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DYNAMIC FOOD SYSTEMS AND CLIMATE-INDUCED RISKS TRANSMISSION FOR FOOD AND NUTRITIONAL SECURITY

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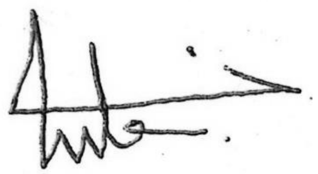
Esame finale anno 2022

Dedicated to My Beloved Parents

CERTIFICATE OF ORIGINALITY

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which, to a substantial extent, has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.



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Executive Summary

Agriculture market instability impedes achieving the global goal of sustainable and resilient food systems. Currently, the support to producers reaches the mammoth *USD 540 billion* a year and is projected to reach USD 1.8 trillion by 2030. This gigantic increase requires a repurposing agricultural support strategy *(RASS)*, considering the market country-specific circumstances. These circumstances may vary with geographic locations, marketing structures, and product value chains. The fruit production system is crucial for *health-conscious consumers* and *profit-oriented producers* for food and nutritional security. Export is one of the main driving forces behind the expansion of the fruit sector, and during the year 2010-2018, trade significantly outpaced production increases. The previous literature states that *irregular and unpredictable behaviour* — *Chaos* — can arise from entirely rational economic decision-making within markets. Different markets' direct/indirect linkages through trade create trade hubs, and uncertainty may function as an avenue to transmit adverse shocks and increase vulnerability rather than contribute to resilience. Therefore, distinguishing *Chaos* into an endogenous and exogenous pattern of behaviour is cradled to formulate an effective *RASS* for resilient food systems and to understand global food crises.

The present research is aimed at studying the market dynamics of three regional trade hubs, *i.e., Brazil (South America), Italy (Europe), and Pakistan (Asia), e*ach representing advanced to traditional value chains to control uncertainty (risks). The present research encompasses 1) a systematic review to highlight the research dynamism and identify grey-areas of research. Based on the findings, we have investigated the 2) nonlinear impacts of climate-induced price responsiveness in monopsony markets. Once we highlighted the importance of marketing structures/arrangements, 3) we developed a risk transmission framework to address the co-evolving impacts in complex dynamic interactions. The pre-modelling data diagnostic framework of *Non-linear Time Series Analysis* was used while applying *Chaos theory* in the dynamic food system. The present study allows us to appraise 1) price instability in agriculture and identify drivers of change, 2) risks patterns in three value chain, 3) differentiate Chaos's nature, and provide ways to repurpose agricultural support to transform the food system.

Objectives

Following are the specific research objectives developed for the present research. These are,

1. *Review of literature on climate-induced fruit price volatility (Chapter 2)*
2. *Nonlinear time series dynamic of climate-induced price responsiveness in monopsony market (Chapter 3)*
3. *What is the anticipated impact of co-variation of climate and price variability on fruit income/production in diverse agro-economies? (Chapter 4)*

The excerpt from the main findings of the research is,

Chapter 2: The multi-dimensional drivers of price volatility have been identified during the food crisis wave to provide an in-depth understanding of price irregularities and theoretical underpinnings for *Global Network against Food Crisis's dimensions I and III* to address the food crisis. There was a clear paradigm shift in the adopted methodologies and data[bases] consulted. In selected studies, the dynamics of chaos and its detrimental impacts were ignored while addressing the issue of price volatility in agriculture. This approach raises a public policy concern about deciding whether to intervene in agriculture markets. The answers to such questions are possible if we assess the "realism" of theoretical models from volatile price series in agriculture while assessing uncertain situations like the food crisis.

The current food crisis is more about supply disruption, which arises from climate-market interactions resulting in market imperfections. Farmers' behaviour is cradled to know the supply responses to climate-induced price/non-price factors. The recent global COVID-19 pandemic fostered the adoption of holistic approaches to create more resilient and sustainable food systems.

Chapter 3: The analysis confirmed that the farmers' decisions were erratic under market imperfection conditions and reflected in adjustments of cultivated land and inputs. The standard negative relationship between cultivated area and yield with technological advancement through the so-called *Borlaug hypothesis* cannot withhold in imperfect competition. Farm inputs, climate fluctuations, and price volatility further disrupt the supply response. Climate exhibits a non-linear relationship with price and non-price factors, requiring attention to incorporate representative variables to investigate complex dynamic interactions.

The *market and R&D uncertainty* resulted in lower yield responses. The vast investments require improving land availability in the short term as farm inputs are only variable inputs whose application can adjust to policy incentives. The lower yield responses were also due to the imbalance in the use of potassium application arising from a lack of awareness and distortion in agriculture incentives. The increased crop and fertilizer prices [here only DAP prices] lowered the crop's supply response instead of boosting the productivity of the crop in such an imperfect marketing arrangement. *The green revolution* brought technological improvements, including better seed varieties, farm management practices, and research and development to enhance productivity. However, imperfect market competition, climate change, and ineffective price mechanisms may lower profitability and disrupt the crop's supply chain.

Chapter 4: The current state of food and nutritional security reports suggests that the world is not on the right track to eradicate hunger, food insecurity, and malnutrition by 2030. The producers' support incentives create distortion and stress in repurposing the agricultural support strategy *(RASS)*. The present research was designed to model the risk transmission, adaptation capacities, and their impacts on dynamic fruit systems. The nonlinear time series approach has provided a way to distinguish endogenous and exogenous risks of *climate – producers – market* nexus in complex dynamics fruit systems. The result indicates that restructuring market supply chains did not dampen the impacts of risks on fruit systems. Instead, *RASS* requires based on specific country/commodity dynamics.

Future research ideas were also reported with contemporary issues in executing/implementing research on the complex food system. Additional details about the data used are available in the respective section of the dissertation. The designated methodology section also detailed descriptions of variables construction and assumptions made.

The structure of the remaining dissertation is as follows. *Chapter 1* highlights the framework adopted for the present research in analysing price distortions (volatility) and their impacts on the food system. *Chapter 2* describes the systematic review of price volatility in agriculture to highlight the important caveats of previous research. *Chapter 3* covers the nonlinear time series dynamics of climate-induced price responsiveness in monopsony markets. A comprehensive investigation was conducted using NLTA to instigate the co-evolution of climate, price, and production nexus in *Chapter 4*. The conclusion, policy recommendations, research limitations, and future research ideas are reported in *Chapter 5*. The additional information is provided as an annex.

Chapter 1 Introduction

The United Nations (UN) has declared that the current trend of agriculture support strategies creates disincentives and disruption in the food system (Lipper et al., 2021). Recent statistics show that the state of food insecurity and malnutrition increased – over 720 million people faced hunger, 2.37 billion did not have access to food and healthy diets were out of reach for ~3 billion people in the world (FAO, IFAD, UNICEF, WFP, and WHO, 2022). These imbalances resulted into a new co-existed global obesity epidemic in both developed and developing world (Miljkovic et al., 2015). Currently, enormous pressure on the food system is generated due to a staggering 14% (food lost) and 17% (food waste) annually. Food system importance may realize with the dependence of 3.2 billion livelihoods, of which 2 billion are related to primary production (Ringler et al., 2022).

The dream of achieving Sustainable Development Goals (SDGs) has been further challenged in the post-COVID era. Transforming (rethinking and updating the approach) agri-food systems to become healthier, sustainable, equitable, and efficient requires several strategies, including producer support (Gliessman, 2021). This revalidation requires highlighting the impact of current impacts on the food system and repurposing support rather than eliminating altogether. There is no *one-size-fits-all solution*, and optimal strategy depends on many factors and country context (Bann et al., 2021).

Present research hypothesizes that price distortion (negative impacts of producer support) results in imperfect market competition (Crawford et al., 2003; Rashid Khan et al., 2019), influences the supply response of crops (Schneider, 2014), penalizes the availability and affordability dimension of food security, and promotes less diversified and nutritious food (staple crop) and often emerges as global Chaos – *food crisis phenomena* (de Araujo et al., 2020). Under such circumstances, the variability (risks) within the food system and their dynamic interactions persistently shapes the system's output and requires distinguishing such risks into endogenous and exogenous components. If these risks are exogenously generated, system forces to interact and naturally dampen their impacts. Contrary to this, endogenously generated risks are sensitive to initial conditions. Any repurposing strategy for a specific country may further exacerbate the conditions in another country/region resulting in enormous disincentives (distortions) – *price instability* – and impeding the UN vision of achieving SDGs by 2030.

In line with this strand of research, the present study was designed to systematically analyse and investigate current policy trade-offs' impacts on the food system (**Figure 1.1**).

Chapter 2 systematically investigated the impacts of price volatility (distortions) in agri-food systems. We can analyse the research dynamism and transition on theoretical and empirical fronts and observe global emergent behaviour as a world food crisis. The drivers of change at each level of food value chains were identified and linked with the economic governance stage. The climate, market, and productions were the important subsystem, and their non-linear dynamics cradle to deciding the fate of sustainable food systems. The two methodological approaches were devised: 1) non-linear dynamics of *climate – market – production nexus* was modelled through dynamic panel models. 2) Alternatively, a framework was developed to investigate the risk transmissions, adaptation capacities of the system, and their impacts on the food system. The pre-modelling data diagnostic framework was identified as a feasible approach to identify and estimate the impacts on the food system through *Chaos theory* (Ray Huffaker et al., 2021).

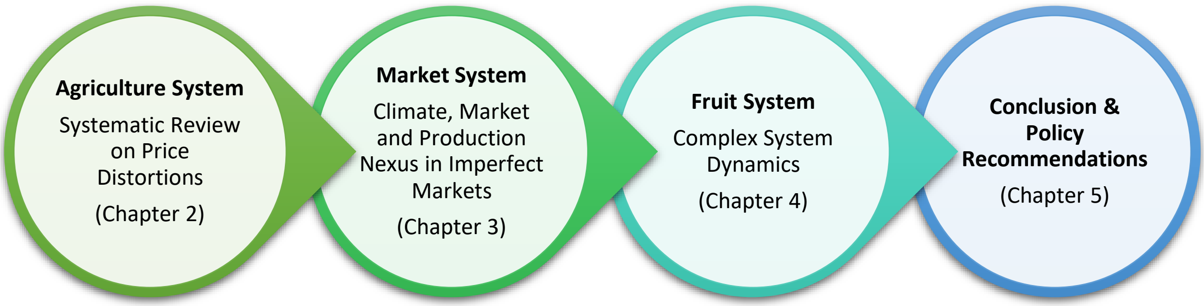

Figure 1.1: *Systematic research framework to analyse price distortion impacts on the food system.*

Chapter 3 was structured based on the key findings of the former section of the dissertation. Price distortion hampered market development and overemphasized asymmetric transmission in a cereal crop. Supply disruptions are the key in a post-COVID era in which food and nutritional security and resilience become crucial. The special case of another cash crop, *i.e.*, sugarcane supply responses, were studied against various price and non-price factors under imperfect competition market condition, *i.e.*, sugar mills' monopsony. Abrupt farmers' decisions and inconsistent agriculture support policies resulted in climate-induced anomalies. These findings prove the hypothesis about the overutilization of resources as farmers are trapped in the Jevons' paradox with technological advancement. Productivity, price volatility, and climate variability remained important public policy concerns in the developing world.

The fruit system (and the vegetable system, often referred to collectively) plays a crucial role in ensuring food and nutritional security. Price distortions influenced the sustainable production/consumption decisions of fruit globally. At least 400 g/day is required to reap health and nutrition benefits. Insufficient fruit intake causes 3.9 million deaths worldwide, of which 14% are gastro-intestinal cancer and 11% ischemic heart disease (Li et al., 2022; Mo et al., 2019). Fruit systems are often neglected regarding tailored policies, research funding, and agribusiness support (Anderson & Birner, 2020). Chapter 4 considered complex trade-offs, adaptation capacities, and impacts on the fruit system. The impacts systematically assess the current support at various supply chains, *i.e.*, traditionally long, medium, and short fruit supply chains. System thinking was adopted through a pre-modelling data diagnostic framework to measure low-dimensional non-linear complex dynamic interactions.

The conclusion and policy recommendations were reported in Chapter 5 to draw a common basis for repurposing agriculture support strategy for the food system transformation.

Chapter 2 A Systematic Review on Price Volatility in Agriculture[1]

Abstract

The recent extreme volatility in agriculture prices determines serious repercussions to various stakeholders and levels in the food value chain, *i.e.*, producers, intermediaries, and customers, at micro-, meso- and macro-economic governance levels, respectively. Persistent high/low degree of agriculture prices leads to unsustainable production/consumption patterns, thus representing an impediment to reaching the goal of *responsible consumption and production* (*UN-SDGs 12*). The lack of comprehensive real-time information on price volatility's internal and external factors often resulted in an inconclusive and counterintuitive outcome while performing empirical estimation. The present review used the *PRISMA* framework to systematically identify and analyse literature from two important databases. Papers have been grouped by volatility drivers, governance levels, theoretical approaches, and background data types. The present review is a valuable starting point for understanding the links between multi-dimensional factors affecting the persistent price volatility and the theoretical and empirical analytics trends to provide the computational advancement needed to cope with model estimation issues. It also highlights the importance of a paradigm shift in researching agriculture price volatility to addressing food crises, considering principal objectives and perspectives such as food security, poverty alleviation, sustainability in food value chains, and resilience of food systems across the globe.

Keywords: Price volatility; food crises; microeconomy; macroeconomy; nonlinear time series analysis.

2.1 Introduction

The recent abrupt surges in agricultural prices have triggered a global crisis requiring researchers' attention to understand its nature, drivers, and destined impacts across the globe. The persistent low and high degrees of price changes refer to *price volatility* in agricultural markets. They determine serious repercussions to various stakeholders' representing or forming various governance levels of the economy, *i.e.*, farmers (production), middlemen (marketing), and customers (consumption) at micro-, meso- and macro-economic levels, respectively (Fofana et al., 2009). The subsequent unsustainable production and consumption decisions (patterns) also impede the UN's global goal of *responsible consumption and production* (SDGs 12).

[1] Present or later version of this chapter is accepted in the Journal of Economic Surveys as a separate publication: Mustafa, Z., Vitali, G., Huffaker, R., & Canavari, M. (2023). A systematic review on price volatility in agriculture. *Journal of Economic Surveys*. https://doi.org/10.1111/joes.12549

Price volatility is the primary source of uncertainty, and its identification and measurement require comprehensive real-time information on internal and external factors, often known as price dynamics. Using known partial price dynamics in any numerical estimation/equation often results in inconclusive and counterintuitive outcomes.

The existing literature on price volatility suggests that agriculture price dynamics synergized with macroeconomic forces [phenomena]. These macroeconomic phenomena are the potential source of explaining economic fluctuations to devise effective policies. However, their [phenomenon] complete dynamic impacts are still unknown (Winne & Peersman, 2016). The numerical estimation/prediction of macroeconomic phenomena like the *food crisis*[1] frequently resulted in contrasting outcomes, and models fall short of the policymakers' expectations. The reason behind inconclusive results is the intrinsic nature of food crisis drivers. These drivers often co-exist, reinforce each other (FSIN, 2021 a), and are linked at various levels of the economy. The existing numerical models on agricultural price volatility used known partial dynamics that increased the modelling error while using a growing number of irrelevant regressors [explanatory variables], called the "*curse of dimensionality*" in literature (Gouel, 2012a). This issue raises the importance of selecting representative factors (internal or external), hereafter *feature selection*, for statistical analysis and to make predictions with various available methods. Without completely known dynamics of agriculture price volatility, there is no *perfect solution*[2] available (Al-Tashi et al., 2020). Therefore, a complete structural/ theoretical estimation (Legrand, 2019) and conclusive results may only be possible once the drivers of price volatility are dynamically mapped against macroeconomic phenomena (such as food crises) at different levels of governance in the economy. This dynamically linked approach will provide answers to *understanding and a methodological way* to address food crises.

Among other things, the literature suggests that volatility comes in waves (pulse) with changing amplitudes that superimpose during crises, with an irreversible growth of prices. Both signals (price) components may be observed at the national and international scale, encompassing complex rippling and memory effects propagating from one country to another (Aizenman & Pinto, 2005). The wave of crisis may change researchers' and policymakers' viewpoints as methodological approaches/issues, frequency of data used, and theoretical framework has been evolving continuously.

Studying past food turmoil in agriculture has an important implication in understanding the food crises and evaluating agriculture markets (Blanco et al., 2017) for public policy concerns and achieving SDGs for sustainable agriculture and resilient food systems. For this reason, the global network against food crises *(GNAFC)* was founded by the European Union (EU), the Food and Agricultural Organisation of the United Nations (FAO), and the United Nations World Food

Programme (WFP). The *GNAFC* aims *"to prevent, prepare for, and respond to food crises and support"* the UN SDGs to *end hunger* (SDGs 2).

This global alliance aims to reduce vulnerabilities related to acute hunger and promote sustainable and resilient food systems, using a *"3x3 approach"* to addressing food crises. This approach has required concentrated efforts to understand food crises (Dimension I), support investment in agriculture, food, and nutritional security (Dimension II), and identify various drivers of food crises and their linkages to the economy (Dimension III) (FSIN, 2021 b). To the best of the authors' knowledge, no comprehensive study is available that addresses the issues of price volatility in agriculture, mapping drivers of change (Dimension III) at various economic (governance) levels to provide answers to the *GNAFC* framework. The present systematic review provides a basis to understand the nature of research dynamism during the wave of food crises (Dimension I) with fruitful insights for future research.

Moreover, the present review also highlights the dynamic research transition related to popular trends about data types (sources) and methods used in commodity and price volatility financialization. This mapping will provide a comprehensive overview of uncertainty in agriculture market dynamics to answer drivers of change and its nature — it helps re-examine conclusive and persistent futuristic results. The final aim is to prepare a background study to find past approaches' weaknesses and gaps and suggest more effective modelling approaches. This approach helps us address agriculture price-volatility-induced food crises and identify key impediments to inclusive growth and sustainable development.

To achieve this goal, we systematically reviewed the current literature available from the two leading and most comprehensive academic research databases (Scopus and Web of Science) from the year 2000 to the year 2021. We report the article selection process using the Preferred Reporting Items for Systematic Reviews *(PRISMA)* framework. The theoretical underpinnings about drivers of change and nature are underlined while empirically analysing the research approaches/method used for various agriculture enterprises. The previously published reviews cover price volatility in agriculture in connection with the oil/energy sector spill over phenomenon, and empirical findings of previously conducted studies showed contrasting outcomes. The agriculture markets (prices) have unique dynamics (endogenous factors) and may be influenced by oil/energy sectors (exogenous factors). However, these dynamics may also change, impeding macro-economic [food] crises.

The structure of the paper is as follows. Section 2.2 describes the search strategy and selection criteria applied to identify the papers for the current literature review. Section 2.3 collects the results on identified categories. Future research areas and conclusions are presented in Section 2.4.

2.2 Methods

Search strings' construction and validation are paramount in a systematic review (Marcos-Pablos & García-Peñalvo, 2018). A three-stage search query was developed to identify articles on price volatility in agriculture. The first two stages were related to the *construction* of search strings, while the third stage validated the selected keywords. In the first stage, during January 2021, general keywords, *i.e.*, agriculture, price, and volatility, were used to formalize the search string. The initial search string results were compared to a set of highly cited manuscripts on agriculture price volatility and covered only 66% of the critical studies. The exclusion rate of 44% suggested re-formulating the search string and including additional keywords, *i.e.*, market and commodity while excluding the studies focusing on energy. Therefore, the search string was revised and re-run in both databases during June 2021: *(price AND volatil* AND agricultu* AND (marke* OR commodit*) AND NOT energy)*. As a confirmatory analysis, retrieved records have been searched for concurrent keywords to validate the search string further at the third stage. The strength of the *top 20 keywords* has been measured in terms of word frequency cloud and co-occurrence dendrogram.

We use the structured PRISMA framework (Moher et al., 2009) to show the procedure we implemented to identify, select and analyse the literature on price volatility in agriculture (**Figure 2.1**). The research papers have been retrieved through a systematic search of peer-reviewed journals cited in reputed databases. Two databases have been consulted to collect the published literature: SCOPUS and Web of Science. The timeframe considered is from the year 2000 to June 2021[3]. Only papers written in English were considered. The search string was performed on the *title, abstract, and keywords* in SCOPUS, while Web of Science covers the *topic* only. We included only peer-reviewed journal articles and review articles. Other documents, such as books, book chapters, and conference papers, were excluded.

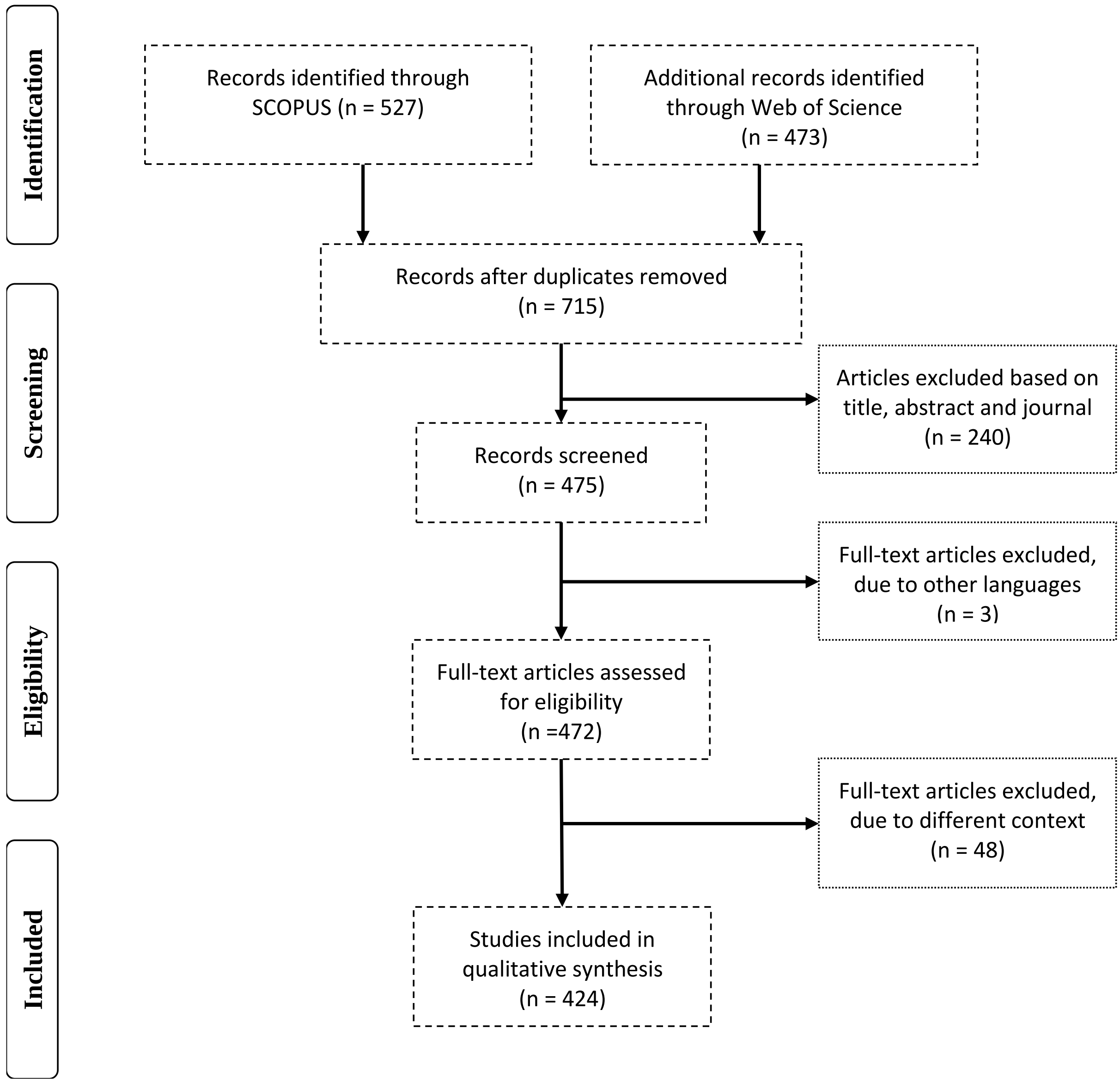

Figure 2.1: *PRISMA framework for present systematic review*

The search conducted on SCOPUS and Web of Science identified 527 and 473 articles, respectively. After removing duplicates, 715 articles have been evaluated based on a) abstract, b) title and c) keywords in line with the defined objective of the research. A total of 240 articles were excluded, and 475 were found eligible. Three articles were further excluded because of the full-text language, and 48 records were found out of context after the full-text assessment. These articles are not exclusively studying the price volatility phenomenon (quantitatively or qualitatively) in agriculture. As a result, the original database was reduced to 424 articles. In contrast, price volatility was also mentioned or reported implicitly to other impeding phenomena, such as rural livelihoods and energy markets.

A comprehensive database was built to record and analyse the critical content of each study. The critical information incorporated are (1) author, (2) year of publication, (3) objective, (4) measurement method, (5) sample size, (6) sample composition, (7) methodology, (8) main research topics, (9) country, (10) crop, (11) theory and (12) issues. This information can be found in Appendix-A. Thematic groups based on drivers of price volatility in agriculture were categorized and linked with levels of the economy. The weather was identified as a cross-cutting category (simultaneously affecting more than one economy level).

2.3 Results and discussion

Agricultural price volatility is studied as an oil (energy) sector spill over phenomenon. Therefore, we cannot recover global phenomena such as climate change, food security, and sustainability in the top 20 keywords. The weighted percentages (how often words appear in the text) showed the overall strength (size based on percentage share in total words in a research article) of words in the word frequency cloud (**Figure 2.2**a). The result shows that the keywords price, market, volatility, agriculture, and commodity were the top five most frequent words used in previous research with percentages (word counts): 1.67% (14,745), 0.82% (7,217), 0.72% (6,383), 0.67% (5,928) and 0.64% (5,674), respectively.

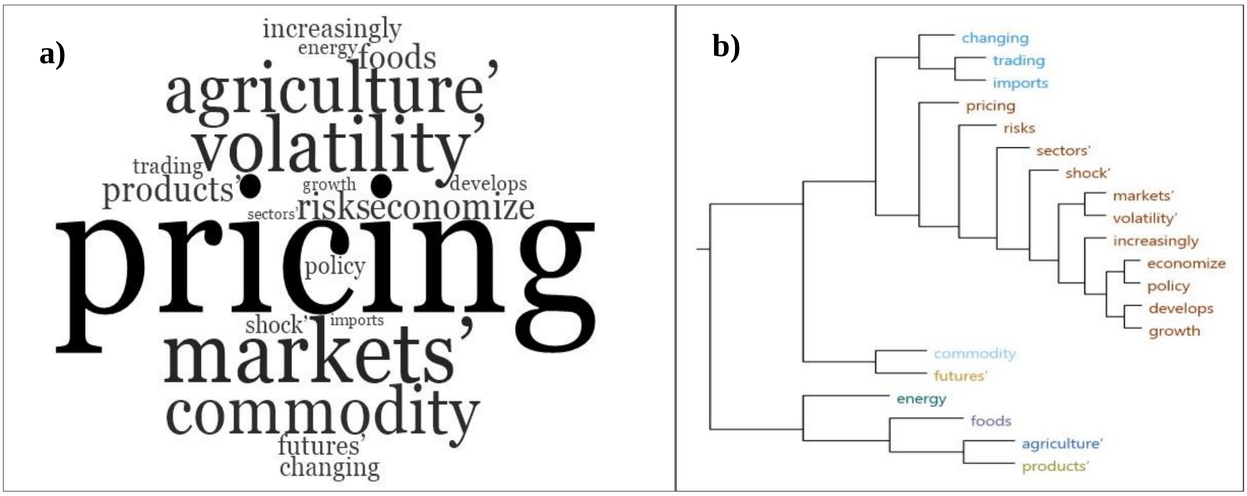

Figure 2.2: *Word frequency cloud shows the most frequent top 20 words in the selected studies.*
b) Word frequency dendrogram shows the other important keywords for any futuristic systematic research. The diagrams have been obtained by NVivo-10 - query search function.

The word frequency cloud validates the inclusion of the additional selected keywords "*markets"* and "*commodity"* in the search string used in this systematic review. The dendrogram (**Figure 2.2**b) highlights four main branches, which can be called clusters. The 'trading' and 'imports' on one side and financial terms like 'commodity' and 'futures' on the other were used in two distinct and separate classes of literature. A separate branch of the literature was characterized by the keywords 'products,' 'foods,' and 'energy.' In contrast, the wider branch, characterized by many interconnected keywords appearing in a cascade, deals with economic and policy aspects within published literature, *i.e.*, 'pricing,' 'risks,' 'sectors,' 'shock,' 'market,' 'policy,' and 'growth.'

2.3.1 The role of the world food crisis

An overarching aspect emerging in this survey is represented by the so-called World Food Crisis, an upsurge in food prices in 2007/2008. Over just a few months, international wheat and maize prices doubled, and international rice prices tripled. This price increase results in over 130 million people being forced into a vicious cycle of poverty and a 56% increase in import bills of developing countries (Headey, 2013). The commodity price volatility has noticeably impacted the governments and farmers/household decision-making (Dehn et al., 2005) and their wellbeing in the presence of hysteresis (Tervala, 2021). These decisions may reinforce the negative impacts and not counterbalance them during better economic conditions (Cariolle & Goujon, 2015).

World food crises dramatically affected the literature, as they changed researchers' and policy makers' viewpoints and methodological approaches, as much as the frequency of data used and the theoretical framework (A. Jones & Hiller, 2017). The food crisis in 2007/2008 served as a cut-off period for our research timeline; we have created three critical timelines, Pre-crisis (before the year 2007), food crisis (during the years 2007 to 2008), and post-crisis (after the year 2008).

Figure 2.3 shows the number of records on the y-axis and the period (years) on the x-axis in the database, highlighting food crisis has caught the attention of various authors as the highest number of articles (an average of about 32 per year) has been published during the post-crisis period. Before this, only 37 records were found in the other two periods (5 per year in pre-crisis and 7 per year during the food crisis period).

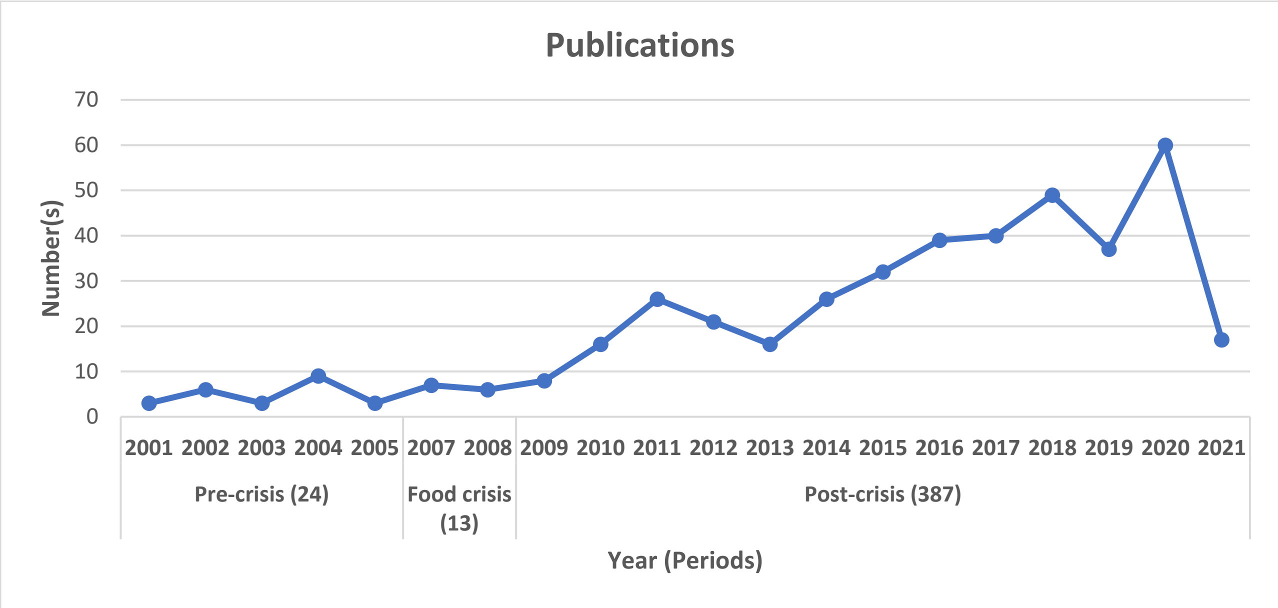

Figure 2.3: *Selected articles by publication year (periods).*
The highest number of articles (an average of about 32 per year) was published post-crisis. Before this, only 37 records were found in the other two periods (5 per year in pre-crisis and 7 per year during the food crisis period).

2.3.2 Volatility drivers

The analysis of 424 papers provided information about several vital multi-dimensional drivers of price volatility in agriculture. These drivers are classified into *six main categories* and linked with *three economic levels* of governance: micro-, meso-, and macro-level (**Figure 2.4**). There are 42 drivers identified and distributed to three economic levels. Marketing (297) is the most diverse category regarding the total number of drivers and frequency count, while weather (5) was the least. Based on existing literature findings, the weather was considered a *cross-cutting category* among all levels (Bhanumurthy et al., 2013; Feng et al., 2014; Kahiluoto, 2020). The weather may influence the changes in production (food availability), disrupt the food volume, and alter the trade patterns in domestic and international markets (Santeramo et al., 2021). In the current literature review, weather can affect the volume of trade and investment (Koizumi 2019; Koizumi & Furuhashi 2020), market imperfections (Larson, 2004 a), and price/productivity risks channels (Mainardi, 2012a).

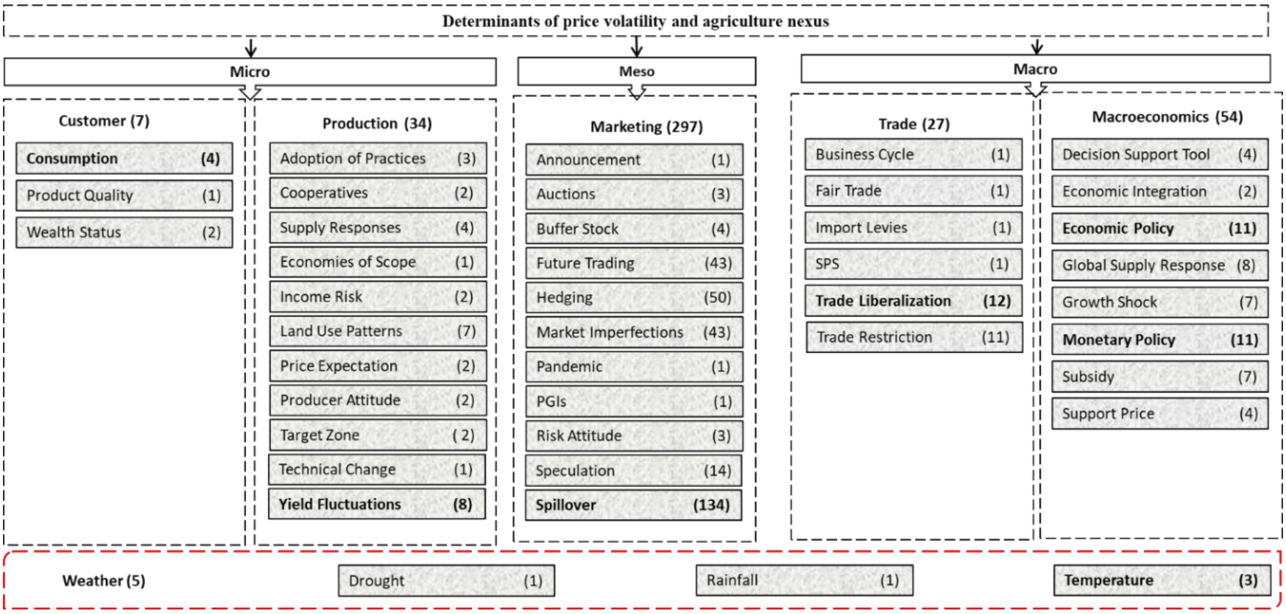

Figure 2.4: *Research topics and frequencies.*
The number inside the parentheses is frequency as the main topic. The drivers in bold have the highest frequency counts in their respective categories.

At the production level, the variability in prices arises from multiple factors ranging from producers' own decisions (Assouto et al., 2020; Bellemare et al., 2020) about land use (cropping) patterns (Liu et al., 2016a), adoption of specific practices, such as environmentally friendly or not (Gródek-Szostak et al., 2019; Lefebvre et al., 2020), and variability in production/area (Fretheim & Kristiansen, 2015; Santeramo et al., 2018). The land-use pattern was studied during the food crisis and post-crisis periods. However, yield fluctuation (8) and land-use patterns (7) were ranked first and second based on total frequency counts. Cooperatives (Bolotova et al., 2008) and producer attitude (Bellemare et al., 2013) were also considered potential sources of price volatility in agriculture at the microeconomic/production level.

Some of the multi-dimensional drivers, *i.e.*, announcement effect of world agricultural supply and demand estimates (Xie et al., 2016), buffer stock (Fraser et al., 2015), pandemic (Ezeaku et al., 2021a), protected geographical indications (Vidaurreta et al., 2020) risk attitude (Franken et al., 2014) and speculation (Bozorgmehr et al., 2013) were the only drivers reported in post-crisis at the marketing level. The most abundant driver was 'spill over,' which appeared 134 times during the pre-crisis (3), food-crisis (1), and post-crisis (130) periods. Most of the researchers' studied commodity market linkages with price volatility, *e.g.*, with energy markets (Awartani et al., 2016; Balcilar & Bekun, 2020) or non-energy markets (Arnade et al., 2017; Awokuse & Wang, 2009). These previous results confirmed that prices move together in response to common macroeconomic shocks, commonly known as the excess co-movement puzzle in literature; for more details, please see (Pindyck & Rotemberg, 1990). The second most frequent factors within the marketing cluster were marketing imperfections and future trading, with 43 items each. These studies were related to government interventions (Misra, 2012), market infrastructure (Shively & Thapa, 2017) related to marketing imperfection while digital trading platforms (Banker et al., 2011), and speculative behaviour (Bohl et al., 2018).

The monetary and economic policies were the only factors studied during the food crisis (1) and post-crisis (10) periods. However, subsidy (7) and support price (4) were studied during pre-crisis (1) and post-crisis periods (6 and 3), respectively. The issue of subsidy and support prices became critical during the post-crisis period of price volatility in agriculture. These issues first appeared in 2002 and 2004, respectively, with studies aiming to investigate the implications of a government price support program on price dynamics (Chavas & Mehta, 2004; Kim & Chavas, 2002). In the post-crisis period, subsidies were studied in connection with food (in)security (Dev & Rao, 2010) and food/biofuel policies (Babcock, 2012).

Extreme weather conditions like drought and climate variability may further exacerbate the conditions and influence different dimensions of food security, bringing undulating effects to various sectors of the economy (Mainardi, 2012b). The researchers have conducted studies highlighting weather's role in increasing production variability (Boyd & Bellemare, 2020), affecting the availability dimension of food security, resulting in product quality issues related to the utilization dimension of food security at the microeconomic level (Carvalho et al., 2016). The missing stability dimension of food security at the meso-economic level has become an essential phenomenon. It has led to study issues related to wildly speculative behaviour (Femenia, 2010) and supply disruption during the current global pandemic (Ezeaku et al., 2021b). Trade liberalization (8) was widespread during the post-crisis period to insulate domestic prices (Kunimitsu et al., 2020), whereas further studies conducted during the post-crisis period to define the impact of joining the World Trade Organisation (Chang et al., 2011) and risk associated with trade (Zhang 2015) in relation with volatility.

Mapping multi-dimensional drivers have revealed the overall variability and important contributing channels in the food crisis wave. The researchers are exaggerating production and marketing anomalies, *e.g.,* yield fluctuations and the co-movement of agriculture price volatility.

The role of weather has been studied as a catalytic factor that affects the various dimensions of food security. Previous research paid little attention to business cycle models[4] and its costs. These models require validation in the presence of externalities and interactions—between different sectors of the economy at the macroeconomic level.

2.3.3 Market theories

Table 2.1 reports the dominant theories used in the different types of markets. There are two main types of markets reported in published articles: spot market – which deals with current (cash) values, and future market – which deals with the financialization (contracts) of commodity markets. Some studies reported spot and futures markets related to the reference date. Therefore, we have created a third category, *mixed* market type, to analyse those articles separately. All three types of markets have reported 34 different theories — spanned over 127 articles in different periods. The rest of the 297 records did not report any specific theory.

Table 2.1: *Dominant theories during different periods.*

Theory (Counts)	**Market Types**		
	Mixed (17)	**Future (37)**	**Spot (73)**
Arbitrage Pricing (5)	2018	*2007*; 2018; 2021	2019
Asymmetric Price Adjustments (1)	-	-	**2004**
Asymptotic (8)	2019	2014; 2018	2009-10; 2012; 2015; 2017
Central Limit (2)	-	2017 (2)	-
Behaviour (4)	2016	-	**2004**; 2015-16
Chaos (3)	2020	-	2014; 2018
Cobweb (6)	-	-	2010; 2017; 2019 (2); 2020-21
Cointegration (1)	-	-	2014
Commodity Price Stabilization (10)	-	-	**2003**; **2005**; *2008*; 2012; 2016 (2); 2017-20
Competitive Storage (22)	2015-16; 2017 (2); 2018; 2020	2010 -11; 2014-15 2016; 2019-20	**2002**; **2004**; 2011; 2014 (2); 2015; 2018 (2); 2019
Contagion (1)	-	2020	-
Contrary Opinion (1)	-	2020	-
Efficient Market (3)	2012	2016; 2019	-
Endogenous Price Fluctuations (5)	-	-	2011; 2013; 2015 2017-18
Expected Utility (8)	-	2021	*2007*; 2014; 2018 (3); 2020 (2)
Expertrons (1)	-	-	2020
Extreme Value (4)	-	2010; 2015; 2019	*2008*
General Equilibrium (4)	2018	-	2016 (2); 2020
International Trade (2)	-	-	2019 (2)
Intraday Patterns (1)	-	2018	-
Islamic Monetary Value (1)	-	2020	-
Market Microstructure (1)	-	2018	-
Microeconomic (3)	-	2010	2009; 2018
Neoclassical (2)	-	-	2017; 2020
Normal Backwardation (2)	2014	2020	-
Political Economy (3)	-	-	2012-13; 2017
Portfolio Management (7)	2017	2014 (2); 2017	2015; 2018; 2020
Probability (8)	-	2012; 2013 (2); 2014; 2020	2010; 2012; 2020
Quantity Money (1)	-	-	2014
Random Walk (2)	-	2016	2017
Rational Expectations (1)	**2005**	-	-
Speculation (2)	2014	2019	-
Standard Cost (1)	2014	-	-
Transactions-Cost (1)	-	-	2010

Notes: **Bold** *and italics fonts represent pre-crisis and food crisis periods, respectively. There was a total of 34 distinct theories reported belonging to 127 different selected articles. The selected records were scrutinized based on market types: spot (current), future, and mixed (combined spot plus future).*

The results reveal that only one study each reported pre-crisis (Yang et al., 2005) and food crisis (Turvey & Komar, 2007) periods representing mixed and future market types, respectively, while other theories were applied during the post-crisis period. The spot market was the most abundant market type in which 73 total articles reported different theories, *i.e.*, pre-crisis (6), food-crisis (3), and post-crisis (64) articles. The remaining 54 records representing 23 different theories fall into the remaining two market types, *i.e.*, mixed, and future markets. The competitive storage theory (22) was the most frequently reported in all market types, while twelve theories were studied only once, each in different markets and periods. The commodity price stabilization theory was the only theory studied in all periods of the spot market.

In comparison, the quantity theory of money (Zhang 2014) was the only dominant theory in spot market studies that appeared in the post-crisis period. These studies have gone into great transition in terms of theory starting from price stabilization (Yang et al., 2001) in both market types towards more sophisticated theories for addressing various issues, *i.e.*, arbitrage pricing for asymmetric price adjustments (Mao et al., 2021), cobweb for sustainable food value chain (Muflikh et al., 2021) and expected utility theory for asymmetric information (Huang et al., 2021). The researchers tried many theories, as agriculture markets do not provide a *"natural correction process"* for price volatility and require distinguishing between endogenous and exogenous price volatility (Ray Huffaker et al., 2018). The wave of the food crisis changed the dynamics of conducting empirical research on agriculture price volatility with diverse theoretical backgrounds.

2.3.4 Model-based approaches

The selected papers used diverse methodological approaches to quantify the dynamics of price volatility. **Figure 2.5** shows the reported methodologies adopted during the wave of food crises in research papers.

We have ten different methodological approaches in the present review compared to Frey & Manera (2007), where only econometric models were discussed in detail. These approaches are characterized by 1) type of data used (qualitative or quantitative), 2) distribution (parametric or non-parametric), 3) inferences (econometric, statistical, or mathematical models), 4) prediction (machine learning or hybrid models[5]), and 5) theoretical framework. The pre-crisis and food crisis periods were not significant in terms of the total number of records [pre-crisis (22) & food crisis (13)]; no. of approaches [pre-crisis (5) and food crisis (6)]. This outcome indicates that approaches used to address the price volatility in agriculture from 2000 to 2008 (both regimes) are similar.

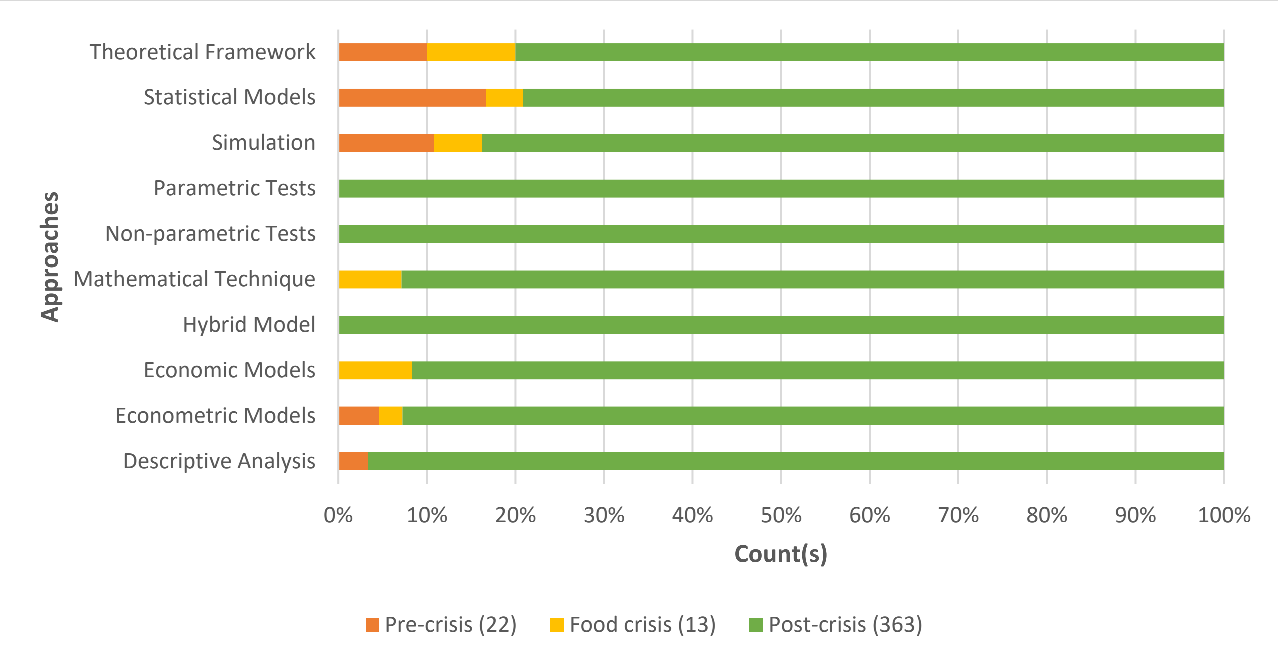

Figure 2.5: *Methodological approaches used in the selected studies.*
Notes: The post-crisis period was the most distinct in terms of no. of approaches used (10) as compared to pre-crisis (5) and food crisis (6).

The post-crisis period was characterized as the most varied period in which all methodologies were used. There were 262 records retrieved, addressing various econometric modelling approaches for short-run and long-run relationships, *such as* autoregressive conditional heteroskedasticity (ARCH/GARCH) models, cointegration, and other dynamic approaches. Contrary to the previous findings of Beck (2001), the researchers' present sampling framework applied both ARCH/GARCH processes to storable and non-storable (perishable) commodities. Moreover, these authors also considered simulation (37) and mathematical techniques (14) to understand better the recursive character of price volatility (continuous repeating cycles of low/high prices). In simulation studies, Multi-agent systems (LI et al., 2018) and general equilibrium models (Valenzuela et al., 2007) were used extensively. In contrast, in studies based on mathematical techniques, the researchers used dynamic optimization models and wavelet coherence analysis (Zivkov et al., 2019) to detect price volatility's presence, persistence, and co-movement. Various machine learning algorithms analysed other essential features of the post-crisis period, such as artificial neural networks with backpropagation algorithms for price volatility forecasting (Ayankoya et al., 2016). The machine learning algorithms and hybrid models were introduced in 2011 (Karia & Bujang, 2011) and 2013 (El Benni & Finger, 2013), respectively.

2.3.5 Data sources

The data(bases) use changes during the food crisis wave were analysed and grouped into nine frequency types (**Figure 2.6**). During the pre-crisis and food-crisis periods, the authors used low-frequency data, *e.g.*, yearly (Yoshimoto, 2005) and monthly (Bonroy et al., 2007) data, to identify the presence of volatility in agriculture markets. However, during the post-crisis period, there was a growing concern over the financialization of commodities, which diverted the attention toward high-frequency data in quantification and volatility spill over from one market to another. The researchers used intraday (Adjemian & Irwin, 2018), daily (Monk et al., 2010), and weekly (Istudor et al., 2014) frequency datasets, considering the seasonal variations. Multiple interval type (Ott, 2014) of data was also used to differentiate inter and intra-seasonal responses where authors retrieved multiple time series data, *e.g.*, monthly and yearly series, simultaneously. Different data types (intraday, daily, weekly, *etc.*) and their regime-switching behaviour (Santeramo, 2022) due to aggregation characteristics (taking averages and converting various data frequencies, *i.e.*, daily into weekly/monthly) have affected empirical findings. This aggregation decreased the average level of F-statistics relative to daily data — during post-crisis (Bachmeier & Griffin, 2003; Bettendorf et al., 2003; Guerra V et al., 2015; Sarris & Hallam, 2006).

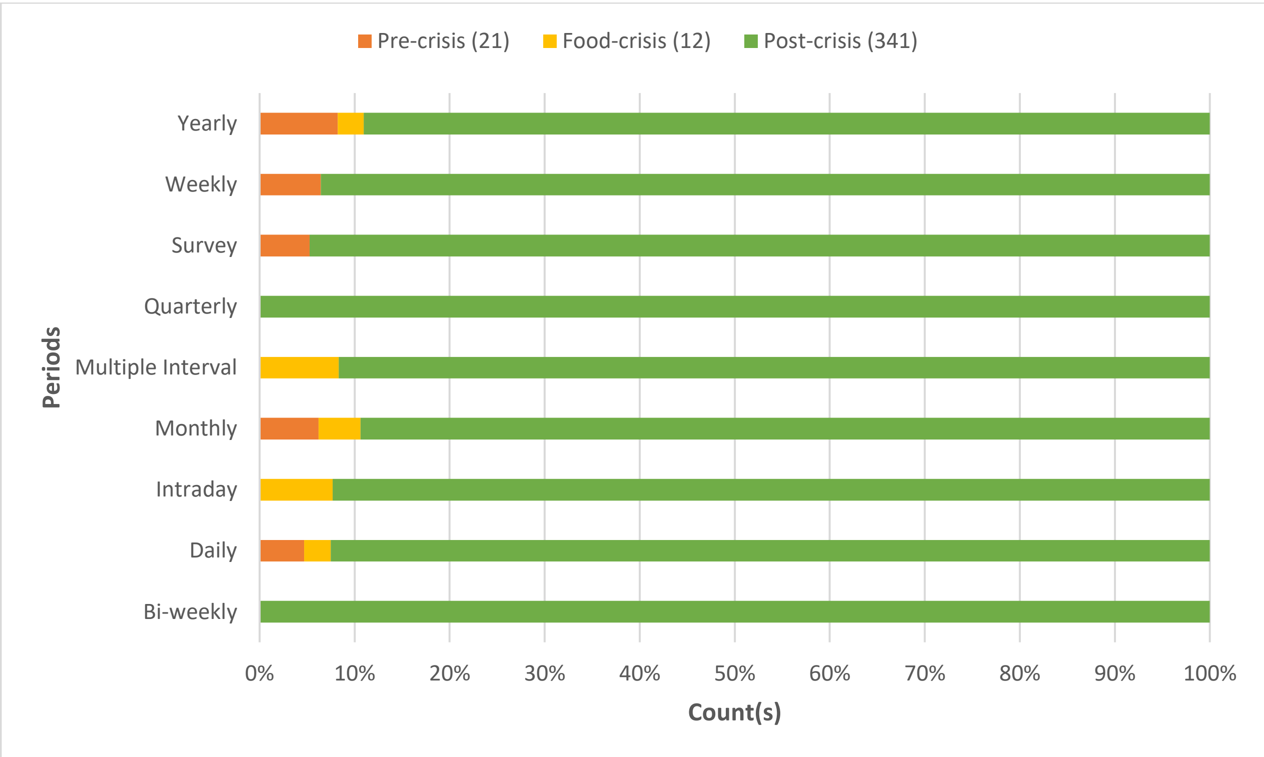

Figure 2.6: *Different types of data frequencies used in selected studies.*
The data(bases) categorization was consulted during the sampling framework and grouped into nine frequency types.

Figure 2.7 categorizes the results of various databases used in selected studies. The most widely used databases were those collecting information about commodity exchange that appeared 118 times post-crisis. The growing financialization of commodities resulted in greater utilization of databases, such as *Bloomberg, Thomson Reuters, and S&P Global.* The upward trend in consulting UN databases, *such as* FAOSTAT, ILOSTAT, and COMTRADE, was also apparent during post-crisis, with 18 records identified in this category.

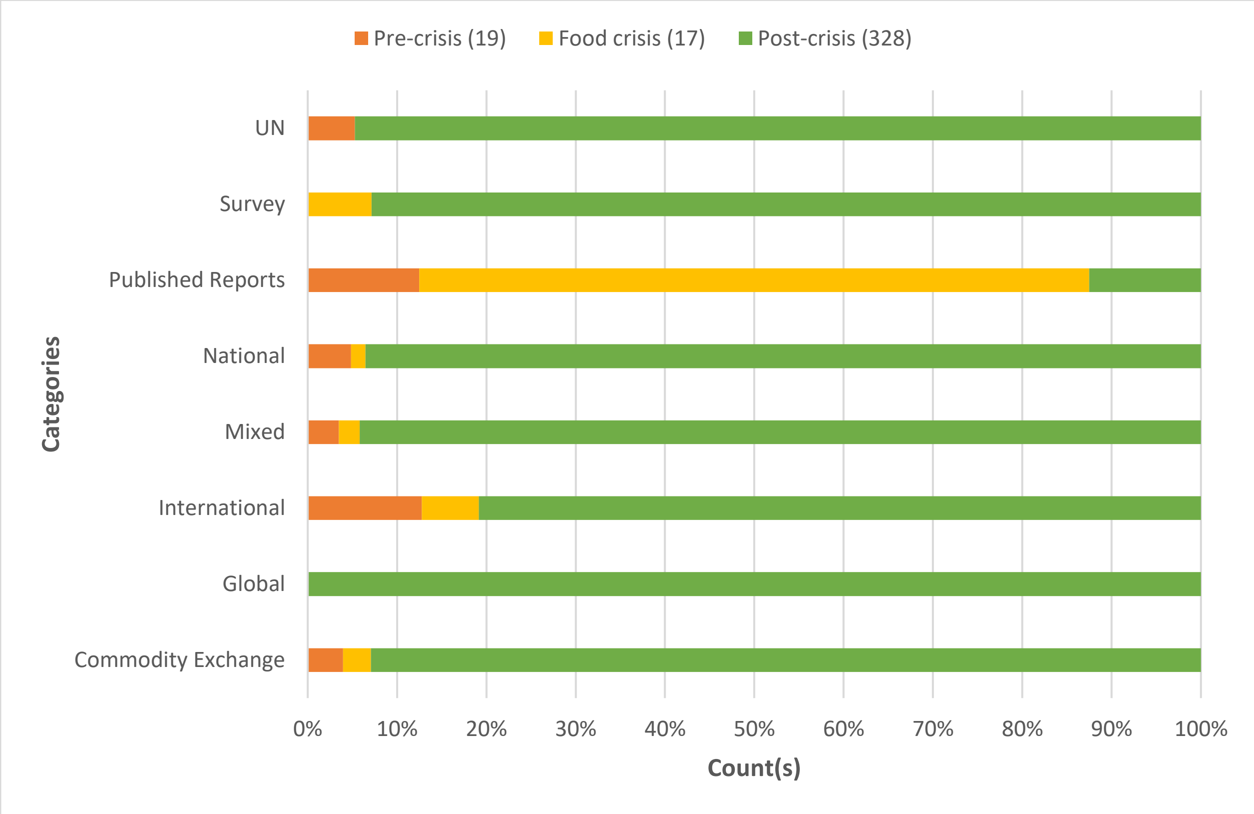

Figure 2.7: *Description of database category used in selected studies.*
Notes: Overall, eight different types of database categories were reported in selected studies. Nineteen database categories were found in pre-crisis, while 17 different database categories were reported during the food crisis period.

The international database category also gained momentum and appeared in various published articles during the food crisis (3) and post-crisis (38) periods. Farm Accountancy Data Network – FADN (Ciaian & Kancs, 2011; El Benni & Finger, 2013), United States Department of Agriculture – USDA (Bozic et al., 2012; Isengildina-Massa et al., 2008), and International Monetary Fund – IMF (Elmarzougui & Larue, 2013; Gontijo et al., 2020) were among the most important databases in this category.

Among other things, the researchers retrieved data from national (62) and mixed category (86) databases in the selected studies. In the mixed category, researchers retrieved data from multiple national and international statistical databases and conducted studies only in post-crisis. The remaining records fell into primary studies (14) through well-defined questionnaire surveys administered in person (Haile et al., 2019) or online surveys (Heyder et al., 2010), while secondary studies (8) retrieved data from published reports– predominantly in the food-crisis period. The result reveals that the dynamics of data sources had changed quite enormously during the wake of the food crises. The use of index-based commodities was quite common during post-crisis period. This was one of the possible sources of irregularities and inconclusive inferences in selected studies. Therefore, the commodity-specific research work required to avoid such irregularities for conclusive results (Ghoshray, 2011).

2.3.6 Geographical locations

Geographical dynamics in previously published research have provided significant insight into current research trends in comparison with drivers of price volatility in agriculture across the globe (**Table 2.2**). The global category was created if research was conducted in more than one country. At the macroeconomics level, two studies were reported in pre- and food-crisis periods. In pre-crisis, studies were related to an agricultural price support program, *i.e.*, subsidy and support price (Chavas & Kim 2004), while studies published during the food crisis catered towards macroeconomic policy measures (Bonroy et al., 2007; Kilima et al., 2008). The global level studies referred to macroeconomics (4), marketing (34), and weather (3) levels, while surprisingly, Asian region studies were prominent at the production (3) level. This result implies that food availability is still an important issue in Asia. Most of the studies at the marketing (meso-economic) level were conducted during the post-crisis period, except for 13 studies in the other two periods (pre-crisis (10) and food-crisis (3)). The highest reported frequencies for Africa (10), Asia (28), Global (34), and North America (17) level studies were for spill over determinants in the marketing category. This finding shows the overemphasis of the researchers on *price transmission* mechanisms for different oil/energy markets onto agriculture commodity markets (spot/future). The EU region (11) also emerged at the marketing level. Still, the researchers aimed to work on hedging mechanisms, *i.e.*, risk management strategies (Roussy et al., 2018) or risk margins in agricultural insurance (Url et al., 2018). The global (5) and Asian (5) level studies were prioritized related to trade (macro-economic level) openness. Most studies were conducted in post-crisis except (Elobeid & Tokgoz, 2008; Srinivasan & Jha, 2001). This implication implies that the researchers were concerned about the greater role of government for public policy interventions in markets and economies at the meso- and macro-economic levels, respectively.

Table 2.2: *Location and year of publications of main research topics.*

Category	Main Topic	Location	Pre-crisis	Food crisis	Post-crisis
Customer (7)	Consumption	Africa (01) **Asia (02)** N. America (01)	-	-	2015-16, 2018-19
	Product Quality	S. America (01)	-	-	2016
	Wealth Status	Africa (01) Oceania (01)	-	-	2016, 2021
Macroeconomics (46)	Decision Support Tool	Africa (01) EU (01) N. America (01) Oceania (01)	-	-	2016, 2018 (02), 2019
	Economic Integration	EU (01) Global (01)	-	-	2019 (02)
	Economic Policy	Africa (01) **Asia (03)** EU (01) **Global (03)** N. America (01)	-	2008	2011-12, 2014, 2016, 2018 (02), 2020 (02)
	Global Supply Response	Asia (01) EU (02) **Global (04))**	-	-	2010-11, 2012 (02), 2013, 2016, 2018
	Growth Shocks	Africa (02) **Asia (03)** EU (01)	-	-	2010-11, 2016 (02), 2019, 2020
	Monetary Policy	Africa (02) Asia (01) **Global (04)** N. America (01)	-	2007	2010-11, 2017-19, 2020 (02)
	Subsidy	Africa (01) Asia (02) Global (02) N. America (02)	2002	-	2010, 2012. 2015, 2017 (02), 2019
	Support Price	Asia (02) N. America (01)	2004	-	2012, 2016
Marketing (209)	Auctions	Asia (01) Global (01) N. America (01)	2004	-	2009-10
	Buffer Stock	Africa (02) Global (02)	-	-	2012, 2015, 2018 (02)
	Future Trading	Africa (03) **Asia (07)** Global (03) N. America (06)	2002	2008	2010 (03), 2011-14, 2016, 2017 (02), 2018 (02), 2020 (04), 2021
	Hedging	Africa (03) Asia (08) **EU (11)** Global (10) N. America (06) S. America (02)	2002, 2004, 2005 (02)	2007	2009 (02), 2010, 2011 (05), 2012 (03), 2013(02), 2014 (03), 2015 (03), 2017 (03), 2018 (08), 2019, 2020 (03), 2021
	Market Imperfections	Africa (01) **Asia (11)** EU (05) Global (05) N. America (06)	2003	-	2011 (04), 2012-13, 2014 (03), 2015 (03), 2016 (02), 2017, 2018 (5), 2019 (03), 2020 (03), 2021
	Protected Geographic Indications	EU (01)	-	-	2020
	Risk Attitude	EU (01) N. America (01)	-	-	2014, 2017
	Speculation	Asia (05) EU (01) Global (02) N. America (01) S. America (01)	-	-	2009-11, 2013,2015, 2017 (02), 2019-21

Category	Main Topic	Location	Pre-crisis	Food crisis	Post-crisis
	Spill over	Africa (10) Asia (28) EU (09) **Global (34)** N. America (17) S. America (04)	2003 (02), 2004	2007	2009 (04), 2010 (03), 2011 (03), 2012, 2013 (04), 2014 (08), 2015 (06), 2016 (11), 2017 (13), 2018 (11), 2019 (10), 2020 (18), 2021 (06)
Production (29)	Adoption of Practices	EU (01) Global (01)	-	-	2017, 2020
	Cooperatives	N. America (02)	-	2008	2016
	Dynamic Supply Responses	Africa (01) Asia (02) Global (01)	-	-	2016, 2018, 2020 (02)
	Economic of Scope	Global (01)	-	-	2018
	Income Risk	Asia (01) EU (01)	-	-	2013, 2015
	Land Use Patterns	**Asia (03)** EU (02) N. America (01) S. America (01)	2002	-	2015 (03), 2016, 2018-19
	Price Expectation	Africa (01)	-	-	2019
	Producer Attitudes	Africa (01) Global (01)	-	-	2013, 2020
	Target Zone	Global (01)	-	-	2018
	Technical Change	EU (01)	-	-	2021
	Yield Fluctuations	Africa (02) Asia (01) EU (01) Global (01) N. America (01)	2002	-	2010, 2014, 2016, 2017 (02)
Trade (23)	Business Cycle	S. America (01)	-	-	2017
	Fair Trade	Global (01)	-	-	2014
	Import Levies	EU (01)	-	-	2021
	SPS	Global (01)	-	-	2019
	Trade Liberalization	**Asia (05)** Global (03) N. America (01)	2001	2008	2010-12, 2015,2016 (02), 2020
	Trade Restrictions	Africa (03) EU (02) **Global (05)**	-	-	2012 (02), 2015 (02), 2016, 2017 (03), 2018-19
Weather (05)	Drought	Africa (01)	-	-	2012
	Rainfall	Asia (01)	-	-	2013
	Temperature	**Global (03)**	-	-	2016, 2019-20
Grand Total		**319**	**15**	**07**	**297**

*Notes: The **bold values** in the location column indicate the highest rank of location within the category based on the number of frequencies in selected studies.*

2.3.7 Agricultural sector

The key information about agriculture sectors was also analysed (**Figure 2.8**). A total of 87 records were excluded because of irrelevance to agriculture. Sub-sectors were created into a two-step verification process. Identifying different sub-sectors (crops) within agriculture was scrutinized based on the highest number of crop (sub-sector) presence in the selected research articles. For example, (Abbott & de Battisti, 2011) first separated biofuel from crops. Then, we categorized millet, rice, sorghum, and wheat into the cereals sub-category. The sub-sector "Fibre” refers to cotton.

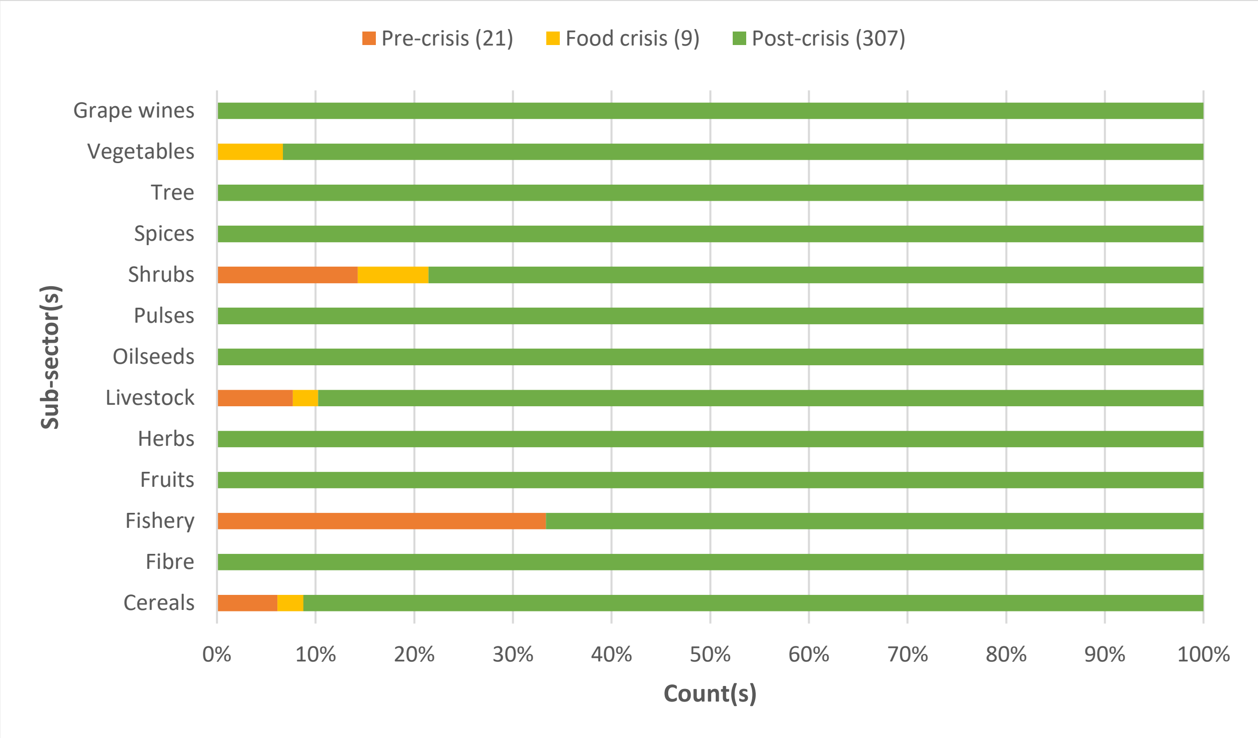

Figure 2.8: *Distribution of agriculture sub-sectors among periods.*
Notes: The distribution of selected articles in terms of agriculture sub-sector shows that cereals (228) were the most prolific sub-sector while the rest of the sub-sectors were least studied, e.g., fibre (1%), fruits (2%), vegetables (5%), etc., within agriculture.

The price volatility studies were saturated with cereals, 228 records, and livestock, 35 records within the studies' sampling framework. The shrubs or small tree crops represent coffee (Larson, 2004 b) got noticeable attention in pre-crisis (2) and post-crisis (11) periods from researchers, while the rest of the sub-sectors were least studied, *e.g.*, fibre (1%), fruits (2%), vegetables (5%), *etc.*, within agriculture. The result reveals that the food crisis wave has skewed sub-sector distribution towards cereals, livestock, and shrubs due to greater food security (poverty alleviation) concerns. Another emerging facet of food security revolves around nutrition and health security (malnutrition) during the last decade. This issue can be ensured by researching stabilizing prices in neglected agricultural sub-sectors to receive added micronutrients from fruits and fishery.

2.3.8 Paradigm shift in research

The present systematic review has also compiled points of contentions discussed in selected studies while researching agriculture price volatility. The timeline of issues was created (**Figure 2.9**) regarding the total number of counts and the first instance of reporting that studied issue within the sampling framework. These results highlight a clear *four-wave (transition) paradigm shift in research* on price volatility in agriculture due to the wake of food crises. Initially, the issue (counts) was addressed at the farm level with production cost (6), and it was gradually moving towards marketing-related issues, such as regulatory measures (34). Secondly, the transition was seen in 2005 when researchers addressed the trade restrictions (10) issue and its economic consequences. The food crisis was a real game-changer for researchers across the globe. Thirdly, a great transition was seen in research orientation towards holistic approaches. These approaches tackle all the dimensions of food security (16), such as food availability, access, utilization, and stability, then involving the private sector through corporate social responsibility (1) and introducing health concerns through food and nutritional security (5) concerns.

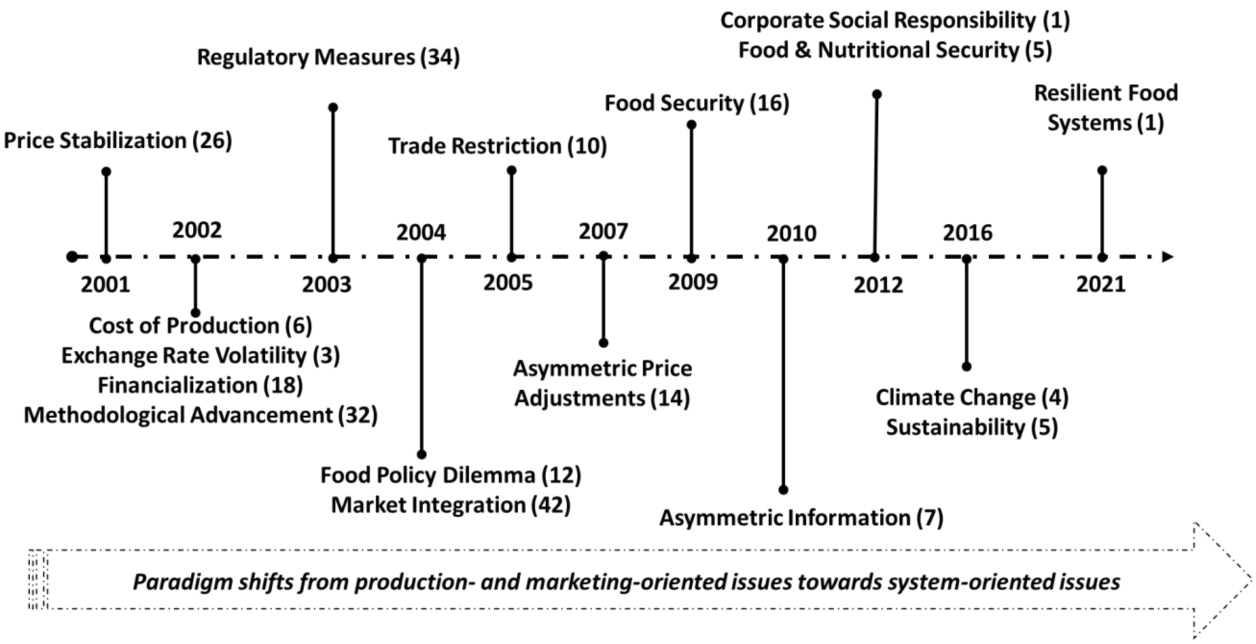

Figure 2.9: *Research issues timeline based on selected studies.*
The waves of research transition resulted in paradigm shifts in price volatility in agriculture and food crisis research.

After the global commitment to *Sustainable Development Goals (SDGs)* in 2015, the researchers brought sustainability (5) and climate change (4) issues into their research domain. The researchers tried to find sustainable solutions to address agriculture price volatility for inclusive and sustainable growth. The fourth transition began right after the world health organization declared COVID-19 as a global pandemic on March 11, 2020. The resilient food systems (1) have now the centre of attention related to agriculture price volatility. The researchers were now concerned about food systems' ability to withstand and recover from disruptions to ensure a sufficient supply of acceptable and accessible food.

2.4 Conclusion

The multi-dimensional drivers of price volatility have been identified during the food crisis wave to provide an in-depth understanding of price irregularities and theoretical underpinnings for *GNFACs dimensions I and III* to address the food crisis. There was a clear paradigm shift in the adopted methodologies and data[bases] consulted. In selected studies, the dynamics of chaos and its detrimental impacts were ignored while addressing the issue of price volatility in agriculture. This approach raises a public policy concern about deciding whether to intervene in agriculture markets. The answers to such questions are possible if we assess the "realism" of theoretical models from volatile price series in agriculture while assessing uncertain situations like the food crisis. Without considering such a modelling framework, the result of the same model using different data frequencies (use of daily, weekly, monthly, etc. data) retrieved from various locations can be counterintuitive. This behaviour may be due to aggregation bias and regime-switching in volatile price series. The sole use of agriculture prices without incorporating quantities was another impediment while empirically analysing the stylized models. Huffaker (2015) had already provided a *pre-modelling data diagnostic framework (PMF)* to provide evidence of correspondence between models and the real-world based on nonlinear time-series analysis. This empirical scheme may validate results, *i.e.,* the magnitude, persistence, and degree of volatility across countries and sectors of the economy (energy *vs.* non-energy) during the unanticipated crisis period. In the present analysis, the various researchers gave overarching importance to cereals and side-lined other important sub-sectors, such as fruits, a major source of micronutrients — *pivotal to food and nutritional security*. This systematic review has shown waves of research paradigm shifts and their triggers for countering price volatility in agriculture. The current food crisis is more about supply disruption revolving around market imperfections. The recent global COVID-19 pandemic fostered the adoption of holistic approaches to create more resilient and sustainable food systems. The adoption of *PMF* before implementing stylized models may provide a way forward to inculcating price volatility dynamics and contemporary food crisis issues within future research outcomes.

Notes

1. During a food crisis wave, one can move from food secure to food insecure.
2. When developing a predictive model, reducing input variables reduces computation costs and improves the model's performance. For more details, see (Al-Tashi et al., 2020).
3. The prior research on price volatility in agriculture was available in books. For information, please read (Harwood et al., 1999; Winters & Sapsford, 1990).
4. These are also called economic or trade cycle models, related to fluctuations of gross domestic product around its long-term growth trend.
5. The hybrid models were constructed by combining two or more different modeling techniques/approaches. For more detail, please see (Fang et al., 2020)

Supplementary Materials: Appendix-A (additional information for Figure 2.5 and 2.7-2.8).

Chapter 3 Sugarcane Supply Response to Prices and Climate in a Monopsony Market[2]

Abstract

Farmers' decisions, practices, and land use planning are strongly affected by climate change resulting from trade-offs between government intervention and the market, especially in the developing world. The present study explores the supply responses for sugarcane growers, using a district-level panel dataset from 1981 to 2010 in a market context characterized by the monopsony power of sugar mills. The analysis confirmed that the farmers' decisions were erratic, contingent upon adjustments of cultivated land and inputs. The standard negative relationship between cultivated area and yield with technological advancement through the so-called *Borlaug hypothesis* cannot withhold in imperfect competition. Farm inputs, climate fluctuations, and price volatility further disrupt the sugarcane supply response. Finally, the lower yield responses were due to the imbalance use of fertilizer and distortion in agriculture incentives, which requires modern extension and agricultural advisory packages.

KEYWORDS

Post-Green Revolution; Supply Disruption; Sugarcane; Monopsony; Sugar Mills; Climate and Price Anomalies.

JEL CLASSIFICATION

Q11, Q13, Q16, Q18

[2] Present or later version of the chapter3 is ready to be submitted in a scientific journal as a separate publication.

Premise - Territorial aspects of Supply Chains

Multifaceted food security strongly connects with rising prices, the international environment, climate glitches, water availability, the energy crisis, and pro-poor agriculture growth issues. A massive country's population may face the burgeoning condition in nourishment directly or indirectly due to inconsistent and interconnected climate-induced price variability that further exacerbates food security (Mamoon & Ijaz, 2017). The post-emergence of the twenty-first century brings a vivid rise in major food and agricultural commodities prices domestically and internationally. Conclusively, prices of food and agricultural commodities characterized by price volatility resulted in serious challenges to market value chain actors such as consumers, producers, and investors. Climate change and price volatility have also influenced macroeconomic indicators and growth (Ismail et al., 2017).

The coupling effect (direct and indirect) of climate and price variability resulted in a state of food insecurity, which adversely affected crop production, influenced land allocation decisions, and remains a critical challenge to the world's poor today. The recent statistics from the Food and Agriculture organization (FAO) portray a grim situation in which every one in nine people in the world cannot meet their dietary energy requirements (Fróna et al., 2019). Although, domestic food production and associated rights play a major role in influencing various factors of food security. Among other things, marginalized farmers have restricted abilities to objectify risk through formal insurance mechanisms due to climatic irregularities (Antwi-Agyei et al., 2018) altering food security access and availability dimensions (Misselhorn et al., 2012). Furthermore, technical and production inefficiencies and lack of farm inputs under the changed climate scenario made natural resources and agriculture very sensitive to livelihoods, particularly in agro-based developing economies.

Marginalized farmers in developing countries face limited adaptive capacities due to poverty and reliance on climate-sensitive livelihoods, making them vulnerable to climate variability. According to UNDP 2016 statistics, 39% of households still live in poverty despite global progress. This is the case also in Pakistan, with disparities among provinces, divisions, and districts. Understanding the impact of climate-induced price variability on food security is crucial, but current impact studies focus separately on climate variability and price variability rather than their co-variation (Wossen et al., 2018).

Agriculture market instability impedes achieving the global goal of sustainable and resilient food systems. Currently, the support to producers reaches the mammoth *USD 540 billion* a year (15 percent of total agriculture production value) that requires a repurposing agricultural support strategy *(RASS)*, considering the market country-specific circumstances. These circumstances may vary with geographic locations, marketing structures, and product value chains. The fruit production system is crucial for *health-conscious consumers* and *profit-oriented producers* for food and nutritional security. Export is one of the main driving forces behind the expansion of the fruit sector, and during the year 2010-2018, trade significantly outpaced production increases. The previous literature states that *irregular and unpredictable behaviour* — *Chaos* — can arise from entirely rational economic decision-making within markets (Akın Ateş et al., 2022; Xi & Zhang, 2020). Different markets' direct/indirect linkages through trade create trade hubs, and uncertainty may function as an avenue to transmit adverse shocks and increase vulnerability rather than contribute to resilience. Therefore, separating *Chaos* into endogenous and exogenous behaviour patterns is crucial to create an effective RASS for resilient food systems and to comprehending global food crises.

A conceptual framework was developed that simultaneously covers the complex interactions of system components and risk transmission (**Figure 3.1**). To consider the adaptation measures capacity, we have selected three types of supply chain for fresh fruits retailing, *i.e.*, long, medium, and short supply chains (Badar et al., 2019; Loiseau et al., 2020; Negi & Anand, 2015). This supply chain varies concerning the number of actors involved, the quality of products, and varying levels of producers' support availability, *etc*.

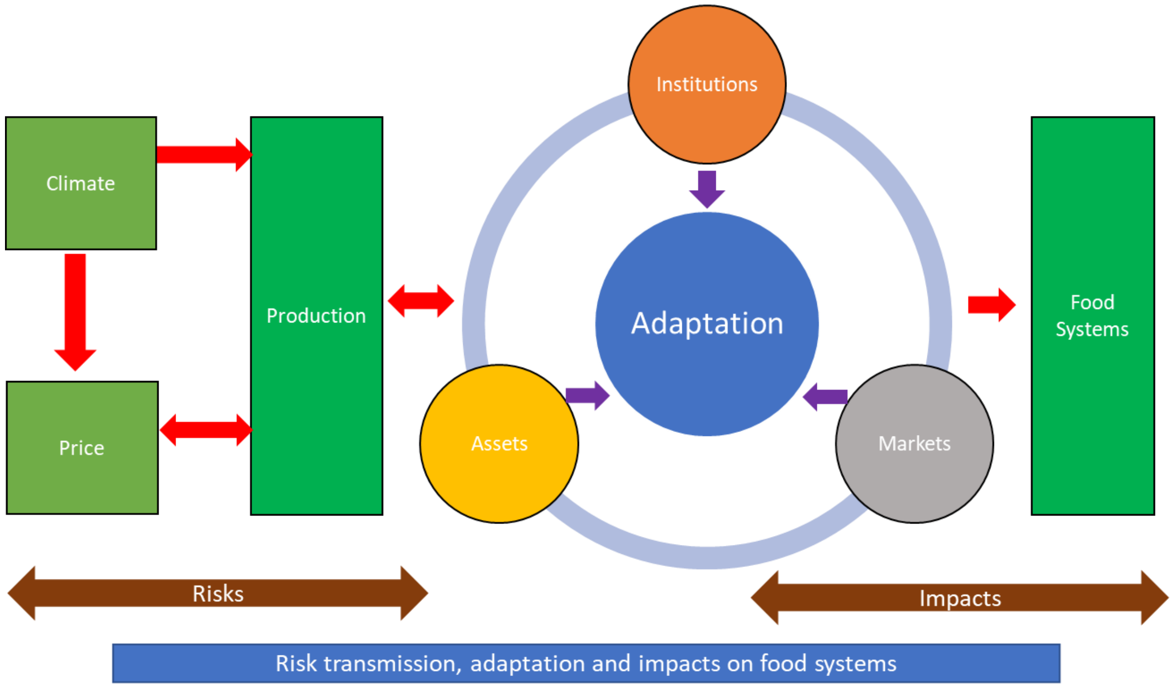

Figure 3.1: *Framework for risk transmission, adaptation, and impacts on the food system. (Adapted from Wossen et al., 2018).*

3.1. Introduction

Sugarcane accounts for 80% of global sugar production and provides a source of livelihood for around one hundred million people worldwide. The developing world accounts for about three-quarters of global sugar consumption (IISD 2020). Asia is one of the biggest sugarcane production regions (world rank) — India (2nd), China (3rd), and Pakistan (6th), with the home of *~4.5 billion people* (The World Bank, 2021). Among top sugarcane producers in Asia, Pakistan has the fastest annual population growth rate (1.9%), per capita sugar consumption (24.64 kg), and increasing trend of importing refined sugar (28,760 metric tons) with looming recurrent sugar crisis (Pakistan Sugar Mills Association, 2021).

According to the statistics, Pakistan has 980 thousand of sugarcane farmers cultivating approximately 1.2 million hectares of land. Its production of 81.01 million tonnes accounts for 3.4% of agriculture's added value and 0.7% of gross domestic product (GDP). The sugar industry (90 mills, out of which seventy-eight are functional) is the second-largest agriculture-based industry after textile. Sugarcane is used in several sectors, including pharmaceuticals, ethanol, bagasse for paper and chipboard manufacturing, and press mud – an organic fertilizer. The domestic market and processing were highly regulated, and the *zoning of sugar mills* was implemented. Since 1987, farmers must sell 80% of the sugarcane produced. The market entrance of new sugar mills is still highly regulated by law, and no other sugar mills can purchase sugarcane raw materials. According to the License Raj, this marketing structure creates a monopoly (Tol, 2011) for sugar by the millers (exclusive control over purchase) because of its perishable nature and transportation restriction in their zone (Aghion et al., 2008).

Previous studies have scarcely analysed the sugarcane supply response in Pakistan. Yaseen & Dronne (2011) have estimated the gross product per hectare cross-price elasticity of ten essential crops of Pakistan, including cotton, maize, rice, sugarcane, and wheat. Mushtaq & Dawson (2002) have computed the area response of cotton, rice, sugarcane, and wheat for Pakistan, incorporating seasonal rainfall as a non-price factor. Saddiq et al. (2013) were the only researchers who studied the sugarcane crop's area response to price and non-price factors (rainfall) in Khyber Pakhtunkhwa province.

Estimates of cultivated land and yield responsiveness to price and non-price factors have been mostly oriented to cereal or cash crops, considered essential for food safety, such as wheat (Bhatti et al., 2011; Farhan et al., 2019; M. N. Khan & Zaman, 2010; Qureshi, 1960; Waqas et al., 2019), and rice (Farooq et al., 2001; S. U. Khan et al., 2019; Nosheen et al., 2011; Shaikh & Shah, 2008). Siddiqui & Mahmood (1994) estimated total supply responses on the expected net income of maize, rice, and wheat in response to technological factors, including irrigated surfaces, improved varieties, and intensification programs. Ali (1990) included sugarcane in evaluating the production supply response of most important cash crops, but only in response to fertilizer price. Further, a synthesis by McKay et al. (1999) highlighted two shortcomings in these analyses: 1) they ignore the marketing structure of sugar mills and their monopsony power entirely while selecting the study area for their research, and 2) macro parameters are derived by averaging the corresponding microparameters (Wade et al., 2019).

The major concern is that the two issues can be strongly interrelated as the panel nature of supply response may determine a major difference between micro and macro behaviour (Wu & Adams, 2002). Each district has its microclimate, *i.e.*, temperature, soil characteristics, irrigation, specific variety, and marketing infrastructure, resulting in varying sugarcane production at scale. The aggregation of these parameters at a higher level (district to divisional or provincial) changed their distribution function, resulting in misrepresented macro-behaviour that leads to inconclusive and biased results (Allen & Rehbeck, 2021; Hannay & Payne, 2022).

To such a dynamic, climate change adds a long-term slow and gradual trend, together with a year-to-year variability. It is exceedingly difficult to capture climate change impacts without using a decadal scale. Studies on the responses of field crops to such gradual climate changes on a decadal scale are scarce. However, several researchers have already investigated the impacts of seasonal and interannual climate variability on crop production (Tao et al., 2006).

The price and non-price factors affect farm management in two ways: cropping pattern (cultivated area redistribution) and technology adjustment (inputs) (Gebremichael et al., 2021). The crop area redistribution was done under the fixed amount of cultivated land or additional lands acquired through backwoods invasion in some cases during the post-green revolution period. As farmers are considered profit maximisers (loss minimizers), they are supposed to search for a trade-off between crop area and crop yield based on information received on various price and non-price factors.

Furthermore, Pakistan is one of the areas on the globe where scattered farms are embedded in the backwoods, and farmers are allowed (to a certain extent) to expand the cropped surface bringing pristine agricultural land under cultivation by deforestation. According to the Borlaug hypothesis, in the case of technological advancement, there is a negative relationship between agricultural productivity (yield) and demand for new lands for cultivation (Rudel et al., 2009). The productivity from existing agricultural land saves natural ecosystems (including forests) from being converted to agriculture for *sustainable development* (Green et al., 2005). This outcome implies that an increase in yield response may offset the area response with improved technology in the economy under sustainable development and the converse. Crop area and yield jointly ensure the agriculture produce supply, control the prices, and bridge any crop's demand and supply gaps in the economy (Nkang et al., 2007). Price elasticity is used in several policy calculations to evaluate agriculture's demand/supply gap, including support price and buffer stock operations (Haile et al., 2016). The agriculture supply response is considered a crucial economic development issue in the developing world due to uncertain future food supply and historic food crises under changing climatic conditions. Technology is a key to improving agriculture productivity. Steensland (2020) suggests that R&D expenditure is a proxy for such technological innovation. We have interpreted the association of yield and area with the technological advancement in major sugarcane production hubs.

Improving resource use efficiency often results from improved *technical efficiency* of sugarcane farmers. Sugarcane farmers could get higher yields as they could shift their production on a higher production possibility curve with resource consumption and efficiency with improved technology. Traditionally, time trends capture other shocks due to institutional or unobservable factors (Magrini et al., 2018).

The present study is designed to estimate 1) critical price and non-price factors of sugarcane supply response and 2) the magnitude and speed of supply responsiveness in the short and long term.

Data have been formerly used to evaluate the Borlaug hypothesis based on the idea that "increasing crop yields can help to prevent cropland expansion and deforestation, thus alleviating hunger and poverty without dramatically increasing environmental impact." Therefore, the relationship between sugarcane yield and the cultivated area has been analysed. Subsequently, the sugarcane supply response was estimated with an improved methodology based on 1) using district-level data to enact the panel nature of sugarcane supply response, 2) district selection maintaining the zoning of sugar mills, and 3) district-based weather data.

The remainder of the chapter is organized as follows. The section 3.2 introduces the methodology, while the results are reported in section 3.3. The section 3.4 highlights the main findings and policy implications. We have interchangeably used sugarcane cultivated area, referred to as crop area or cultivated land, in the rest of the sections.

3.2. Materials & methods

The analysis encompasses two important procedures. a) We have analysed the yield ratio over cultivated land from 1981 to 2010 to assess the *Borlaug hypothesis* regarding technological advancement. This analysis will provide added information to know the behaviour of the farmers under prevailing climatic and marketing conditions. Later, b) the sugarcane supply response was estimated with an improved methodology based on 1) using district-level data to highlight the panel nature of sugarcane supply response, 2) district selection maintaining the zoning of sugar mills, and 3) district-based weather data.

3.2.1 Data

At provincial levels, sugarcane production accounts for 66% of Punjab, 26% of Sindh, and 8% of Khyber Pakhtunkhwa (KP). The empirical analysis is based on a *30-year* time series of repeated cross-section yearly survey data from twenty sugarcane-producing districts of Pakistan (for details, see the supplementary information - SI). The characteristics of sugarcane producers are reserved while *grouping* the farmers into similar district panels from 1951 to 2010. Several new districts emerge after 2010, and historic data for such districts' metrological observatories are unavailable. Therefore, the final sample was restricted until the year 2010. The selection of a sample district is based on *considering a)* a high sugarcane production district (>5% share in national sugarcane production) and represents the mutually exclusive cluster of sugar mills across Pakistan, *b)* the presence of meteorological observatories since the early 1960s, and *c)* selection of only those districts created in 1980-81 or earlier. Based on these *criteria*, nine selected districts are from Punjab, eight from Sindh, and three from KP from the selected districts.

The district-level data on variables such as area, yield, total macro-elements uptake (NPK nutrients), and prices of crops, *i.e.*, cotton, maize, rice, sugarcane, wheat, and fertilizers, *i.e., Di-ammonium phosphate (DAP)* was obtained from the *Pakistan Bureau of Statistics (PBS)*. The present study uses the research and development (R&D) expenditure collected from National Agricultural Research Centre, Islamabad, Pakistan, as a proxy for *technological development* in the national sugarcane research system (NSRS). As climatic variables, district-level temperature and precipitation data were obtained from *Pakistan Meteorological Department (PMD)*. The list of variables and data sources is reported in **Table 3.1**.

Table 3.1: *Detailed description of variables (sample 1981-2010).*

Variable	Description	Units (Estimation)	Sources
A	Cultivated area	(x 1000) hectares	Pakistan Bureau of Statistics, Islamabad
Y	Yield	ton/ha	
****Prices & costs***			
CP	Cotton	Pakistan rupees per 40 kg	
MP	Maize		
RP	Rice		
SP	**Sugarcane**		
WP	Wheat		
DAPP	Di-ammonium phosphate	Pakistan rupees per 50 kg	
Inputs			
TN	Total nutrients uptake	NPK in kg/hectares	National Fertilizer Development Centre, Islamabad
N	Nitrogen uptake	kg/hectares	
P	Phosphorus uptake		
K	Potassium uptake		
PK	Phosphorus /potassium ratio	Index	Own calculation
PNPK	Phosphorous, total ratio nutrients	Index	
PN	Phosphorus /nitrogen ratio	Index	
PIC	Irrigated area ratio	Index	
R&D	Research & Development expenditure	Millions Pak rupees	National Agriculture Research Centre, Islamabad
Climate			
Prec.	Average rainfall (30-year moving average)	mm	Pakistan Meteorological Department, Islamabad
Temp.	Average temperature (30-year moving average)	°C	
PG	Precipitation at germination	Average precipitation at sugarcane growth stages in mm	Own calculation
PT	Precipitation at tillering		
PGG	Precipitation at grand growth		
PM	Precipitation at maturity		
PS	Precipitation shocks	Index (Coefficient of variation)	
PSG	Precipitation shocks at germination		
PST	Precipitation shocks at tillering		
PSGG	Precipitation shocks at grand growth		
PSM	Precipitation shocks at maturity		
TG	Temperature at germination	Average temperature at sugarcane growth stages in °C	
TT	Temperature at tillering		
TGG	Temperature at grand growth		
TM	Temperature at maturity		
TS	Temperature shocks	Index (Coefficient of variation)	
TSG	Temperature shocks at germination		
TST	Temperature shocks at tillering		
TSGG	Temperature shocks at grand growth		
TSM	Temperature shocks at maturity		
PaDI	Pálfai drought index	Index	Jahangir & Danehkar, 2022

Notes: The real prices used before deflating nominal prices of crops and fertilizers with consumer price index (CPI) retrieved from the World Bank in actual model estimation. All the variables were used in logarithmic form except drought categories.

3.2.2 Construction of the Variables

Fertilizer is an essential input in crop supply response. As district-level fertilizer usage data is unavailable, estimates produced by the National Fertilizer Development Centre (NFDC) (NPK nutrients kg per hectare) on fertilizer uptake are used. Phosphatic fertilizers are expensive, and their application determines the plant's availability from soils (Aimen et al., 2022). We used only DAP prices as an essential input for crop supply response. All the crop and fertilizer prices were deflated with the consumer price index.

Precipitation and temperature are essential climatic variables while studying crop yield because of the high sensitivity to water availability and temperatures. Although mean values typically do not vary much during the sugarcane production season, optimal crop values change for each growth stage. Since we aim to see the impact of gradual change on the sugarcane supply response, rather than considering the annual weather variables values, we have computed a 30-year moving average series of climatic variables at each crop growth stage (He et al., 2020; Rezaei et al., 2018). Then, the climatic variables computed for the year 1981 are the average of the previous 30 years, and so on (Reusen et al., 2019; van der Wiel & Bintanja, 2021).

The present study used a decadal time step to explore the nexus between supply response and climate change. We have computed climatic variables, *e.g.,* precipitation and temperature, concerning each growth stage of the sugarcane crop for the present study.

The impact of climate change (mean effects) is incomplete without modelling the influence of climate variability and extreme events (implication of range). These two can provide the shape and distribution of the climate variables (Thornton et al., 2014). Hence, the present study used climate shocks (climate anomalies) to quantify their impacts on the sugarcane supply response, given by the coefficients of variation from the monthly mean of precipitation and temperature, also computed at each crop development stage a (Table SI-I) *(see details on phenological observations in supplementary material).*

Sugarcane is a drought-sensitive crop; therefore, a frequency increase of extreme events, such as heat stress and floods, may negatively impact the crop. Sugarcane is a high delta crop, and drought is considered a critical indicator of the area/yield responsiveness (Asghar et al., 2022; Shehzad et al., 2022). Pálfai drought index (PaDI) was computed (Jahangir & Danehkar, 2022) for all the selected districts to capture the impact of extreme events on the sugarcane supply response.

$$PaDI_0 = \frac{\left[\sum_{i=apr}^{aug} T_i\right]/5 * 100}{c + \sum_{i=oct}^{sep} (P_i * w_i)} \tag{2.1}$$

Where:

$PaDI_0$ = base-value of drought index (°C/100 mm)

T_i = monthly mean temperature from April to August (°C)

P_i = monthly sum of precipitation from October to September (mm)

w_i = weighting factor

c = constant value (10 mm).

3.2.3 Method of analysis

To estimate the magnitude and speed of adjustments in the response of cultivated land and yield to exogenous factors, a commonly reduced form of the Nerlovian model has been used (Ngoc et al., 2022). Equations 2.2 and 2.3 describe the current level of cultivated land and yield as determined by the previous year's expected values (cultivated land and yield, respectively, $it - 1$).

$$A'_{it} = a_0 + a_1 P'_{it-1} + a_2 Z'_{it} + a_3 A'_{it-1} + \mu_{it} \quad (2.2)$$

$$Y'_{it} = \beta_0 + \beta_1 P'_{it-1} + \beta_2 Z'_{it} + \beta_3 Y'_{it-1} + \vartheta_{it} \quad (2.3)$$

Where A is cultivated land (ha), Y yield (tons/ha), P is the price of produce and fertilizers (cost), and Z includes every exogenous variable (non-price factors). The models also include an offset parameter (a_0,β_0) and a noise component (μ_{it},ϑ_{it}). Parameters a_1,a_2,a_3 for cultivated land equation, and β_1, β_2, β_3 for yield, represent short-term elasticities *(percentage rate of change)* to price and non-price factors, respectively.

All the variables are used in the logarithmic form (e.g., $A' = \log A$); therefore, the total supply elasticities (A + Y) are obtained by adding area and yield elasticities. If the elasticity of area (yield) is greater than one (elastic), the sugarcane farmers quickly adjust their area (yield) to correspond to the price and non-price changes and the converse. All long-term elasticities are greater than the short-term elasticities assumed in this model (Tenaye, 2020).

The estimated coefficients of each explanatory variable represent short-term elasticities, while long-term elasticities can be obtained by dividing short-term elasticities by (1-a_3) for the area and (1-β_3) for yield, respectively: the coefficient of lagged dependent variables in the area and yield response equations (a_3, β_3), called the adjustment coefficient in the reduced form distributed lag model (Y. Wang et al., 2020).

The present study hypotheses that the sugarcane farmers are rationally efficient (Liu et al., 2016b), and all long-term elasticities exceed the short-term elasticities in this model. The farmers quickly adjust their actual cultivated land level to the desired level if the adjustment coefficient is close to one and the converse. The future price will be adjusted to the difference between the previous and next year's levels based on average "normal" price levels rather than the price forecast. For example, farmers always refer to the past year (previous year) prices and adjust differences with their decision based on the current year (next year) prices instead of using the forecasted prices. There is no forecast price data available to these farmers.

Including lagged cultivated land and input and output price variables as independent variables in the supply response models may create an endogeneity problem. In addition, the presence of lagged dependent variables also gives rise to auto-correlation. Appropriately, these inherited issues must be addressed in such a dynamic panel data model. To overcome such issues, the *generalized two-step* *method of moments (GMM) with variable instrumental technique* is used to compute area and yield response estimates to ensure robust homoscedasticity and autocorrelation consistency.

3.3. Results and discussions

3.3.1 Descriptive analysis

Data collected on sugarcane crops from 1981 to 2010 show that Punjab has the highest surface, ≈57,000 ha, while Sindh ranks second with ≈41,000 ha. However, the farmers' allocation decisions result in significant variations in sugarcane cultivated areas in Sindh than in the other two provinces (**Table 3.2**). This dynamic has been ascribed to increased sugar mill installation and a favourable environment for sugarcane cultivation during this period (Khushk et al., 2011). Similar trends of higher variation were also observed in the average sugarcane yield in Sindh and Punjab.

There is a skewed distribution of funding in NSRS, where the highest R&D expenditure was spent in Punjab (≈14 million) compared to KP (0.20 million) from 1981 to 2010. This imperfect fund allocation in provinces may result in indifferent impacts on sugarcane supply response while modelling the R&D variable in panel settings.

The climatic variables' descriptive analysis reveals the highest annual and monthly mean of precipitation and temperature reported in KP (41 mm) and Sindh (28 °C) provinces, respectively. This average temperature is 1°C above the optimal value (27 °C level for maximum sugarcane production). However, the optimum temperature values vary throughout the sugarcane crop cycle (Ebrahim et al., 1998). For climate variability (Chen & Chang, 2005), in rainfall and temperature, the result highlighted the highest variability (deviations from the long-term mean) in KP (12 points) and Sindh (5 points), respectively. In terms of shocks (coefficient of variation), on the contrary, precipitation and temperature variability is higher in Sindh (125%) than in KP (40%). These variabilities are also computed for each growth stage in final response models (**Table A.4**).

A severe drought-like situation has been observed in Punjab compared to Sindh (moderate drought) and KP (mild drought) within sugarcane-producing districts. This situation is another reason for the high natural potential of KP to produce sugarcane comparable with Punjab. Further details can be accessed in the SI.

Table 3.2: *Descriptive statistics of variables (sample 1981-2010).*

Variable	**Mean (± SD)**		
	KP.	**Punjab**	**Sindh**
A	30.03 (18.17)	57.27 (32.72)	40.51 (39.78)
Y	41.85 (6.77)	42.32 (6.92)	46.67 (13.44)
TN	582.65 (452.02)	913.36 (1533.25)	1341.98 (986.64)
CP	851.75 (288.77)	851.75 (288.15)	851.75 (288.25)
MP	315.83 (87.69)	316.60 (82.37)	319.93 (79.56)
RP	672.45 (714.05)	672.45 (710.05)	672.45 (710.30)
SP	45.66 (28.33)	45.30 (28.03)	46.07 (28.31)
WP	391.70 (277.26)	391.70 (275.70)	391.70 (275.80)
DAPP	869.23 (645.00)	869.23 (641.39)	869.23 (641.61)
PaDI	4.83 (2.02)	11.02 (6.04)	6.74 (6.91)
PS	7.00 (1.41)	6.86 (3.00)	5.52 (2.39)
TS	1.99 (0.59)	2.59 (0.25)	3.05 (0.51)
PIC	1.16 (0.44)	0.94 (0.35)	0.70 (0.31)
PK.	54.76 (68.16)	38.65 (69.05)	24.31 (20.72)
PNPK	0.19 (0.06)	0.18 (0.05)	0.18 (0.04)
PN	0.24 (0.11)	0.229 (0.08)	0.24 (0.12)
Prec.	40.95 (13.72)	34.76 (18.43)	15.54 (8.60)
Temp.	22.33 (2.28)	25.65 (1.56)	27.51 (1.21)
R&D	0.20 (0.23)	14.20 (10.91)	2.04 (3.00)

Notes: The total nutrients were estimated from N, P, and K uptakes. The average values of climatic variables (temperature and precipitation) were reported here. Their interactions and other climatic variables to crop phenology were omitted for simplification.

3.3.2 Area and yield relationship

The behaviour of sugarcane growers is represented through their area allocation decisions (**Figure 3.2**). The result shows that farmers' decision is erratic depending on additional land and input resources. There is a total of 8 out of 20 districts in which sugarcane-cultivated land has grown significantly **—** R^2 of linear trend (cultivated land ~ year) ranging from 0.79 to 0.22. These cropland increases result from re-adjustment in cropping patterns or backwoods of new land invasion, especially in the D. I. Khan district of Khyber Pakhtunkhwa. Recent studies also support our results as they reported a higher deforestation rate in the D.I. Khan district (Hussain & Khan, 2021).

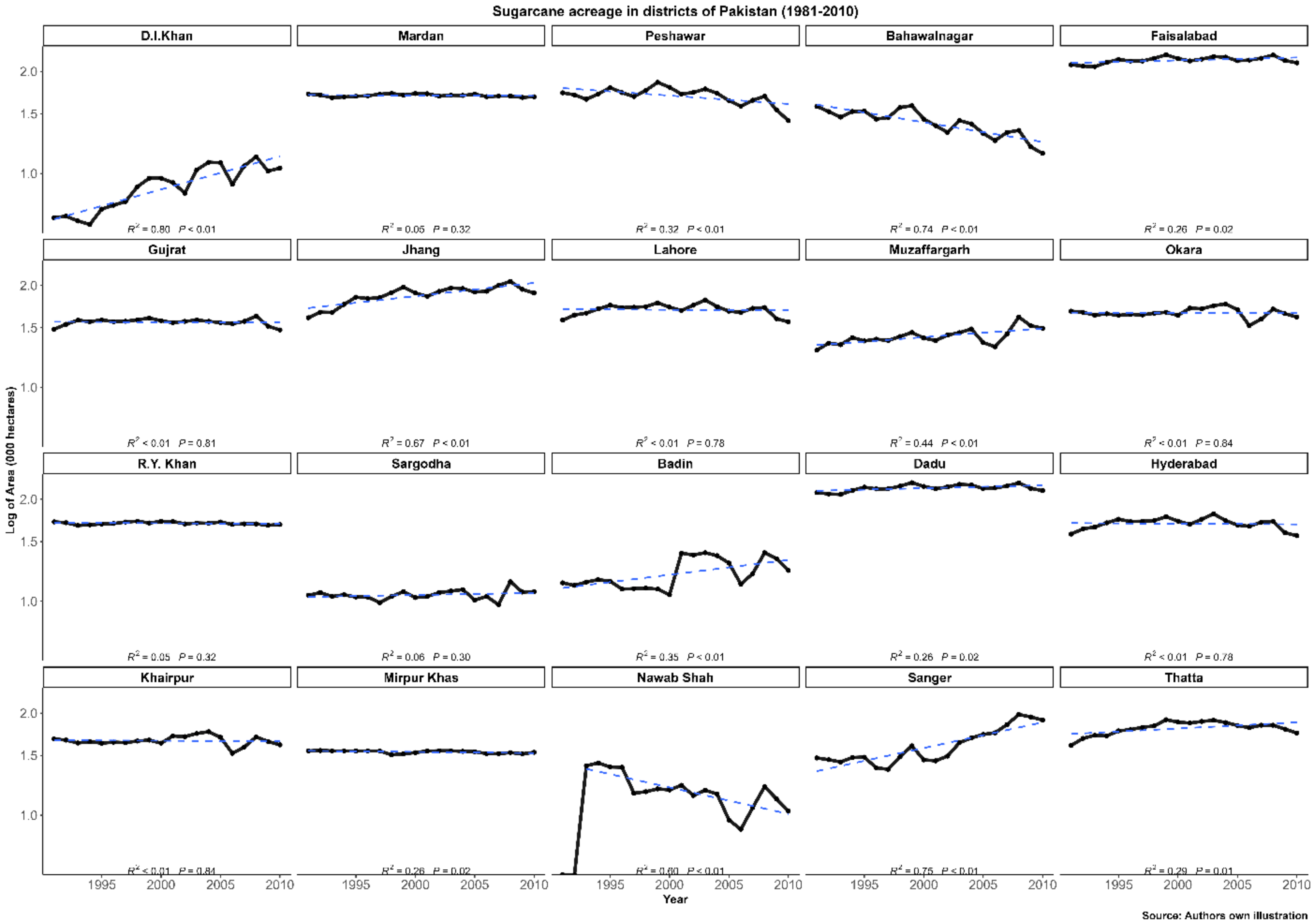

Figure 3.2: *Sugarcane cultivated land from 1981-2010 by the district.*
Note ***Khyber Pakhtunkhwa*** *(D. I. Khan, Mardan, and Peshawar);* ***Punjab*** *(Bahawalnagar, Faisalabad, Gujrat, Jhang, Lahore, Muzaffargarh, Okara, R. Y. Khan, and Sargodha);* ***Sindh*** *(Badin, Dadu, Hyderabad, Khairpur, Mirpur Khas, Nawab Shah, Sanger, and Thatta). District Nawab Shah was renamed district Shaheed Benazirabad in the year 2008.*

In the Bahawalnagar district, Punjab farmers exchanged land for other profitable crops like rice, resulting in a drastic decrease in sugarcane land. Considering the cropping patterns changes, the Government of Punjab established Rice Research Station at Bahawalnagar in 2012 (https://aari.punjab.gov.pk/rrs_bahawalnagar). In the rest of the districts, abrupt changes in sugarcane-cultivated areas are not observed.

Borlaug hypothesis - The relationship between area and yield is vital to know the impact of technological advancement during the year. With improved technology, farmers improved their resource use efficiency to increase the overall yield. Alternatively, farmers were trying to increase cultivated area either from the redistribution of cropland or through deforestation. With improved technology, the standard relationship between yield and cultivated land is believed to be negative (ratios positive).

No uniform relationship was observed within districts (**Figure 3.3**), and only a few shows a marked relation between A and Y (in terms of Y/A ratio).

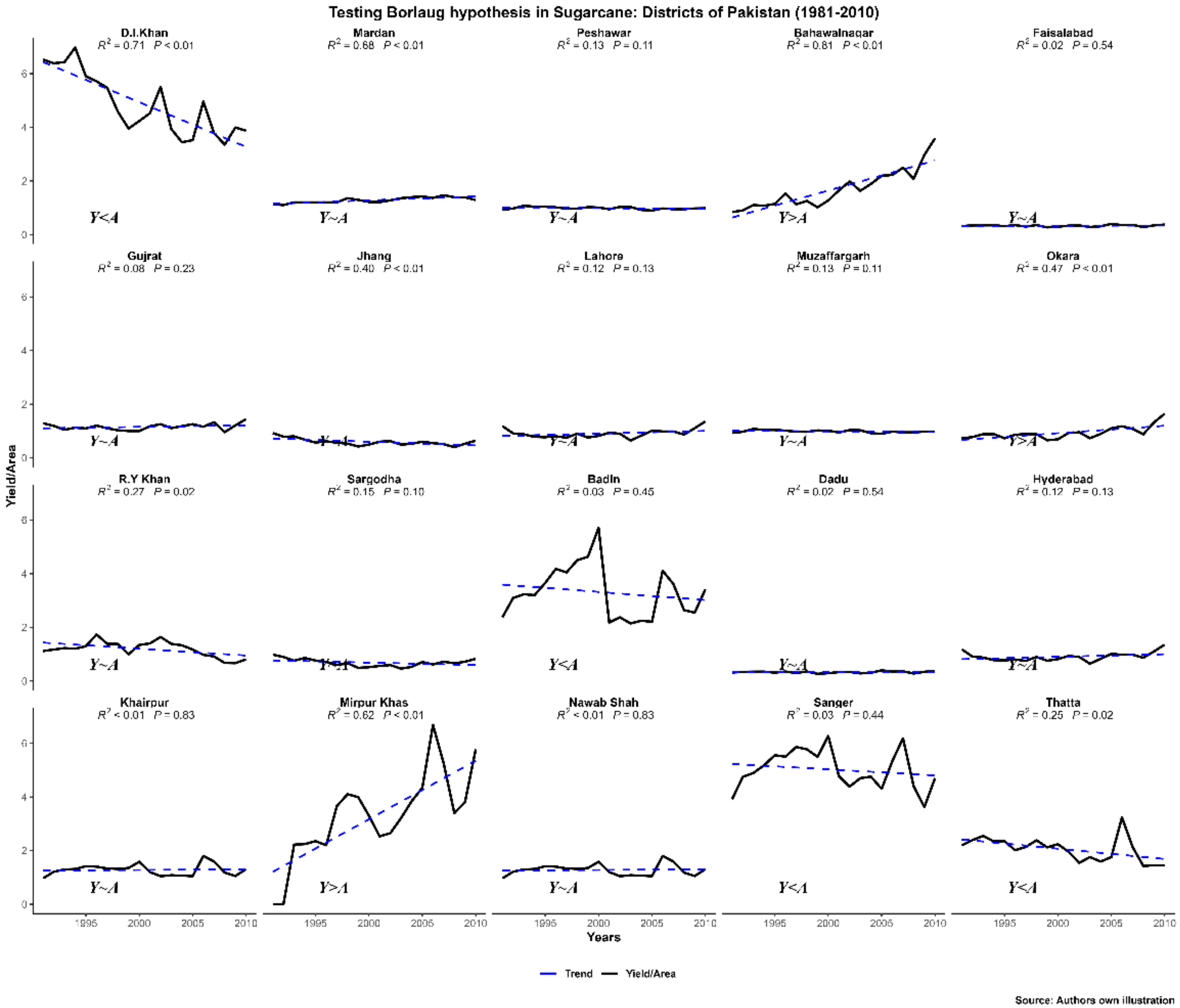

Figure 3.3: *Ratios of yield/ cultivated land during the period 1981-2010 by the district.*
Note ***Khyber Pakhtunkhwa*** *(D. I. Khan, Mardan, and Peshawar);* ***Punjab*** *(Bahawalnagar, Faisalabad, Gujrat, Jhang, Lahore, Muzaffargarh, Okara, R. Y. Khan, and Sargodha);* ***Sindh*** *(Badin, Dadu, Hyderabad, Khairpur, Mirpur Khas, Nawab Shah, Sanger, and Thatta).*

The negative (extensification as area augmentation) and positive (intensification as yield augmentation) relationships between yield and area were reported in six districts, and only three of them have a high R^2; 0.81 in Bahawalnagar, 0.62 in Mirpur Khas, for intensification and 0.71 in D. I. Khan district for extensification. In this last case, the statistically robust negative trend proves our previous findings of strong area augmentation due to higher deforestation. These yield results over cultivated area relationships over time also provide an opportunity to understand the nature of the agriculture/environment nexus. The farmers are making quick adjustments in area allocation and optimization of farm inputs as mitigation and adaptation strategies to offset the negative impacts of climate change.

The paradoxical response of sugarcane farmers is due to the speculative behaviour emerging from persistent higher cane sugar prices in Pakistan, resulting in sugarcane area extensification instead of yield intensification. In other words, farmers are trapped in an induced *Jevons paradox* (York & McGee, 2016). With improved technology, farmers are not opting for higher productivity led by enhanced resource use efficiency with the same parcel of land; instead, they overexploit the resources. The result confirms that the *Borlaug hypothesis does not hold, as the higher sugarcane production* was achieved due to *horizontal expansion* (crop redistribution) of the sugarcane cultivated area from 1981 to 2010. The sugarcane farmers often adjusted the land based on price expectations. These decisions were frequently changing, at least for one whole crop cycle. Past crop prices and future expectations were adjusted in the following crop calendar.

3.3.3 Model interpretation

The second part of the analysis aims to know the magnitude and speed of adjustment of area and yield response of sugarcane crops. The results of the model (eq.2.2-2.3) are provided in **Table 3.3**.

Table 3.3: *Area and yield response of sugarcane, Pakistan (1981-2010): Two-step GMM.*

Variables	**Area Response (000 hectares)**	**Yield Response (Tonnes per hectare)**	**Variables**	**Area Response (000 hectares)**	**Yield Response (Tonnes per hectare)**
	β (SE)	***β (SE)***		***β (SE)***	***β (SE)***
R&D	0.014	-0.127^{**}	***A (t-1)***	0.936^{***}	-
	(0.017)	(0.072)		(0.020)	
PIC	0.050^{**}	-0.084	***Y (t-1)***	-	0.565^{***}
	(0.026)	(0.094)			(0.062)
PK	-0.016^{*}	-0.016	***PN***	0.250^{*}	0.270
	(0.009)	(0.019)		(0.143)	(0.538)
TT	-0.465^{**}	0.257	***PNPK***	-0.193^{*}	-0.230
	(0.192)	(0.792)		(0.106)	(0.398)
TGG	0.837^{***}	-0.594	***Constant***	-0.339^{***}	0.146
	(0.292)	(0.975)		(0.120)	(0.317)
TM	-0.435^{*}	0.509	***PT^2***	0.202^{***}	0.059
	(0.227)	(0.825)		(0.069)	(0.142)
PSGG	0.387^{***}	-0.859	***TGG^2***	0.081^{*}	-0.180
	(0.115)	(0.624)		(0.048)	(0.132)
PSM	0.506^{**}	-0.216	***TSG***	-0.302^{*}	0.346
	(0.222)	(0.506)		(0.174)	(0.760)
TG x PG	-0.148	0.934^{*}	***TST***	0.107^{**}	0.016
	(0.218)	(0.560)		(0.051)	(0.131)
TT x PT	0.135^{*}	-0.068	***CP***	0.090^{**}	0.360^{***}
	(0.076)	(0.253)		(0.039)	(0.117)
TGG x PGG	0.102^{**}	-0.247^{**}	***RP***	0.140^{***}	-0.006
	(0.049)	(0.109)		(0.043)	(0.156)
DAPP	-0.085	-0.285**	***SP***	-0.264^{***}	-0.013
	(0.052)	(0.142)		(0.076)	(0.181)
DAPP x CP	-0.133^{**}	-0.661^{***}	***DAP x SP***	0.225^{***}	0.467^{**}
	(0.058)	(0.208)		(0.082)	(0.235)
DAPP x RP	-0.286^{***}	-0.330^{**}	***DAP x WP***	0.126	0.420^{*}
	(0.067)	(0.163)		(0.113)	(0.246)

	Area	***Yield***
Observations	380	380
Under identification test		
Kleibergen-Paap rk LM statistic	*42.912^{***}*	*55.735^{***}*
Weak identification test		
Cragg-Donald Wald F statistic	*1742.677^{NS}*	*1696.233^{NS}*
Overidentification test		
Hansen J statistic (p-value)	*0.237*	*0.409*
F-test for joint significance (p-value)	*0.000*	*0.000*

*Note: All variables standardize before deflating all price series (crop and fertilizer) with the consumer price index. Statistics are robust to heteroskedasticity and autocorrelation. Coefficients are two-step system-GMM estimates with the lagged dependent variable and price variables treated as predetermined. Starts *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively, while N.S. represents no significant coefficients.*

The validity of the estimated effects is supported by various diagnostic tests: under-identification, weak identification, and Hansen test(s) for the over-identification of restrictions. Unobserved heterogeneity was also controlled using panel data sets.

The GMM estimator is consistent only if these estimates validate their instruments (including and excluding). The *Kleibergen-Paap statistic* was significant and rejected the probability of under-identification (*p-value <0.05*). The *Cragg-Donald Wald* test for weak identification proved that the higher F statistic (1742.677) does not fall in critical values and rejects the possibility of weak identification in our area and yield response models. The *Hansen J-statistics* (*p-value* >0.05) show that our model is valid as there is no problem of over-identification present. All these tests indicated the consistency of the GMM estimators.

The lagged coefficient of the area (0.94) is higher than the yield (0.57) response model in line with the outcome of the previous section. The higher sugarcane production is due to farmers' greater *horizontal expansion*, ascribed to decisions taken under the influence of the monopsony of sugar mills.

The adjustment coefficient measures the magnitude and speed of changes in the actual and desired area level (yield). It is computed by *one minus the lagged dependent variable*. The value of the yield (area) adjustment coefficient is lower than < 0.5, indicating that sugarcane farmers have a low elasticity in adjusting desired yield (area) levels. However, the sugarcane farmers are making 43% and 6% adjustments to variation in yield and area within a year. The current pace of farmers' decisions can bring back yield to equilibrium in almost *27 months (≈2.3 years) in case of an unexpected price shock and non-price factors* (equation 2.3).

The nexus of sugarcane supply response and climate change is addressed through *linear and nonlinear parameterization* of climatic variables. A pronounced (nonlinear) impact of precipitation at the tillering stage resulted in a 0.20% increase (≈200 additional hectares) in the sugarcane cultivated area. The optimal rainfall is also crucial for a higher number of tillers and enhanced sugarcane yield (Vasantha et al., 2012). The long-term impact of precipitation on area (yield) response was not robust in other crop stages. Rainfall alone cannot influence sugarcane's supply (area combined to yield) response.

These impacts are more pronounced with an increasing/decreasing temperature trend during the sugarcane crop cycle. The sugarcane farmers were more area responsive to the linear changes in temperature than to its nonlinear fluctuations. About *470 hectares increase* is reported in sugarcane land due to *a one percent* increase in temperature at tillering stage from 1981 to 2010. The temperature at the grand growth stage behaves *parabolically, as described by the significant square terms in the model.* Short-term elasticity varies from 0.08 to 0.84%, influencing the cultivated area of the sugarcane crop. The temperature increases linearly at the maturity stage and has a significant negative -0.44% short-term elasticity (de Medeiros Silva et al., 2019).

If the temperature increases, there is a reported statistically significant declining trend of *440 hectares* in the cultivated area of sugarcane crops. The average temperature during this stage in our sampling framework was 25 °C, well above the optimum level. In contrast, the optimum temperature for sucrose accumulation lies between 12 and 14 °C at the maturity stage (Verma et al., 2019). This gap is the probable reason for the lower area response found in the present study.

The shocks in precipitation at the last two stages of the crop, *i.e.*, grand growth (0.39%) and maturity (0.51%), resulted in positive shifts in area response only, as reported in a combined 900 hectares increase in allocation of sugarcane area by the farmers. Whereas the climate shocks in temperature have more pronounced robust effects at the first two stages of the crop. However, the short-term elasticities move opposite: at germination (-0.30%) and tillering (0.11%). The temperature is already exceeding its optimum level compared to precipitation. Therefore, temperature shocks further exacerbate the sugarcane supply response in Pakistan compared to precipitation extremes.

The combined effects of precipitation and temperature were also considered while estimating the sugarcane supply response. Previously, we have discussed that the rains are not influencing the area and yield of the sugarcane crop alone. However, once we have modelled precipitation in combination with temperature, their impacts are more visible at various stages of the crop. Both response equations have an opposite sign for combined precipitation and temperature elasticity at the germination stage: yield (0.93%) is higher than the area (-0.15%) response. All the statistically significant results of yield response are stronger than the area response, proving our hypothesis of a higher yield response.

In previous studies, researchers have modelled technological advancement as ad-hoc fashioned while incorporating time trends as a proxy for technological advancement in their estimates (Fulginiti & Perrin, 1993). Technology does not constantly increase, raising the question of validating previously computed results. In the present study, we have used the actual R&D expenditure to quantify their impacts on area and yield responses. Our results show that R&D significantly and adversely affects yield response with -0.13% short-term elasticity, while its impact on area response is insignificant. These results show the presence of uncertainty in R&D and the cane sugar market under the monopsony of sugar mills (Mai & Lin, 2021).

In contrast, farm inputs, *i.e.*, availability of fertilizers, improved seeds, and pesticides, are the only variable inputs whose application can adjust to policy incentives in the short term. Nevertheless, the higher short-term elasticities may also depend upon the balanced use of fertilizers. Three fertilizer nutrients are essential, 1) nitrogen for influencing the yield and quality of cane; 2) phosphorous, which is related to an increase in tiller production, weight per cane, and final stalk population; and 3) potassium, which positively affects cane volume, girth, and weight per cane, drought and disease resistance and reduced lodging (Gopalasundaram et al., 2012). All the fertilizer indexes were insignificant (imbalance use of fertilizers), contributing to low R&D elasticity and delayed adjustments in yield response. The short-term elasticity of phosphorus/nitrogen was 0.25%, resulting in a higher area response than phosphorus/potassium (-0.02%) and phosphorus/total nutrients uptake (-0.19%), leading to decreasing sugarcane area response. This result shows that the imbalance of fertilizer use arises from the potassium nutrient uptake, which may reduce the area for the sugarcane crop. These imbalances are due to the importation of potassium nutrient source fertilizer, lack of subsidies, and increasing prices in Pakistan (Ali et al., 2016).

The announcement of crop support prices and subsidies on farm inputs are essential pillars of effective agriculture policy to ensure the country's food security and crop supply (Kennedy et al., 2020). Crop and fertilizer prices are deflated with the consumer price index, and it is assumed that sugarcane farmers were adjusting their area (yield) to the real price changes.

According to economic theory, complementary crops have a positive response and converse (Fabio Gaetano Santeramo, Di Gioia, et al., 2021). The analysis of support prices of produce alone suggests that the cotton crop's price has a significantly positive short-term area (0.09%) and yield (0.36%) elasticities. There is little possibility for the sugarcane farmers to adjust their cultivated area, especially for conventional cotton cultivation, due to its sowing time – *overlapping with sugarcane sowing starting in mid–February* – compared with Bt. Cotton (*genetically engineered cotton variety*) in Pakistan. The yield response for the cotton price was higher as sugarcane farmers could have higher profits in September from conventional cotton harvesting. The farmers can purchase inputs for the sugarcane crop on time, just before the maturity stage of the sugarcane crop. Rice has also worked as a complementary crop as its price brings about a 0.14% increase in the area allocation of the sugarcane crop. These results can only be possible if rice harvesting coincides with the harvesting of sugarcane crops and the unavailability of more inputs to sugarcane. The short-term elasticity of rice price is negative in the yield response equation, and the crop calendar for rice shows that its harvesting overlaps with the harvesting of the sugarcane crop. Therefore, sugarcane farmers adjusted 14% in their actual area level for a brief period.

The sugarcane support price is inefficient for improving Pakistan's area and yield supply response under a monopsony marketing structure. The relationship between sugarcane price and area (yield) is negative. This outcome violates standard production theory (Yu et al., 2012). The result shows that sugarcane farmers reallocate only ¼ of their desired level within a year as their own price elasticity is -0.26%. The sugar mill owners often paid late or less than the announced support price. These adjustments are further exacerbated by increased fertilizer (DAP) prices and an additional 0.09% area reduced by sugarcane farmers in the short term. The impacts of increased DAP prices are more pronounced in yield response, as ≈30% reduction accounted for such price surges.

The two instruments of agriculture policy are modelled together while incorporating an interaction term of all the crops with DAP prices in monopsony settings. The results were consistent with standard production theory. The combined increase in cotton price with DAP prices resulted in a 0.13% and 0.66% reduction in area and yield. The yield decline was higher than the area due to the financial constraint faced by sugarcane farmers in the whole enterprise mix – more physical and financial resources exhausted by the cotton crop and an increase in cotton price, offset by the increase in DAP prices. The mutual effect of rice prices with DAP prices has a similar negative impact on the area (0.29%) and yield (0.33%) of the sugarcane crop. The area difference and yield reduction between cotton and rice were (+0.16%) and (-0.33%). These differences are significant sources of price fluctuation in Pakistan between the two crops.

3.3.4 Price elasticity and non-price factors

The short-term and long-term supply (area and yield) elasticity of the sugarcane crop are reported in **Table 3.4** (*α1-α3* and *β1-β3* from eq. 2.2 and 2.3). For the area, the price of rice and wheat have positive short-term elasticities, while maize and sugarcane prices have negative values. Overall, the short-term elasticities of price and non-price factors for area response are inelastic except for precipitation and temperature at the grand growth stage $\beta<0.50$.

Table 3.4: *Short- and long-term supply elasticities of sugarcane, Pakistan (1981-2010).*

Variables	**Short term**			**Long term**		
	Area	**Yield**	**Supply**	**Area**	**Yield**	**Supply**
CP	-0.133**	0.360***	0.227	1.397*	0.827***	2.224
RP	0.140***	-0.006	0.134	2.181***	-0.014	2.167
MP	-0.004	-0.051	-0.055	-0.057	-0.117	-0.174
SP	-0.264***	-0.013	-0.277	-4.117***	-0.029	-4.146
WP	0.144	0.041	0.185	2.248	0.093	2.341
DAPP	-0.085	-0.285**	-0.370	-1.327	-0.655	-1.982
Average	***-0.034***	***0.008***	***-0.026***	***0.054***	***0.018***	***0.072***
PG	0.005	0.214	0.219	0.075	0.493	0.568
PT	-0.099	-0.274	-0.373	-1.538	-0.630	-2.168
PGG	-0.608	0.839	0.231	-9.480	1.928	-7.552
PM	-0.358	0.336	-0.022	-5.587	0.771	-4.816
TG	0.463	-0.671	-0.208	7.216	-1.542	5.674
TT	-0.465**	0.257	-0.208	-7.248***	0.591	-6.657
TGG	0.837***	-0.594	0.243	13.054***	-1.366	11.688
TM	-0.435*	0.509	0.074	-6.783*	1.170	-5.613
Average	***-0.083***	***0.077***	***-0.006***	***-1.286***	***0.177***	***-1.110***

*Note: The long-term supply elasticities were calculated by dividing short-term elasticities with ($1-\beta_3$). Starts *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively, while N.S. represents no significant coefficients.*

Regarding yield response, four non-price factors, *i.e.*, precipitation at grand growth (0.84%) and temperature at germination (-0.67%), grand growth (-0.59%), and maturity (0.51%) stages, show higher short-term elasticities. In the short term, the average supply response of all price factors (average crop and DAP) and non-price factors (average precipitation and temperature) is -0.03% and -0.01%, respectively. Overall, the influence of prices brings positive changes in the supply response of the sugarcane crop, where a one percent average price increase may increase the supply response by 0.07% in the long term. The non-price factors, *e.g.*, precipitation and temperature, have negative long-term average elasticities. This outcome confirms that the average non-price supply response was higher than price responses.

3.4. Discussion & conclusions

The agricultural-pricing policy is the most effective tool to ensure crop production and food security in the developing world. Farmers are responsive to various price and non-price factors from effective agriculture policy to adjust farmland use. The previous findings on sugarcane cultivated land and yield response due to price and non-price factors vary due to the failure to incorporate important non-price factors like temperature and precipitation. The sign of the sugarcane's own price elasticities for cultivated land was positive when important non-price factors were not considered. In Pakistan, the inconsistent and abrupt changes in agriculture policy resulted in sugar mills' prevailing monopsonic market. During the study period, the sugarcane farmers switched abruptly between yield and area augmentation to find an optimal farm mix and maximize (minimize) their profit (cost).

The present study is designed to revisit the sugarcane supply response to the climate change nexus under monopsony structures of sugar mills in Pakistan. These responses are evaluated in two stages. Firstly, the *Borlaug hypothesis* was assessed initially to confirm the intuition about the relationship between yield and cultivated area of sugarcane crops with technological advancement. Secondly, the magnitude and speed of area (yield) adjustments to various price and non-price factors were computed, the latter including those factors allowing us to estimate the effects of climate change. These yield results over cultivated area relationships over time also provide an opportunity to understand the nature of the agriculture/environment nexus.

The robustness of these results may further enhance using accurate statistics on labour engaged in sugarcane crops, soil fertility status, and data on frost — crucial climatic factors influencing the seed quality, plant, and leaf growth. Recently, the Food and Agricultural Organization of the United Nations implemented a United States Department of Agriculture-funded project where they developed soil fertility atlases for all the provinces of Pakistan. These statistics should be maintained at regular intervals.

The study results show that the *Borlaug hypothesis* does not hold in the absence of perfect competition (specifically, in a monopsonist market regime), and the sugarcane farmers were trapped in the *Jevons paradox* with the increased technological advancement. The sugarcane farmers could not obtain endless benefits of growing technology and often made quick adjustments in their desired level of area (yield) responses.

The adjustment coefficient of yield response shows that sugarcane farmers are quickly adjusting their desired yield level compared to the area within a year. The rigidity of area response is due to two factors: 1) the long sugarcane crop cycle, *i.e., 9*-11 months, and even more if farmers were interested in other crops (e.g., ratooning); 2) the reduced possibility of land-use adjustments because of the mill's payment policy, whose delay prevents them from investing in other crops.

Climate change undoubtedly influences the sugarcane supply response in which both climatic variables, *i.e.*, precipitation and temperature, have profound, significant combined impacts. The specific effect of temperature is more visible in the sugarcane area response than yield response, and temperature shows a rising trend at the maturity stage. It results in a low recovery of sugar content from sugarcane. Climate shocks in precipitation are frequent and show positive impacts on cultivated land response, especially at the last two stages of the sugarcane crop cycle. In the event of climate extremes in temperature at the germination stage of the crop, the farmers quickly reduce their desired cultivated land level by 0.30% (≈ 300 hectares decrease in sugarcane cultivated land) with a one percent increase above the mean temperature. These adjustments in area and yield resulted in counterintuitive outcomes, which is why *the Borlaug hypothesis is* unattended.

The *sugar market and R&D uncertainty* resulted in lower yield responses. The vast investments require improving land availability in the short term as farm inputs are only variable inputs whose application can adjust to policy incentives. The lower yield responses were also due to the imbalance in the use of potassium application arising from a lack of awareness and distortion in agriculture incentives in Pakistan. The increased crop and fertilizer prices [here only DAP prices] lowered sugarcane's supply response instead of boosting the productivity of the crop in such an imperfect marketing arrangement. *The green revolution* brought technological improvements, including better seed varieties, farm management practices, and research and development to enhance sugarcane productivity. However, imperfect market competition, climate change, and ineffective price mechanisms may lower profitability and disrupt the supply chain of the sugarcane crop.

The sugarcane crop's support price lost effectiveness when the payments were delayed. The perishable nature of the crop also does not allow storing or waiting for a longer time—these practices of sugar mills are against the true spirit of fair competition. Moreover, there should be a consistent allocation of *R&D* funds to reduce uncertainty, induce sugarcane intensification with technological advancement, and protect biodiversity. The policy should also contribute to developing new drought- and heat-resistant sugarcane varieties. Finally, there is a need for extension and agricultural advisory service providers to work with sugarcane crop growers to enhance *labour-management skills* and promote the *4R nutrient stewardship* framework *(right fertilizer - right rate - right time - right place) in the spirit of Precision Agriculture*.

Chapter 4 Fruit Market Instability and Climate-Production Nexus in Complex Dynamic Systems[3]

Abstract

Agriculture market instability impedes achieving the global goal of sustainable and resilient food systems. Currently, the support to producers reaches the mammoth *USD 540 billion* a year (15 percent of total agriculture production value) that requires a repurposing agricultural support strategy *(RASS)*, considering the market country-specific circumstances. These circumstances may vary with geographic locations, marketing structures, and product value chains. The fruit production system is crucial for *health-conscious consumers* and *profit-oriented producers* for food and nutritional security. Export is one of the main driving forces behind the expansion of the fruit sector, and during the year 2010-2018, trade significantly outpaced production increases. The previous literature states that *irregular and unpredictable behaviour* — *Chaos* — can arise from entirely rational economic decision-making within markets. Different markets' direct/indirect linkages through trade create trade hubs, and uncertainty may function as an avenue to transmit adverse shocks and increase vulnerability rather than contribute to resilience. Therefore, distinguishing *Chaos* into an endogenous and exogenous pattern of behaviour is cradled to formulate an effective *RASS* for resilient food systems and to understand global food crises.

The present research is aimed at studying the fruit market dynamics of three region-representative fruit trade hubs, *i.e., Brazil (South America), Italy (Europe), and Pakistan (Asia), e*ach representing advanced to traditional fruit value chains to control uncertainty (risks). The pre-modelling data diagnostic framework of *Non-linear Time Series Analysis* is used to understand the complex fruit system considering Chaos theory. Three state variables, *i.e.,* production, prices, and temperature, are selected to represent farm production, marketing, and environment interactions and associated risks in a complex fruit system. The present study allows us to evaluate 1) risks patterns in three value chain, 2) differentiate Chaos's nature, and provide ways to repurpose agricultural support to transform the food system.

Keywords: *Chaos; Price distortions; Regional trade; Food networks.*

[3] Present or later version of the chapter 3 is ready to be submitted in a scientific journal as a separate publication.

Premise: The Fruit Supply Chain System

The fruit system (FS) is determined by their component properties and its dynamic relations with other systems components. The fruit system has two major components: 1) the production system and 2) the supply system. Each component is characterized by several other subsystems that exhibit complex dynamic interactions.

Production system

The following are the important subsystems in fruit production systems (FPS). **Soil** is the most important building block in fruit production systems. The various parameters of soil, like pH, moisture, type, and organic matter, are important integral parts of sustainable fruit production (Cerutti et al., 2011). The **land use pattern** and its slope (layout or arrangement of land uses) may also be considered an important factor (Sharma et al., 2021). **Plants' (orchards) structure** depends on the selection of fruit variety (Holb et al., 2012), considering a plant design in each geographical context. These varieties are selected upon production (annual bearer) (Robinson et al., 2014), stage of fruit-bearing (early in life) (Smith & Samach, 2013), appearance (size), and skin (hard enough to absorb minor hail damages) (Amarante et al., 2008).

Planting density is characterized by layout (e.g., square system) and direction (for road, noon orientation) (Haque & Sakimin, 2022). While **cropping technology** in many countries includes transplanting and plants substitution at a given age. Although in many areas, propagation is also practiced, both through seed (sexual method) or budding and grafting (asexual method) (Janick, 1998). **Weeding** is another important practice to reduce the water and nutrient sink from weeds and related competition. **Treatments:** sustainable weeding is today performed by mechanization, including hoeing and ploughing; in many cases, we still observe chemical treatments, hard to be substituted in the case of pests (insects, mycosis) (Brunner, 1994).

The **irrigation schedule** may or may not vary with seasonal fluctuations or rainfall in general (Fereres & Evans, 2006). In areas with a dry season (e.g., the Mediterranean), irrigation is also performed where there is enough water availability. Normal activity in orchard production is fertilization (Ge et al., 2018) and management of nutrients (Z. Wang et al., 2020). Other crops can be included as **intercrops** in the plant (orchard) to be grown depending upon the stage of the fruits (Cheng et al., 2022). Some crops are also considered a substitute/integration of fertilizing (e.g., legumes), those grown to be buried. Important practices in every orchard are pruning and thinning.

Picking and harvesting are mechanical and automatic depending upon the farmers' socio-economic status, type of fruit, availability of technology, and marketing structures (K. Zhang et al., 2022; Z. Zhang et al., 2016). The **Laboure** are involved in several stages of FPS and play their role in enhanced production in terms of quantity as well as quality (nutritious) fruit. Together with pre-production activities such as pruning and thinning, they are enrolled in the picking season. The agriculture extension services play a pivotal role in supporting farmers in any occurring problem and, more recently, in increasing sustainable fruit production (Degrande et al., 2006).

Supply system

The fruit supply system (FSS) is mainly started after post – production of the fruit. Soto-Silva et al. (2016) defined “fresh fruits and reported that they [fresh fruit] are consumed raw, whether whole or prepared. Preparation involves mainly peeling, slicing, or shredding, having not undergone any treatment (chemical, physical or biological) to ensure preservation other than chilling”.

The FPS begins with transportation to the wholesale/terminal markets and involves several storage points. The selection at storage points can be performed upon the arrival of fruits (bins) and when extracted from the fridges before going to the packaging chain (for details, please see (Parajuli et al., 2019).

Laboure participate in post-harvesting activities as sorters/graders, packers (one or two persons for finally closing) and marking and strapping the cartoons/crates. Post-harvesting issues include product quality, taste (related to varieties and other cropping techniques, e.g., irrigation), and shape. Such aspects affect the quality level of a product and the price paid to the farmer.

Climate is one of the key elements that may play a decisive role in FS. The trend of temperature, precipitation, wind velocity, sunshine, frost, and drought represent climate. The important drivers of climate are altitude, distance from the sea, and seasonality, including monsoon and hail zone. Landforms and soils also depend on climate history.

The value chain actors as agents in the fruit system

Several actors engage in describing and performing the functionality of fruit systems. These actors are dynamically embedded with each other, leaving long-term memory effects over time (Paut et al., 2021). Their [actors] interactions are complex and influence the outcome of dynamic systems. Therefore, it is important to identify the representative subsystem actors to represent the fruit system. The fruit system involves several agents, represented by people with a definitive role. These agents may be:

- A farm is characterized by its structure, location, area, soil characteristics, etc.
- A farmer is characterized by their competencies, opinions, labour contribution, etc.

- Farmer associations, *e.g.*, cooperatives owning fruit facilities for reception and storage, have their branding.
- Fruit pickers are specialized team workers.
- Fruit picker association.
- Truckers (transporters).
- Logistic/transporters association.
- Gross markets for medium-large scale distributions.
- Fruit resellers and
- customers.

Climate as an agent

Climate synthesizes weather, whose records are weighted to characterize a certain region. A common way to get a regional climate is to get temperature and rainfall charts by multi-annual average temperature and rainfall pattern (commonly monthly). Because of recent growth in awareness of climate drift, such multiannual averages are changing too, and climate representing a region is becoming a fuzzy concept. Nevertheless, most people expect that, despite climate change and increased extreme events, typical patterns can still be identified in a regional climate.

Within a dynamic process, besides weather records, we can consider climate as an exogenous machine manoeuvring the weather, and so we can consider it as an agent. We are interested in understanding such patterns' effects on price dynamics (volatility). As a main driver of product availability, climate influences customer demand as a main market agent.

The market as an agent

There are several agents (actors) involved in the fruit market subsystem. Their interactions further complicated the fruit system dynamically. Following are the few important agents in the fruit market systems. These are,

- village/Orchard-direct selling
- wholesale market
- commission agents
- transporter
- exporter
- cold storage operator
- processor
- supermarket
- retail (street vendors)
- input supplier
- farmer
- pre-harvest contractor
- nursery developer
- fertilizer/fungicide/pesticide companies
- value-added companies/players/processors.

The price is the most effective proxy to represent the fruit system. There are three types of prices. Each represents a fruit subsystem and exhibits risk transmission dynamically. These are,

- farm gate
- wholesale
- retail

To process such complex information, we used ontologies, a formal representation of domain knowledge easily interpreted by machines and highlighted the complexities within a network (**Figure 4.1**).

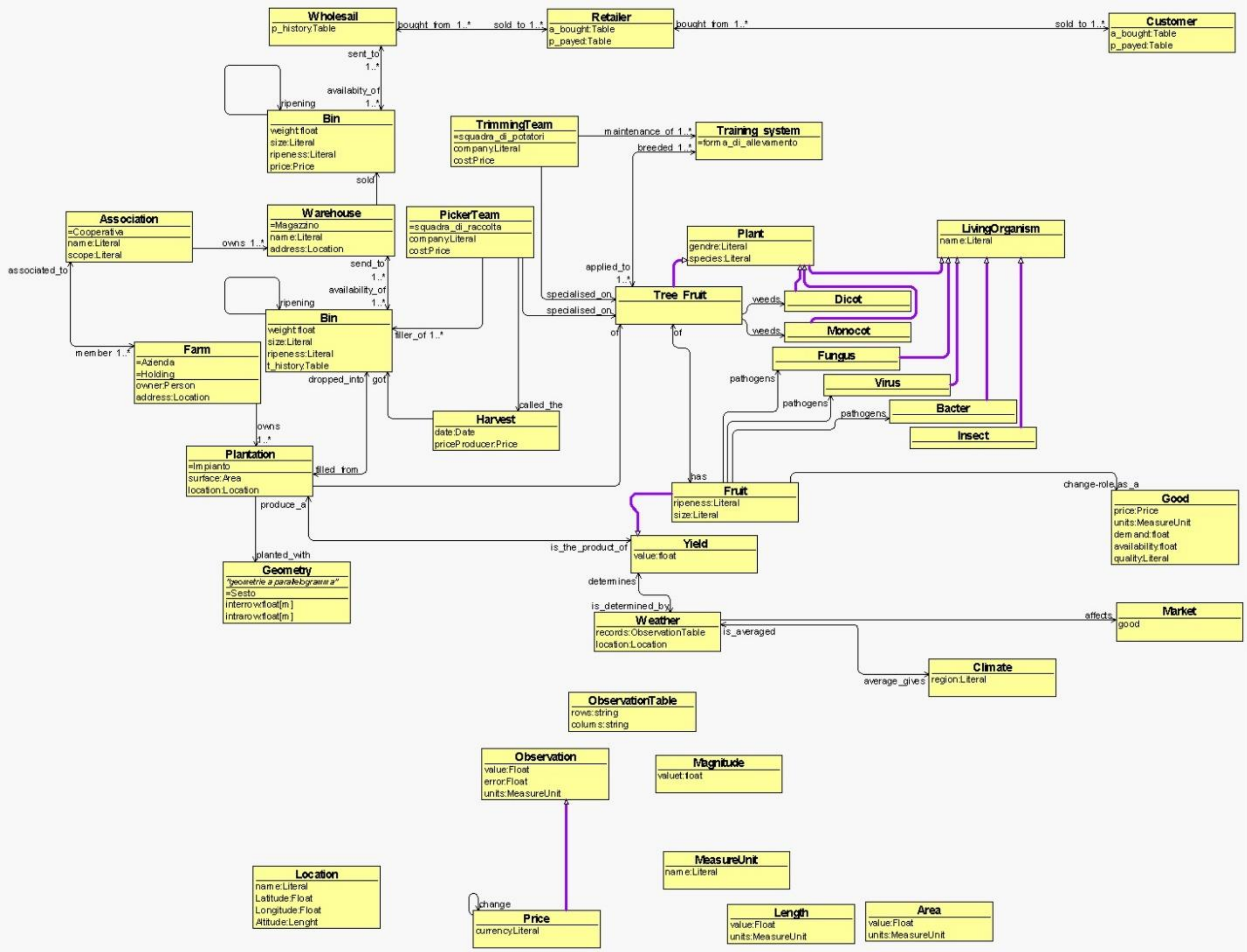

Figure 4.1: *Ontological representation of fruit value chain system*

Comprehensive data on supply chain actors are not easily available or require large funding and collaboration from national/international stakeholders.

It is for this reason that three major variables have been selected to represent the biggest actors in the scene:

- Climate has been represented by Temperature, with values averaged on different time scales, weekly to monthly.
- The market has been represented by Price, as declared by large retail offices.
- Farmer production has been represented by products collected by major gross market suppliers and recorded by associations.

Related data used in the analysis is obtained from:

- Temperatures data were obtained from the Weather Network of Emilia Romagna, a freely available public source.
- *Bologna Chamber of Commerce* weekly price records have been collected for the decade 2010-2020, with indicated the varieties of the selected fruit - https://www.bo.camcom.gov.it/sites/default/files/borsa-merci-e-rilevazione-prezzi/borsa-ortofrutticola/anno-2017/19%20gennaio%202017.pdf).
- *Centro Servizi Ortofrutticoli (CSO)* production data for Peach and Nectarine, without distinction of varieties. Obtaining production transcripts is not always simple, as production represents sensible trade information.

4.1 Introduction

The fruit production system (Nath et al., 2019) is crucial for *health-conscious consumers* (Maoto et al., 2019) and *profit-oriented producers* (Reig-Martínez & Picazo-Tadeo, 2004) for food and nutritional security. The dynamic production systems exhibit complex interactions (J. W. Jones et al., 2017) and systemic risk transmission (Challinor et al., 2018) within the system, which requires an adaptative measure to transform into sustainable and resilient food systems globally. Key fruit producers/exporters have various marketing arrangements to dampen risk impacts from traditional to modern value chain structures (Gouel, 2012b).

Export is one of the main driving forces behind the expansion of the fruit sector, and during the year 2010-2018, trade significantly outpaced production increases. The fruits are perishable commodities that involve substantial investment and cost for long-term storage, leaving instantaneous trade feasible (von Cramon-Taubadel & Goodwin, 2021) to form new (expand existing) trade networks (Bornal et al., 2021) at the regional scale.

Within trade networks, different markets' direct/indirect linkages through trade create trade hubs. Uncertainty may function as an avenue to transmit adverse shocks and increase vulnerability rather than contribute to resilience. The previous literature states that *irregular and unpredictable behaviour* — *Chaos* — can arise from entirely rational economic decision-making within markets (Demir et al., 2015). Therefore, distinguishing *Chaos* into an endogenous and exogenous pattern of behaviour (Berg & Huffaker, 2015) is cradled to formulate an effective repurposing agricultural support strategy *(RASS)* for resilient food systems and to understand global food crises. Currently, the risk support to producers reaches the mammoth *USD 540 billion* a year (15 percent of total agriculture production value) that requires a *RASS*, considering the market country-specific circumstances (Gautam et al., 2022). These circumstances may vary with geographic locations, marketing structures, and product value chains.

Modelling the components (reductionism) of complex dynamic interactions and their major influences on the food system in isolation is insufficient to conclude (Hieronymi, 2013). These components are exposed to the external environment (here, climate) and change the overall behaviour of the food system. Often such models face the *curse of dimensionality* (Lavergne & Patilea, 2008), which requires *integrating the rigor of reductionism with the comprehensiveness of holism* (Banks, 2022; Fardet & Rock, 2015). Such models cannot provide information for supporting decisions and policies implemented under public policy measures. Therefore, a modelling approach and theoretical framework must reflect a comprehensive abstraction of real-world food systems.

A conceptual framework was developed that simultaneously covers the complex interactions of system components and risk transmission (**Figure 4.2**). To consider the adaptation measures capacity, we have selected three types of supply chain for fresh fruits retailing, *i.e.*, long, medium, and short supply chains (Badar et al., 2019; Loiseau et al., 2020; Negi & Anand, 2015). This supply chain varies concerning the number of actors involved, the quality of products, and varying levels of producers' support availability, etc. Another important facet of the present research is using the pre-modelling data diagnostic nonlinear time series analysis (NLTA) framework (R. Huffaker et al., 2018; Ray Huffaker, 2015).

The NLTA framework was used to reconstruct the dynamic system of fruit systems from a time series based on Takens' theorem (Deyle & Sugihara, 2011) for nonlinear state space reconstruction.

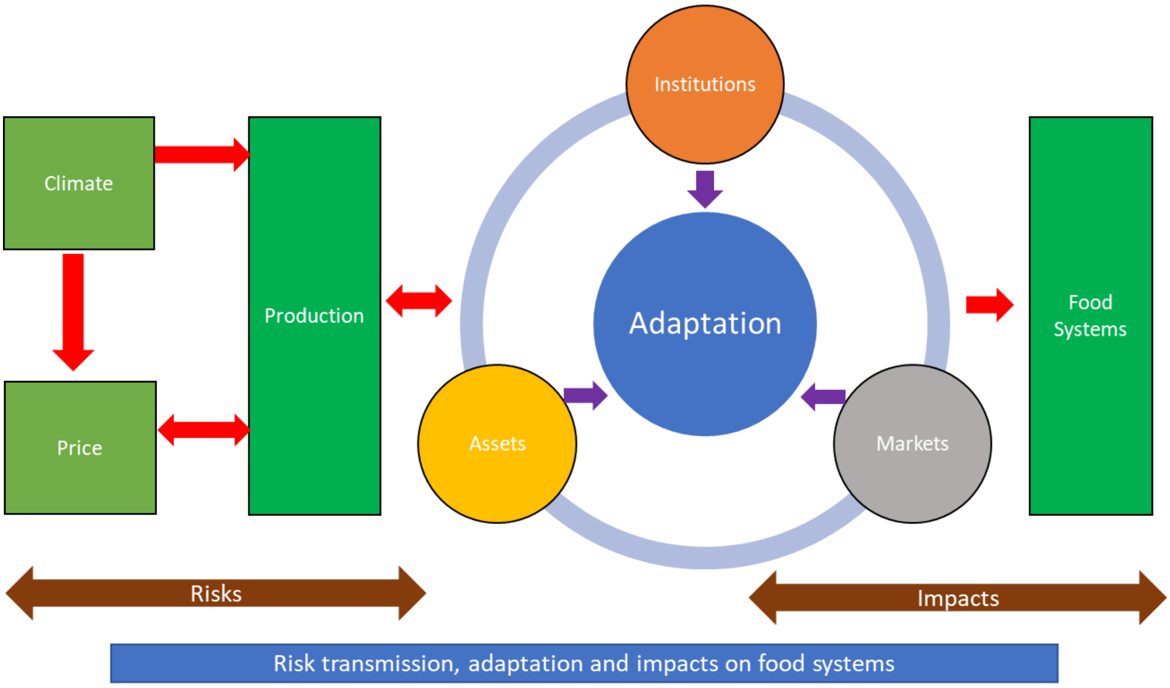

Figure 4.2: *Framework for risk transmission, adaptation, and impacts on the food system.*
(Adapted from Wossen et al., 2018).

The present research is aimed at studying the fruit market dynamics of three region-representative fruit trade hubs, *i.e.*, *Brazil (South America), Italy (Europe), and Pakistan (Asia), e*ach representing traditional to advance (long to short) fruit supply chains to control uncertainty (risks). The NLTA framework is used to understand the complex fruit system considering Chaos theory. Three state variables, *i.e.*, production, prices, and temperature, are selected to represent farm production, marketing, and environment interactions and associated risks in a complex fruit system. The present study allows us to evaluate 1) risks patterns in three value chain, 2) differentiate Chaos's nature, and provide ways to repurpose agricultural support to transform the food system.

The remainder of the chapter is organized as follows. The 4.2 section briefly introduces data and the NLTA framework, while the results are reported in the 4.3 section. The last (4.4) section highlights the main findings and policy implications.

4.2 Materials & methods

4.2.1 Data

For the present study, we have retrieved the data from three regional fruit trade hubs, *i.e.*, *Brazil (South America), Italy (Europe), and Pakistan (Asia), e*ach representing traditional to advance (long to short) fruit supply chains. The details of retrieved data are reported in **Table 4.1**. Data frequency plays an important role in capturing dynamic causal linkages. High-frequency data is useful compared to low frequency, e.g., monthly, quarterly, etc. (Nazlioglu, 2011). Therefore, we have used weekly data on prices, production, and temperature. For Pakistan, we have also used quantity arrivals in wholesale markets in Punjab. These variables best suits supply disruption measures (Mahajan & Tomar, 2021). The fruits were selected based on (inter)national and overall production contribution to the economy.

Table 4.1: *Details of retrieved data used for the present research.*

	Brazil	**Italy**	**Pakistan**
Supply chain type	Medium	Short	Long
Database (Year)	2011 - 2020	2016 - 2020	2017 - 2020
Regions	Fraiburgo São Joaquim São Paulo Vacaria	Emilia Romagna	Punjab
Fruits	Apple	Nectarine Peaches	Apple Banana Mango
***Variables**	**Prices (R$/18kg box) Temperature (°C)	Price (€/kg) Production (tonnes) Temperature (°C)	Arrivals (tonnes) Price (PKR/100 kg) Temperature (°C)
Frequency	Weekly	Weekly	Weekly
Total obs.	418	261	209
Source(s)	Brazilian Institute of Geography and Statistics Hortifruti/Cepea National Institute of Meteorology	Centro Servizi Ortofrutticoli (CSO) The Italian National Institute of Statistics	AMIS Agriculture Marketing Punjab Metrological Department of Punjab

*Note: *Consumer price index data retrieved from World bank; **For Brazil, farmgate and wholesale prices, while resting of the regions, wholesale only.*

4.2.2 Variables construction

Understanding the complex interaction of fruit systems requires studying fruit growth and development. For this, growing degree[4] days (GDDs) of fruits are important variables instead of average temperature (Souza et al., 2019). The following formula is used for the calculation of GDDs. These are,

$$GDD = {(T_{max} + T_{min})}/{2} - T_{base} \tag{4.1}$$

For equation 4.1, we have used a base temperature of 5°C for apple (Stanley et al., 2000), 13°C for banana (Calberto et al., 2015), 10°C for mango (Salvi et al., 2019), 4.4°C for nectarine (Fallahi et al., 2009) and 7.2°C for peaches (Chun & Changnon, 2019). All the prices were deflated with the consumer price index. The out-of-season values are replaced with standardized seasonal values to compare and extract meaningful inferences (Enoksen et al., 2020).

4.2.3 Pre-data diagnostic NLTA framework

The contemporary dynamic system(s) have required robust models and estimation techniques to accurately make a long-term prediction or assessment, inculcating uncertainty to pave the way for sustainable development. The nonlinear time-series analysis is the leading *data-centric approach* that helps dissect time series variables to identify structured patterns before making decisions about the presence of nonlinearity in dynamic systems. Endogenous or exogenous factors may influence the deterministic nonlinear dynamic system. The *NLTA* analysis may provide information after converting time series into signal processing about i) dominants cycles/frequencies and their relevant length; ii) constituents of time series, *i.e.*, signal, noise, cyclical and trend components; iii) indication about presence of robust structured (deterministic) components; iv) decomposition of time series into various frequency cycles and their explained variations; v) reconstruction of co-variates as they co-evolve for suitable substitutes in a dynamic system and vi) hypothesis testing about the generation of structured components, *i.e.,* linear stochastic dynamic or deterministic nonlinear dynamic. The empirical outcomes from NLTA may set the directionality of conducting time series analysis more intuitively and structured patterns present in any datasets instead of making biased presumptions beforehand.

In **Figure 4.3**, we have summarized all the steps involved in the application of *NLTA* analysis succinctly. The first important method in *NLTA* is *Singular Spectrum Analysis (SSA)*. The time series is decomposed into structured variations (signal, trend, and cycles) and unstructured variations

[4] Growing degrees (GDs) is defined as the mean daily temperature (daily average maximum and minimum temperatures) above a certain threshold base temperature accumulated daily over a period. Negative values are treated as zeros (ignored).

(noise/volatile component). The noise variations can be used for further *extreme value statistics (ignored in current research)*. If isolated signals' variation is >50%, then we can assume that time series predominantly constitutes structured components (noise is low). The next important thing is to know that the structured time series is endogenous or exogenously influenced. For this, we have used the time-delayed embedded technique. The time series co-variates in the dynamic system are co-evolving and attracted towards some visual attractor. The symmetry/resemblance of the geometric shadow attractor with the original attractor confirms that structured time series is influenced endogenously.

The confirmation of an endogenous structure in time series proves that their historic generation process and intrinsic patterns are deterministic and reject the possibility of randomness. The *Surrogate Data Testing Approach (SDA)* tests the hypothesis about deterministic statistics. The nonlinear short-term prediction skills for ensembled Amplitude Adjusted Fourier Transform (*AAFT*) surrogates are measured with the *Nash-Sutcliffe coefficient of efficiency* (*nse*) with the single-tailed test. The generated surrogates were ranked in descending order. The prediction skills (higher-tailed test) and permutation entropy (lower-tailed test) were provided with a decision about "deterministic" or "stochastic" deterministic structured in time series.

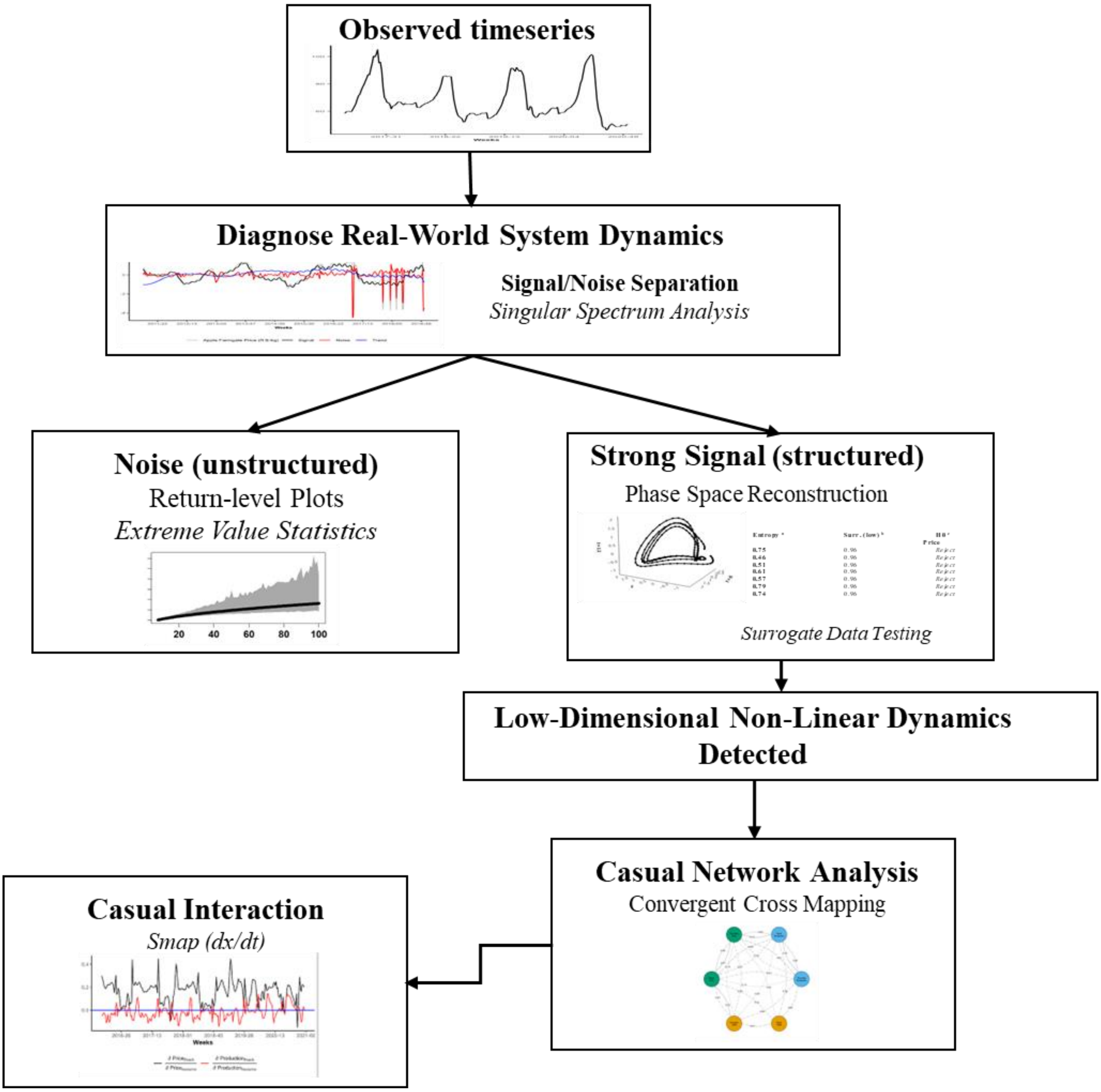

Figure 4.3: *Schematic diagram of conducting nonlinear time series analysis (NLTA).*
In ***Singular Spectrum Analysis (SSA)****, observed time series converted into structured (signal) and unstructured (noise) variations. The great than 50% variation in signal explained by SSA indicated that the series is deterministic and has the possibility of being endogenously volatile in structure. The extracted noise component will be further use for Extreme Value Statistics while the signal may pass through Phase Space Reconstruction (PSR). The possibility of endogenous may confirm through plotting shadow attractor of series in PSR. If the attractor robustly resembles its shadow attractor, we can infer the possibility of deterministic nonlinear dynamics in time series. The Surrogate Data Testing Approach (SDA) may provide intuition about the structural component of a series that may or may not be generated through deterministic nonlinear dynamics. The passed singles were plotted for Casual Network Analysis through Convergent Cross Mapping and S-map (growth rate).*

The values of *nse* and permutation entropy (h) vary between 0 – 1. The *nse* thresh hold value is >0.65. At the same time, permutation entropy (*h*) varies between zero to one, *i.e.*, h=0 means perfectly predictable from past values as the time series is highly structured and vice versa. Sometimes *SDA* results are inconclusive as prediction skills and permutation entropy provide contrasting intuition. In that case, the decision is based upon a borderline statistic ceiling. If the difference between time series statistics and ensembled surrogate data is miniscule, then we can infer that *SDA* did not fully reject the intuition about deterministic nonlinear dynamics.

If surrogate data analysis supports low-dimensional nonlinear dynamics, we apply convergent cross-mapping (CCM) to detect causality between variables of interest. In general, CCM tests whether there is correspondence between reconstructed phase spaces for two observed time series variables. The underlying logic is that causally related variables reconstruct the same real-world phase space dynamic. For example, if Y drives X, then phase space reconstructed from X can be used to estimate ('cross map') values of Y, but not vice versa. If Y and X have a bi-causal relationship, then each can be cross-mapped from the reconstructed phase space of the other (Ray Huffaker & Fearne, 2014). In the end, we have estimated the growth rate for the classification of pairwise interactions.

4.3 Results

4.3.1 Signal processing

The time series of state variables are decomposed with the help of Singular Spectrum Analysis (SSA) into structured (signals including trend and annual/semi-annual cycles) and unstructured components (noise). **Figure 4.4** details the retrieved price signal (red line) and actual series values (grey line). The difference between the two lines may represent the noises in the respective series.

We have observed the differences between red and black lines in the graph, indicating the presence of noise components in each series in **Figure 4.4** in panels (a) – (g). The strong trend component is isolated from Brazil's apple (farmgate and wholesale) and Pakistan's apple/banana prices. In Brazil, apple prices were highly volatile during 2013 – 2015 and again early weeks of 2018. In Italy, the nectarine and peaches prices exhibited greater fluctuations during 2019 – 2020, which coincided with the banana price fluctuations in the Pakistan market. The prices of mango from Pakistan show extreme synchronization and the lead-lag relationship between signal – noise retrieved through SSA. In conclusion, we can infer that prices were generated with low dimensional frequency and constituted predominantly structured components.

Figure 4.4: *Plot of fruit prices with decomposed components.*
Note Panels a) & b) for Brazil, c) & d) for Italy, and e) – g) represent the analysis of Pakistan fruit prices.

Similarly, the decomposition of production (quantity arrivals for Pakistan) was performed (**Figure 4.5**). In Pakistan, apple, and banana quantity arrivals, while in Italy, nectarine and peaches were highly synchronized. Mango arrivals experienced noises during 2018 and mid-2019. However, the overall signal strength was >50% in all production (arrivals) signals.

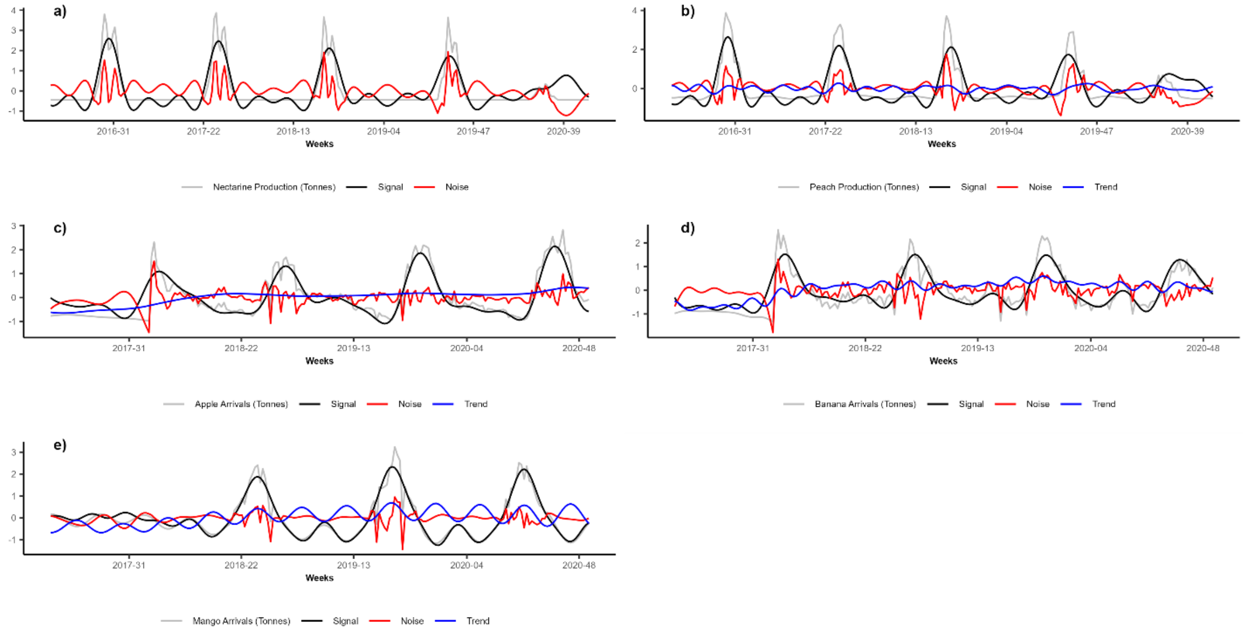

Figure 4.5: *Plot of fruit production (arrivals) with decomposed components.*
Note Panel a) & b) for Italy; c) – e) represent analysis from Pakistan's fruit arrivals.

Multi-annual cycles were retrieved in all the series, *i.e.*, prices, production (arrivals), and growing degree days of various fruits studied in the present research. In medium fruit supply chains, annual cycles were dominated, while quarterly cycles reported abundance in long/short supply chains. For example, mango depicts 3 – 5 monthly cycles (~16% signal strength) while ~14% average signal strength for 9-monthly cycles of wholesale prices. Once the dynamic fruit system evolves and interacts with other state variables, the nectarine production shows half-year cycles (~26% strength) and mango 3 – 5 monthly cycles (21%). Multi-annual cycles are identified in both prices and production of peaches. The retrieved signals from GDD of fruits show the presence of seasonal cyclicity in short and long fruit supply chains—although > 5% on an average basis.

The next objective is to know how the fruit system evolves. All the state variables are plotted together to observe the behaviour, representing different supply chains (**Figure 4.6**). In modern supply chains where fruit quality is given prime importance, the apple farmgate price level is higher than wholesale prices. A sharp decline was observed during 2013 – 2015 in farm gate prices. However, the wholesale prices experienced a decline (bust cycle) after September 2014 and recovered in early 2015. Farm gate prices were volatile compared to the two prices and exhibited nonlinear regime shifting behaviour.

Table 4.2: Signal processing with singular spectrum analysis.

Country	Fruits	Strength		Strength Cycles (weekly)						
		Signal [a]	**Nonlinear trend cycle**	**(5,7,11,12)**	**(14,15,18,20)**	**(21,25,27)**	**(28,30,31)**	**(35,36,37)**	**52**	**(110,117,122)**
		Price								
Brazil	Apple (Farmgate)	77%	17%	1%	1%	-	-	-	73%	1%
	Apple (Wholesale)	77%	11%	1%	1%	-	-	-	73%	1%
Pakistan	Apple	97%	6%	1%	-	-	4%	-	91%	-
	Banana	97%	64%	1%	-	4%	1%	-	91%	-
	Mango	74%	-	5%	16%	-	8%	-	45%	-
Italy	Nectarine	75%	-	-	-	9%	-	9%	49%	8%
	Peach	78%	-	3%	-	-	-	18%	53%	4%
		Production/Arrivals								
Pakistan	Apple	74%	7%	5%	16%	-	8%	-	45%	-
	Banana	74%	17%	5%	16%	-	8%	-	45%	-
	Mango	74%	-	5%	16%	-	8%	-	45%	-
Italy	Nectarine	77%	-	-	13%	22%	4%	-	38%	-
	Peach	78%	5%	3%	-	-	-	18%	53%	4%
		Growing Degree Days								
Brazil	Apple	77%	-	1%	1%	-	1%	-	73%	1%
Pakistan	Apple	96%	-	-	-	-	-	-	89%	-
	Banana	96%	-	1%	-	5%	1%	-	89%	-
	Mango	96%	-	1%	-	5%	1%	-	89%	-
Italy	Nectarine	88%	1%	-	1%	1%	-	2%	83%	-
	Peach	91%	-	-	-	2%	-	-	89%	-

[a] *Signal strength measured as a percent of total variation (from the mean) accounted for in the observed record.*

Contrary to modern supply chains in the short fruit supply chain, prices, production, and growing degree days are highly synchronized. There is a reported variability (risk transmission) in nectarine fruit cycles between 2017 and 2019. The slow development of nectarine GDDs resulted in an explosion of price signals in early 2020. A similar trend was observed in peaches except for an apparent boom – bust cycle in early 2020. In a traditional long supply chain, no persistent synchronization structure is observed. Apple prices stagnated during January 2020 due to a sharp decline in GDDs. Afterwards, prices lag the production while synchronized with GDDs signal growth.

For mangoes, supply disruption from 2016 to mid-2018. Similar bust cycle in early 2020, production and prices go together. Banana prices and GDDs synchronized during 2020, resulting in another bust cycle after 2018 – though dissimilar in the pattern. Subsequently reported a rise in banana production.

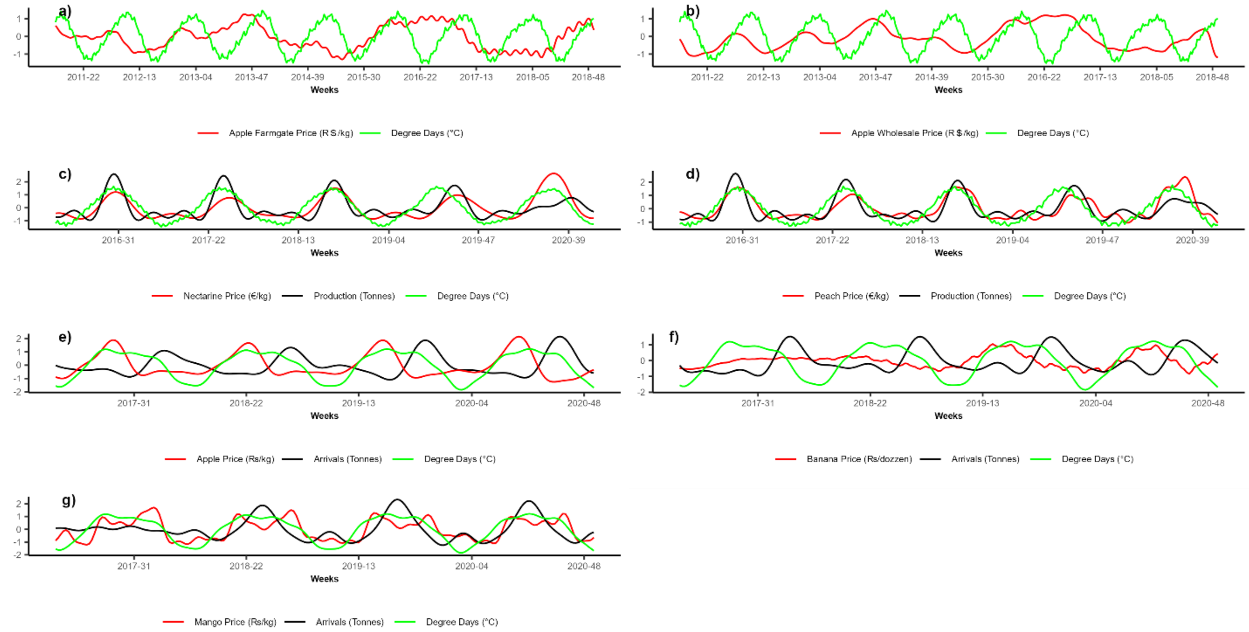

Figure 4.6: *Describing co-evolvement of fruit systems' state variables through isolated signals.*
Note Panel a) & b) for Brazil; c) & d) for Italy, and e) – g) represent the analysis of Pakistani state variables.

4.3.2 Phase space reconstruction

The reconstructed attractors were estimated using the isolated signals to depict the fruit system dynamics. The geometric structures may provide information about the magnitude of nonlinear dynamics and the presence of low-dimensional signals – indicating that deterministic nonlinear need to be tested via surrogate data.

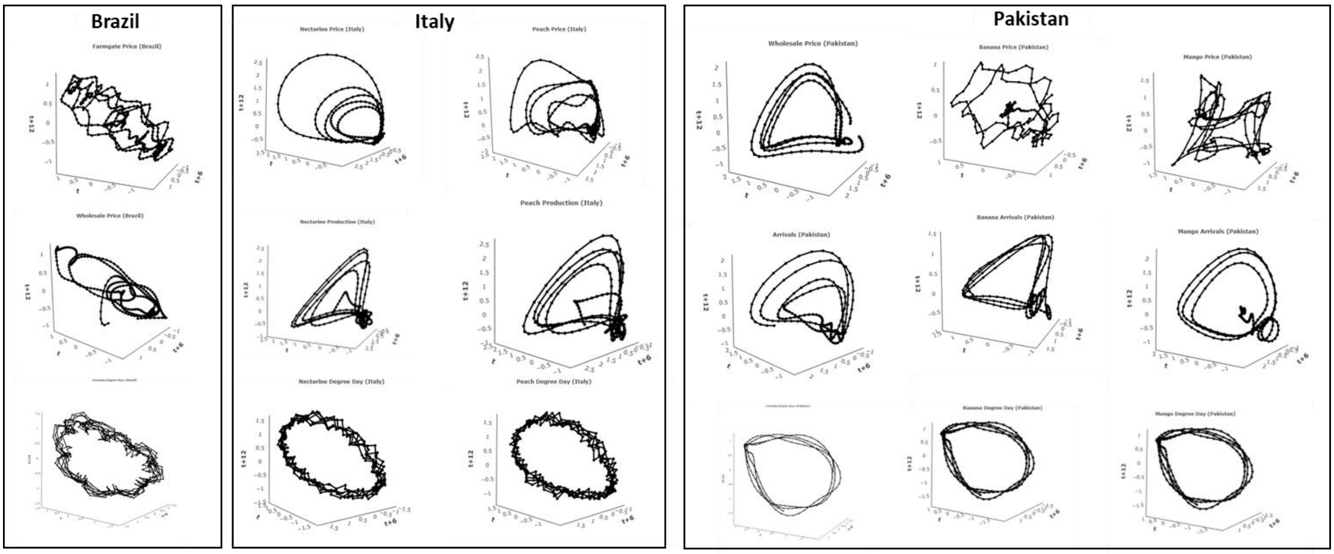

Figure 4.7: *Reconstructed attractors for all state variables.*
Note: We successfully reconstructed low-dimensional shadow attractors. Several attractors exhibit striking geometric regularity characterized by oscillatory behaviour detected in signal processing. Reconstructed attractors show the magnitude of chaos (nonlinear dynamics) in fruit production systems.

We have summarized all the reconstructed attractors in **Figure 4.7**, confirming the likelihood of nonlinear dynamic structures. We ran a lower-tailed test with 199 AAFT surrogates and an $\alpha = 0.05$ significance level to reject the null hypothesis only if permutation entropy computed from the signal falls within the lower extreme surrogate values.

To perform *SDA*, we have destroyed all signals' temporal structure so that their surrogates (clones) will be Independent and Identically Distributed (*IID*) – drawn observation randomly without replacement, and the main statistical properties are the same as the original series. We have performed ***discriminating statistics*** because of better handling/nonlinear prediction skills with short time-series. In the nonlinear prediction algorithm, we have divided datasets into two, *i.e.,* the learning set. At the same time, the rest of the observations were used as a learning set to predict their values. This algorithm continues to perform until we predict all the rows (observation) in the learning set *except the last value*. The analysis of *Amplitude Adjusted Fourier Transform (AAFT)* surrogates ranked-order test was reported in **Table 4.3**.

Table 4.3: *Results of surrogate data testing.*

Country	Fruits	Entropy [a]	Surr. (low) [b]	H0 [c]
		Price		
Brazil	Apple Farmgate	0.75	0.96	*Reject*
	Apple Wholesale	0.46	0.96	*Reject*
Italy	Nectarine	0.51	0.96	*Reject*
	Peach	0.61	0.96	*Reject*
Pakistan	Apple	0.57	0.96	*Reject*
	Banana	0.79	0.96	*Reject*
	Mango	0.74	0.96	*Reject*
		Production/Arrivals		
Pakistan	Apple	0.55	0.96	*Reject*
	Banana	0.58	0.95	*Reject*
	Mango	0.60	0.95	*Reject*
Italy	Nectarine	0.59	0.96	*Reject*
	Peach	0.60	0.96	*Reject*
		Growing Degree Days		
Brazil	Apple	0.67	0.96	*Reject*
Italy	Nectarine	0.61	0.96	*Reject*
	Peach	0.61	0.96	*Reject*
Pakistan	Apple	0.56	0.96	*Reject*
	Banana	0.56	0.95	*Reject*
	Mango	0.56	0.96	*Reject*

[a] Permutation entropy has taken from the empirically-reconstructed attractor for a record.
[b] the lower bound on entropies measured for 199 AAFT surrogates ($\alpha = 0.05$)
[c] If the entropy measurement for the empirically-reconstructed attractor does not fall below the surrogate lower bound, we accept the null hypothesis of linear stochastic
dynamics. Otherwise, untested dynamic structures (such as nonlinear deterministic dynamics) remain possibilities. We do not attempt to reconstruct nonlinear dynamics from signals for which the null hypothesis is accepted and delete them from further analysis.

The analysis of fruit time-series *AAFT* surrogates using ranked order (upper-tailed test) divulges that the deterministic components are generated with determined nonlinear dynamics as H_0 rejects the presence of linear stochastic dynamics. The value of entropy is reported in column III above, and which null hypothesis is accepted. This result implies that the value of entropy falls among lower-tailed surrogate measures/values (arranged in descending order). It shows greater performance skills using surrogates for the original series.

The permutation entropy *h* value is 0.51 lower than the original nectarine price of 0.96. Therefore, we can reject *H0*: linear stochastic dynamics alternatively deterministic nonlinear dynamic in nectarine price series. Although, we cannot fully agree that the original time series can be perfectly predicted only with historic/past values. The permutation entropy (*h*) value equal to zero indicates the perfect predictability of time series with past values.

4.3.3 Convergent cross mapping

We have visualized the causal interactions detected with convergent cross mapping (CCM) in a *'community interaction diagram'* (**Figure 4.8**). Each node represents state variables signals screened for nonlinear deterministic dynamic behaviour. Nodes were connected through directed arrows to indicate signal interaction within the same reconstructed real-world market system. The strength of the interaction is reported, which are the *convergent correlation coefficients* for each cross mapping (**Figure 4.9**). For example, the convergent correlation coefficient is 0.81 for the nectarine cross-mapping price *x-map* production, which indicates that production drives prices. We include interactions in the diagram associated with CCM curves exhibiting convergent correlations exceeding 0.33 (the strength of interactions increases as convergent correlations approach 1) and resting at or above 95% confidence levels (**Figure 4.9** top-left panel red-lines). In addition, we include interactions whose cross mappings pass delayed (extended) CCM tests to rule out non-causal synchronous behaviour, as demonstrated by delayed CCM curves with peaks at nonpositive delays (**Figure 4.10**).

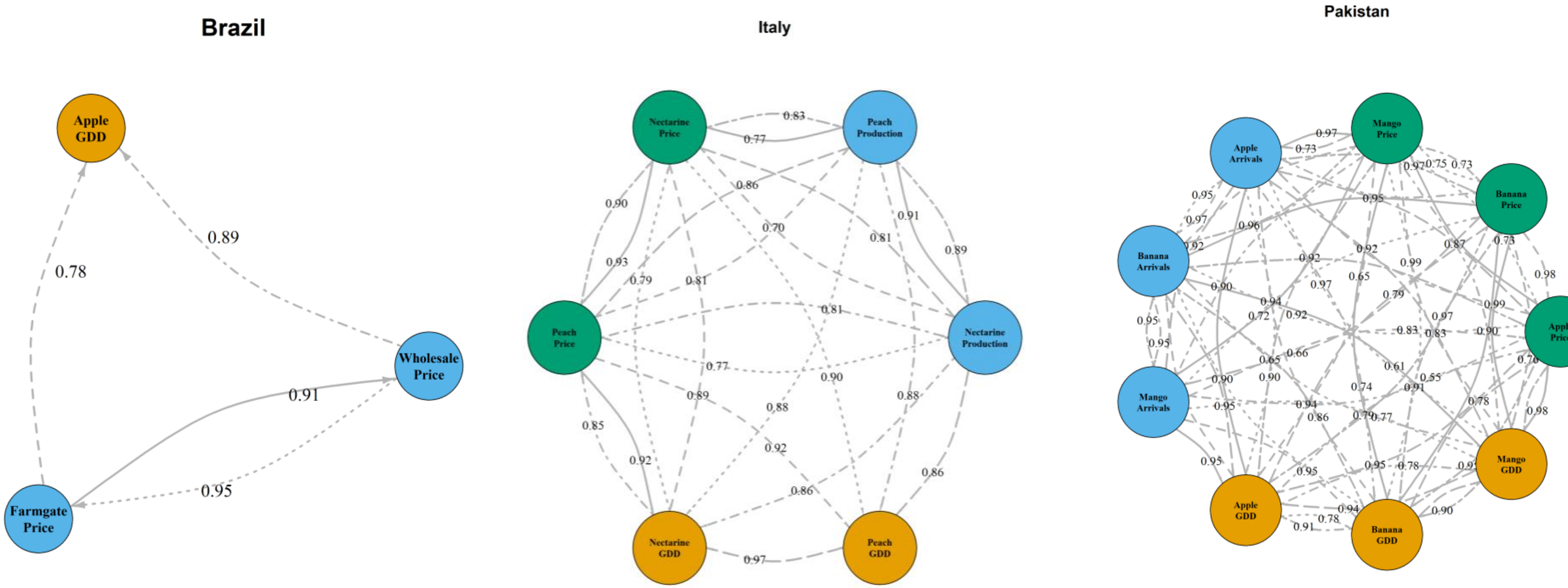

Figure 4.8: *Community interaction diagram.*
We summarize causal interactions detected with CCM in a community interaction diagram whose nodes are state variables, i.e., price, production (arrivals), and growing degree days. Arrows between nodes indicate the direction of the interaction. The fractions give the strength of the interaction near each arrowhead, which are the convergent correlation coefficients for each cross-mapping. ***Brazil)*** *there is a bilateral interaction between farmgate and wholesale apple prices.* ***Italy)*** *three state variables can form complex dynamic interactions. Each state variable may have bilateral or multilateral interactions and influence the fruit systems dynamically. Pakistan) incorporating various types of fruits in the long supply chain may further increase the complexity, where different fruits sub-system interacts within broader fruit networks.*

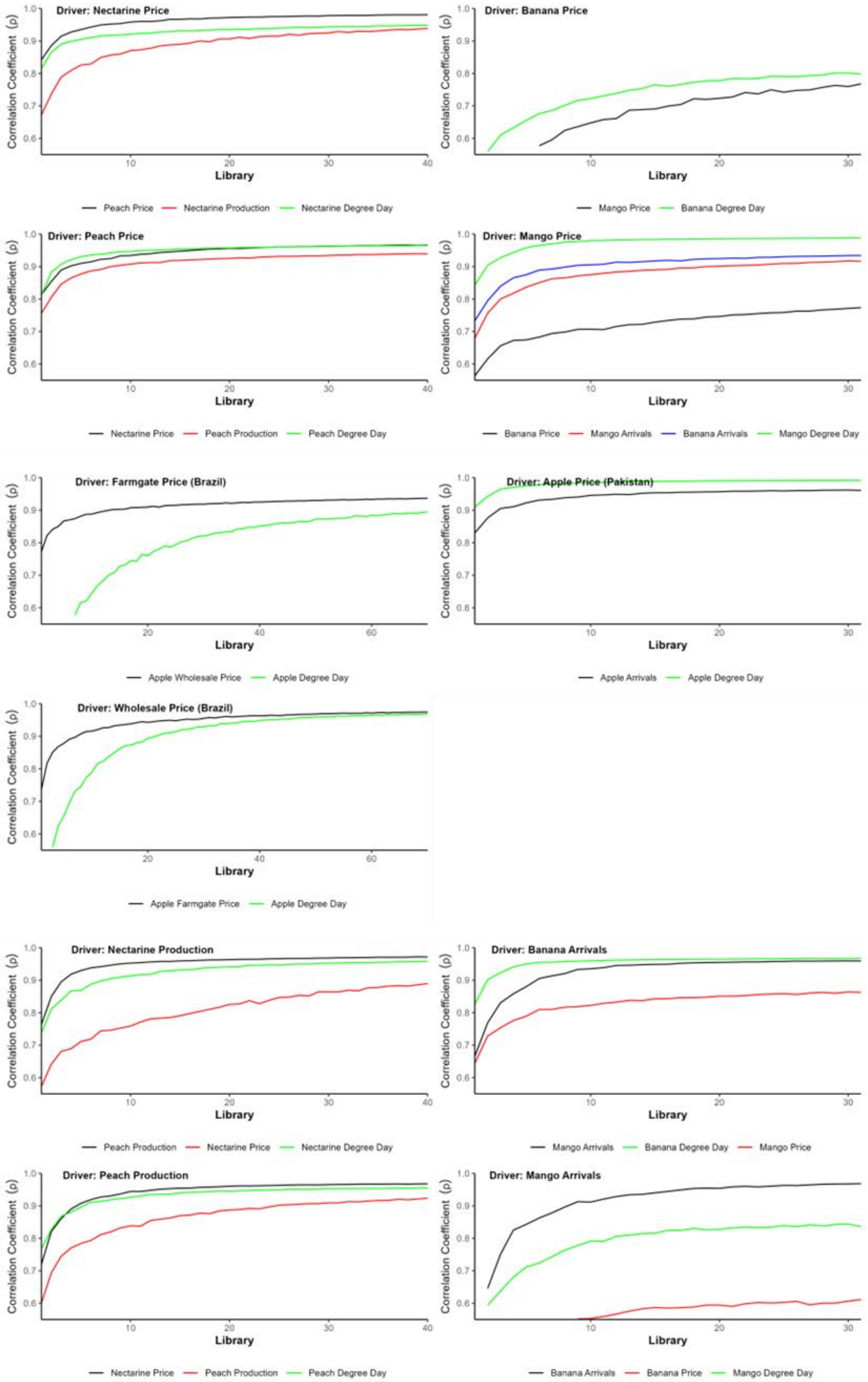

Figure 4.9: *Convergent cross-mapping results.*
We use Convergent Cross Mapping to ascertain whether attractors reconstructed from observed time series represent the dynamics of the same real-world system and thus causally interact.

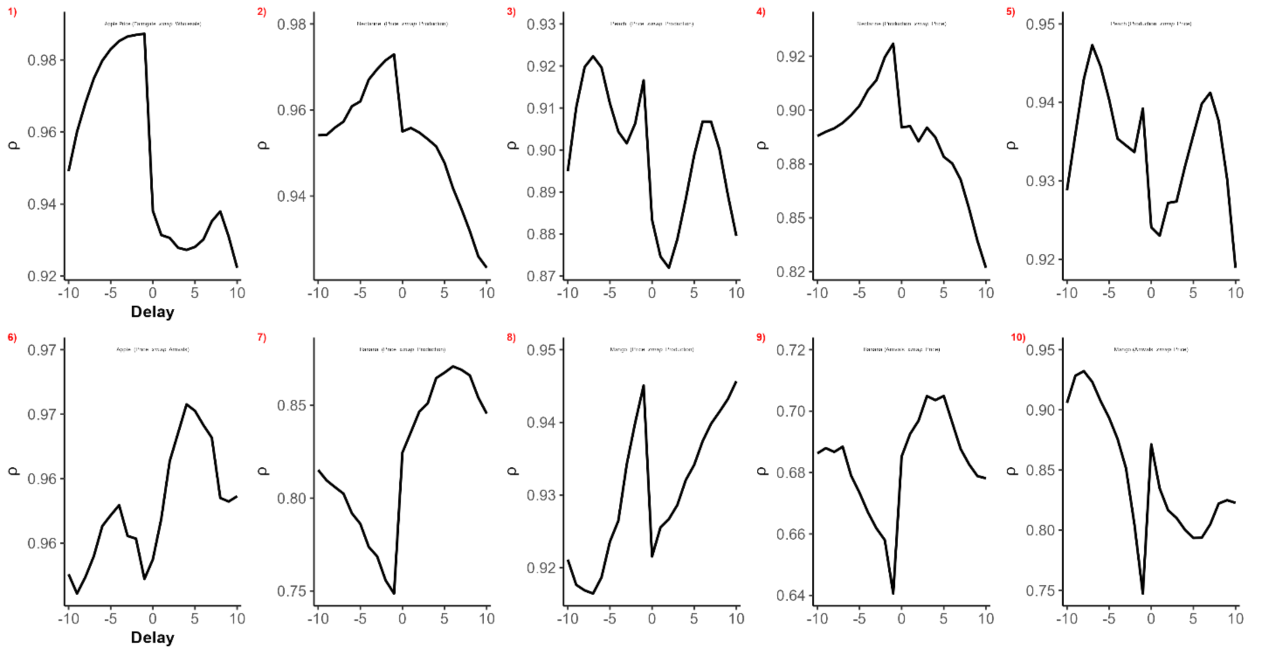

Figure 4.10: *Delayed (extended) CCM.*
We screened for interactions whose cross mappings pass delayed (extended) CCM tests to rule out non-causal synchronous behaviour, as demonstrated by the figure's delayed CCM curves with peaks at nonpositive delays.

The community interaction diagram (**Figure 4.8**) has provided important insights about risk transmission (volatility/variability) among state variables.

4.3.4 Quantifying causal interactions with S-mapping

The next important step is quantifying the interactions with *S-mapping* in reconstructed dynamic systems. The computed partial derivatives quantify each interaction over time (**Figure 4.11**). The horizontal line (blue) is to highlight the positive/negative weekly interactions. The partial derivates are computed after applying singular spectrum analysis to isolate the signals measuring systematic, interactive behaviour.

The partial-derivatives signals are mostly either positive or negative over time. We have illustrated these interactions (regularity and importance) with two measures: 1) weekly percentages that each partial-derivate signal is mostly positive/negative, and 2) the relative magnitude of positive/negative areas between the curve and zero axis. We report these measures in the heading (blue-box). For example, $\partial Price_{nectarine}/\partial Production_{nectarine}$ interactions (Positive: 0.35, 0.39) report 35% positive partial derivatives within weeks, while overall, 39% of the total area reports the positive magnitude of partial derivatives [**Figure 4.11 (1)**]. We can quantify the negative interaction while deducting positive values (and vice versa in case of negative values) from the total (100%-35%=65%, 100%-39%=61%). Similarly, we reported the inverse interaction ($\partial Production_{nectarine}/\partial Price_{nectarine}$) but highlighted the (Negative: 0.31, 0.16) opposite values.

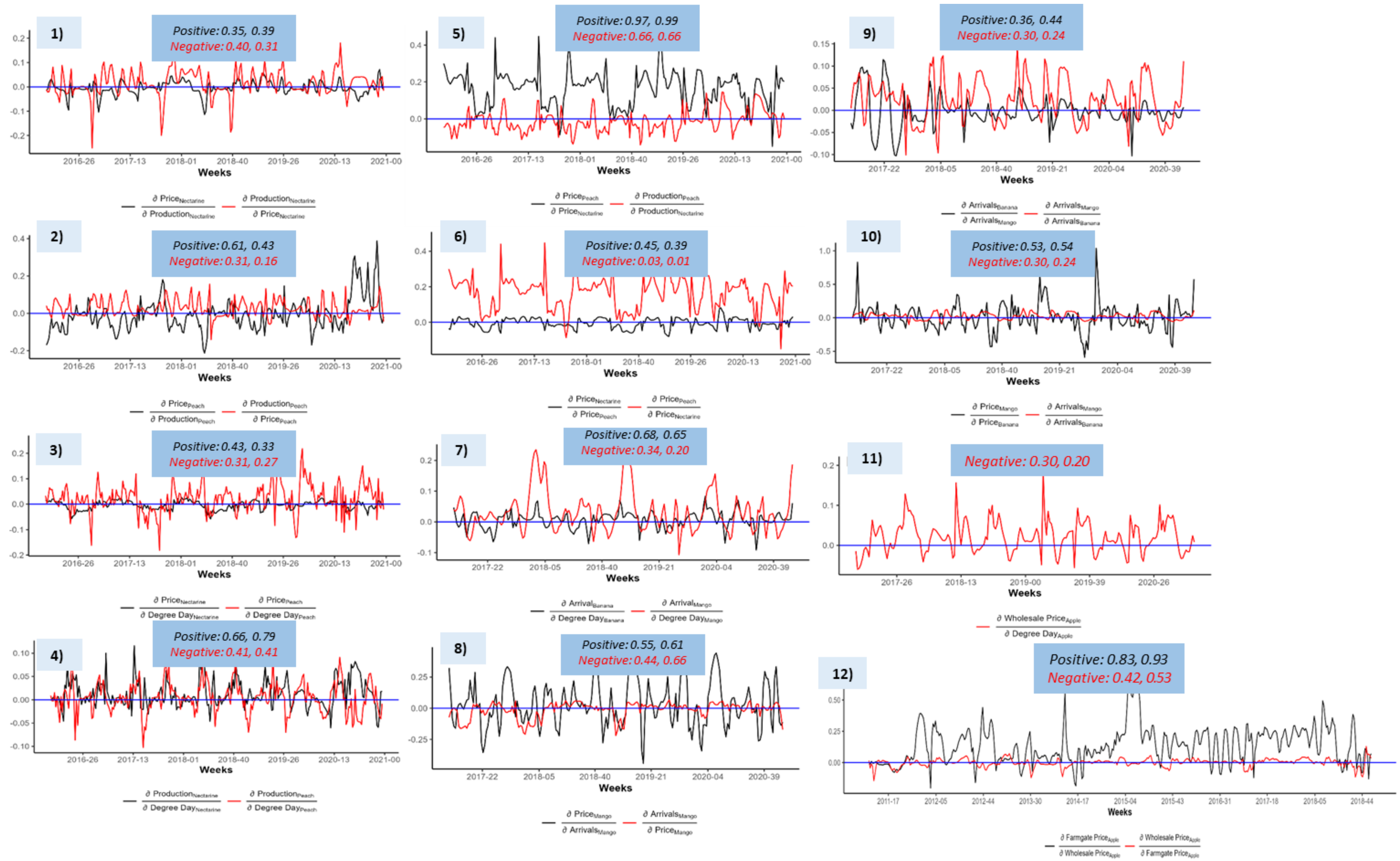

Figure 4.11: *Quantified interactions within long to short supply chains.*
We embedded an empirical attractor with phase space coordinates provided by state variables. We applied S-mapping to compute partial derivatives quantifying interactions among these variables over time (black curves) and the reciprocal of such interactions (red curves). The areas between the curves and the zero-axis are shaded blue to highlight weeks when interactions are positive or negative.

Long supply chains

In traditional long supply chains, quantity arrivals in the fruit markers exhibit strong growth (partial derivates) trend with growing degree days and price of the commodities [**Figure 4.11 (7-8)**]. However, the arrivals quantities show negative interaction among various fruits. The prices of fruits (banana and mango) reported a complementary relationship over time. This positive interaction span over 54% of the total area. While in the case of apple commodity, a robust positive trend (70% within weeks and 80% in magnitude of overall area) was estimated between price and growing degree days.

Medium supply chains

The forward (farmgate to wholesale) and backward (wholesale to farmgate) are important features of the present research. The positive trend prevails 58% within a week while 47% in overall magnitude during the study period. The strength of the interactions is even stronger in backward interactions in which almost 83% and 93% positive trends prevail within a week and overall, of total area, respectively [**Figure 4.11 (12)**].

Short-supply fruit chains

We first investigated the relationship between nectarine prices and production in short-supply chains in Italy. We observe that ∂Price/∂Production was positive 35% of the week, indicating a robust decline (negative 65%) in nectarine prices due to increased production. Taking an ecological interpretation, the production preyed on its prices. A similar, predatory relationship exists in peaches [**Figure 4.11** (2)]. The relationship between production and growing degree days highlighted the overall strong positive interactions (on average 60% of the week and total area) and indicated the *symbiotic association* [**Figure 4.11**(4)]. The nectarine prices drive peaches' prices while competition in production [**Figure 4.11**(5)].

4.3.5 Classification of pair-wise interactions – monthly basis

The last stage of NLTA is to classify all the causal interactions to know their ultimate dynamic influences within fruit systems. To compute the classification, we have calculated the cross-derivates of all the interactions (**Table 4.4**). For example, from January to April, both cross derivatives were negative; production (peach) – production (nectarine) interactions exhibit a competitive association between two fruit production. From May to June, their partial derivatives turned into positive/negative growth rates showing their predatory interactions. Further growth in these two productions from July – August resulted in positive partial derivatives in which both grew together. During the remaining months, both productions switch between predator-prey and competitive relationships for two months each in the short fruit supply chain.

Table 4.4: *Classification of pairwise monthly interactions*

Interactions	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Brazil												
Price $_{\text{apple farmgate}}$ – Price $_{\text{apple wholesale}}$												
Predator-Prey [a]	X	X						X	X	X	X	
Symbiotic			X	X	X	X	X					X
Italy												
Price $_{\text{peach}}$ – Price $_{\text{nectarine}}$												
Predator-Prey [b]	X				X	X	X	X	X	X		
Symbiotic		X	X	X							X	X
Production $_{\text{peach}}$ – Production $_{\text{nectarine}}$												
Competitive	X	X	X	X							X	X
Predator-Prey [c]					X	X			X	X		
Symbiotic							X	X				
Price $_{\text{nectarine}}$ – Production $_{\text{nectarine}}$												
Competitive									X			
Predator-Prey [d]				X	X	X	X	X		X		
Symbiotic	X	X	X								X	X
Price $_{\text{peach}}$ – Production $_{\text{nectarine}}$												
Competitive												
Predator-Prey [e]	X	X	X	X	X	X	X	X	X	X	X	X
Symbiotic												
Price $_{\text{nectarine}}$ – Production $_{\text{peach}}$												
Competitive					X							
Predator-Prey [f]			X	X			X	X	X			X
Symbiotic	X	X				X				X	X	
Pakistan												
Price $_{\text{banana}}$ – Price $_{\text{mango}}$												
Competitive									X			
Predator-Prey [g]	X	X	X		X	X		X				
Symbiotic				X			X			X	X	X
Arrivals $_{\text{banana}}$ – Price $_{\text{banana}}$												
Competitive		X							X		X	X
Predator-Prey [h]	X		X	X	X			X		X		
Symbiotic						X	X					
Arrivals $_{\text{banana}}$ – Arrivals $_{\text{mango}}$												
Competitive									X	X	X	
Predator-Prey [i]				X	X		X	X				
Symbiotic	X	X	X			X						X
Price $_{\text{mango}}$ – Arrivals $_{\text{mango}}$												
Competitive	X			X							X	X
Predator-Prey [j]		X	X			X			X	X		
Symbiotic					X		X	X				
Arrivals $_{\text{mango}}$ – Price $_{\text{banana}}$												
Competitive				X							X	
Predator-Prey [k]	X		X		X	X				X		X
Symbiotic		X					X	X	X			
Arrivals $_{\text{banana}}$ – Price $_{\text{mango}}$												
Competitive							X					X
Predator-Prey [l]				X	X	X		X	X	X		
Symbiotic	X	X	X								X	
Price $_{\text{apple}}$ – Arrivals $_{\text{apple}}$												
Competitive			X		X		X	X	X	X	X	
Predator-Prey [m]	X	X		X		X						X
Symbiotic												

[a] Predator (Price $_{\text{apple wholesale}}$) – Prey (Price $_{\text{apple farmgate}}$); [b] Predator (Price $_{\text{nectarine}}$) – Prey (Price $_{\text{peach}}$); [c] Predator (Production $_{\text{nectarine}}$) – Prey (Production $_{\text{peach}}$); [d] Predator (Production $_{\text{nectarine}}$) – Prey (Price $_{\text{nectarine}}$); [e] Predator (Production $_{\text{nectarine}}$) – Prey (Price $_{\text{peach}}$); [f] Predator (Production $_{\text{peach}}$) – Prey (Price $_{\text{nectarine}}$); [g] Predator (Price $_{\text{mango}}$) – Prey (Price $_{\text{banana}}$); [h] Predator (Price $_{\text{banana}}$) – Prey (Arrivals $_{\text{banana}}$); [i] Predator (Arrivals $_{\text{mango}}$) – Prey (Arrivals $_{\text{banana}}$); [j] Predator (Arrivals $_{\text{mango}}$) – Prey (Price $_{\text{mango}}$); [k] Predator (Price $_{\text{banana}}$) – Prey (Arrivals $_{\text{mango}}$); [l] Predator (Price $_{\text{mango}}$) – Prey (Arrivals $_{\text{banana}}$); [m] Predator (Arrivals $_{\text{apple}}$) – Prey (Price $_{\text{apple}}$).

In medium supply chains, the interactions were equally classified into predator – prey and symbiotic relationships. However, the classification varies within months throughout the year.

The interactions ($Price_{\ apple\ farmgate} - Price_{\ apple\ wholesale}$) started with a predatory relationship (January – February) and then switched to a symbiotic relationship for the next 5 months (March – July). Another regime shift was observed from August to November, in which predatory relationship was examined. The dynamic interactions ended again with the symbiotic nature of behaviour.

In traditional fruit supply chains, most of the commodity receives predatory behaviour (from January – April and June/October) between prices and quantity arrivals of the same fruits in the wholesale markets. Competitive behaviour between quantity arrivals and prices of the same fruits was also observed during September and November/December. The symbiotic association was only observed in July. For cross derivatives of arrivals and prices for bananas and mangoes, symbiotic relationships observe in February and May/June. The month of October witnessed predatory interactions. Other important interactions were between different fruits' prices and quantity arrivals. May and August were predatory, while September (competitive) and December (symbiotic) relationships were reported.

4.4 Discussion

For food security assessment (R. Huffaker et al., 2018), a single variable is not enough (Schreiber, 1999) to reconstruct the skeleton of real-world attractors (Ghil et al., 2002). Therefore, we have developed an extended framework to assess the risk transmission from the *environment–farm–market nexus on* fruit systems. To reflect the adaptation capacities, we have considered three different fruit supply chains, *i.e.*, long (Pakistan), medium (Brazil), and short (Italy), that form regional trade hubs. The empirical evidence showed that observed risks in fruit markets are due to inherent market instability – *irrespective of fruit supply chains* – governed by a low-dimensional non-linear dynamic. The long-term market dynamics evolved along a three-dimensional attractor empirically constructed from detected signals. Surrogate data sets strongly reject the *null hypothesis* that the attractors are reconstructed from a random stochastic process. The framework provided the characterization of dynamic interactions driven by endogenously generated risks.

The Brazilian fruit markets face several issues, including severe weather conditions, the tendency to prefer exports over domestic supply, and a sharp decline in consumption. The low diversification index of apple species is another reason frequent fruit fly attacks resulted in lower quality/production of apples (Monteiro et al., 2019). The result indicates that 2013 – 15 and 2017 – 2018 were the periods where high price volatility was observed, which coincides with a 28% increase reported in export (year on year basis) and apple destined in additional 41 international markets compared to 25 countries last year (Ming, 2019).

The analysis reveals that despite strong networks of fruit producers' cooperatives in Italy, the nectarine and peaches prices exhibited greater fluctuations during 2019 – 2020. The productivity of fruits was adversely affected by the plum pox virus (Sharka disease), continuous decline in planted areas (Bettini, 2017), and frost occurring during the end of March – early April, resulting in a 29% reduction in nectarine/peach production in Emilia – Romagna region (Kole, 2020). Valverde (2020) highlighted that no new trees of nectarine/peaches were planted after grubbing. The inefficiency of the short supply chain, *i.e.*, producers, was due to low markup compared to high markup for processors (H. Lee & Van Cayseele, 2022).

The traditional fruit supply chains are characterized by periodic cycles and asymmetric risk transmissions. Apple shows strong positive vertical risk transmission (from one market to another) ~70% within a week with 80% magnitude overtime for price and growing degree days. Our results align with H. Khan & Jayasuriya's (2018) findings. In mango, a lead-lag relationship exists due to frequent fruit flies attacks (Sarwar et al., 2014). The intensity of the insect-pest attacks was up to 57% in mango (Jose et al., 2013). The reported production constraints in the case of mangoes are the incidence of insects/pests (18.5%), substandard insecticides (11.1%), and natural calamities (7.4%) (Badar & Ahmad, 2021). The quality and size of the fruits are important factors that are often ignored while supplying fruits in traditional fruit supply chains (Balagamwala & Gazdar, 2014).

Current research findings confirm that fruit markets are inherently unstable, requiring coercive measures as a public policy initiative. Restructuring fruit supply chains without considering the dynamic complexities and country-specific context resulting in asymmetric risk transmissions.

4.5 Conclusion

The current state of food and nutritional security reports suggests that the world is not on the right track to eradicate hunger, food insecurity, and malnutrition in all forms by 2030. The producers' support reached USD 540 billion annually and is projected to be over USD 1.8 trillion by 2030. These incentives create distortion and stress in repurposing the agricultural support strategy *(RASS)*. The current business-as-usual model overemphasizes the production of emission-intensive and unhealthy commodities. Therefore, the United Nations declares the year 2021 as the international year of fruits and vegetables to highlight the importance of food and nutritional security across the globe.

The present research was designed to model the risk transmission, adaptation capacities, and their impacts on dynamic fruit systems. The nonlinear time series approach has provided a way to distinguish endogenous and exogenous risks of *climate – producers – market* nexus in complex dynamics fruit systems. The result indicates that restructuring market supply chains did not dampen the impacts of risks on fruit systems. Instead, *RASS* requires based on specific country/commodity dynamics.

Chapter 5 Conclusion and Policy Recommendations

The present research has outlined the implications from systematic review and empirical research findings to understand underline causes of price volatility, market imperfections and complex food system dynamics. There is no *"one size fits"* all solution available to transform food systems across the globe. The dynamics of each food [sub]system varies depending on market/country characteristics. The multi-dimensional drivers of price volatility need to be identified in respective marketing structures to understand the nature and drivers of crisis during and after post-crisis periods. The research paradigm must adopt the dynamics of chaos and its detrimental impacts while addressing the issue of price volatility.

The previous [food] crisis were related to food availability – failure of production – while current food crisis is more about supply disruption revolving around market imperfections and requires macroeconomic adaptive policy measures with consistent financing. Currently, the question about how much any region/country export [trade] compared to how much they produce is more relevant. The countries like Russia and Ukraine are the biggest exporter of food commodities around the globe compared to production – ~10% production vs. gigantic shares of export *e.g.*, sunflower (56%), barley (19%), wheat (13%) etc. The *Russia – Ukraine* war proves our research implications as world experienced another surge in prices due to supply disruption. The recent global COVID-19 pandemic is another prima facia and reiterated the significance of fostered holistic approaches of adoption to create more resilient and sustainable food systems. In the developing world, the inconsistent and abrupt changes in agriculture [food system] policy support hampered market development, idiosyncratic behaviours of value chain actors, overutilization of farm inputs, and widened productivity gaps.

In developing world, the fruits of the green revolution are over now. The historic increased in production due to area augmentation resulting in loss of natural habitats (if deforestation) and future intensify the rift between agriculture and environment nexus. Under imperfect marketing conditions, lower supply responses to price and non-price factors were due to the nature of the crop cycle and payment policy. The delayed payments prevent farmers from investing in other crops or diversifying their food system.

The climate system undoubtedly influences the supply response independently and collectively –the combined effect of both climatic variables, *i.e.,* precipitation and temperature, have profound, significant combined impacts. These impacts vary with the crop phenological stages, and aggregation of climatic variables resulted in spurious results. The previous models fail to provide reasonable burden of proof for validation of model results with real world.

Huffaker (2015) had already provided a *pre-modelling data diagnostic framework (PMF)* to provide evidence of correspondence between models and the real-world based on nonlinear time-series analysis. At the same time, Medina et al. (2021) developed a correspondence framework with a multi-agent system. These two frameworks may serve as a reasonable *burden of proof* to audit public policy models and intervention decisions before *RASS*. This empirical scheme may validate results, *i.e.*, the magnitude, persistence, and degree of volatility across countries and sectors of the economy (energy *vs.* non-energy) during the unanticipated crisis period.

Moreover, the market and R&D uncertainty resulted in lower yield responses. The vast investments require improving land availability in the short term as farm inputs are only variable inputs whose application can adjust to policy incentives. The lower yield responses were also due to the imbalance in fertilizer use – here, potassium – application arising from a lack of awareness and distortion in agriculture incentives in the developing world. The increased crop and fertilizer prices [here only DAP prices] lowered crop supply response instead of boosting the productivity of the crop in such an imperfect marketing arrangement. Finally, there is a need for extension and agricultural advisory service providers to work with crop growers to enhance *labor-management skills* and promote the *4R nutrient stewardship* framework *(right fertilizer - right rate - right time - right place) in the spirit of Precision Agriculture*.

The present research has highlighted the various conceptual framework and empirical models to assess/quantify the impacts of current policies on the food system. The current policies prove to be inefficient and dented the overall productivity. Restructuring supply chain actors based on product quality, transaction cost, and bargaining powers was also not stabilizing the shocks in complex dynamic systems. The shocks in dynamic fruit systems are endogenously generated and have low-dimensional nonlinear dynamics. There is a need to understand the complex dynamic systems and the interactions of their components at each level of the value chain in a specific country/commodity context before devising any comprehensive *RASS* for agri-food system transformation to achieve global SDGs by 2030.

Limitations and Future Research

The curation of data was the most difficult part of executing planned research. Farm gate prices (Pakistan) and production (Brazil) data were not accessible to further investigate the interactions of prices and climate for long and medium fruit supply chains, respectively. For Italy, we could not get sufficiently long time series data for nectarine and peaches production from CSO. The available data from CSO were pooled over weekly observations, and difficult to isolate/incorporate the effects of fruit cultivars within the modelling framework. It is better to have daily observational data to isolate such effects. We have also planned two additional research components (manuscripts) that may be finalized for forthcoming publications.

Forecasting signals through machine learning algorithms

Ten different machine learning algorithms (MLA) were identified, and preliminary results were obtained. The research idea is to forecast the signals (prices/production) through MLA and reconstruct the dynamic attractors to develop the correspondence with the original/surrogate time series attractors. The signals data is ready to apply Echo-State Neural Network (Lin et al., 2009) and reconstruct dynamic attractors with forecasted values.

Impact of price volatility of fruit trade: An application of gravity model

Another future research component is price volatility impacts fresh fruit trade through the gravity model. The planned research will provide a way to know the macroeconomic impacts of price volatility on trade.

Developing a comprehensive ABM for fruit systems requires comprehensive efforts and financial support from national/international organizations/institutions. The transformation of the fruit system was not realized until we explored novel approaches to develop correspondence between the real world through data-driven or model-centric approaches.

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Annexes

Annex 1

A Systematic Review on Price Volatility in Agriculture

Table A.1: *Methodological approaches used in the selected studies.*

Approach(es)	Pre-crisis	Food crisis	Post-crisis	Total	Authors ID
Descriptive Analysis	1	-	29	30	1 - 30
Econometric Models	12	7	243	262	31 - 292
Economic Models	-	1	11	12	293 - 304
Hybrid Model	-	-	2	2	305 - 306
Mathematical Technique	-	1	13	14	307 - 320
Non-parametric Tests	-	-	6	6	321 - 326
Parametric Tests	-	-	1	1	327
Simulation	4	2	31	37	328 - 364
Statistical Models	4	1	19	24	365 - 388
Theoretical Framework	1	1	8	10	389 - 398
Total	**22**	**13**	**363**	**398**	

Notes: Authors' ID details are available in Appendix-A. The post-crisis period was the most distinct in terms of no. of approaches used (10) as compared to pre-crisis (5) and food crisis (6).

Table A.2: *Description of database category used in selected studies.*

Category	Pre-crisis	Food crisis	Post-crisis	Overall
Commodity Exchange	5	4	118	127
Global	-	-	1	1
International	6	3	38	47
Mixed	3	2	81	86
National	3	1	58	62
Published Reports	1	6	1	8
Survey	-	1	13	14
UN	1	-	18	19
Total	**19**	**17**	**328**	**364**

Notes: Overall, eight different types of database categories were reported in selected studies. In pre-crisis, 19 database categories were found, while 17 categories were reported during the food crisis period.

Table A.3: *Distribution of agriculture sub-sectors among periods.*

Sub-sectors	Pre-crisis	Food crisis	Post-crisis	Overall
Cereals	14	6	208	228
Fibre	-	-	3	3
Fishery	2	-	4	6
Fruits	-	-	7	7
Herbs	-	-	1	1
Livestock	3	1	35	39
Oilseeds	-	-	13	13
Pulses	-	-	2	2
Shrubs	2	1	11	14
Spices	-	-	4	4
Tree	-	-	4	4
Vegetables	-	1	14	15
Grape wines	-	-	1	1
Total	**21**	**9**	**307**	**337**

Notes: The distribution of selected articles in terms of agriculture sub-sector shows that cereals (228) were the most prolific sub-sector and while the rest of the sub-sectors were least studied, e.g., fibre (1%), fruits (2%), vegetables (5%), etc., within agriculture.

Annex 2

Sugarcane Supply Response to Prices and Climate in a Monopsony Market

Introduction

This supplementary information was prepared to provide additional insights about the present study. Following are the selected twenty districts from three important provinces of Pakistan. These are,

Sindh (08): Badin, Dadu, Hyderabad, Khairpur, Mirpur Khas, [5]Nawab Shah, Sanger, and Thatta. **Punjab (09):** Bahawalnagar, Faisalabad, Gujrat, Jhang, Lahore, Muzaffargarh, Okara, Rahim Yar Khan, and Sargodha. **Khyber Pakhtunkhwa (03):** Dera Ismail Khan, Mardan, and Peshawar.

According to the national sugarcane experts[6], there are four main stages with their duration for the sugarcane crop (**Table A.4**).

Table A.4: *Phenological stages of sugarcane crop*

Phenological Stages	Months
Sowing and Germination (G)	Jan-Mar.
Tillering (TIL)	Apr.- Jun
Grand Growth (GG)	July – Aug
Maturity and Harvesting (M)	Sep-Nov

Source: *Pakistan Agricultural Research Council, Islamabad and Ayub Agriculture Research Institute, Faisalabad*

The Pálfai Drought Index (PaDI)

For the numerical characterization of droughts, the Pálfai drought index (PAI) has been used for agriculture and water management users. This index characterizes the strength of the drought for an agricultural year with one numerical value, which has a strong correspondence with crop failure. For the present study, this drought index is computed for the first time for Pakistan's Agriculture, like Lee and Nadolnyak (2012) Palmer Drought Severity Index (PDSI) for the USA.

However, in the formula of PAI, determining three correction factors based on daily temperature and precipitation values, as well as groundwater levels, is difficult. For easier practical use, Palfai and Herceg (2011) have worked out a new, simpler method for calculating these factors, which is based on monthly mean air temperature and the monthly sum of precipitation. The formula of the base value of the modified index, named Palfai's Drought Index (PaDI), is:

$$PaDI_0 = \frac{\left[\sum_{i=apr}^{aug} T_i\right]/5 * 100}{c + \sum_{i=oct}^{sep}(P_i * w_i)} \qquad (A.1)$$

Where:

$PaDI_0$ = base-value of drought index (°C/100 mm)

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[5] *District Nawab Shah renamed as district Shaheed Benazirabad in year 2008.*

6 Coordinator Sugarcane Program, National Agriculture Research Centre, Islamabad.

T_i = monthly mean temperature from April to August (°C)

P_i = monthly sum of precipitation from October to September (mm)

w_i = weighting factor

c = constant value (10 mm).

The weight factors (w_i) of precipitation are given in **Table A.5**. Express the difference between soil moisture accumulation and plants' water demand.

Table A.5: *Weight Factors.*

Month	Weight Factors (w_i)
October	0.1
November, December	0.4
January-April	0.5
May	0.8
June	1.2
July	1.6
August	0.9
September	0.1

Calculation of drought index correction factors (k_1, k_2, k_3)

The k_1 substitute is the correction factor k_t which represents the number of hot days. The calculation is as follows:

$$k_1 = \frac{\left(T_{jun} + T_{jul} + T_{aug}\right)/3}{\left(\overline{T}_{jun} + \overline{T}_{jul} + \overline{T}_{aug}\right)/3} \qquad (A.2)$$

Where:

k_1 = Temperature correction factor

$T_{jun,jul,aug}$= Annual mean temperature for June -August (°C)

$\overline{T}_{jun,jul,aug} = Multiannual\ mean\ temperature\ for\ June - August\ (for\ period\ 1981 - 2010, °C)$

The k_2 substitute is the correction factor k_p representing the length of a rainless period. The calculation is as follows:

$$k_2 = \sqrt[4]{\frac{2 * \bar{P}_{sum}^{min}}{MIN\left(P_{jun}, P_{jul}, P_{aug}\right) + \bar{P}_{sum}^{min}}} \qquad (A.3)$$

Where:

k_2 = Precipitation correction factor.

$\bar{P}_{sum}^{min}$= The lowest value from multiannual precipitation sums of three summer months (June, July, August), mm,

$MIN(P_{jun}, P_{jul}, P_{aug})$ The lowest value from annual precipitation is three summer months (June, July, August), mm.

The k_3 substitute is the correction factor k_{gw} which represents groundwater circumstances. Here calculation is based on the previous 3 years' precipitation values:

$$k_3 = \sqrt[n]{\frac{\bar{P}}{P_{36m}}} \qquad (A.4)$$

Where:

k_3 = characterize the precipitation circumstances of the previous period, Correction factor,

$\bar{P}$ = Average multiannual precipitation sums for the period October-September, mm,

P_{36m} = average precipitation for October-September for previous 3 years, mm,

n =Exponent value is 3.0 on the plain area, and on hilly or higher territories, is 5.0.

Calculation of PaDI

$$PaDI = PaDI_0 * k_1 * k_2 * k_3 \qquad (A.5)$$

$PaDI$=Palfai drought index (°C/100 mm)

k_1= temperature correction factor

k_2= precipitation correction factor

k_3= correction factor, which characterizes the precipitation circumstances of the previous 36 month

k_1 represent the relation between examined and annual summer mean temperature, k_2 represent the relation between examined and annual summer precipitation sum from temperature and precipitation correction factors, respectively while k_3 represent the effect of precipitation circumstances of the previous 36 months. For all the districts of Pakistan, we have determined the PAI and PaDI values for the period 1981-2010. The classification of drought strength is wider for PaDI shown in **Table A.6**.

Table A.6: *Drought categories.*

PaDI (°C/100 mm)	Description
< 4	Drought less Year
4 –6	Mild Drought
6 –8	Moderate Drought
8 –10	Heavy Drought
10 –15	Serious Drought
15 –30	Very Serious Drought
> 30	Extreme Drought

Pakistan is blessed with fertile lands and all four seasons, suitable for growing various crops, including food, fibre, and cash crops. Based on the cropping pattern and cropping schedule, sugarcane crops face competition from wheat and cotton (Bt.) for land and resources. Any drastic change in the agricultural support price for wheat and cotton crop has increased the area allocated to these crops and production but at the cost of sugarcane crops. This response will distort the equilibrium of demand and supply of sugarcane in the country. The shares of crop acreage in the total cropped area under five major crops in twenty main sugarcane-producing districts are presented in **Table A.7**.

Table A.7: *Share of crop acreage in the total cultivated area in selected districts.*

Crop(s)	**Area (%)**			
	Punjab	**Sindh**	**KP (Khyber Pakhtunkhwa)**	**Pakistan**
Sugarcane	9.6	13.0	19.5	14.0
Cotton	19.7	27.4	0.3	15.8
Wheat	53.8	44.8	54.2	50.9
Rice	11.9	14.1	1.9	9.3
Maize	4.9	0.7	24.1	9.9
Total	**100**	**100**	**100**	**100**

Source: Author's calculation

It confirms that wheat and cotton are the major competing crops for sugarcane crops in our study area, accounting for 50.9% and 15.8% of the total cultivated area in major crop categories. The fertilizer uptake rate was calculated based on sugarcane share in total fertilizer uptakes within districts from 1981 to 2010 (**Table A.8**).

Table A.8: *Share of sugarcane in total fertilizer uptake.*

Year	**Share (%)**
1981-83	9
1984-88	8
1989-96	11
1997-98	8.1
1999-2004	10
2005-10	8

Source: National Fertilizer Development Centre, Islamabad.

Annex 3

Fruit Market Instability and Climate-Production Nexus in Complex Dynamic Systems

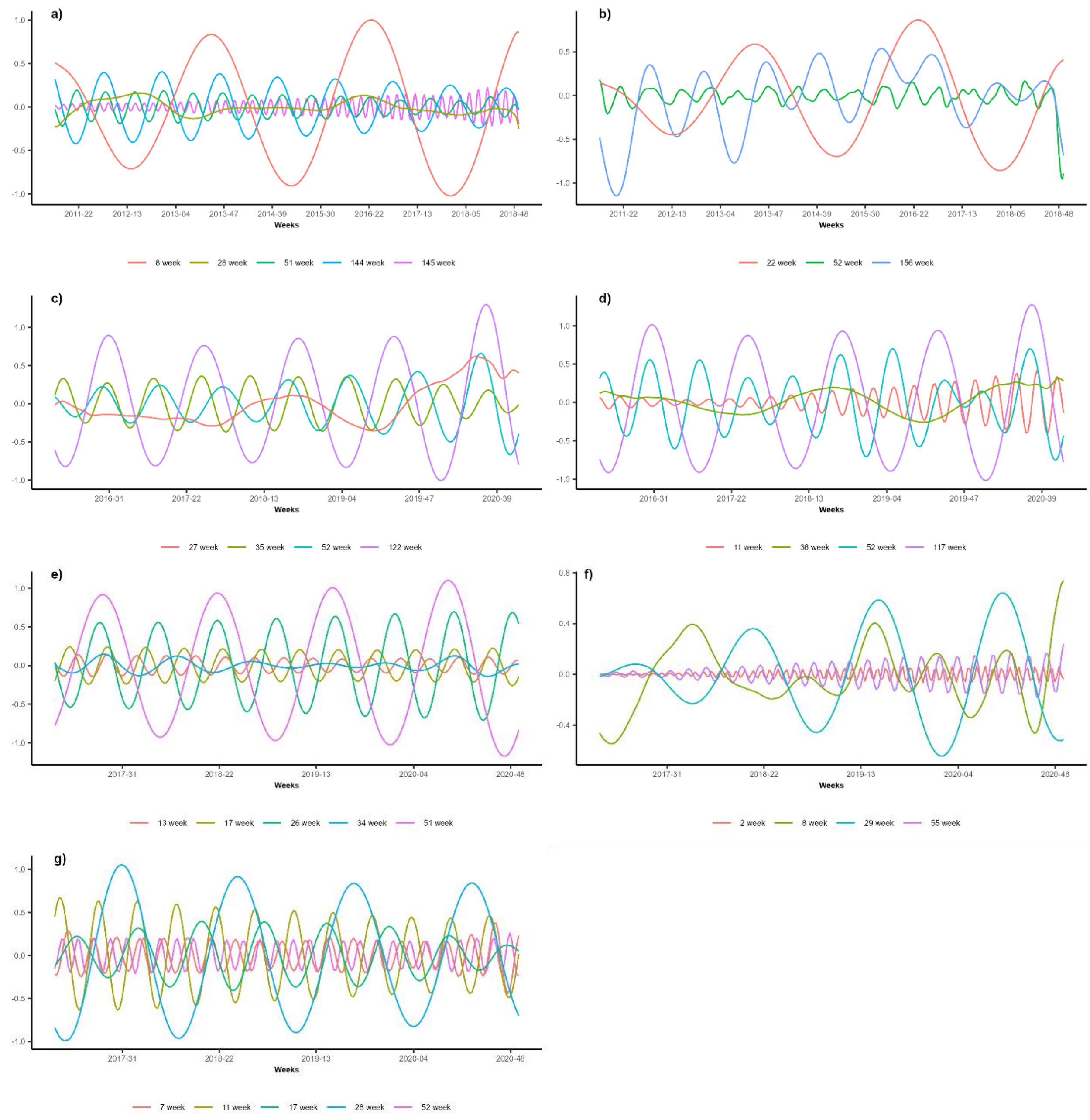

Figure A.1: *Plot of fruit price cycles.*
Note: Panels a) & b) for Brazil, c) & d) for Italy, and e) – g) represent the analysis of Pakistan fruit prices.

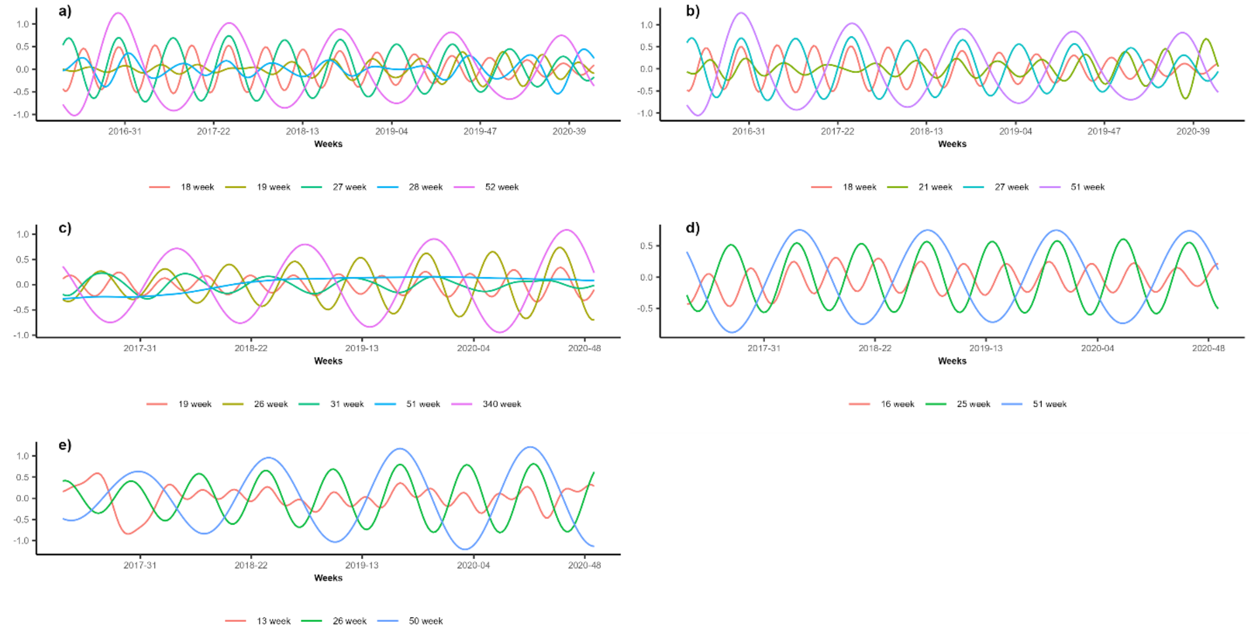

Figure A.2: *Plot of fruit arrivals (production) cycles.*
Note Panel a) & b) for Italy; c) – e) represent data from Pakistan.