011). Smallholders adaptation to climate change in Mali. *Climatic Change*, *108*, 423–436.
14. Esfandiari, M., Mirzaei Khalilabad, H. R., Boshrabadi, H. M., & Mehrjerdi, M. R. Z. (2020). Factors influencing the use of adaptation strategies to climate change in paddy lands of Kamfiruz, Iran. *Land Use Policy*, *95*. https://doi.org/10.1016/j.landusepol.2020.104628
15. Esteve, P., Varela-Ortega, C., & Downing, T. (2018). A stakeholder-based assessment of barriers to climate change adaptation in a water-scarce basin in Spain. *Regional Environmental Change*, *18*, 2505–2517.
16. Fagariba, C. J., Song, S., & Baoro, S. K. G. S. (2018). Climate change in Upper East Region of Ghana; Challenges existing in farming practices and new mitigation policies. *Open Agriculture*, *3*(1), 524–536. https://doi.org/10.1515/opag-2018-0057
17. Fahad, S., Inayat, T., Wang, J., Dong, L., Hu, G., Khan, S., & Khan, A. (2020). Farmers' awareness level and their perceptions of climate change: A case of Khyber Pakhtunkhwa province, Pakistan. *Land Use Policy*, *96*. https://doi.org/10.1016/j.landusepol.2020.104669
18. Funk, C., Raghavan Sathyan, A., Winker, P., & Breuer, L. (2020). Changing climate - Changing livelihood: Smallholder's perceptions and adaption strategies. *Journal of Environmental Management*, *259*. https://doi.org/10.1016/j.jenvman.2019.109702
19. Graveline, N., & Grémont, M. (2021). The role of perceptions, goals and characteristics of wine growers on irrigation adoption in the context of climate change. *Agricultural Water Management*, *250*. https://doi.org/10.1016/j.agwat.2021.106837

20. Herwehe, L., & Scott, C. A. (2017). Drought adaptation and development: small-scale irrigated agriculture in northeast Brazil. *Climate and Development*, *10*(4), 337–346.
21. Jamil, I., Jun, W., Mughal, B., Raza, M. H., Imran, M. A., & Waheed, A. (2021). Does the adaptation of climate-smart agricultural practices increase farmers' resilience to climate change? *Environmental Science and Pollution Research*, *28*, 27238–27249.
22. Jha, C. K., & Gupta, V. (2021). Farmer's perception and factors determining the adaptation decisions to cope with climate change: An evidence from rural India. *Environmental and Sustainability Indicators*, *10*. https://doi.org/10.1016/j.indic.2021.100112
23. Kabir, M. J., Cramb, R., Alauddin, M., Roth, C., & Crimp, S. (2017). Farmers' perceptions of and responses to environmental change in southwest coastal Bangladesh. *Asia Pacific Viewpoint*, *58*(3), 362–378.
24. Kalele, D. N., Ogara, W. O., Oludhe, C., & Onono, J. O. (2021). Climate change impacts and relevance of smallholder farmers' response in arid and semi-arid lands in Kenya. *Scientific African*, *12*. https://doi.org/10.1016/j.sciaf.2021.e00814
25. Kephe, P. N., Ayisi, K. K., & Petja, B. M. (2020). A decision support system for institutional support to farmers in the face of climate change challenges in Limpopo province. *Heliyon*, *6*(11). https://doi.org/10.1016/j.heliyon.2020.e04989
26. Keshavarz, M., & Moqadas, R. S. (2021). Assessing rural households' resilience and adaptation strategies to climate variability and change. *Journal of Arid Environments*, *184*. https://doi.org/10.1016/j.jaridenv.2020.104323
27. Khanal, U., Wilson, C., Hoang, V. N., & Lee, B. (2018). Farmers' Adaptation to Climate Change, Its Determinants and Impacts on Rice Yield in Nepal. *Ecological Economics*, *144*, 139–147. https://doi.org/10.1016/j.ecolecon.2017.08.006
28. Knapp, T., & Huang, Q. (2017). Do climate factors matter for producers' irrigation practices decisions? *Journal of Hydrology*, *552*, 81–91. https://doi.org/10.1016/j.jhydrol.2017.06.037
29. Koech, R., Haase, M., Grima, B., & Taylor, B. (2020). Barriers and measures to improve adoption of irrigation technologies: A case study from the Bundaberg region in Queensland, Australia.
30. Kumasi, T. C., Antwi-Agyei, P., & Obiri-Danso, K. (2019). Small-holder farmers' climate change adaptation practices in the Upper east region of Ghana. *Environment, Development and Sustainability*, *21*, 745–762.
31. Leroy, D. (2019). Farmers' Perceptions of and Adaptations to Water Scarcity in Colombian and Venezuelan Paramos in the Context of Climate Change. *Mountain Research and Development*, *39*.
32. Li, S., An, P. L., Pan, Z. H., Wang, F. T., Li, X. M., & Liu, Y. (2015). Farmers' initiative on adaptation to climate change in the Northern Agro-pastoral Ecotone. *International Journal of Disaster Risk Reduction*, *12*, 278–284. https://doi.org/10.1016/j.ijdrr.2015.02.002
33. Li, W., Ruiz-Menjivar, J., Zhang, L., & Zhang, J. (2021). Climate change perceptions and the adoption of low-carbon agricultural technologies: Evidence from rice production systems in the Yangtze River Basin. *Science of the Total Environment*, *759*. https://doi.org/10.1016/j.scitotenv.2020.143554
34. Mango, N., Makate, C., Tamene, L., Mponela, P., & Ndengu, G. (2018). Adoption of small-scale irrigation farming as a climate-smart agriculture practice and its influence on household income in the Chinyanja Triangle, Southern Africa. *Land*, *7*(2). https://doi.org/10.3390/land7020049
35. Marie, M., Yirga, F., Haile, M., & Tquabo, F. (2020). Farmers' choices and factors affecting adoption of climate change adaptation strategies: evidence from northwestern Ethiopia. *Heliyon*, *6*(4). https://doi.org/10.1016/j.heliyon.2020.e03867
36. Masud, M. M., Azam, M. N., Mohiuddin, M., Banna, H., Akhtar, R., Alam, A. S. A. F., & Begum, H. (2017). Adaptation barriers and strategies towards climate change:

Challenges in the agricultural sector. *Journal of Cleaner Production*, *156*, 698–706. https://doi.org/10.1016/j.jclepro.2017.04.060
37. Matewos, T. (2020). The state of local adaptive capacity to climate change in drought-prone districts of rural Sidama, southern Ethiopia. *Climate Risk Management*, *27*. https://doi.org/10.1016/j.crm.2019.100209
38. Mi, Q., Li, X., Li, X., Yu, G., & Gao, J. (2021). Cotton farmers' adaptation to arid climates: Waiting times to adopt water-saving technology. *Agricultural Water Management*, *244*. https://doi.org/10.1016/j.agwat.2020.106596
39. NGANGO, J., & HONG, S. (2021). Adoption of small-scale irrigation technologies and its impact on land productivity: Evidence from Rwanda. *Journal of Integrative Agriculture*, *20*(8), 2302–2312. https://doi.org/10.1016/S2095-3119(20)63417-7
40. Nguyen, N., & Drakou, E. G. (2021). Farmers intention to adopt sustainable agriculture hinges on climate awareness: The case of Vietnamese coffee. *Journal of Cleaner Production*, *303*. https://doi.org/10.1016/j.jclepro.2021.126828
41. Nigussie, Y., van der Werf, E., Zhu, X., Simane, B., & van Ierland, E. C. (2018). Evaluation of Climate Change Adaptation Alternatives for Smallholder Farmers in the Upper Blue-Nile Basin. *Ecological Economics*, *151*, 142–150. https://doi.org/10.1016/j.ecolecon.2018.05.006
42. Nyang'au, J. O., Mohamed, J. H., Mango, N., Makate, C., & Wangeci, A. N. (2021). Smallholder farmers' perception of climate change and adoption of climate smart agriculture practices in Masaba South Sub-county, Kisii, Kenya. *Heliyon*, *7*(4). https://doi.org/10.1016/j.heliyon.2021.e06789
43. Ojo, T. O., Adetoro, A. A., Ogundeji, A. A., & Belle, J. A. (2021). Quantifying the determinants of climate change adaptation strategies and farmers' access to credit in South Africa. *Science of the Total Environment*, *792*. https://doi.org/10.1016/j.scitotenv.2021.148499
44. Orduño Torres, M. A., Kallas, Z., & Ornelas Herrera, S. I. (2020). Farmers' environmental perceptions and preferences regarding climate change adaptation and mitigation actions; towards a sustainable agricultural system in México. *Land Use Policy*, *99*. https://doi.org/10.1016/j.landusepol.2020.105031
45. Pittman, J., Wittrock, V., Kulshreshtha, S., & Wheaton, E. (2011). Vulnerability to climate change in rural Saskatchewan: Case study of the Rural Municipality of Rudy No. 284. *Journal of Rural Studies*, *27*(1), 83–94. https://doi.org/10.1016/j.jrurstud.2010.07.004
46. Rico, L., Poblete, D., Meza, F., & Kerrigan, G. (2016). Farmers' Options to Address Water Scarcity in a Changing Climate: Case Studies from two Basins in Mediterranean Chile. *Environmental Management*, *109*, 958–971.
47. Sertse, S. F., Khan, N. A., Shah, A. A., Liu, Y., & Naqvi, S. A. A. (2021). Farm households' perceptions and adaptation strategies to climate change risks and their determinants: Evidence from Raya Azebo district, Ethiopia. *International Journal of Disaster Risk Reduction*, *60*. https://doi.org/10.1016/j.ijdrr.2021.102255
48. Shikuku, K. M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez, J. G., Mwongera, C., & Läderach, P. (2017). Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. *Climate Risk Management*, *16*, 234–245. https://doi.org/10.1016/j.crm.2017.03.001
49. Udmale, P., Ichikawa, Y., Manandhar, S., Ishidaira, H., & Kiem, A. S. (2014). Farmers' perception of drought impacts, local adaptation and administrative mitigation measures in Maharashtra State, India. *International Journal of Disaster Risk Reduction*, *10*(PA), 250–269. https://doi.org/10.1016/j.ijdrr.2014.09.011
50. Zizinga, A., Kangalawe, R. Y. M., Ainslie, A., Tenywa, M. M., Majaliwa, J., Saronga, N. J., & Amoako, E. E. (2017). Analysis of Farmer's Choices for Climate Change Adaptation Practices in South-Western Uganda, 1980-2009. *Climate*, *5*(4), 89.

References

1. Sauer, T.; Havlik, P.; Schneider, U.; Schmid, E.; Kindermann, G.E.; Obersteiner, M. Agriculture and resource availability in a changing world: The role of irrigation. *Water Resour. Res.* **2010**, *46*, W06503. [CrossRef]
2. Yadav, P.; Jaiswal, D.K.; Sinha, R.K. Climate change. In *Global Climate Change*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 151–174. [CrossRef]
3. Kurukulasuriya, P.; Rosenthal, S. *Climate Change and Agriculture A Review of Impacts and Adaptations*; World Bank: Washington, DC, USA, 2003.
4. Smit, B.; Skinner, M.W. Adaptation Options in Agriculture to Climate Change: A Typology. *Mitig. Adapt. Strateg. Glob. Chang.* **2002**, *7*, 85–114. [CrossRef]
5. Allouche, J. The sustainability and resilience of global water and food systems: Political analysis of the interplay between security, resource scarcity, political systems and global trade. *Food Policy* **2011**, *36*, S3–S8. [CrossRef]
6. Kogo, B.K.; Kumar, L.; Richard, K. Climate change and variability in Kenya: A review of impacts on agriculture and food security. *Environ. Dev. Sustain.* **2021**, *23*, 23–43. [CrossRef]
7. Cassman, K.G.; Dobermann, A.; Walters, D.T.; Yang, H. Meeting cereal demand while protecting natural resources and improving environmental quality. *Annu. Rev. Environ. Resour.* **2003**, *28*, 315–358. [CrossRef]
8. Sakschewski, B.; Von Bloh, W.; Huber, V.; Müller, C.; Bondeau, A. Feeding 10 billion people under climate change: How large is the production gap of current agricultural systems? *Ecol. Modell.* **2014**, *288*, 103–111. [CrossRef]
9. Calzadilla, A.; Rehdanz, K.; Betts, R.; Falloon, P.; Wiltshire, A.; Tol, R. Climate change impacts on global agriculture. *Clim. Change* **2013**, *120*, 357–374. [CrossRef]
10. Shiferaw, B.; Tesfaye, K.; Kassie, M.; Abate, T.; Prasanna, B.; Menkir, A. Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather Clim. Extrem.* **2014**, *3*, 67–79. [CrossRef]
11. Wilson, R.S.; Herziger, A.; Hamilton, M.; Brooks, J.S. From incremental to transformative adaptation in individual responses to climate-exacerbated hazards. *Nat. Clim. Change* **2020**, *10*, 200–208. [CrossRef]
12. Intergovernmental Panel on Climate Change. Adaptation Needs and Options. In *Climate Change 2014—Impacts, Adaptation and Vulnerability: Part A: Global and Sectoral Aspects: Working Group II Contribution to the IPCC Fifth Assessment Report: Volume 1: Global and Sectoral Aspects*; Intergovernmental Panel on Climate Change, Ed.; Cambridge University Press: Cambridge, UK, 2014; Volume 1, pp. 833–868.
13. Tack, J.; Barkley, A.; Hendricks, N. Irrigation offsets wheat yield reductions from warming temperatures. *Environ. Res. Lett.* **2017**, *12*, 114027. [CrossRef]
14. Troy, T.J.; Kipgen, C.; Pal, I. The impact of climate extremes and irrigation on US crop yields. *Environ. Res. Lett.* **2015**, *10*, 54013. [CrossRef]
15. Hejazi, M.I.; Edmonds, J.A.; Chaturvedi, V. Global Irrigation Demand? A Holistic Approach. *Irrig. Drain. Syst. Eng.* **2012**, *1*, 2–5. [CrossRef]
16. Angelakıs, A.N.; Zaccaria, D.; Krasilnikoff, J.; Salgot, M.; Bazza, M.; Roccaro, P.; Jimenez, B.; Kumar, A.; Yinghua, W.; Baba, A.; et al. Irrigation of world agricultural lands: Evolution through the Millennia. *Water* **2020**, *12*, 1285. [CrossRef]
17. Hussain, I.; Hanjra, M.A. Irrigation and poverty alleviation: Review of the empirical evidence. *Irrig. Drain.* **2004**, *53*, 1–15. [CrossRef]
18. International Commission on Irrigation & Drainage. ICID Database—World Irrigated Area. 2021. Available online: https://icid-ciid.org/Knowledge/world_irrigated_area (accessed on 30 March 2022).
19. Knoema. Total Area Equipped for Irrigation. 2019. Available online: https://knoema.com/atlas/topics/Land-Use/Area/Total-area-equipped-for-irrigation?type=maps (accessed on 18 March 2022).
20. Mottaleb, K.A. Perception and adoption of a new agricultural technology: Evidence from a developing country. *Technol. Soc.* **2018**, *55*, 126–135. [CrossRef]
21. McDonald, R.I.; Girvetz, E.H. Two Challenges for U.S. Irrigation Due to Climate Change: Increasing Irrigated Area in Wet States and Increasing Irrigation Rates in Dry States. *PLoS ONE* **2013**, *8*, e65589. [CrossRef]
22. United States Government Accountability Office (US GAO). *Irrigated Agriculture; Science, Technology Assessment, and Analytics, Natural Resources and Environment, Report to Congressional Requesters, Technologies, Practices, and Implications for Water Scarcity*; US GAO: Washington, DC, USA, 2019.
23. Combs, P. Evaluation of Factors Influencing Irrigation Adoption among Farmers in the Southeast. In *All Theses*; Clemson University: Clemson, SC, USA, 2019.
24. Patle, G.T.; Kumar, M.; Khanna, M. Climate-smart water technologies for sustainable agriculture: A review. *J. Water Clim. Chang.* **2019**, *11*, 1455–1466. [CrossRef]
25. Mbuli, C.S.; Fonjong, L.N.; Fletcher, A.J. Climate Change and Small Farmers' Vulnerability to Food Insecurity in Cameroon. *Sustainability* **2021**, *13*, 1523. [CrossRef]
26. Giannakis, E.; Bruggeman, A.; Djuma, H.; Kozyra, J.; Hammer, J. Water pricing and irrigation across Europe: Opportunities and constraints for adopting irrigation scheduling decision support systems. *Water Sci. Technol. Water Supply* **2016**, *16*, 245–252. [CrossRef]

27. Esham, M.; Garforth, C. Agricultural adaptation to climate change: Insights from a farming community in Sri Lanka. *Mitig. Adapt. Strateg. Glob. Chang.* **2013**, *18*, 535–549. [CrossRef]
28. Asare-Baah, L.; Zabawa, R.; Findlay, H.J.; Findlay, H. Participation in Selected USDA Programs by Socially Disadvantaged Farmers in Selected Black Belt Counties in Georgia. *J. Rural. Soc. Sci.* **2018**, *33*, 2.
29. Ruzzante, S.; Labarta, R.; Bilton, A. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Dev.* **2021**, *146*, 105599. [CrossRef]
30. Martin, L.; Blossey, B.; Ellis, E. Mapping where ecologists work: Biases in the global distribution of terrestrial ecological observations. *Front. Ecol. Environ.* **2012**, *10*, 195–201. [CrossRef] [PubMed]
31. Prokopy, L.S.; Floress, K.; Klotthor-Weinkauf, D.; Baumgart-Getz, A. Determinants of agricultural best management practice adoption: Evidence from the literature. *J. Soil Water Conserv.* **2008**, *63*, 300–311. Available online: www.swcs.org (accessed on 15 November 2022).
32. Da Cunha, D.A.; Coelho, A.B.; Féres, J.G. Irrigation as an adaptive strategy to climate change: An economic perspective on Brazilian agriculture. *Environ. Dev. Econ.* **2015**, *20*, 57–79. [CrossRef]
33. Trapolino, M. Irrigation Technology in Agriculture: How New Technologies Overcome Challenges. 2019. Available online: https://www.agritechtomorrow.com/article/2019/01/top-article-from-2019-irrigation-technology-in-agriculture-how-new-technologies-overcome-challenges/11230 (accessed on 3 May 2021).
34. USDA Economic Research Service. Irrigation & Water Use. 2022. Available online: https://www.ers.usda.gov/topics/farm-practices-management/irrigation-water-use/ (accessed on 1 May 2022).
35. USGS. Irrigation Methods. 2018. Available online: https://www.usgs.gov/special-topics/water-science-school/science/irrigation-methods-quick-look (accessed on 1 May 2022).
36. Barta, R.; Broner, I.; Schneekloth, J.; Waskom, R. Farm Irrigation Systems. 2015. Available online: https://irrigazette.com/en/news/farm-irrigation-systems (accessed on 9 May 2022).
37. Michael, C.H.; Charles, H.U.; James, R.E.; Stefan, S.O.; Graham, V.M. World Atlas of Desertification, Publication Office of the European Union. 2018. Available online: https://wad.jrc.ec.europa.eu/ (accessed on 30 March 2022).
38. Rosegrant, M.W.; Ringler, C.; Zhu, T. Water for Agriculture: Maintaining Food Security under Growing Scarcity. *Annu. Rev. Environ. Resour.* **2009**, *34*, 205–222. [CrossRef]
39. Turral, H.; Svendsen, M.; Faures, J.M. Turral—Investing in Irrigation_Reviewing the past and looking to the future. *Agric. Water Manag.* **2010**, *97*, 551–560. [CrossRef]
40. FAO. The Irrigation Challenge. 2003. Available online: https://www.fao.org/publications/card/en/c/c72fbe14-0a6f-52d1-92b5-f29eea8e2ab7/ (accessed on 30 March 2022).
41. Khan, S.; Tariq, R.; Yuanlai, C.; Blackwell, J. Can irrigation be sustainable? In *Agricultural Water Management*; Elsevier: Amsterdam, The Netherlands, 2006; Volume 80, pp. 87–99.
42. Gibson, K.E.; Yang, H.S.; Franz, T.; Eisenhauer, D.; Gates, J.B.; Nasta, P.; Farmaha, B.S.; Grassini, P. Assessing explanatory factors for variation in on-farm irrigation in US maize-soybean systems. *Agric. Water Manag.* **2018**, *197*, 34–40. [CrossRef]
43. Grassini, P.; van Bussel, L.G.; Van Wart, J.; Wolf, J.; Claessens, L.; Yang, H.; Boogaard, H.; de Groot, H.; van Ittersum, M.K.; Cassman, K.G. How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. *Field Crop. Res.* **2015**, *177*, 49–63. [CrossRef]
44. Agriculture Victoria. Irrigation Management. 2022. Available online: https://agriculture.vic.gov.au/farm-management/water/irrigation/irrigation-management (accessed on 18 March 2022).
45. Lauer, S.; Sanderson, M. Irrigated agriculture and human development: A county-level analysis 1980–2010. *Environ. Dev. Sustain.* **2020**, *22*, 4407–4423. [CrossRef]
46. Mpanga, I.K.; Idowu, O.J. A decade of irrigation water use trends in Southwest USA: The role of irrigation technology, best management practices, and outreach education programs. *Agric. Water Manag.* **2021**, *243*, 106438. [CrossRef]
47. Evans, R.G.; Sadler, E.J. Methods and technologies to improve efficiency of water use. *Water Resour. Res.* **2008**, *44*. [CrossRef]
48. Fraiture, C.; Wichelns, D.C. Satisfying future water demands for agriculture. *Agric. Water Manag.* **2010**, *97*, 502–511. [CrossRef]
49. Zaveri, E.; Lobell, D.B. The role of irrigation in changing wheat yields and heat sensitivity in India. *Nat. Commun.* **2019**, *10*, 4144. [CrossRef] [PubMed]
50. Bhattarai, M.; Barker, R.; Narayanamoorthy, A. Who benefits from irrigation development in India? Implication of irrigation multipliers for irrigation financing. *Irrig. Drain.* **2007**, *56*, 207–225. [CrossRef]
51. Rogers, E.M. *Diffusion of Innovations*, 3rd ed.; Free Press: New York, NY, USA, 1962.
52. Kee, K.F. Adoption and Diffusion. In *The International Encyclopedia of Organizational Communication*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2017; Volume 1, pp. 41–54.
53. Driessen, P.H.; Hillebrand, B. Adoption and Diffusion of Green Innovations. In *Marketing for Sustainability: Towards Transactional Policy-Making*; Bartels, G.C., Nelissen, W.J.A., Eds.; IOS Press: Amsterdam, The Netherlands, 2002; pp. 343–355. Available online: https://ssrn.com/abstract=2363527 (accessed on 5 April 2022).
54. Sunding, D.; Zilberman, D. The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector. In *Handbook of Agricultural Economics*; Elsevier: Amsterdam, The Netherlands, 1999.
55. Straub, E.T. Understanding technology adoption: Theory and future directions for informal learning. *Rev. Educ. Res.* **2009**, *79*, 625–649. [CrossRef]

56. Kapoor, K.; Dwivedi, Y.; Williams, M. Innovation adoption attributes: A review and synthesis of research findings. *Eur. J. Innov. Manag.* **2015**, *17*, 327–348. [CrossRef]
57. Mwangi, M.; Kariuki, S. Factors determining adoption of new agricultural technology by smallholder farmers in developing countries. *J. Econ. Sustain. Dev.* **2015**, *6*, 208–217.
58. Feder, G.; Umali, D.L. The Adoption of Agricultural Innovations A Review. *Technol. Forecast. Soc. Chang.* **1993**, *43*, 215–239. [CrossRef]
59. Pham, H.-G.; Chuah, S.-H.; Feeny, S. Factors affecting the adoption of sustainable agricultural practices: Findings from panel data for Vietnam. *Ecol. Econ.* **2021**, *184*, 107000. [CrossRef]
60. Li, J.; Feng, S.; Luo, T.; Guan, Z. What drives the adoption of sustainable production technology? Evidence from the large scale farming sector in East China. *J. Clean. Prod.* **2020**, *257*, 120611. [CrossRef]
61. Meijer, S.S.; Catacutan, D.; Ajayi, O.C.; Sileshi, G.W.; Nieuwenhuis, M. The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in sub-Saharan Africa. *Int. J. Agric. Sustain.* **2015**, *13*, 40–54. [CrossRef]
62. Herrero, M.; Thornton, P.K.; Mason-D'Croz, D.; Palmer, J.; Benton, T.G.; Bodirsky, B.L.; Bogard, J.R.; Hall, A.; Lee, B.; Nyborg, K.; et al. Innovation can accelerate the transition towards a sustainable food system. *Nat. Food* **2020**, *1*, 266–272. [CrossRef]
63. Woltering, L.; Fehlenberg, K.; Gerard, B.; Ubels, J.; Cooley, L. Scaling—From "reaching many" to sustainable systems change at scale: A critical shift in mindset. *Agric. Syst.* **2019**, *176*, 102652. [CrossRef]
64. Genius, M.; Koundouri, P.; Nauges, C.; Tzouvelekas, V. Information transmission in irrigation technology adoption and diffusion: Social learning, extension services, and spatial effects. *Am. J. Agric. Econ.* **2013**, *96*, 328–344. [CrossRef]
65. Chen, H.; Wang, J.; Huang, J. Policy support, social capital, and farmers' adaptation to drought in China. *Glob. Environ. Chang.* **2014**, *24*, 193–202. [CrossRef]
66. Wossen, T.; Berger, T.; Di Falco, S. Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. *Agric. Econ.* **2015**, *46*, 81–97. [CrossRef]
67. Hunecke, C.; Engler, A.; Jara-Rojas, R.; Poortvliet, P.M. Understanding the role of social capital in adoption decisions: An application to irrigation technology. *Agric. Syst.* **2017**, *153*, 221–231. [CrossRef]
68. Wang, J.; Klein, K.K.; Bjornlund, H.; Zhang, L.; Zhang, W. Adoption of improved irrigation scheduling methods in Alberta: An empirical analysis. *Can. Water Resour. J. Rev. Can. Des. Ressour. Hydr.* **2015**, *40*, 47–61. [CrossRef]
69. Chavas, J.P.; Nauges, C. Uncertainty, Learning, and Technology Adoption in Agriculture. *Appl. Econ. Perspect. Policy* **2020**, *42*, 42–53. [CrossRef]
70. Luu, T.D. Factors Influencing Farmers' Adoption of Climate-Smart Agriculture in Rice Production in Vietnam's Mekong Delta. *Asian J. Agric. Dev.* **2020**, *17*, 109–124. [CrossRef]
71. Amadu, F.O.; McNamara, P.E.; Miller, D.C. Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi. *World Dev.* **2020**, *126*, 104692. [CrossRef]
72. de Witt, M.; de Clercq, W.P.; Velazquez, F.J.B.; Altobelli, F.; Marta, A.D. An in-depth evaluation of personal barriers to technology adoption in irrigated agriculture in South Africa. *Outlook Agric.* **2021**, *50*, 259–268. [CrossRef]
73. Hamdy, A.; Ragab, R.; Scarascia-Mugnozza, E. Coping with water scarcity: Water saving and increasing water productivity. *Irrig. Drain.* **2003**, *52*, 3–20. [CrossRef]
74. Annandale, J.G.; Stirzaker, R.J.; Singels, A.; van der Laan, M.; Laker, M.C. Irrigation scheduling research: South African experiences and future prospects. *Water SA* **2011**, *37*, 751–764. [CrossRef]
75. Garb, Y.; Friedlander, L. From transfer to translation: Using systemic understandings of technology to understand drip irrigation uptake. *Agric. Syst.* **2014**, *128*, 13–24. [CrossRef]
76. Zongo, B.; Diarra, A.; Barbier, B.; Zorom, M.; Yacouba, H.; Dogot, T. Farmers' Practices and Willingness to Adopt Supplemental Irrigation in Burkina Faso. *Int. J. Food Agric. Econ.* **2015**, *3*, 101–117.
77. Afrakhteh, H.; Armand, M.; Bozayeh, F. Analysis of Factors Affecting Adoption and Application of Sprinkler Irrigation by Farmers in Famenin County, Iran. *Int. J. Agric. Manag. Dev.* **2015**, *5*, 89–99. [CrossRef]
78. Salazar, C.; Rand, J. Production risk and adoption of irrigation technology: Evidence from small-scale farmers in Chile. *Lat. Am. Econ. Rev.* **2016**, *25*, 2. [CrossRef]
79. Zhai, S.-Y.; Song, G.-X.; Qin, Y.-C.; Ye, X.-Y.; Leipnik, M. Climate change and Chinese farmers: Perceptions and determinants of adaptive strategies. *J. Integr. Agric.* **2018**, *17*, 949–963. [CrossRef]
80. Hall, B.H.; Khan, B. Adoption of New Technology. 2003. Available online: http://www.nber.org/papers/w9730 (accessed on 5 August 2021).
81. Freydank, K.; Siebert, S. Towards Mapping the Extent of Irrigation in the Last Century: Time Series of Irrigated Area per Country. 2008. Available online: http://photogallery.nrcs.usda.gov/Index.asp (accessed on 29 April 2021).
82. GADM. GADM Maps and Data. 2022. Available online: https://gadm.org/data.html (accessed on 19 April 2021).
83. Willmott, C.; Matsuura, K. Terrestrial Air Temperature and Precipitation: Monthly and Annual Climatologies. 2001. Available online: http://climate.geog.udel.edu/~{}climate/html_pages/README.ghcn_clim2.html (accessed on 9 May 2022).
84. Klein Goldewijk, K.; Beusen, A.; Van Drecht, G.; De Vos, M. The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years. *Glob. Ecol. Biogeogr.* **2011**, *20*, 73–86. [CrossRef]

85. Verburg, P.H.; Ellis, E.C.; Letourneau, A. A global assessment of market accessibility and market influence for global environmental change studies. *Environ. Res. Lett.* **2011**, *6*, 034019. [CrossRef]
86. Siebert, S.; Döll, P.; Hoogeveen, J.; Faures, J.-M.; Frenken, K.; Feick, S. Development and validation of the global map of irrigation areas. *Hydrol. Earth Syst. Sci.* **2005**, *9*, 535–547. [CrossRef]
87. Abebaw, D.; Haile, M.G. The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. *Food Policy* **2013**, *38*, 82–91. [CrossRef]
88. Abdulai, A.N.; Abdul-Rahaman, A.; Issahaku, G. Adoption and diffusion of conservation agriculture technology in Zambia: The role of social and institutional networks. *Environ. Econ. Policy Stud.* **2021**, *23*, 761–780. [CrossRef]
89. Abegunde, V.O.; Sibanda, M.; Obi, A. Determinants of the adoption of climate-smart agricultural practices by small-scale farming households in King Cetshwayo district municipality, South Africa. *Sustainability* **2020**, *12*, 195. [CrossRef]
90. Mase, A.S.; Gramig, B.M.; Prokopy, L.S. Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern U.S. crop farmers. *Clim. Risk Manag.* **2017**, *15*, 8–17. [CrossRef]
91. Hassan, R.; Nhemachena, C.; Hassan, R.; Nhemachena, C. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *Afr. J. Agric. Resour. Econ.* **2008**, *2*, 83–104. Available online: http://ageconsearch.umn.edu (accessed on 15 November 2022).
92. Wheeler, S.; Zuo, A.; Bjornlund, H. Farmers' climate change beliefs and adaptation strategies for a water scarce future in Australia. *Glob. Environ. Chang.* **2013**, *23*, 537–547. [CrossRef]
93. Ortiz, R.; Sayre, K.D.; Govaerts, B.; Gupta, R.; Subbarao, G.V.; Ban, T.; Hodson, D.; Dixon, J.M.; Ortiz-Monasterio, J.I.; Reynolds, M. Climate change: Can wheat beat the heat? *Agric. Ecosyst. Environ.* **2008**, *126*, 46–58. [CrossRef]
94. Saadi, S.; Todorovic, M.; Tanasijevic, L.; Pereira, L.S.; Pizzigalli, C.; Lionello, P. Climate change and Mediterranean agriculture: Impacts on winter wheat and tomato crop evapotranspiration, irrigation requirements and yield. *Agric. Water Manag.* **2015**, *147*, 103–115. [CrossRef]
95. Zilberman, D.; Zhao, J.; Heiman, A. Adoption versus adaptation, with Emphasis on climate change. *Annu. Rev. Resour. Econ.* **2012**, *4*, 27–53. [CrossRef]
96. Schmill, M.D.; Gordon, L.M.; Magliocca, N.R.; Ellis, E.C.; Oates, T. GLOBE: Analytics for assessing global representativeness. In Proceedings of the 5th International Conference on Computing for Geospatial Research and Application, Washington, DC, USA, 25 September 2014. [CrossRef]
97. GLOBE. Global Representativeness Analysis. 2012. Available online: http://globe.umbc.edu/documentation-overview/representativeness/ (accessed on 4 March 2021).
98. Olson, D.M.; Dinerstein, E.; Wikramanayake, E.D.; Burgess, N.D.; Powell, G.V.; Underwood, E.C.; D'amico, J.A.; Itoua, I.; Strand, H.E.; Morrison, J.C.; et al. Terrestrial Ecoregions of the World: A New Map of Life on Earth: A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. *Bioscience* **2001**, *51*, 933–938. [CrossRef]
99. IIASA Global Agro-Ecological Zones (GAEZ). Slope Suitability Classes. 2001. Available online: https://gaez.fao.org/ (accessed on 9 May 2022).
100. Kabacoff, R. Correspondence Analysis. 2017. Available online: https://www.statmethods.net/advstats/ca.html (accessed on 29 August 2022).
101. TIBCO Software Inc. What Is Correspondence Analysis? 2022. Available online: https://www.tibco.com/reference-center/what-is-correspondence-analysis (accessed on 29 August 2022).
102. Sourial, N.; Wolfson, C.; Zhu, B.; Quail, J.; Fletcher, J.; Karunananthan, S.; Bandeen-Roche, K.; Béland, F.; Bergman, H. Correspondence analysis is a useful tool to uncover the relationships among categorical variables. *J. Clin. Epidemiol.* **2010**, *63*, 638–646. [CrossRef]
103. Bock, T. How Correspondence Analysis Works (A Simple Explanation). Available online: https://www.displayr.com/how-correspondence-analysis-works/ (accessed on 29 August 2022).
104. Doey, L.; Kurta, J. Correspondence Analysis applied to psychological research. *Tutor. Quant. Methods Psychol.* **2011**, *7*, 5–14. [CrossRef]
105. Pelletier, C.; Pousette, A.; Ward, K.; Fox, G. Exploring the perspectives of community members as research partners in rural and remote areas. *Res. Involv. Engagem.* **2020**, *6*, 3. [CrossRef] [PubMed]
106. Mwangi, J.K.; Crewett, W. The impact of irrigation on small-scale African indigenous vegetable growers' market access in peri-urban Kenya. *Agric. Water Manag.* **2019**, *212*, 295–305. [CrossRef]
107. Dhawan, B. Impact of Irrigation on Farm Economy in High Rainfall Areas: The Kal Project. *Econ. Polit. Wkly.* **1988**, *23*, A173–A175 + A177–A180.
108. Adeoti, A.I. Factors Influencing Irrigation Technology Adoption and its Impact on Household Poverty in Ghana. *J. Agric. Rural. Dev. Trop. Subtrop.* **2009**, *109*, 51–63.
109. Fischer, J.; Abson, D.J.; Dorresteijn, I.; Hanspach, J.; Hartel, T.; Schultner, J.; Sherren, K. Using a leverage points perspective to compare social-ecological systems: A case study on rural landscapes. *Ecosyst. People* **2022**, *18*, 119–130. [CrossRef]
110. Wozniak, G.D. Human Capital, Information, and the Early Adoption of New Technology. *J. Hum. Resour.* **1987**, *22*, 101–112. Available online: https://about.jstor.org/terms (accessed on 20 August 2022). [CrossRef]

111. Diederen, P.; Van Meijl, H.; Wolters, A.; Bijak, K. Innovation Adoption in Agriculture: Innovators, Early Adopters and Laggards Innovation Adoption in Agriculture: Innovators, Early Adopters and Laggards. 2003. Available online: https://hal.archives-ouvertes.fr/hal-01201041 (accessed on 20 August 2022).
112. Asfaw, S.; Shiferaw, B.; Simtowe, F.; Hagos, M. Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. *J. Dev. Agric. Econ.* **2011**, *3*, 436–447.
113. Teha, D.; Jianjun, L. Factors Affecting Adoption of Small Scale Irrigation Technology: Insights from Sire Woreda, Oromiya Region, Ethiopia. *Am. J. Appl. Sci. Res.* **2021**, *7*, 84–101. [CrossRef]
114. Makate, C.; Makate, M.; Mutenje, M.; Mango, N.; Siziba, S. Synergistic impacts of agricultural credit and extension on adoption of climate-smartagricultural technologies in southern Africa. *Environ. Dev.* **2019**, *32*, 100458. [CrossRef]
115. Ajayi, T.; Fatunbi, O.; Yemi, A. *Strategies for Scaling Agricultural Technologies in Africa*; FARA Africa: Accra, Ghana, 2018.
116. Kim, J.; Shah, P.; Gaskell, J.C.; Prasann, A.; Luthra, A. *Scaling up Disruptive Agricultural Technologies in Africa*; The World Bank: Washington, DC, USA, 2020.
117. Esteve, P.; Varela-Ortega, C.; Downing, T. A stakeholder-based assessment of barriers to climate change adaptation in a water-scarce basin in Spain. *Reg. Environ. Chang.* **2018**, *18*, 2505–2517. [CrossRef]
118. Budhathoki, N.K.; Paton, D.; ALassa, J.; Zander, K.K. Assessing farmers' preparedness to cope with the impacts of multiple climate change-related hazards in the Terai lowlands of Nepal. *Int. J. Disaster Risk Reduct.* **2020**, *49*, 101656. [CrossRef]
119. Ray, D.K.; West, P.C.; Clark, M.; Gerber, J.S.; Prishchepov, A.V.; Chatterjee, S. Climate change has likely already affected global food production. *PLoS ONE* **2019**, *14*, e0217148. [CrossRef]
120. Ranganathan, J.; Waite, R.; Searchinger, T.; Zionts, J. *Regenerative Agriculture: Good for Soil Health, but Limited Potential to Mitigate Climate Change*; WRI: Washington, DC, USA, 2020.
121. Falkenmark, M.; Molden, D. Wake up to realities of river basin closure. *Int. J. Water Resour. Dev.* **2008**, *24*, 201–215. [CrossRef]
122. Lankford, B.; Closas, A.; Dalton, J.; Gunn, E.L.; Hess, T.; Knox, J.W.; van der Kooij, S.; Lautze, J.; Molden, D.; Orr, S.; et al. A scale-based framework to understand the promises, pitfalls and paradoxes of irrigation efficiency to meet major water challenges. *Glob. Environ. Chang.* **2020**, *65*, 102182. [CrossRef]
123. Graveline, N.; Grémont, M. The role of perceptions, goals and characteristics of wine growers on irrigation adoption in the context of climate change. *Agric. Water Manag.* **2021**, *250*, 106837. [CrossRef]
124. Andersson, J.A.; D'Souza, S. From adoption claims to understanding farmers and contexts: A literature review of Conservation Agriculture (CA) adoption among smallholder farmers in southern Africa. *Agric. Ecosyst. Environ.* **2014**, *187*, 116–132. [CrossRef]