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Article

Climatic Damage Cause Variations of Agricultural Insurance Loss for the Pacific Northwest Region of the United States

Erich Seamon [1,*], Paul E. Gessler [2], John T. Abatzoglou [3], Philip W. Mote [4] and Stephen S. Lee [5]

1 Institute for Modeling Collaboration and Innovation, University of Idaho, Moscow, ID 83844, USA
2 Department of Forest, Rangeland and Fire Sciences, University of Idaho, Moscow, ID 83844, USA; paulg@uidaho.edu
3 Department of Management of Complex Systems, University of California Merced, Merced, CA 95343, USA; jabatzoglou@ucmerced.edu
4 The Graduate School, Oregon State University, Corvallis, OR 97331, USA; philip.mote@oregonstate.edu
5 Department of Mathematics and Statistical Science, University of Idaho, Moscow, ID 83844, USA; stevel@uidaho.edu
* Correspondence: erichs@uidaho.edu; Tel.: +1-208-310-2140

Abstract: Agricultural crop insurance is an important component for mitigating farm risk, particularly given the potential for unexpected climatic events. Using a 2.8 million nationwide insurance claim dataset from the United States Department of Agriculture (USDA), this research study examines spatiotemporal variations of over 31,000 agricultural insurance loss claims across the 24-county region of the inland Pacific Northwest (iPNW) portion of the United States from 2001 to 2022. Wheat is the dominant insurance loss crop for the region, accounting for over USD 2.8 billion in indemnities, with over USD 1.5 billion resulting in claims due to drought (across the 22 year time period). While fruit production generates considerably lesser insurance losses (USD 400 million) as a primary result of freeze, frost, and hail, overall revenue ranks number one for the region, with USD 2 billion in sales, across the same time range. Principal components analysis of crop insurance claims showed distinct spatial and temporal differentiation in wheat and apples insurance losses using the range of damage causes as factor loadings. The first two factor loadings for wheat accounts for approximately 50 percent of total variance for the region, while a separate analysis of apples accounts for over 60 percent of total variance. These distinct orthogonal differences in losses by year and commodity in relationship to damage causes suggest that insurance loss analysis may serve as an effective barometer in gauging climatic influences.

Keywords: Pacific Northwest; agriculture; insurance; wheat; apples; drought

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1. Introduction

Crop insurance is an important component for mitigating agricultural risk [1–3]. In 1996 the United States Department of Agriculture (USDA) formed their Risk Management Agency (RMA), which works to increase the availability and effectiveness of federal crop insurance as a risk management tool. With the implementation of the Federal Crop Insurance Act (FCIA) and the USDA RMA, program improvements (providing direct payments to farmers, implementing subsidies) grew the level of program participation to over 90 percent of all U.S. farmed land by 1998. Crop insurance program efforts have also had a dramatic impact on overall farm management, including the reduction in income risk around crop production, increasing land values, increasing farm survivability rates, stabilizing cash flow, and liquidity improvement [4]. By 2021, the USDA insured over 400 million acres of farmland, with an insurance liability net worth almost USD 200 billion [5]. Regionally, agriculture in the Pacific Northwest (PNW) accounts for over 600,000 jobs over the three state region of Idaho, Oregon, and Washington [6–8]. All three states consistently rank in the top five in terms of U.S. crop production for a range of agricultural commodities, including apples and wheat (Washington), potatoes and barley (Idaho), as well as hay, blackberries, and hazelnuts (Oregon) [9]. In terms of agricultural exports, Washington ranks second behind California (2021), with Oregon placing eighth and Idaho, eleventh [10]. While indemnities and overall program costs have increased considerably since 2000, loss ratios (a measure of total indemnities to total premiums) since the late 1990s have leveled off at around 80 percent mainly due to mandatory participation stipulations, underwriting changes, and other legislative changes [5]. Given these combined efforts of (1) insurance protection, as well as (2) risk mitigation (e.g., agricultural practices) which provide farmers protection against unforeseen natural disasters and economic events, our research focus is twofold: (1) to evaluate the variations of agricultural insurance loss for top commodities for the Pacific Northwest (PNW) as well as the subregion of the inland Pacific Northwest (iPNW) (Figure 1) and (2) to examine how these variations align with climatically associated causes of damage using dimensionality reduction and clustering methods.

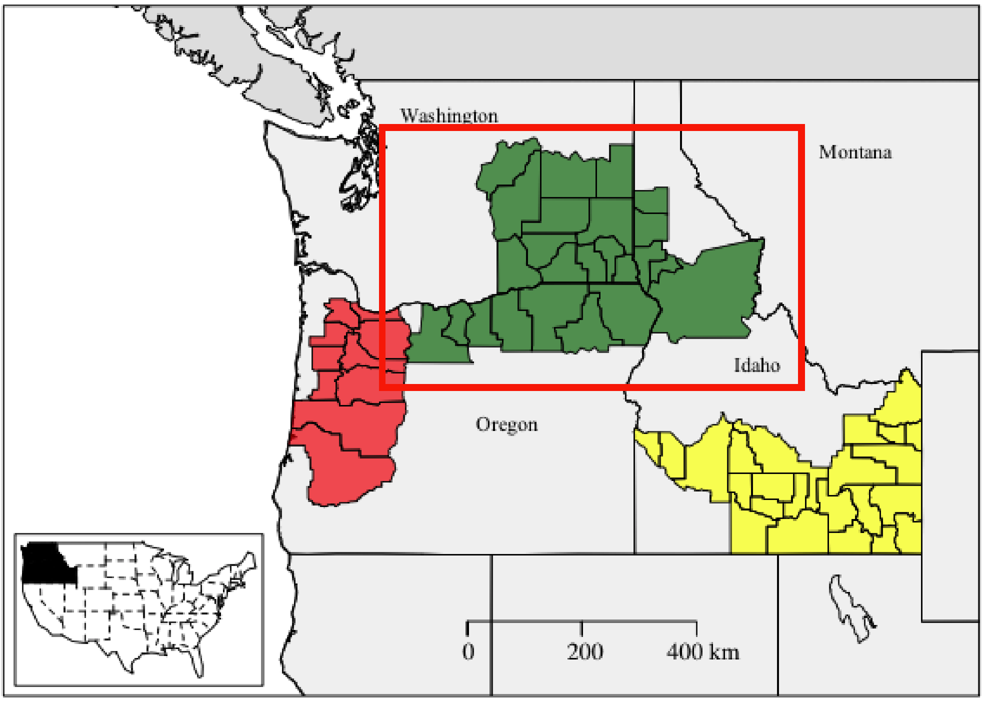


Figure 1. Key agricultural regions in the Pacific Northwest (PNW) portion of the United States, with the 24-county inland Pacific Northwest (iPNW) study area indicated by the rectangular bounding box. Map construction was performed using the R v4.0.5 *ggmap* package v3.0.0 [11].

2. Background

Weather and climate extremes, including those associated with climate change, have direct impacts on food security and resilience [12,13]. These interactions may vary due to a number of factors, including crop type, geographic location, and farming practices. Previous studies have examined climate–yield relationships [14,15], with a number of analyses examining climatic relationships related to crop insurance loss [16–19]. Drought, in particular, plays an important role in the success or failure of many agricultural systems. Redmond [20] conceptually defines drought as "insufficient water to meet needs", with a particular note of the varied relationships of supply and demand. Wilhite and Glantz [21] describe drought broadly as a "deficiency of precipitation that results in water shortage for some activity or for some group" and emphasize the difficulties in having one overarching definition of drought, given its impacts from agricultural, climatological, meteorological, atmospheric, hydrologic, and water management perspectives. Operationally, drought is often quantified in terms of frequency, severity, intensity, and duration, compared to a historical time frame, with human, biological, and climatological influences on both water supply and demand. Typically referred to as a “creeping phenomenon”, the impacts of drought on society can persist for a number of years, dependent upon the level of vulnerability [20]. Agricultural drought often refers to a period with anomalously low soil moisture that substantially limits crop production [22]. Drought related impacts are evident in agricultural insurance loss claims, both nationally as well within the PNW. For example, drought conditions in 2015 resulted in agricultural insurance losses for PNW wheat alone totaling USD 183 million, with total financial losses for all commodities ranging between USD 633 million and 773 million [6].

Cropping systems are particularly impacted by increased temperatures. Considerable research has examined the range of temperature impacts on grain yields [23] indicating that progressive temperature increases may initially result in increased yields, with an accelerating decrease over time, given an inverse temperature/precipitation relationship [24]. While increased temperatures will likely decrease wheat yields in the region, the effects of carbon dioxide fertilization may modestly offset these yield reductions over time. In contrast, Schlenker and Roberts [15] suggest that yields for alternative forms of cropping systems, such as soybeans, corn, and cotton, would slightly increase with initial temperature increases up to 32 degrees Celsius, and then sharply decrease as temperatures rise above that threshold. To make matters more complex, Rezaei et al. [25] as well as Asseng et al. [26] indicate that unique cultivars within a species may have varying phenological cycles, suggesting that any agricultural climate impacts assessment should include a variety of sub-species for proper threshold analysis. Comparatively, low temperatures at differing seasonal time periods can additionally have both positive and negative effects, while chilling temperatures have value with regards to dormancy breaking and species selection for cultivation, freezing and frost accounts for more losses of fruits and vegetables than any other environmental hazard [27,28]. Such negative effects can temporally range from severe winter temperature, as well as untimely spring frosts, which hinder initial budding and flowering. Similar to drought, freezing temperatures at select periods of fruit systems phenological cycles can impact critical growing stages, that manifest in smaller fruits, lower yields, and overall lower quality of fruit outputs (Wisniewski, Arora 1993). When examined in total, climatic relationships to agriculture are extremely variable, with changing outcomes due to cropping system, regionalization, farming practices, and genetic diversity. This complexity is encapsulated in agricultural insurance loss management, in order to effectively hedge agricultural risk, associated variability and complexity, and incorporated into a time-adjusted financial premium/payout process. Under this premise, evaluating insurance losses in relationship to sub-seasonal climatic impacts provides a reasonable approach to assess patterns and predictability, without delving into the underlying crop processes and their biophysical effects due to a changing climate.

From a seasonal perspective, adverse growing conditions (such as during drought, frost, and freezing conditions) can force farmers to consider additional risk management approaches that complement insurance mechanisms, including irrigation, selective crop abandonment, crop diversification, as well as unique crop rotation practices, which may mitigate current and future losses and preserve long-term economic viability of cropping systems [29,30]. Crop producers who utilize conservation tillage are often able to improve the capture and storage of soil moisture, which provides their crops an important buffer against drought impacts. By increasing the number of crop types as part of a rotation cycle, altering seeding dates, as well as using drought-sensitive breeds, farmers can retain more available soil moisture (reducing long term drawdown), while maximizing production and sales by spreading risk across a larger set of commodities [31]. The economic implications of more severe drought conditions, as well as changes in drought characteristics, may encourage farmers to consider alternative crop systems that are more economically viable. In total, these added risk management efforts, in combination with crop insurance, provide farmers with a diversified ability to mitigate potential financial loss in the face of changing economic and climatic conditions.

Given the spatial diversity in terms of cropping systems across Idaho, Oregon, and Washington, the iPNW sub-region provides a more homogeneous, well distributed dryland farming region, allowing us to explore spatial and temporal variations, while maintaining a fairly consistent county level claim total across the area as a whole. This narrowing also allows for the elimination of counties where little or no insurance claims were filed, primarily due to landscape, urbanization, or profitability constraints. From a damage cause perspective, the focus is on losses due to weather and climate extremes, particularly those due to drought and heat (wheat) and freeze, frost, and hail (apples).

3. Materials and Methods

The USDA's data archive of agricultural insurance claim records for the PNW from 1989 to 2022 was the primary dataset for this analysis [9], with insurance claims provided at monthly temporal and county level spatial scales. Each insurance record represented a unique claim associated with a farm property, containing the USD amount of the insured loss, the commodity type related to the loss (e.g., wheat, barley, canola), the acreage for the loss, the insurance company associated with the claim, and most notably, a cause for the crop damage (e.g., heat, drought, hail, decline in price, or failure of irrigation supply). The extent of this data archive is considerable: for example, from 1989 to 2022, the USDA's crop insurance data collection for the United States (all commodities) totals approximately 2.8 million claims, with $\sim$31,000 claims originating in the Pacific Northwest (Idaho, Oregon, and Washington) for over 35 different commodities, across 30 different damage causes. For our analysis, we construct a basic three step analysis methodology which allows us to examine commodity-specific insurance loss across damage causes. Given our research goal to examine iPNW spatiotemporal variation of agricultural insurance loss, the results of these steps not only permits us to narrow our factorial analyses by geography, time, commodity, and damage cause, but also enable comparisons of how water scarcity (drought and heat) and water excess/cold (freeze, frost, and hail) damage causes vary based on commodity type and geography.

We initially perform a full examination of insurance loss across all commodities and damage causes, for the entire PNW region, from 1989 to 2022. As part of this step, we aggregate the data by county, commodity, year, and damage cause. An initial data review indicates that approximately 83 percent of insurance loss for the region occurred after 2000 (Supplemental Figure S2), which comports with farm bill policy incentives implemented in 1998, increasing crop insurance participation (acres) to over 90 percent [5]. Across the three state PNW region, over 75 percent of insurance losses occurred within the iPNW, with wheat losses being the overwhelming dominant commodity. In addition, acreage data was not recorded for individual claims until after 2000 as well. As such, we limit our time frame of insurance loss examination to 2001 to 2022 and narrow our study area region to the 24-county region of the iPNW (Figure 1). This reduction in data by year additionally helps to resolve missing data issues in some counties that have no insurance claims, and thus no revenue loss.

We then use principal component analysis (PCA) to identify commonalities in insurance claims across years, counties, commodities, and damage claims in the iPNW. PCA is a data dimensionality reduction technique which computes a new set of variables by maximizing the variance of all input variables, and then examines the linear combinations of said variables in orthogonal space [32,33]. PCA notation can be described as follows:

$$\alpha_k' x = \sum_{j=1}^{p} \alpha_k' j^x j \tag{1}$$

where

x is a vector of random variables (p);
α_k is a vector of p constants.

The process is to initially find a linear function of $(x, \alpha_1' k)$ with a maximum variance. Next, we find another linear function of $(x, \alpha_2' k)$ which is uncorrelated with the maximum variance of $(x, \alpha_1' k)$. The approach is iterated over the extent of available variables. Ideally the most variation in x will be accounted for by m principal components where $m < p$.

Given the nested structure of the data (insurance claims by county, year, commodity, and damage cause), we construct a multitude of principal components analyses (with damage cause insurance loss totals (USD) as our factor loadings), using differing combinations of county, commodity, month, and year (county by year, county by month, and county by commodity), for both the entire PNW three state area, as well as for the wheat growing region of the iPNW (Supplemental Figures S15–S22). The full range of PCA outputs are provided in our supplemental materials. Using this approach, we create a set of input variables for our PCA, to examine how damage cause factors were associated, as well as how counties and years were aligned to these individual factor loading vectors. In order to evaluate how PCA variables group together, we apply a kmeans algorithm method [34] to estimate optimal clusters (based on Euclidean distance) for both county and year, based on our PCA outputs. Kmeans clustering is a vector quantization method which maps input values from larger to smaller sets. By iteratively partitioning n observations into a known set of clusters, the kmeans algorithm attempts to converge on an optimum grouping of clusters, based on a common spatial extent. This two-step clustering analysis has been noted as an effective approach in combining dimensionality reduction with unsupervised learning methods [35].

From the results of our initial data inspection and kmeans-applied PCA, we limit our commodity analyses to wheat and apples, and narrow our set of damage cause claims to areas of water scarcity (drought and heat) as well as water excess/cold (freeze, frost, and hail). We then examine losses for the region, exploring temporal and spatial relationships on an annual basis. In addition, we compare insurance loss with overall commodity production across the 24-county study area from 2001 to 2022.

4. Results

PNW insurance claims from 2001 to 2022 totaled over 33,000, for all commodities, with overall insured losses of USD ∼6.5 billion. Wheat, the dominant commodity for insurance claims in the three-state region, accounted for approximately 20,600 filings, with total losses of USD 3.5 billion for the same time period. Apples and cherries were a distant second and third in terms of overall losses (Supplemental Figure S5), each with approximately USD 600 million, with potatoes and peas adding a minimal contribution to the overall total (USD ∼250 million each). Narrowing our analysis to the iPNW, we see that insurance losses in the region made up approximately 72 percent of the total amount of loss for PNW as a whole. Wheat was similarly the predominant commodity incurring insurance loss for the iPNW, with over USD 2.5 billion in claims, with apples coming in a distant second, at USD 325 million. In terms of damage cause, drought resulted in the largest amount of insurance loss for the PNW overall, at over USD 1.8 billion, with decline in price (USD 850 million) and heat (USD 800 million) coming in second and third, respectively. Focusing in on the iPNW, the leading damage causes for this region were drought and heat, which combined to account for approximately USD 2.65 billion in losses from 2001 to 2022. For all commodities, drought and heat-related claims for the iPNW accounted for 68 percent of all insurance losses in total for the 2001 to 2022 time period. There was additionally considerable variability across iPNW crop types with regards to damage-specific insurance claims. For example, wheat insurance losses were dominated by drought and heat, with apples and cherries claims aligned with freeze, frost, and cold weather (Figure 2).

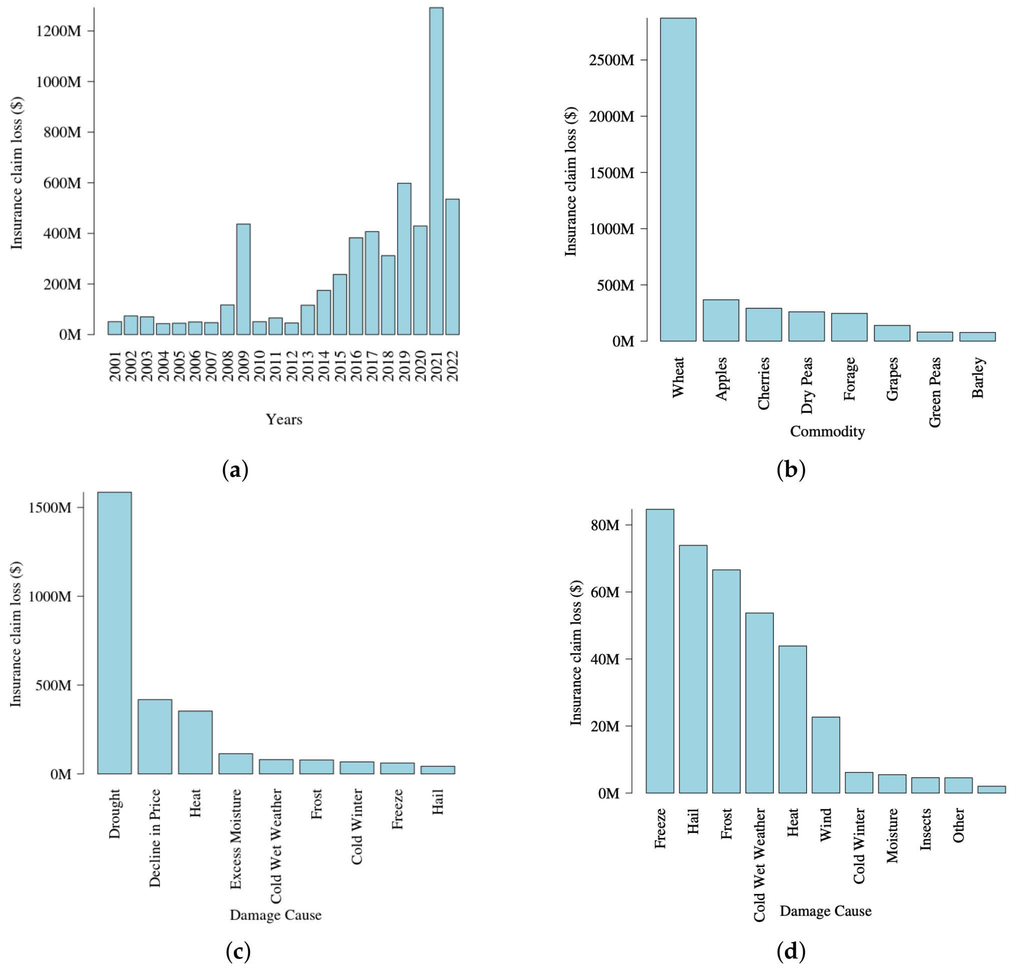


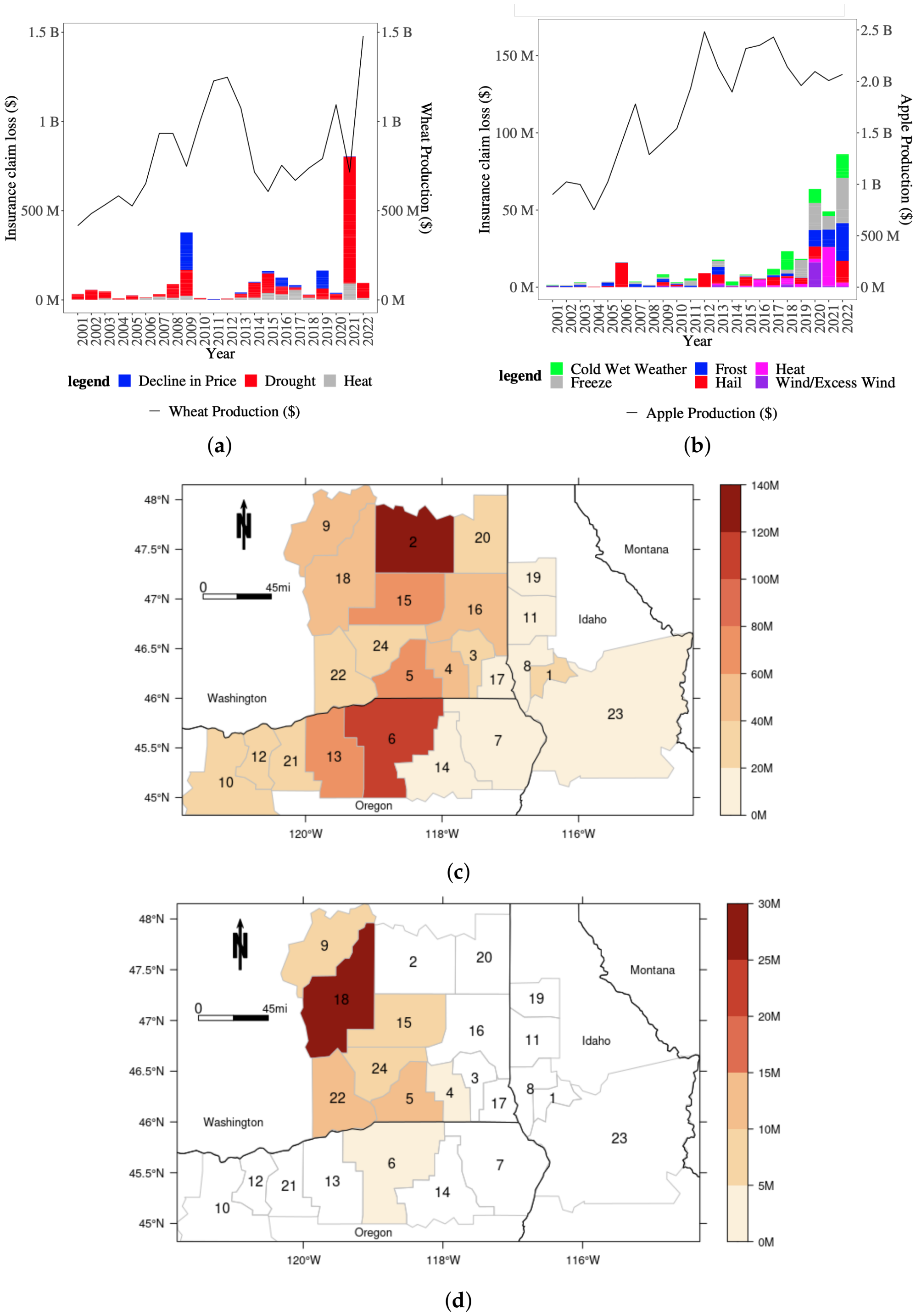
Figure 2. Agricultural insurance loss summaries for the inland Pacific Northwest (iPNW): (**a**) total losses by year for all commodities, for the iPNW from 2001 to 2022; (**b**) total losses by commodity, from 2001 to 2022; (**c**) wheat total losses by damage cause, for the iPNW from 2001 to 2022; (**d**) apples total losses by damage cause, for the iPNW from 2001 to 2022. Analysis of data generated using the R v.4.0.5 *ggplot2* v.3.4.4 package [36].

In order to address our research questions around spatial and temporal variations of insurance loss, we narrowed our commodity analysis to apples and wheat, the two dominant commodities for the region. Annual wheat losses specifically due to drought, heat, and excessive moisture for the iPNW were analyzed for each year in the period from 2001 to 2022, while apples were examined for the same period, focusing on freeze, frost, and hail. Our results for this 2001–2022 time period show that the year-to-year variation of losses for wheat are dominated by drought, with peak years of 2009 and 2021. In contrast, 2011 had almost no drought or heat insurance losses, with excessive moisture and rain being the dominant damage cause factors. This annual variability aligns with historical climatological variations; while 2011 was a particularly wet year for the PNW [37], 2021 experienced a significant drought primarily attributed to extreme summer temperatures during a two week window in June and early July. This event resulted in the highest recorded mean summer near-surface air temperatures for the PNW from 1950 to 2021 [38], which is evident in the more than double annual wheat insurance losses, in the range of USD 700 million (Figure 3).

When decline in price is incorporated into this annual view for wheat, we see certain years where a large majority of claims are associated with economic decline; for example, in 2009, decline in price claims align with wheat prices declines from 430 USD/metric ton to 220 USD/metric ton. Wheat production varies inversely with losses, with the lowest levels of production occurring in years with the highest levels of drought/heat insurance loss. Comparatively, apple insurance loss for the region shows a more gradual increase from 2001 to 2022, with 2020-2022 having a considerable increase in freeze/frost/hail losses. Apples show a peak loss year of 2022, which coincides with relatively lower losses for wheat associated with drought and heat, during the same time frame. Additionally, apple losses, while not typically effected by heat/drought events, still had relatively large losses in 2021, which is a testament to the severity of 2021 drought/heat impacts across many commodities. Unlike wheat, apple production is roughly 15 times larger than insurance loss claims, which may have associations with economic systems, as well as water availability influences (e.g., drought may have a much greater impact on insurance claim submittals vs. freeze/frost/hail claims).

Spatially, while total 2001 to 2022 wheat losses (all damage causes) were highest in Adams county, Washington (USD 232 million), wheat insurance loss due to drought and heat were highest in Lincoln county, Washington (USD 133 million), as well as counties along the northeastern portion of the Oregon high desert (Umatilla county, Oregon at USD 119 million and Morrow county, Oregon at USD 68 million). From a percentage breakdown, over 50 percent of all damage cause losses in Umatilla were a result of drought/heat, with over 40 percent attributable to drought/heat in Adams and Lincoln counties, Washington. If we specifically examine spatial differences in wheat drought/heat insurance loss by year, we see notably different patterns of loss concentrations between 2009 and 2021. For 2009, the region's few drought and heat claims were concentrated in the north central portion of the region, with losses in the highly productive Columbia river region being relatively low. In contrast, 2021 wheat losses due to drought and heat were concentrated in the upper portion of the Washington Palouse region (Whitman, Lincoln, Adams, and Douglas counties), with additional loss concentrations falling along the Columbia river valley and in the western portion of the Palouse (Figure 3).

In order to better understand the factorial relationships of damage causes, two principal component analyses were run for the iPNW region for both wheat and apples, to explore (1) spatial (county) as well as (2) temporal (year) variation. Both PC analyses use damage causes as the factor loadings, with all data scaled by the unit variance. Additionally we use singular value decomposition (SVD), a form of matrix factorization which is considered a superior method for PCA computation [39]. For wheat by county, approximately 53 percent of total variance of insurance loss by county level damage cause can be attributed to the first two principal components, with water scarcity (drought/heat/fire) damage causes having a negative coordinate alignment in terms of the first principal component (PC1) vector loading directions. For apples by county, over 90 percent of total variance can be attributed to the first two principal components, with excessive water- and cold-related damage causes. When we examine variation by year, we see less explained variance for the first two principal components, with wheat accounting for 48 percent explainability and 62 percent for apples (Figure 4). Examining PC loadings by county, we see a clear alignment of water scarcity damage causes in highly productive wheat counties (Umatilla county, Oregon; Lincoln and Whitman counties, Washington), with orthogonal damage causes (excessive moisture/freeze/frost) aligning with counties that are typically in highly productive fruit production regions (e.g., Grant and Benton counties, Washington). Applying a kmeans clustering algorithm with an elbow cluster optimization selection method, we identified two key clusters in the two-dimensional PCA space, that additionally support the differentiation of water scarcity PC1 loadings from PC2 water excess. When PCA was run using year as the independent factor (2001 to 2022) and applying a kmeans clustering algorithm with an elbow cluster optimization selection method, we identified two key clusters. The identified clusters support the differentiation of water scarcity PC1 loadings from PC2 water excess. Most notably, 2009, 2018, and 2021 are within a distinct cluster falling along damage cause groupings for drought, fire, and heat (Figure 4).



1 Lewis: 2 Lincoln: 3 Garfield: 4 Columbia: 5 Walla Walla: 6 Umatilla: 7 Wallowa: 8 Nez Perce: 9 Douglas: 10 Wasco: 11 Latah: 12 Sherman: 13 Morrow: 14 Union: 15 Adams: 16 Whitman: 17 Asotin: 18 Grant: 19 Benewah: 20 Spokane: 21 Gilliam: 22 Benton: 23 Idaho: 24 Franklin

Figure 3. (**a**) Stacked barplot of losses from 2001 to 2022 for wheat; (**b**) stacked barplot of losses from 2001 to 2022 for apples; (**c**) map of wheat insurance loss due to heat and drought; and (**d**) map of apples insurance loss due to cold weather, freeze, frost, hail, heat, and wind. Analysis of data generated using the R v4.0.5 *ggplot2* package v.3.4.4 [36].

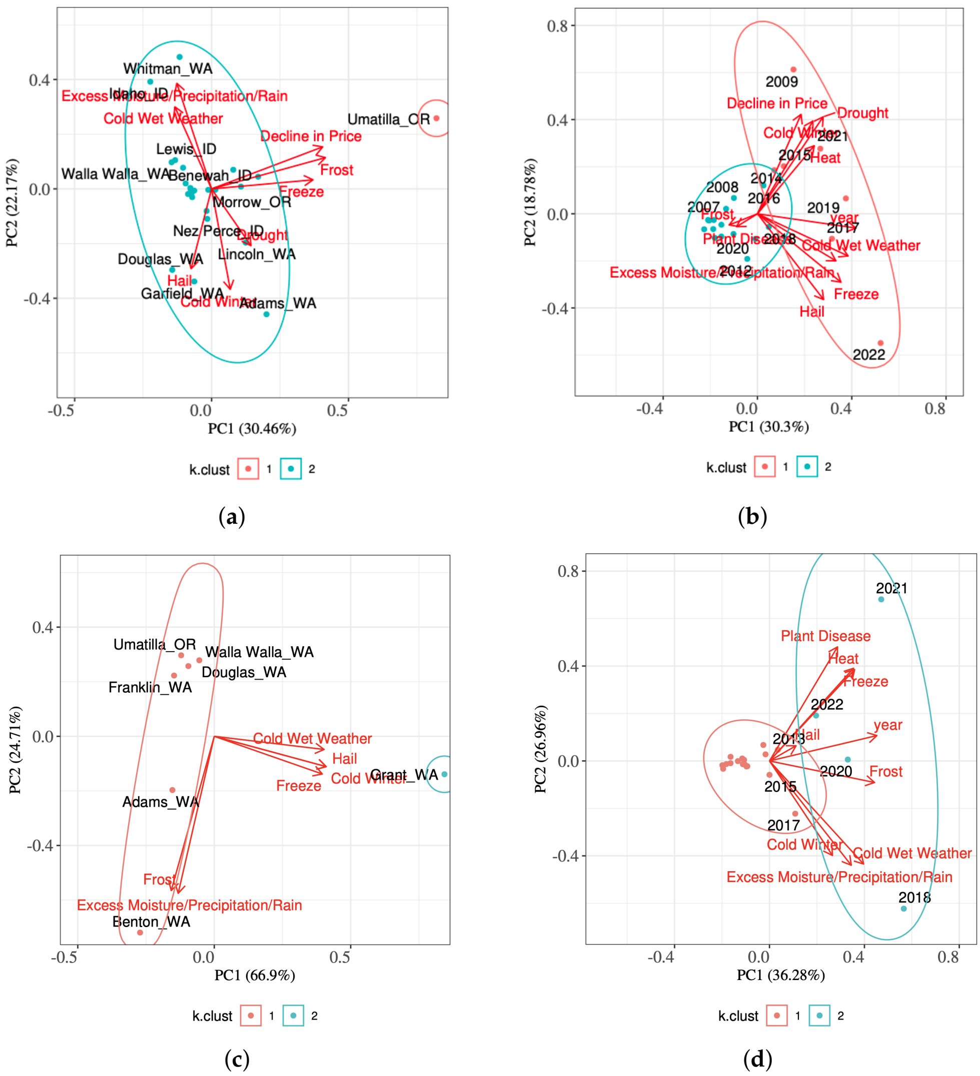


Figure 4. Principal component analysis (PCA) showing top damage cause factor loadings for iPNW wheat and apples insurance loss, from 2001 to 2022: (**a**) wheat PCA for counties as the independent variable; (**b**) wheat PCA for years as the independent variable; (**c**) apples PCA for counties as the independent variable; and (**d**) apples PCA for years as the independent variable. Clustering was constructed using a kmeans technique. Analysis of data generated by R v.4.0.5 packages *ggplot2* v3.4.4 and the *base stats* package [36].

5. Discussion

Given our exploratory data analysis to examine iPNW spatiotemporal variations of insurance loss in relationship to climatic damage causes, our results identify several unique spatial and temporal patterns that appear to align with historical climatological trends. The considerable crop-specific variations in terms of damage causes (e.g., wheat effects due to drought and heat vs. excessive freeze/cold weather for apples) provide a clear and straightforward signal for generalized climatological extreme comparisons with crop insurance fluctuations. As previously noted, the extreme increases in drought and heat claims for 2021 closely align with the extreme summer heat event in the PNW, which effect not only cereal systems, but also impact fruit commodities [40]. In addition, such patterns provide an important perspective on climate variability vs. economics and the sensitivities of agricultural systems to differing effects. Of particular interest were the differences in iPNW wheat insurance loss, comparing 2009, 2021, and 2022, in terms of the drought, heat, excessive moisture, and decline in price total losses. While 2009 and

2021 have large dollar losses in terms of drought and heat, 2022 additionally had relatively larger values with regards to cold weather, rain, and freeze. Increased drought and heat losses in 2021 align well with regional drought conditions [41], while increased drought and heat claims for 2009 seem to conflict with comparable climate conditions for that year, indicating that the iPNW was not in a period of drought [42]. These insurance loss comparisons between 2009 and 2021 suggest that, in compromised economic conditions (e.g., price decline), claims due to climatic damage causes may increase, even though actual climatic conditions do not warrant such increases [43,44]. This may also indicate that particular commodity-specific thresholds exist where economic factors dominate over climatic impacts, resulting in a broad distribution of claim loss across a range of damage causes. 2011 losses were interestingly juxtaposed to 2009 and 2021, with very little drought or heat insurance claims, but with the largest amount of excessive moisture filings of any year in the period of analysis. We additionally see an inverse relationship between annual wheat production and drought/heat insurance loss, with 2021 being the only year in this time period where losses were higher than production. Work by Quiggin et al. [45], Miranda and Glauber [3], and Glauber [46] all reference the relationships of insurance loss with overall crop production, supporting this inverse relationship scenario. Spatial variations of wheat insurance losses due to drought and heat provide an additional perspective in terms of locational sensitivities to climate. With variations of phenology, claim frequency, regional crop development, irrigation, and cropping practices, commodity-based insurance claim analysis for agriculturally homogeneous regions may provide the best framework for delineating differences in claim/loss variation, based on time and the cause of damage.

6. Conclusions

The distinct differences in annual variation, as well as commodity/damage cause, suggest insurance loss analysis may serve as an effective barometer in gauging climatic influences [47]. Our results additionally highlight that insurance losses likely integrate aspects of climate and economic impact together (e.g., comparisons of 2009 and 2015 damage causes), given that farmer decisions regarding whether to file a loss claim or not typically take into account these two factors simultaneously. Decisions regarding whether to file a crop insurance claim depend upon a multitude of dynamic and changing factors, which may be directly or indirectly impacted by extreme climatological/meteorological events [48]. For example, during economically stable periods (e.g., high commodity prices), a farmer may be disincentivized to file a drought-associated claim, particularly given the balance between production value and insurance payout. Conversely, during periods of economic instability when commodity prices may be declining, farmers may be incentivized to initiate a claim in periods of moderate drought. These moral hazard factors present a challenge when evaluating the effects of climate on a complex insurance/premium environmental system [49].

There are several limiting factors to this research. Given the coarse spatial scale of insurance loss claims (only available at a county level), assessments of climatic impacts are challenging. This aspect could be addressed by developing algorithmic techniques to estimate loss at finer spatial scales using other proxy variables, including property values and landscape types based on remote sensing information. Insurance premiums and their incorporation into loss calculations is an additional component that may improve assessments on indemnification [50]. As a whole, the results of this work highlight several areas of potential future research, particularly around understanding the interactions between insurance loss, conservation practices, economic factors, climate influences, and policy effects, as well as regional differences/similarities of damage cause influences across a range of commodities other than wheat. Under changing climate and conservation practice conditions, there may be situations where crop insurance risk management may incentivize, or disincentivize, farm practices that reduce agricultural climate change impacts, given their individualized economic implications. Additionally, this work may assist future research in identifying the financial impacts of a changing climate on the agricultural insurance industry in relationship to ecological protection measures over time and differing geographies.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture13122214/s1.

Author Contributions: Conceptualization, E.S. and P.E.G.; methodology, E.S.; software, E.S.; validation, E.S.; formal analysis, E.S. and P.E.G.; investigation, E.S.; resources, P.E.G. and P.W.M.; data curation, E.S.; writing—original draft preparation, E.S. and P.E.G.; writing—review and editing, E.S., P.E.G., J.T.A., P.W.M. and S.S.L.; visualization, E.S.; supervision, P.E.G., J.T.A., P.W.M. and S.S.L.; project administration, E.S.; funding acquisition, P.E.G. and P.W.M. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. Christensen, L.R. Concepts and Measurement of Agricultural Productivity. *Am. J. Agric. Econ.* **1975**, *57*, 910–915. [CrossRef]
2. Diskin, P. *Agricultural Productivity Indicators Measurement Guide*; Technical Report January; Academy for Educational Development: Washington, DC, USA, 1997.
3. Miranda, M.J.; Glauber, J.W. Systemic Risk, Reinsurance, and the Failure of Crop Insurance Markets. *Am. J. Agric. Econ.* **1997**, *79*, 206–215. [CrossRef]
4. Yu, J.; Sumner, D.A. Effects of subsidized crop insurance on crop choices. *Agric. Econ.* **2018** , *49*, 533–545. [CrossRef]
5. United States Department of Agriculture. *Crop Insurance Program*; USDA Risk Management Agency : Washington, DC, USA, 2022.
6. Sorte, B.; Rahe, M. *Oregon Agriculture, Food and Fiber: An Economic Analysis*; Technical Report December; Oregon State University: Corvallis, OR, USA, 2021.
7. Sandison, D. *2015 Drought and Agriculture* Technical Report; Washington State Department of Agriculture: Olympia, WA, USA, 2015.
8. Aviles, G.; Lee, D.; Robinchtein.; Zoe Zadworny, Z. *2016 Agricultural Workforce Report, Washington State Employment Security Department Workforce Information and Technology Services*; Technical Report; Washington State Employment Security Department: Olympia, WA, USA, 2018.
9. United States Department of Agriculture. *Census of Agriculture, National Agricultural Statistics Service. Vol. 1: Part 51, Chapter 2, AC97-A-51, United States Summary and State Data*; Technical Report; United States Department of Agriculture: Washington, DC, USA, 2021.
10. Padilla, S.; Ufer, D.J.; Morgan, S.; Link, N.; Ufer, D.J.; Morgan, S.; Link, N.; Export, M.U.S. *U.S. Export Competitiveness in Select Crop Markets*; Technical Report 313; U.S. Department of Agriculture, Economic Research Service (ERS): Washington, DC, USA, 2023.
11. Kahle, D.; Wickham, H. *ggmap: Spatial Visualization with ggplot2*; The R Foundation: Vienna, VA, USA, 2013.
12. Barrett, C.B. Measuring Food Insecurity Christopher B. Barrett. *Science* **2010**, *327*, 825–828. [CrossRef] [PubMed]
13. Gundersen, C.; Kreider, B.; Pepper, J. The economics of food insecurity in the United States. *Appl. Econ. Perspect. Policy* **2011**, *33*, 281–303. [CrossRef]
14. Lobell, D.B.; Burke, M.B. On the use of statistical models to predict crop yield responses to climate change. *Agric. For. Meteorol.* **2010**, *150*, 1443–1452. [CrossRef]
15. Schlenker, W.; Roberts, M.J. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 15594–15598. [CrossRef]
16. Claassen, R.; Langpap, C.; Wu, J. Impacts of Federal Crop Insurance on Land Use and Environmental Quality. *Am. J. Agric. Econ.* **2016**, *3*, aaw075. [CrossRef]

17. Schoengold, K.; Ding, Y.; Headlee, R. The impact of AD HOC disaster and crop insurance programs on the use of risk-reducing conservation tillage practices. *Am. J. Agric. Econ.* **2014**, *97*, 897–919. [CrossRef]
18. Diffenbaugh, N.S.; Davenport, F.V.; Burke, M. Historical warming has increased U.S. Crop insurance losses. *Environ. Res. Lett.* **2021**, *16*, 084025. [CrossRef]
19. Seamon, E.; Gessler, P.E.; Abatzoglou, J.T.; Mote, P.W.; Lee, S.S. A climatic random forest model of agricultural insurance loss for the Northwest United States. *Environ. Data Sci.* **2022**, *1*, 1–9. [CrossRef]
20. Redmond, K.T. The Depiction of Drought. *Bull. Am. Meteorol. Soc.* **2002**, *83*, 1143–1148. [CrossRef]
21. Wilhite, D.; Glantz, M. Understanding the Drought Phenomenon: The Role of Definitions. *Water Int.* **1985**, *10*, 111–120. [CrossRef]
22. Mishra, A.K.; Singh, V.P. *A Review of Drought Concepts*; Elsevier: Amsterdam, The Netherlands, 2010. [CrossRef]
23. Sacks, W.J.; Kucharik, C.J. Crop management and phenology trends in the U.S. Corn Belt: Impacts on yields, evapotranspiration and energy balance. *Agric. For. Meteorol.* **2011**, *151*, 882–894. [CrossRef]
24. Stöckle, C.O.; Higgins, S.; Nelson, R.; Abatzoglou, J.; Huggins, D.; Pan, W.; Karimi, T.; Antle, J.; Eigenbrode, S.D.; Brooks, E. Evaluating opportunities for an increased role of winter crops as adaptation to climate change in dryland cropping systems of the U.S. Inland Pacific Northwest. *Clim. Chang.* **2018**, *146*, 247–261. [CrossRef]
25. Rezaei, E.E.; Siebert, S.; Hüging, H.; Ewert, F. Climate change effect on wheat phenology depends on cultivar change. *Sci. Rep.* **2018**, *8*, 4891. [CrossRef]
26. Asseng, S.; Ewert, F.; Rosenzweig, C.; Jones, J.W.; Hatfield, J.L.; Ruane, A.C.; Boote, K.J.; Thorburn, P.J.; Rötter, R.P.; Cammarano, D.; et al. Uncertainty in simulating wheat yields under climate change. *Nat. Clim. Chang.* **2013**, *3*, 827–832. [CrossRef]
27. Rieger, M. Freeze Protection for Horticultural Crops. In *Horticultural Reviews*; Janick, J., Ed.; Wiley: Hoboken, NJ, USA, 1989; pp. 45–109.
28. Rodrigo, J. Spring frosts in deciduous fruit trees. Morphological damage and flower hardiness. *Sci. Hortic.* **2000**, *85*, 155–173. [CrossRef]
29. Wallander, S.; Aillery, M.; Hellerstein, D.; Hand, M. *The Role of Conservation Programs in Drought Risk Adaptation*; Economic Research Service; United States Department of Agriculture: Washington, DC, USA, 2013; pp. 1–68.
30. Yorgey, G.; Kruger, C.E. *Advances in Dryland Farming in the Inland Pacific Northwest*; Extension Mimeo; Washington State University Extension Publications: Pullman, WA, USA, 2017.
31. Antle, J.M.; Capalbo, S.M. Adaptation of agricultural and food systems to climate change: An economic and policy perspective. *Appl. Econ. Perspect. Policy* **2010**, *32*, 386–416. [CrossRef]
32. Tukey, J.W. Exploratory Data Analysis (Book Section). In *Exploratory Data Analysis*; Springer: New York, NY, USA, 1977 . [CrossRef]
33. Jolliffe, I. Principal Component Analysis, Second Edition. In *Encyclopedia of Statistics in Behavioral Science*; American Society for Quality and the American Statistical Association: Alexandria, VA, USA, 2002 . [CrossRef]
34. Ding, C. K -means Clustering via Principal Component Analysis. In Proceedings of the 21st Century International Conference on Machine Learning, Banff, AB, Canada, 4–8 July 2004.
35. Ibes, D.C. A multi-dimensional classification and equity analysis of an urban park system: A novel methodology and case study application. *LAndscape Urban Plan.* **2015** , *137*, 122–137. [CrossRef]
36. Wickham, H. *ggplot2: Elegant Graphics for Data Analysis*; Springer: New York, NY, USA, 2016 .
37. National Oceanic and Atmospheric Administration. *State of the Climate, National Centers for Environmental Information*; Technical Report; NOAA: Washington, DC, USA, 2011.
38. Heeter, K.J.; Harley, G.L.; Abatzoglou, J.T.; Anchukaitis, K.J.; Cook, E.R.; Coulthard, B.L.; Dye, L.A.; Homfeld, I.K. Unprecedented 21st century heat across the Pacific Northwest of North America. *NPJ Clim. Atmos. Sci.* **2023**, *6*, 5. [CrossRef]
39. Tanwar, S.; Ramani, T.; Tyagi, S. Dimensionality reduction using PCA and SVD in big data: A comparative case study. In Proceedings of the Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST, Surat, India, 31 August–2 September 2017; Patel, Z.; Gupta, S., Eds.; Springer: Cham , Switzerland, 2018; Volume 220, pp. 116–125. [CrossRef]
40. McKinnon, K.A.; Simpson, I.R. How Unexpected Was the 2021 Pacific Northwest Heatwave? *Geophys. Res. Lett.* **2022**, *49*, 1–9. [CrossRef]
41. Ansah, E.O.; Walsh, O.S. Impact of 2021 Drought in the Pacific Northwest. *Crop. Soils* **2021**, *54*, 46–49. [CrossRef]
42. Shukla, S.; Safeeq, M.; Aghakouchak, A.; Guan, K.; Funk, C. Temperature impacts on the water year 2014 drought in California. *Geophys. Res. Lett.* **2015**, *42*, 4384–4393. [CrossRef]
43. Miranda, M.; Vedenov, D.V. Innovations in agricultural and natural disaster insurance. *Am. J. Agric. Econ.* **2001** , *83*, 650–655. [CrossRef]
44. Botzen, W.J.; Van Den Bergh, J.C. Insurance against climate change and flooding in the Netherlands: Present, future, and comparison with other countries. *Risk Anal.* **2008**, *28*, 413–426. [CrossRef] [PubMed]
45. Quiggin, J.C.; Karagiannis, G.; Stanton, J. Crop Insurance and crop production: an empirical study of moral hazard and adverse selection. *Aust. J. Agric. Econ.* **1993** , *37*, 95–113. [CrossRef]
46. Glauber, J.W. Crop insurance reconsidered. *Am. J. Agric. Econ.* **2004** , *86*, 1179–1195. [CrossRef]
47. Fan, M.; Pena, A.A.; Perloff, J.M. Effects of the Great Recession on the U.S. Agricultural Labor Market. *Am. J. Agric. Econ.* **2016**, *98*, 1146–1157. [CrossRef]

48. Farhangfar, S.; Bannayan, M.; Khazaei, H.R.; Baygi, M.M. Vulnerability assessment of wheat and maize production affected by drought and climate change. *Int. J. Disaster Risk Reduct.* **2015**, *13*, 37–51. [CrossRef]
49. Wu, S.; Goodwin, B.K.; Coble, K. Moral hazard and subsidized crop insurance. *Agric. Econ.* **2020**, *51*, 131–142. [CrossRef]
50. Woodard, J.D.; Schnitkey, G.D.; Sherrick, B.J.; Lozano-Gracia, N.; Anselin, L. A Spatial Econometric Analysis of Loss Experience in the U.S. Crop Insurance Program. *J. Risk Insur.* **2012**, *79*, 261–286. [CrossRef]
51. Seamon, E.; Gessler, P.; Abatzoglou, J.T.; Mote, P.W.; Lee, S.S. Agricultural Insurance Loss and Relationships to Climate across the Inland Pacific Northwest Region of the United States. Ph.D. Thesis, University of Idaho, Washington, DC, USA, 2019.