RURAL TRANSFORMATION DEVELOPMENT IN PAKISTAN: THEORY AND EVIDENCE

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Dedication

This thesis is dedicated to my husband

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I highly acknowledge the support of my family, supervisors, and my friends

ABSTRACT

Rural Transformation Development (RTD) is about the reconstruction of the rural economies their regional patterns through rapid industrialization, urbanization, changing cropping patterns, and employment structure transformation. However, existing literature overlooks the spatial disparities, and multidimensional nature of this transformation, leaving a significant gap. Hence, the aim of this study is to investigate not only the spatial dynamics of rural transformation but also its drivers and outcomes in detail. For the sake of understanding the spatial pattern and trends, this study employs a holistic approach where Principal Component Analysis (PCA) is used to construct the Rural Transformation Development Index (RTDI) for 78 districts in Pakistan over the period of 2004-2019. The indicators of RTDI are share of high-valued agriculture, share of livestock, share of non-farm employment, urbanization, and land use intensity. The study classifies districts into five RTDI categories, highlighting the varied pace of rural transformation over time. From this analysis, it is evident that rural transformation is not uniform rather it represents large inter-district disparities. Exploratory spatial data analysis shows the existence of clustering in the dataset, analyzed through five different categories of RTDI. It underscores the need for multidimensional, region-specific policies tailored to the unique characteristics of each district and its cluster, rather than a uniform approach across the country. Given the varying capabilities and characteristics of rural areas, levels of RTD may differ, resulting in advanced, normal, or lagging stages. These disparities can create regional development imbalances, making it essential to understand these differences and identify their key drivers.

Investigation of the drivers of RTD in districts across Pakistan using spatial analysis for the period 2004-2019 is done by employing the "Dynamic Spatial Durbin Model" with time fixed effects, the research assesses the direct and spillover effects of various factors on RTD. The findings reveal that education and irrigation are pivotal in driving RTD at all stages. The positive and significant time lag term implies temporal dynamics and hence rural transformation in each subsequent period is influenced by its past values. Additionally, the positive and significant spatial lag term indicates that RTD in one district is positively affected by the RTD in neighboring districts.

Spatial heterogeneities have also been identified in this research across districts using the cross-section data for the year 2019. Integrating the localized regression coefficients from the Geographically Weighted Regression (GWR) analysis with the cluster-based categorization of districts reveals significant cross-sectional heterogeneity in the drivers of RTD across Pakistan. Each cluster exhibits distinct characteristics: Low and intermediate-low clusters require foundational investments in education, irrigation, and credit access, while the Medium, Intermediate-High, and High clusters can build on existing strengths through refined and targeted interventions.

Additionally, the study regards the outcomes as well, for which the impact of RTDI on per capita agricultural income has been captured. It is found that higher levels of rural transformation significantly increase per capita agricultural income, highlighting the positive economic effects of multidimensional development.

Overall, the results of the study call for differentiated and targeted rural development strategies based on RTDI categories. Such policies can promote balanced and sustainable growth across different regions of Pakistan. The study highlights the importance of

tailored policy interventions to address the specific needs and capabilities of various rural areas which are at their varying stages of transformation. The districts at the low stage of transformation require substantial investment in education and irrigation, as the experience of high-stage districts demonstrates that these drivers play a critical role in accelerating the process of rural transformation by improving resource use efficiency, supporting the adoption of high-value agricultural practices, and enabling a structural shift towards non-farm employment.

Key words: Rural transformation, non-farm employment, land intensity, urbanization, spatial clusters, high-valued agriculture, PCA, spatial heterogeneities, spatial dependencies, per capita agriculture income

JEL Classification: O18, Q12, Q15, R12, C38.

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List of Abbreviations

1	AIC	Akaike Information Criterion
2	AMIS	Agriculture Marketing Information Services
3	BIC	Bayesian Information Criterion
4	CV	Coefficient of Variation
5	DEFRA	Department of Environment, Food and Rural Affairs
6	DSDM	Dynamic Spatial Durbin Model
7	ESDA	Exploratory Spatial Data Analysis
8	EUROSTAT	Statistical Office of the European Union
9	FAO	Food and Agriculture Organization
10	GDP	Gross Domestic Product
11	GIS	Geographic Information System
12	GoP	Government of Pakistan
13	GWR	Geographically Weighted Regression
14	HIES	Household Income and Expenditure Survey
15	ICT	Information Communication Technology
16	IFAD	International Fund for Agricultural Development
17	IRDP	Integrated Rural Development Programme
18	KM	Kilometer
19	KPK	Khyber Pakhtunkhwa
20	KPP	Khushal Pakistan Program
21	LFS	Labor Force Survey
22	LR	Likelihood Ratio
23	NUTS	Nomenclature of Statistical Territorial Units
24	OECD	Organization for Economic Co-operation and Development
25	PCA	Principal Component Analysis
26	PSLM	Pakistan Social and Living Measurement Survey
27	RT	Rural Transformation
28	RTD	Rural Transformation Development
29	RTDI	Rural Transformation Development Index
30	S1	Stage 1

31	S2	Stage 2
32	S3	Stage 3
33	SAR	Spatial Auto Regressive
34	SDG	Sustainable Development Goal
35	SDM	Spatial Durbin Model
36	UNESCO	United Nations Educational, Scientific and Cultural Organization
37	US	United States
38	ZTBL	Zarai Tarqiyati Bank Limited

CHAPTER I

INTRODUCTION

1.1. Background

This chapter sets the background of the study by defining major concepts and terminologies with a rigorous support of the literature. It is setting the base for rest of the study by clearly stating the significance and objectives.

1.1.1. Rural Transformation Development

Rural Transformation Development (RTD) is about the reconstruction of the rural economies and their regional patterns through rapid industrialization, urbanization, changing cropping patterns and employment structure transformation, etc. (Zhang & Zhang, 2022). Such shifts and changes in the pattern of employment are initially observed in developed economies in the mid-20th century followed by developing economies (Weersink, et al., 1998; Woldenhanna and Oskan, 2001 and Lamb 2003). In several Asian nations too, rural, and agricultural transformation is witnessed in the late 20th century when farming systems become more commercialized due to mechanization and varying economic conditions. Even small farming households use modern agricultural technologies due to the growing labor shortage in the agriculture sector, increasing wage rate, migration to cities and other countries, and the aging of farmers (Rola-Rubzen et al., 2020). It is widely believed that these increasing roles of agricultural technologies can boost productivity, and farm revenues and can reduce poverty when used properly and in the appropriate combination (Tambo and Mockshell, 2018; Rola-Rubzen et al., 2019).

Due to differences in the endogenous capabilities and characteristics of rurality, there would be a possibility of a differentiated degree of rural transformation development i.e., advanced, normal, or lagging, which ultimately generate regional development imbalances (Liao & Chen, 2017 and Lu et. al., 2020). To develop a balanced rural revitalization strategy, there is a need to ensure the proper allocation of resources in multiple dimensions like rural civilization, governance, industrial production, ecological livability, etc. (Liao & Chen, 2017; Lu et. al., 2020). Nonetheless, the coordination and balance in various dimensions of RTD are important but also the policy stimulus, investment, infrastructure, increase in agriculture GDP, etc. are important drivers for boosting the speed of RTD (Morris et al., 2017; Abreu & Mesias, 2020; Casini et al., 2021).

Rural transformation is not a static phenomenon, rather it exhibits spatial characteristics (Yang et al., 2019 and Zhang & Zhang, 2022). Over the past 40 years, Pakistan has experienced significant shifts in cropping patterns, livestock holdings, employment, and rural income, reflecting ongoing rural transformation. Farmers have increasingly shifted from low to high-valued crops, with the share rising from 53% in 1980 to 80% in 2019. Additionally, non-farm employment in rural areas has grown from 43% in 1986 to 75% in 2019, indicating a structural shift from agriculture to non-agriculture sectors (GoP, 2019). These changes highlight the dynamic nature of rural transformation in Pakistan's economy, but they are not uniform across the country. Each district exhibits a different pace in progressing through various stages of transformation (Wang et al, 2025). Districts less impacted by climate change have experienced transformation differently compared to more affected districts (Alam et al., 2007). Additionally, districts benefiting from development programs like Khushali Bank (World Bank, 2002), Khushal Pakistan Program (KPP) (World Bank, 2005), and the Integrated Rural Development Programme (IRDP) (World Bank, 2023) have undergone diversification, specialization, and mechanization at a different pace than those that have not benefited from such initiatives. Interventionist, uncoordinated and distortionary policies are another feature of rural economy that calls for the need of transformation. Land fragmentation and land inequality severely affect the land use patterns across various districts. The selection of crops is highly dependent on the protectionist policies and the support price by the government. Regional disparities on account of irrigation facilities affect the whole rural system and its pace of transformation (World Bank, 2024). These spatial variations further emphasize the complexity of rural transformation in Pakistan and demand a holistic analysis.

1.1.2. Drivers of Rural Transformation Development

Rural Transformation Development (RTD) is a fundamental aspect of contemporary rural development, encompassing various components such as the development of rural economic systems, transformation in social and consumption structures, and changes in urban-rural relationships (Liu et al., 2016). Long et al. (2011) enriched this understanding by proposing evaluation dimensions that integrate these components, thus providing a cohesive framework for assessing the multifaceted nature of RTD. Additionally, RTD involves the reconstruction of rural spatial patterns and socio-economic forms in the process of rapid industrialization and urbanization. Local participants respond to these changes due to the recombination and interaction of urban and rural populations and socio-economic developments (Long et al., 2019). There are numerous studies that focus mainly on the sociological aspects of rural transformation, but there are other important aspects to consider, such as examining the regional differences in RTD (Phatharathananunth, 2016 and Li et. al., 2018), investigating influencing factors and drivers (Li, et. al., 2015 and Ge, et al., 2019) and identifying regional patterns (Klaniecki et. al., 2020 and Suesse and Wolf, 2020). It is important to consider the dimensions like agricultural production, human resource, land use pattern and industrial production to review the internal mechanism of RTD and to investigate and assess the long-term viability of RTD (Zhang & Zhang, 2022). This comprehensive approach helps in addressing the regional differences and ensuring a more balanced and effective rural transformation strategy.

Despite significant changes in rural economies of Pakistan over the last few decades, including shifts in cropping patterns, livestock production, non-farm employment, and income levels, the extent and pattern of Rural Transformation Development (RTD) remains poorly understood at the district level. Existing studies are limited in scope, often considering only one or two indicators and ignoring the multidimensional and spatial nature of rural transformation. Moreover, spatial-temporal dependence and spillover effects of key drivers such as infrastructure, irrigation, credit, and education are rarely examined, leaving critical gaps in understanding how rural transformation propagates across districts. This gap hinders the formulation of effective, targeted policies to promote balanced and sustainable rural development across Pakistan. Therefore, there is a pressing need for a comprehensive, spatially explicit analysis of RTD to capture both its drivers and economic impacts, including on per capita agricultural income.

1.2. Contribution and Significance of the Study

There is a growing amount of literature about rural transformation but most of them have taken one or two indicators of rural transformation i.e., share of high-valued agriculture and the share of non-farm employment (Berdegue, et. al., 2013; IFAD, 2016; FAO, 2017; Bank, 2018; Huang, 2018; Mujamdar, 2020, Huang and Shi, 2021 and Abedullah, 2023) and Rate of change of total agricultural production in terms of grain-based to high-value products (Timmer, 2017 and Fan, 2019) and the rate of change of employment from farm-based to non-farm based (Reardon et al., 2007; Haggblade, et al., 2010 and Otsuka & Fan, 2021) are used as indicators. In Pakistan, the combined impact of the rural agriculture sector and rural non-farm sector has been evaluated to see its impact on the rural poverty incidence (Dorosh et al., 2003). Several studies have reflected that the combined use of modern agricultural technologies, skilled labor force and sustainable prices in the commodity markets collectively drive the rural growth and transformation at a high speed in 1970s and 1980s despite all the domestic and political issues in Pakistan (Heston & Kumar, 1983 and Qureshi et al., 2004). But as discussed earlier, given the versatile features of rural economy of Pakistan one or two indicators are insufficient to capture the phenomenon.

This particular study is designed for a more comprehensive analysis to quantify the extent and pattern of the rural transformation in last two decades. Notably, studies on rural transformation at the regional level are limited, and the incorporation of spatial analysis is entirely absent. This research seeks to bridge these gaps and generate valuable insights to inform future policy formulation.

In Pakistan, research on Rural Transformation Development (RTD) is still limited, with only a few studies focusing on rural development, and even fewer addressing the specific drivers of RTD. The importance of credit is recognized in this process, but the Pakistani farmers primarily depend on traditional moneylenders which leads to high interest rates and significant indebtedness (Rehman et al., 2017). Institutions like ZTBL provides loan on a lower interest rate than the other commercial banks (Shah et al., 2016), it still faces a number of constraints including *red-tapism*, poor banking infrastructure in rural areas, and a higher share of non-performing loans (Chandio et al., 2017). Most existing studies focus on the challenges associated with traditional moneylenders and institutional credit issues, yet there is limited research on how these credit constraints directly impact the broader process of RTD. Some studies have highlighted the importance of irrigation water management for subjective wellbeing of rural families and increased crop productivity (Fiaz et al., 2016; Khana et al., 2017 and Nadeem et al., 2021) but these studies are often limited to specific areas or cities, lacking a comprehensive, nationwide perspective. Also, there is a noticeable gap in research that examines how effective irrigation practices can drive broader rural transformation across districts of Pakistan. Education driver is also studied but in terms of its impact on rural poverty (Tasleem, 2024) and not in terms of its role in RTD.

Not only the comprehensive study on drivers is missing but previous research has often overlooked the spatial-temporal dependence and spillover impacts of various drivers, which are essential for comprehending the interconnected nature of rural communities. RTD is a phenomenon with very strong theoretical spatial dependence, ignoring it may lead to bias results (Betz et al., 2021). To better understand the drivers of RTD, it is crucial to incorporate spatial analysis and account for spatial spillovers.

This study aims to address these significant gaps by performing a detailed analysis at the district level across Pakistan, with a specific focus on learning spatial temporal dependence and spillover impacts of various drivers on rural transformation. Understanding these dynamics is essential for identifying and overcoming key obstacles that hinder RTD. This study seeks to contribute to more effective rural transformation strategies and stimulate broader economic benefits.

Not only learning the spatial dependence is important but the spatial heterogeneity is also crucial to understand the spatial data. This is also a missing research gap and aimed to be filled in this study.

Based on the discussion above, the study addresses several key research questions aimed at understanding the extent, pattern, and drivers of Rural Transformation Development (RTD) across districts of Pakistan. These questions focus on the construction of a comprehensive RTDI, the spatial and temporal patterns of RTD, the role of key drivers including infrastructure, credit, irrigation, and education, as well as the impact of RTD on outcomes like per capita agricultural income. The objectives outlined below are designed to directly answer these research questions, providing a structured approach to comprehensively analyze rural transformation in Pakistan.

1.3. Objectives of the Study

Considering the above research gaps, the objectives and sub-objectives of the study are to:

- device a robust and comprehensive measure of rural transformation development for the districts of Pakistan[1]
- analyze the pattern and extent of RTD overtime
- identify the clusters, if any, to uncover regional dynamics and disparities.
- evaluate the spatial impact of infrastructure, credit, irrigation, climate change, and agriculture income on rural transformation development.
    - to learn the temporal dynamics of RTD
    - to see the direct, indirect effects (spatial spillover) of each driver of RTD, focusing on the spatial dependencies among districts
    - to see how the spatial relationship, vary along various stages of RT.
- analyze the cross-sectional spatial heterogeneities present across districts of Pakistan and the factors responsible for these heterogeneities.
- understand the impact of RTD on per capita agriculture income of the rural population

1.4. Organization of the Thesis

This study is organized as follows: Chapter I contain the comprehensive introduction. Chapter II reviews the literature in RTD and its drivers. Chapter III is about data description, study area and methodology. Chapter IV has result and discussion on rural transformation index. Chapter V has results of seeing the impacts of multiple drivers on RTD. Chapter VI contains the discussion on cross sectional spatial

[1] "Rural areas" of included districts have been taken for the analysis. In the rural development literature "rural" term has been defined differently. In some contexts, it is defined as geographic regions characterized by low population density (Cromartie & Bucholtz, 2008 and Ratcliffe et. al., 2016), while in some other contexts rural are defined as the areas where agriculture is the primary economic activity. In our study, we defined rural as taken in the official published datasets of Pakistan which rely on administrative boundaries.

heterogeneity among districts. Chapter VII is elaborating the impact of rural transformation on per capita agriculture income. Chapter VIII is based on conclusion of the study.

CHAPTER II

LITERATURE REVIEW

2.1. Introduction

This section of the chapter provides a comprehensive review of the relevant literature. It begins by exploring various perspectives on defining and understanding the concept of "rural." Subsequently, it delves into the literature on Rural Transformation Development (RTD), focusing on its key drivers. Finally, the chapter examines the spatial and temporal dynamics of RTD as discussed in the existing body of research.

2.1.1. Rural

Before understanding the idea of RTD from literature, it is worth mentioning the brief debate on definition of "rural" from the existing literature. Many classifications are used by researchers and policymakers to distinguish rural from urban locations, which can lead to unnecessary confusion and mismatches in policy eligibility. However, the fact that there are various rural definitions underlines the fact that rural and urban notions are complex. In certain contexts, population density is the predominant consideration, whereas in others, geographic seclusion is the foremost focus.

"Rural" was linked to agriculture during the period after World War II and the 1970s. At that time the economies struggled to bring a structural change by leaving behind agriculture and focusing much and more on industry and services. Also, Rural development policies strived to modernize agriculture to improve well-being of the rural population (Hayami and Rutton, 1971; Johnston and Mellor, 1961; Lipton, 1968 & Schultz, 1968). In 1970s the association of "rural" with agriculture gets weaken as it was realized that it is not only the agriculture that matters rather intra-household dynamics and equity, market and policy become the focus of scientists, economists, and agronomics (Sebillote, 1974). Moreover, power concerns and social involvement were also focused by Chambers (1983). Followed by Carney (1998) “rural” context was no more discussed as a static phenomenon where it was only linked to farms rather it started to evolve as part of interacting system where there existed inter-sectoral linkages, linkages between urban and rural, gender considerations, policy, and institutional focus etc.

As far as the geographical demarcation of “rural” is concerned, there are varying definitions adopted by various countries. According to OECD (1994), the member countries are subdivided into three geographical hierarchies i.e., national, regional, and local where local is further sub clustered into rural and urban classifications. Thus “rural” characterized as territories with population densities of less than 150 people per square kilometer. Lenders et, al., (2007) mentioned that for Japan the definition would be revised due to higher population density and here it would be a threshold of 500 people per square kilometer for recognizing an area as “rural”. Agriculture Division of Statistics Canada considers the geographical classifications to define “rural”. It firstly identified “building blocks” and then individuals would be categorized as "rural" if they live in a rural-designated territorial entity. There are four building blocks to serve the rural identification purpose i.e. enumeration area, census subdivision, census consolidated subdivision and census division (Statistics Canada, 1999a and Statistics Canada, 1999b). According to Census Bureau of US “rural” is defined indirectly via process of elimination; rural is the area which is neither an urbanized area nor an urban cluster. Urbanized area is the one which is having dense population with at least 50000 people, whereas urban cluster is the one having population in the range 2500-49999. This ultimately implies that “rural” would be an area having population 2499 or less (Cromartie & Bucholtz, 2008 and Ratcliffe et. al., 2016). This mentioned urban-rural definition is based on population density.

In the European Union they adopted territorial classification instead of binominal typology of rural-urban. Eurostat established the "Nomenclature of Statistical Territorial Units (NUTS)” at the beginning of the 1970s as a single, standard framework for splitting up the European Union's territory to provide regional data for the Community. As a result, the areas are split into three categories: densely populated, intermediately inhabited, and sparsely populated (EUROSTAT[2], 2007). Another trend is to include more than one criterion or additional factors to the territorial categorization process, in addition to or instead of population density. In the United Kingdom, for example, census output regions are divided into eight rural/urban categories, six of which are classed as rural (DEFRA[3], 2005). Australian Standard Geographical Classification (2001) defines urban area as Urban Centers and or called as population clusters of 1000 or more people with a population density of at least 200 persons per km^2, the rest would be termed as rural.

The rural term is often misunderstood in Pakistan. In Pakistan it is the responsibility of local government and revenue department to identify the rural and urban demarcations. The criterion for the purpose is highly controversial, as the said criteria is not published and unveiled through any medium and form. In the 1951 census all municipalities, civil lines, cantonments, and any other area inhabited by not less 5000

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[2] Statistical Office of the European Communities.

[3] Department for Environment Food and Rural Affairs (DEFRA)

persons and consisting of a continuous collection of houses were classified as urban areas. In a few cases, however, places inhabited by less than 5000 persons and having certain urban characteristics were also classified as urban areas, such as common utilities, roads, sanitation, schools, centers for trade and commerce, with substantially non-agriculture population and those possessing high literacy rate were classified as urban till 1972 census. On a discussion with a civil representative, it is pointed out that before 1981 rurality is declared based on civic facilities available and population. In 1981 census, the size specific criterion was dropped, and an administrative criterion was adopted; all localities which were either metropolitan, municipal cooperation, town committees or cantonment at the time of census were treated as urban. The same definition of urban was adopted in the 1998 census. In other words, only the areas notified as urban by the provincial governments were treated as urban. The same notified criteria are adopted in various Census and surveys conducted in Pakistan[4]. Because of issues in clear boundary identification of rural and urban it would be difficult to make comparison across the country, also due to lack of coordination between provincial Revenue Department, Local Government and Census staff during delimitation process agitates the issue.

To recapitulate, the rural terminology has a wide range of meanings, which necessitates the following adjustments (as suggested in literature) to further describe the terminology (Fig. 2.1).

[4] Population Census, PSLM, HIES

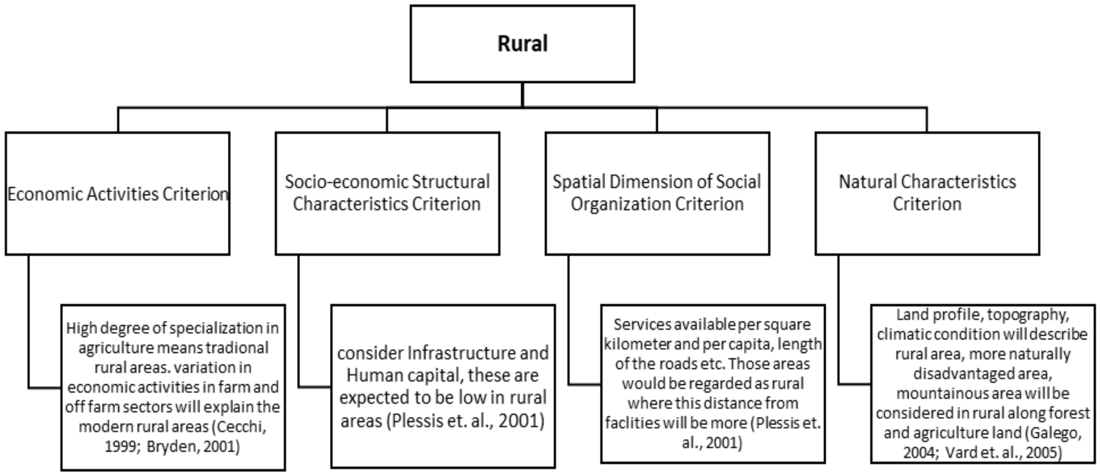

Fig. 2.1: Rural Terminology

Source: Author's composition

All the aforementioned criteria mentioned in Fig. 2.1 can be used separately, in some combination or all at once through construction of an index for the purpose of defining rurality. Bennett et. al (2019) provide the possible solution as rural might be defined as an indicator that includes factors like population density, travel or distance, geographic isolation, resources, socioeconomic features, local perceptions or culture, and amenities. To contribute to the category, each component would comprise numerous sub-measures. Each category might also be given a weighting, thereby giving certain categories more clout than others. Each category's components, how they were indexed, and how the weights were given could all be tweaked to generate an overall rural index that would show a region's rurality on a continuous scale.

2.1.2. Rural Transformation Development and its drivers

Although the coordination and balance in various dimensions of RTD are important, the policy stimulus, investment, infrastructure, and increase in agriculture GDP are also important drivers for boosting up the speed of RTD (Morris et al., 2017; Abreu

& Mesias, 2020; Casini et al., 2021). Numerous studies have demonstrated that through supportive policies, rural investment raises agricultural gross domestic product (GDP) and lowers rural poverty (He et al., 2016 and Watts, 2020). Simultaneously, increasing rural employment and promoting agricultural intensification, investing in land resources, and expanding rural industry are important drivers in effectively improving rural transformation (Mao et al., 2019). Education and possession of multiple skills are helpful in enhancing crop production and engaging in non-farm income-generating activities (Tacoli, 2007). Rural transformation drives through education also provides pathways out of rural poverty (Li et al., 2016). Social networks are essential for acquiring information about markets and technology (Meartens & Barrett, 2013), as well as for accessing credit (Okten & Osili, 2004), all of which significantly drive rural transformation. Economic factors which include the number of workers, household income, and land ownership play a crucial role in rural transformation (Douglass, 1998 and Bah et al., 2003). An increased number of working hands and land ownership enhance household capacity and alter the dependency ratio (Motsholapheko et al., 2012) thereby fostering higher income levels and facilitating rural transformation (Bhattacharjee & Behera, 2018). Governance and institutional structures, whether urban or rural, significantly influence the trajectory of rural development (Tacoli, 2003). For instance, credit institutions provide essential financing, training institutions facilitate skill development, and extension services guide farmers on cropping patterns (Bah et al., 2003 and Abid et al., 2016). Access to financial services is generally linked to productivity growth in the agricultural sector through agricultural investment, innovations (Demirgüç-Kunt & Levine, (2009), technology upgradation, and ease in purchasing mechanical inputs (Aleem, 1990 & Saqib, 2018). Infrastructure facilities, including transport systems, telecommunications, electricity, roads, markets, and educational institutions, are essential determinants of rural development. These components critically influence both the farm and non-farm sectors, driving growth, enhancing connectivity, and fostering sustainable development (Lynch, 2005 and Jamshed et al., 2020). Environmental aspects are also essential and cannot be overlooked, as the quality of soil and availability of water are fundamental for agriculture (Bah et al., 2003). Poor soil quality and water scarcity can lead to unused land and force people to migrate, either seasonally or permanently, thereby altering the structure of rural communities (Joarder and Miller, 2013).

Countries around the world have experienced varying pace of rural transformation and identified various drivers and determinants. India, China, Brazil, and others have recognized the significance of providing accessible and affordable credit to farmers to drive agricultural growth and uplift rural communities. In India, for instance, schemes like the "Kisan Credit Card" have enabled farmers to raise productivity through investment in machinery and modern technology (Kumar et al., 2023). China's emphasis on agricultural credit has boosted farming technologies and rural development (Peng et al., 2021). Brazil's dynamic credit system has supported small-scale farmers and agribusinesses, contributing to economic growth in rural regions (Nascimento et al., 2023). Studies on Afghanistan (Torell & Ward, 2010) and Nigeria (Ogunniyi et al., 2018) demonstrate that irrigation technologies can significantly boost crop yields, enhance food security, and improve rural livelihoods. In India, education is a key determinant of inter-generational occupational mobility. Individuals having lower levels of education, skills and disadvantaged social class tend to experience intergenerational persistence (Kundu & Sen, 2023), often remaining in agriculture, following the footsteps of their parents (Motiram & Singh, 2012). When education leads to a change in occupation, it often results in moving up the career ladder (Guha & Roy, 2022 and Sen, 2024). In such cases, structural change and transformation are evident, breaking the cycle of occupational inheritance. Job opportunities in secondary industries, rural income and investment (Qi et al., 2022), natural resource endowment (Yan & Chen, 2018), geographical factors (Gong et al., 2023), financial development, and policy support (Shen et al., 2024) are additional drivers identified in various studies concerning China.

2.1.3. Stages of Rural Transformation

The theoretical framework of RT is often conceptualized through a multi-stage evolutionary process that describes the structural shift of rural economies from subsistence-based agriculture to integrated high-value systems.

Haung (2018) has proposed the stage segmentation model in which transformation initiates with the Stage 1. In this stage, farmers dominantly grow staple crops and follow traditional cropping practices. With the increase in productivity, the economy moves into stage 2 where the major characteristics are agricultural diversification and commercialization. In this stage, the farmers start moving from subsistence towards market demand driven farming. Further advancement in specialization and mechanization marked the stage 3 of the transformation. In the stage 3 off-farm employment also started showing a significant growth which is the reflection of linkage between agriculture and industrial sectors (Haung & Shi, 2021). Finally, the most advance stage is stage 4 which is identified by the high-valued sustainable agriculture practices along with a comprehensive urban-rural integration (Haung & Shi, 2021). This systematic progression along the 4 stages highlights the significant role of technological adoption and market integration for the sake of long-term rural development.

2.1.4. Spatial Temporal Dynamics of Rural Transformation

The spatial patterns of urban and rural areas also play a key role in the dynamics of RT. Critical factors include the size of proximate urban centers and the relative distance of rural localities from these centers (Berdegue et al., 2015). The size of a city, characterized by its functional and economic diversity, significantly impacts the level of exposure and the provision of facilities and services available to rural areas (Hsu, 2012 and Romic, 2018), thereby supporting rural transformation. Rural households in close proximity to urban centers typically exhibit higher levels of economic development and benefit from diversified livelihoods which contributes to a more dynamic rural transformation process (Deichman et al., 2009). Additionally, access to nearby urban markets by rural farmers' influence access to economic opportunities and services, ensures timely purchase of inputs, and enhances flow of information about innovative agriculture methods (Sharma, 2016) which are not only crucial for rural transformation but also enhance rural adaptability to climate change (Maddison, 2007). Rural workers who live close to urban areas benefit from higher-paying jobs and more opportunities to engage in non-farm activities. This proximity allows them to access better economic opportunities and improve their overall livelihoods (Duvivier, 2013).

2.1.5 Review of Policies

RT is basically such a long-term transition that is fueled by improvement in agriculture productivity and crop diversification, development and expansion of non-farm enterprises, reallocation of factors of production and institutional transformation. In the case of Pakistan, such transition moves along the shifts in the agriculture policy. Since the mid-2000s, agriculture policies of Pakistan remained along five domains; infrastructure and resource management, guidance on seeds and technology, credit and risk management, market integration and institutional reforms. The first major post-devolution strategy was the Medium-Term Development Framework (2005-10), that addressed agriculture as a vital part of economic growth. It strongly emphasized irrigation, quality of seed and credit access to farmers on account of efficiency and productivity improvements. Similarly, the Agricultural Policy Institute's Vision 2030 (2007) and National Food Security and Nutrition Policy (2013) recognized the role of agriculture in food security, poverty eradication through modernization of agriculture sector.

The Prime Minister's Agriculture Transformation Plan (2020) provided support for seed regulatory reforms, farm mechanization, digital tools, and high-value crops. This plan has the purpose of raising farmer incomes and preparing the rural economy for structural transition. Recently, the Punjab Agriculture Policy 2018 and Sindh Agriculture Policy 2018 localized the reforms with a strong emphasis on value chains, agriculture water management and rural employment. The aforementioned policy reforms are a gradual move towards supporting the structural transformation and ultimately rural development in Pakistan.

In order to address the specific policy instruments which, drive RT in Pakistan, we may categorize interventions into credit access, technology adoption, and market reforms across different eras:

- Transformation of rural economies from staple food to agriculture diversification has started in early 1990s through the introduction of Integrated Rural Development Programme (IRDP). At that time policy focus was to bring market oriented reforms, land redistribution, and infrastructure development in order to support rural development. At this period there was seen an extensive growth in agriculture through area expansion instead of intensive growth through technological progress (Gill, 1999).
- During the mid-2000s and 2010s, the government launched targeted initiatives like the Khushali Bank and the Khushal Pakistan Program to improve financial inclusion for smallholder farmers. These instruments were designed to provide the liquidity necessary for transitioning from subsistence to commercial farming (World Bank, 2002, 2005).
- Significant policy shifts occurred after the 2010 floods, focusing on income shock protection and rebuilding rural livelihoods to sustain the transformation process against environmental stressors.

Post-2015, the Prime Minister’s Kissan Package emerged as a flagship policy, providing direct subsidies for fertilizers, solar-powered tube wells, and subsidized loans for farm mechanization. This shifted the focus toward high-value crop specialization and increased agricultural productivity (Hussain et al, 2022).

2.2. Theoretical Framework

The theoretical framework for understanding rural transformation and structural change is rooted in the dual sector models developed by Arthur Lewis and later modified by Fei and Ranis, Jorgenson, and others. Lewis (1954) model describes the interaction between a small, industrialized capitalist sector and a large, traditional subsistence sector, with surplus labor migrating from rural to urban areas leading to industrial growth and eventual changes in the subsistence sector. Lewis (1954) work is modified by Fei and Ranis (1963) through overcoming the shortcomings of former model and by emphasizing much and more on significance of agriculture sector in development. Later, Jorgenson (1967) emphasize more on dynamic dual economy role but with more realistic assumptions; wages determine in the inter-sector labor market even at the early stage of development as opposite to institutionally determined wage rate in Fei and Ranis (1963) model. In Jorgenson (1967) model the generation of agriculture surplus is based on technical progress, population growth rate and elasticity of agri-output due to change in agri-labor.

Furthermore, Johnston and Mellor (1961) and Johnston (1970) have stressed the importance of agricultural expansion in structural transformation. Productivity in agriculture and non-agriculture sector pushed up due to this structural transformation. 21st century literature explains structural transformation through the processes include fall in share of agriculture in GDP and in employment, increase in urbanization rate, industrial and services sector development, and decline in death rates and birth rates

(Barrett et. al., 2010). Dynamic models of structural change are still imperative in development, alongside rural restructuring was noticed in Western Europe, North America, and Israel in the late twentieth and early twenty-first centuries (Capo, 1995; Cloke et al., 1997; Mahon et al., 2009; Nelson, 2001; Sofer & Applebaum, 2006). Around the same time, rural regions in emerging nations such as China, India, Philippines, Zimbabwe, and Ecuador have undergone similar transformations (Ahmed, 1993; Cai, 1999; Su et al., 2011; Dandekar, 1988; Gibson et al., 2010; Kamusoko et al., 2009 and Lopez & Sierra, 2010). Precisely RTD is a term used to describe this type of quick and extremely rural restructuring (Cai, 2001; Liu, 2007). The process of transforming traditional rural industry, production mode, and consumption structure, as well as the continuous transformation from an urban–rural dual structure to urban–rural integrated development, is known as rural transformation development. The goal is to achieve an all-around transformation of regional urban–rural relations and the relationships between industry and agriculture (Liu, 2007).

The theoretical framework in this study integrates key elements from foundational models of structural transformation, including those of Lewis (1954), Fei and Ranis (1963), and Jorgenson (1967), while situating them within the contemporary context of rural transformation development (RTD). The current study explicitly incorporats the spatial dimension of rural transformation, a component not extensively addressed in traditional models. The study is an effort to highlight the spatial heterogeneities in cropping patterns, employment structures, land use intensity, and then it linked these heterogeneities with existing theories through their role in regional disparities and spatial clustering. Such an approach complements the classical models alongside integration of spatial analysis in understanding RT. It ultimately addresses a critical gap in the literature and set a comprehensive ground and framework for future studies. The summary to the theoretical discussion of agriculture and rural transformation in development theories is presented as under:

Table 2.1: Evolution of Economic Development Theories and Their Perspectives on Rural Transformation

Theory	**Focus**	**Rural Transformation View**
Lewis Dual-Sector Model (1954)	Labor shifts from agriculture to industry	Agriculture = surplus labor; transformation means moving workers out of farming.
Harrod–Domar (1950s)	Capital accumulation & investment	Little role for agriculture; RT seen as more investment in rural capital.
Rostow's Stages of Growth (1960)	Linear stages of development	Agriculture modernization = pre-condition for "take-off".
Structuralist Theories (1960s)	State-led industrialization	Agriculture is often neglected; RT secondary to industrial push.
Dependency Theory (1970s)	Underdevelopment = external exploitation	Rural areas locked in primary commodity dependence.
Basic Needs Approach (1970s)	Meeting food, health, education needs	RT = improving rural services & welfare, not just productivity.
Washington Consensus / Neoclassical (1980s)	Market liberalization & privatization	Rural sector = adjust to markets; reduced state role in RT.

Theory	Focus	Rural Transformation View
Endogenous Growth Theory (1980s–90s)	Human capital & innovation	RT = education, technology, knowledge spillovers in rural areas.
New Institutional Economics (1990s)	Institutions & governance	property rights, credit markets, rural institutions.
New Structural Economics (Lin, 2010)	Comparative advantage + state facilitation	Balanced approach: agriculture + non-farm + infrastructure = RT.
New Economic Geography (NEG)	Krugman (1991); Fujita et al. (1999)	Emphasizes that economic activities are spatially interdependent due to agglomeration economies and market integration. In the context of rural transformation, such interdependencies arise naturally because districts are not isolated units but are connected through flows of labor, goods, technology, and infrastructure networks.

After understanding what RTD, next it to see what drives it. We have multiple set of drivers which includes Irrigation, Credit, Education, Infrastructure, Climate change etc. All of them hold varying degree of importance in driving the whole process. The channels could be positive or negative. The channel of each driver present in Fig. 2.2.

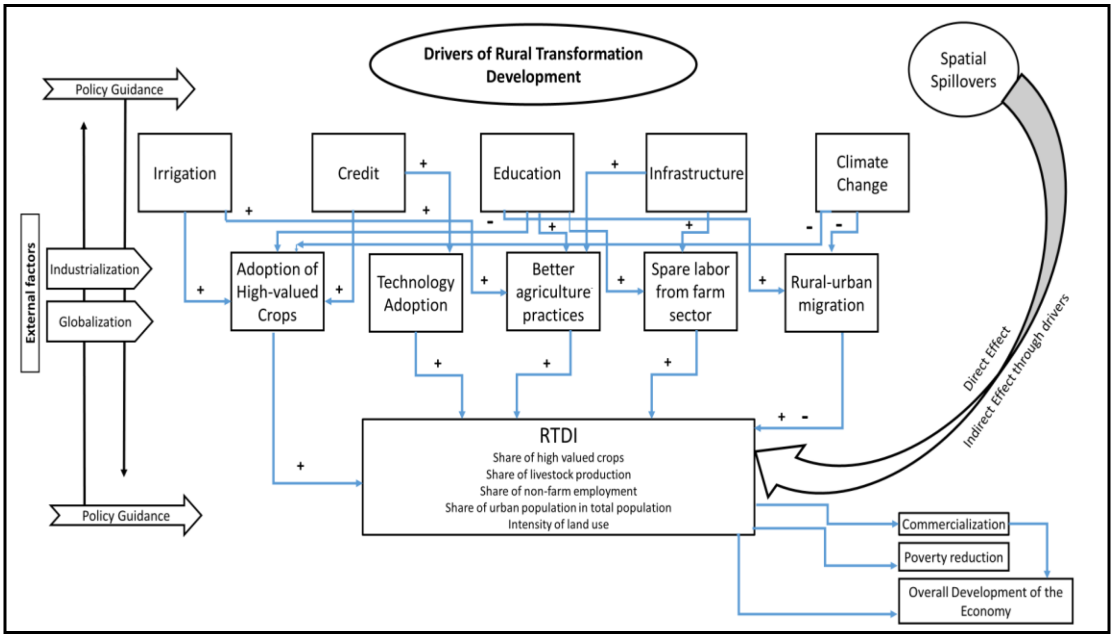

Fig. 2.2 Conceptual Framework

Education is one of the important drivers of rural transformation (Stiglbauer & Weiss, 2000; Agarwal & Agarwal, 2017). Education facilitates technology adoption, better agriculture practices, and an understanding of financial models by the farmers (Bansal, 2018). Moreover, the know-how of ICT provides the farmers with up-to-date information regarding weather forecasts, market prices, crop management techniques, pest control strategies, etc. which in turn is helpful in enhancing farm productivity (Bhalla, 2018). Moreover, education also promotes entrepreneurship, encouraging the establishment of small businesses and micro-enterprises (Hynes and Richardson, 2007) which symbolizes a structural shift from farm to off-farm sector. There are also confounding factors that may work along the education driver. On the one hand, these factors facilitate the role of education in rural transformation, and on the other hand, they directly contribute in speeding up the process of rural transformation. Natural resource endowment is one of such factors which constitutes the availability of farmland, water, favorable weather, and ecological conditions. Infrastructure which includes better road network, efficient irrigation system, power supply, etc. play a supportive role as well as the direct role in rural transformation. Institutional efficiency (i.e., access to credit etc.), socio-cultural development and human development (i.e., skill development, vocational training etc.) are also the part of list of confounding factors (McCulloch et al., 2007; IFAD, 2011).

Next driver to see the theoretical linkage of it with RTD is Irrigation. High value crops such as fruits and vegetables are assumed to be sensitive to water availability (Fereres, et al., 2003) and therefore, it is hypothesized that availability of water (irrigation facilities) may lead to transform agriculture from low value to high value crops. The competing demand for irrigation water leads to the emergence of the demand for water conservation technologies such as sprinklers which promise enhanced water productivity. On the other hand, fruits and vegetable are also assumed to be labor intensive (Calvin & Martin, 2010) which is compensated by the adoption of modern technologies to maintain the comparative advantage of these crops. Such adoption is not only observed among newly converted farms from low value crops to high value crops but also among old farms which are growing fruits and vegetable that lead to release the surplus labor for non-agriculture sector. We named these transformations i.e., shifting from low value to high value crops and farm employment to non-farm employment as rural transformation. The literature supports our hypothesis that irrigation has a strong potential to affect the pace of rural transformation, either through enhancing productivity of the crops or by releasing the labor for non-farm sector, ultimately bringing a change in the rural sector of the economy (Torell & Ward, 2010; Ogunniyi et al., 2018). It is generally hypothesized that higher level of rural transformation is strongly linked with resource use efficiency which is achieved either by improving management practices or by adopting resource conservation technologies (Jin et al., 2012; Jha et al., 2016). To achieve higher productivity of inputs such as canal or tube well irrigation farmers shift towards high value crops. The improvement of water productivity is expected to be further strengthened as the rural transformation process enters in higher stages.

Next driver in the list is Credit. In developing countries, the rural population majorly rely on informal credit to break their financial constraints. But informal credit markets are generally inefficient and charge high interest rates, ultimately there are less gain and more burden. But opposite to this, an efficient credit market may help positively in the RTD. Provision of credit supports the farmers with their productivity through access to better inputs (Ahmad, 2011) and also help them in adoption of high-valued crops and technology adoption (Khandkar & Faruqee, 2003). Credit alone may not do much wonders but along with efficient markets, better social capital and the understanding of how to effectively utilize it and where to allocate it, all these factors collectively enhance the benefits of credit (Hussain & Taqi, 2014).

Next on the list is Infrastructure. Infrastructure is the source of boosting agriculture productivity by lowering the input cost (Nirala, 2020). Better infrastructure is helpful in adoption of better agriculture practices. When the farm sector is flourished and become productive, it spares the labor for non-farm sector as well (Pal, 2023), hence rural transformation is the result. Road infrastructure boasts agriculture productivity through better access to market (Kaur et al., 2023), financial accessibility infrastructure supports the investment in farm and non-farm sector (Zhanseitov et al., 2024), irrigation related infrastructure enhance the water productivity (Kaur & Neena, 2023) etc. Lastly, climate change influence agricultural productivity and rural livelihoods. Adverse climate events, such as unexpected rainfall or excessively high temperatures, can negatively impact agriculture by disrupting cropping patterns and reducing yields (Lou & Duo, 2024). These unfavorable conditions often drive rural-to-urban migration (Dale & Ajibade, 2024), contributing to a structural shift in the economy and reshaping the dynamics of rural transformation (Fig. 2.2).

So far, the conceptual framework has been precisely developed for explaining the concept of RTD and its key drivers. Moving forward, it is essential to emphasize that spatial spillovers play a crucial role in shaping the dynamics of this phenomenon. For the purpose, "neighborhood effect" is used as primary explanation where imitation and learning mechanism (Plotnick and Hoffman, 1999) can be rightly applied to the process of rural transformation development i.e., farmers frequently learn from and imitate their neighbors. Farmers may follow comparable business tactics or planting decisions if their neighbors have surplus earnings because of optimizing factor inputs, modifying the quantity of acreage used, or changing the planting layout etc. Moreover, various degrees of the "knowledge spillovers" through infrastructure has implications for RTD (Wang et. al., 2016). The spatial spillover and linkage does not remain confined to rural areas only rather it has implication for urban-rural linkage as well (Wang et al., 2023). These spillovers can be either direct or indirect. Direct spillovers refer to the influence of rural transformation in one time period directly impacting rural transformation in a subsequent period. In contrast, indirect spillovers occur when the drivers from one spatial unit affect rural transformation in another spatial unit also known as spatial lag affect. This represents the spillover effect of drivers, ultimately influencing RTD (Hazrana et al., 2019; Tang & Chen, 2022).

There are also exogenous drivers, such as industrialization and globalization, that influence the entire mechanism and form an integral part of the framework (Fig. 2.2). These external factors initiate changes in the internal dynamics of the drivers, shaping their roles and impacts (Hualou & Shuangshuang, 2017). Depending on the interactions, these factors may either accelerate development or produce adverse outcomes. In such a context, policy guidance from the government plays a critical role in steering the system. As depicted in Fig. 2.2, the upward arrow on the left side signifies that effective policy guidance can amplify and enhance positive effects, while the downward arrow indicates its potential to mitigate the negative impacts resulting from exogenous factors (Wang et al., 2022). Rural transformation is crucial for resource diversification at both the household and regional levels and also for commercialization (Huang & Shi, 2021). Evidence suggests that faster rural poverty reduction is often associated with faster rural transformation (Timmer, 2017; Fan, 2019; Otsuka & Fan, 2021; Haung & Shi, 2021). This transformation may not be confined to rural areas alone, rather it could contribute to the overall growth and development of the economy while promoting sustainable rural progress (Medvedeva & Zemlyakova, 2024).

The conceptual framework illustrated in Figure 2.2 represents the operationalization of the core theories discussed in this chapter. For instance, the transition from Stage I to Stage II in the model is fundamentally driven by the Lewis Model of Economic Development, where the wage differential between the subsistence rural sector and the expanding urban sector acts as the primary trigger for rural-urban migration. Similarly, the spatial clusters observed in the framework are grounded in New Economic Geography, which posits that market integration and infrastructure flows prevent districts from acting as isolated units. By linking these theories to the specific indicators in the framework, the study ensures that the structural shifts and spatial interdependencies of rural transformation are analyzed through a validated theoretical lens.

CHAPTER III

RESEARCH METHEDOLOGY

3.1. Data and Study Area

District-level panel data between 2004-2019 covering almost fifteen years is employed in this study. Although, a longer panel data is preferable, but Pakistan Social and Living Measurement Survey (PLSM) was not conducted before 2004. Hence, data for this study was taken at the district level from various sources at four points in time (2004, 2009, 2014 and 2019) to construct a district-level panel over the last fifteen years. Some variables were extracted from the PSLM survey but information related to crop yield and prices of crops, were obtained from the provincial Agricultural and Development Statistics.

This study considers 78 districts in 2004 that represents 95 districts (Fig. 3.1) in 2019 because 17 new districts emerged between 2004-2019. To handle this issue, the number of districts at 2004 are considered as threshold, and in the later periods the data for the bifurcated districts is merged back to their parent district in order to ensure data consistency across all four time periods (2004, 2009, 2014, and 2019).

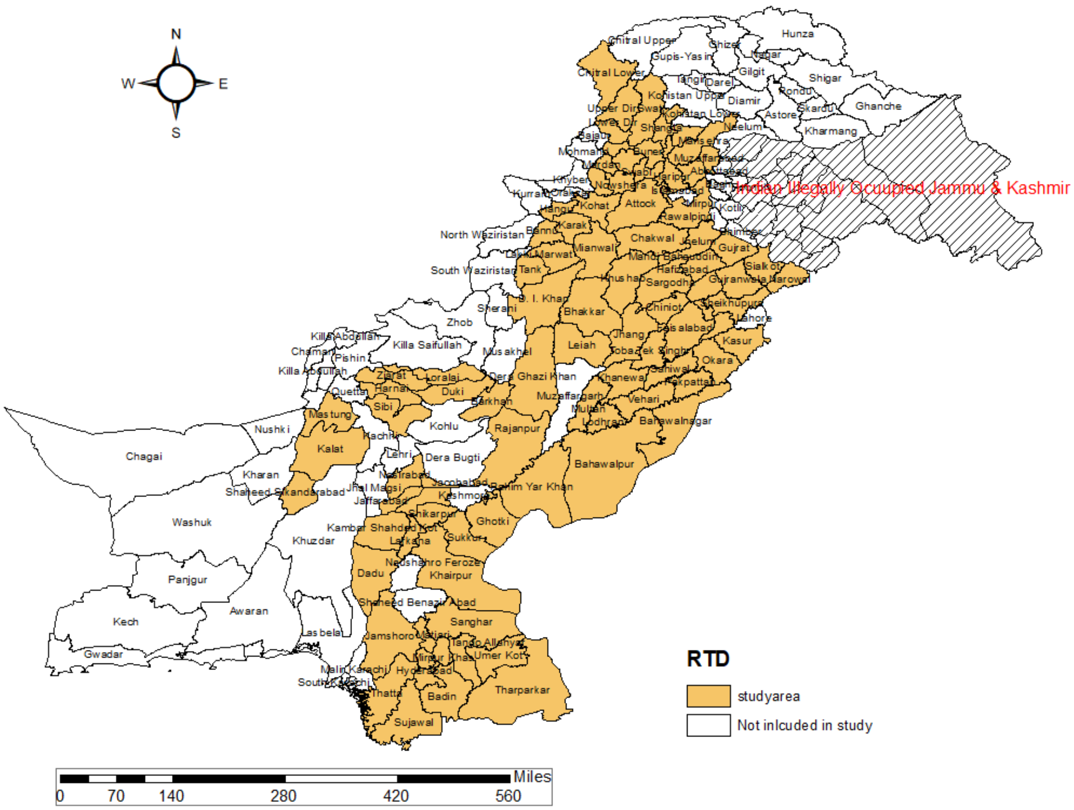

Fig. 3.1 Study Area Map

The rationale for this merging lies in the fact that many of these new districts were officially created after 2009, and historical data prior to their creation is only available under their parent districts. For instance, Chiniot was part of Jhang district until 2009. Including Chiniot separately for later years while retaining Jhang for earlier years would introduce temporal inconsistency and misalignment in district boundaries, which would compromise the validity of intertemporal comparisons fundamental to the construction of the RTDI. The dataset preserves a consistent spatial framework by merging such districts back into their original administrative units. It also helps in avoiding artificial fluctuations in the index that may cause solely by administrative boundary changes. Table 3.1 reports the list of these districts.

Table 3.1 List of Bifurcated Districts

Parent district	Newly bifurcated district
Jhang	Chiniot
Sheikhupura	Nankana Sahib
Jacobabad	Kashmore
Larkana	Kambar Shahdadkot
Dadu	Jamshoro
Hyderabad	Matiari + Tando Allah Yar + Tando Muhammad
Thatta	Sujawal
Mansehra	Tor Ghar
Chaghi	Nushki
Sibbi	Harnai
Kalat	Shaheed Sikandarabad
Kharan	Washuk
Zhob	Sherani
Lorali	Duki
Jaferabad	Sohbat Pur

There are total 124 districts in 2019 (in four provinces of Pakistan) but the remaining 29 districts were not included in the study either due to unavailability of data or districts were purely urban. Since this study focuses on rural transformation, urban districts were excluded in the analysis. Districts that do not cultivate crops were excluded from the analysis, as they do not contribute to the evaluation of the share of high-value agriculture, which is a crucial element of rural transformation development. The inclusion of such districts would compromise the validity of comparisons with other districts.

3.2. Variable Construction and Methodology

The study has utilized the secondary data gathered from various sources, including the provincial development statistics, livestock census, PSLM, economics survey of Pakistan, State bank of Pakistan reports, labor force survey. The further details to data is present in following subsections. Section 3.2.1 is about the methodology of construction of RTD index and about the ESDA for understanding the extent and pattern of RTD. Section 3.2.2 is about the construction of drivers and methodology of seeing the relationship of these drivers with RTD. Section 3.2.3 is about understanding the methodology for cross sectional spatial heterogeneity analysis.

3.2.1. Section 1: Rural Transformation Development

3.2.1.1. Variables and Data Sources

Data for the construction of the Rural Transformation Development Index is taken from various sources (as mentioned in Table 3.2) at the district level for the years 2004, 2009, 2014 and 2019, although it was initially intended to consider time points from 1981-2019[5] but due to the unavailability of data on many variables before 2004 the study period is reduced.

Table 3.2. Variables and Data Sources

Variable	Definition	Construction details	Data Source
Share of high valued crops	It is the percentage share of total output values of high valued crop[6]	Each crop's output is multiplied by its respective market price to calculate its value, ensuring all crops are	Provincial Development Statistics, Crop Reporting

[5] We cannot go beyond 2019 because of no release for data for various variables in the datset.
[6] High-valued crops are altogether 60 in number

Variable	Definition	Construction details	Data Source
	(cotton, tobacco, oil crop[7], sugar crops[8], and horticulture[9]) in gross agricultural output values from all crops.	expressed in monetary terms. This makes them comparable and allows for valid aggregation. The final indicator reflects the economic contribution of high-valued crops, and since price-based weighting is already embedded, no further weighting is required. Farm gate prices are not being reported for all crops therefore, in the construction of RT1, wholesale prices of the respective year have been taken which are then deflated by 15% for non-perishable output and 20% for perishable output in	Services of each province, Agriculture Statistics of Pakistan, Agriculture Marketing Information Services (AMIS), Agriculture statistics of Pakistan, 'Agriculture, Supply & Price Department, Government of Sindh', and Ministry of Food Security

[7] castor seed, groundnut, linseed, R&M seed, sesamum, soybean, and sunflower
[8] Sugarcane and sugar beet
[9] 17 fruits and 22 vegetables

Variable	Definition	Construction details	Data Source
		order to arrive at farm gate prices. A similar method is used by the Pakistan Bureau of Statistics for the sake of calculating farm gate prices from wholesale prices[10].	and Research
Share of livestock production	It is the percentage share of total output values of livestock products (milk and meat) in gross agricultural output.	Since no livestock census has been done after 2006, so the quantity of milk and meat is based on growth estimates between 1996 and 2006 census values. For output values of milk and meat, quantities are multiplied with their wholesale price of the respective years. For prices it is made sure that beef, mutton and camel meat	Pakistan Census of Livestock 1996 and 2006 (Special Reports)

[10] The application of 15% and 20% deflation rates is a deliberate methodological choice to align with the standard protocols used by the Pakistan Bureau of Statistics (PBS) for deriving farm-gate prices from wholesale market prices. Such approach is helpful in handling post-harvest losses and high marketing margins which are traditionally inherent in local agriculture supply chain. Through this method the study will ensure that the agricultural output value is a reflection of revenue received by producers.

Variable	Definition	Construction details	Data Source
		prices are separately dealt. In the livestock census they have given the number of animals for slaughter, from that the average meat from each animal is taken as meat product. Average weight of animals is as follows: Bullocks 250 kg Cows 200 kg Young stock male 60 kg Young stock female 50 kg Male buffalo 325 kg Female buffalo 275 kg Young stock male 80 kg Young stock female 60 kg Camel 450 kg Young camel 220 Sheep 25 Young Sheep 12 Goat 22 Goat Young 10	

Variable	Definition	Construction details	Data Source
Urbanization	Percentage share of urban population in total population		Population Census (District reports)
Share of non-farm employment	It is calculated by subtracting agriculture, forestry, hunting and fishing from total employment in a particular district and then divide it by total employment of that particular district.		PSLM (Various Rounds). LFS (Various Rounds)
Land intensity	It is the percentage share of cultivated area [11] in total culturable area[12].		Provincial Development Statistics

[11] Cultivated area=current fellow + net area sown
[12] Culturable area=cultivated area + culturable waste

3.2.1.2. Method and Construction of Rural Transformation Development Index (RTDI)

In this research RTDI is developed for districts of Pakistan in dimensions of agriculture production, employment structure, population structure and land use pattern. The elements and index layers are presented in table 3.3. Each elements or domain have indicator(s) which have been selected for the purpose of development of RTDI. In previous studies, the share of high-value crops often included the share of livestock as a combined measure (Wang et al., 2023; Shi & Huang, 2023; Sudaryanto et al, 2023; Abedullah et al, 2023). However, in this study, these two components are analyzed separately. The rationale for this separation lies in the significant shift in the contribution of the livestock sector to agricultural GDP over time. According to the State Bank of Pakistan (2022), the share of livestock in agricultural GDP increased remarkably from 27% in 1980 to 61% in 2019. In contrast, the share of crops declined from 78% in 1980 to 35% in 2019. These statistics shows that livestock is the dominant sector of Pakistan, which makes it necessary to treat this sector's indicator separately from the high-valued crops indicator in order to reflect its distinct role in RT. Such an approach will ensure a better representation of the agricultural sector in the composite index.

For employment structure domain, share of non-farm employment has been used as an indicator because it represents the structural change in the rural areas. Structural shifts are the vital part of rural transformation process. Urbanization is the indicator for representing the change in the population structure. Urbanization can both be an indicator and driver, but it is more suitable to take is as an indicator because it directly reflects shifts in demographic patterns (Wang 2013; Ohlan 2016; Zhang & Zhang, 2022. Urbanization is a consequence of multiple drivers, like economic opportunities and infrastructure development. Urbanization happens as a result of broader structural changes rather than a cause. By treating urbanization as an indicator, we focus on its role in capturing these population shifts, without confusing it with the factors that drive those shifts. Lastly, it is important to see how the rural land has been used, for that the intensity of land use is the appropriate measure used in this study (Ohlan, 2016).

The selection of above mentioned five indicators was governed by three criteria: (i) their alignment with the theoretical stages of rural transformation (Huang, 2018), (ii) their availability as consistent district-level secondary data, and (iii) their statistical contribution to the total variance in the Principal Component Analysis (PCA) framework especially in the context of Pakistan.

Table 3.3. Description of Index System

Index	**Elements/Domains**	**Indicators**
RTD	Agriculture Production	Share of high valued crops $(RT1_{crops})$
		Share of livestock production$(RT1_{livestock})$
	Employment Structure	Share of non-farm employment ($RT2$)
	Population Structure	Share of urban population in total population ($urbanization$)
	Land Use pattern	Intensity of land use ($land\ intensity$)

For construction of RTDI, principal component analysis (PCA) is used in this study. It is a statistical technique for identification of relationships in complex dataset. It operates on the premise that observed variables are linked to a limited set of unmeasurable factors, also called as latent variables. These latent variables are presumed to drive correlations among the observed variables, enabling PCA to uncover and explore these hidden relationships within the dataset. It also creates artificial variables or components in order to explain the maximum variation in the data (Pearson, 1901). PCA could also be used as dimension-reduction technique (Statacorp, 2007).

In process of identification of independent factors explaining the mutual correlations and hence construction of index, it works as follows (Harman, 1976; Kleinbaum, et al., 1988):

(i) Initially a line is constructed that has minimum distance from the data points of standardized variables. The line is drawn using the least sum of square technique and represent the first principal component (PC1).

(ii) Then a perpendicular is drawn to the line which crosses from the point of greatest concentration of data. This second line explains the rest of the variations which are not explained by the PC1 and hence called as PC2.

(iii) This iterative process continues until the count of principal components matches the number of variables in the dataset.

(iv) In order to achieve the general equation of PCA, the Eigen vectors and Eigen values are calculated. These eigenvectors represent the principal components, which are orthogonal to each other and capture the maximum variance in the data.

(v) The association of principal components with the original variables is measured by factor loadings. It explains how much each variable contributes to a particular principal component. These factor loading are used to calculate weights and hence the index is constructed using the equation (3.1) where X_k are standardized variables and W_k are weights allotted to the 5 indicators of RTDI. For each year, a separate equation is constructed in order to capture the inherent temporal dynamics and heterogeneity present in the data (Prvan and Bowman, 2002; Kinson et al., 2020).

$$RTDI = \sum_{k=1}^{5} X_k W_k \qquad (3.1)$$

3.2.1.3. Exploratory Spatial Data Analysis (ESDA)

The ESDA is adopted to understand the extend and pattern of RTDI. The extent is analyzed through mapping the RTDI difference overtime, whereas the patterns are studied with the help of grading assign to the districts and identifying the clusters accordingly. ESDA also involves the spatial dependence calculation through Global Moran’s I.

Spatial Autocorrelation Analysis

Tobler (2004) presents the first law of geography which states that things interact with each other, but two items that are close together are more likely to do so than two objects that are far apart. To characterize this closeness using descriptive indications we use spatial autocorrelation (Floch & Saout, 2011). The spatial-temporal pattern of RTD across district of Pakistan are measured by Global Moran's I. The following models are used to see the global spatial patterns (Bivand, 2004; Cao et. al., 2019 and Moura & Fonseca, 2020). It is calculated with the help of below mentioned theoretical model as (3.2):

$$I(d) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(X_i - \bar{X})\,(X_j - \bar{X})}{S^2\,\sum_{i=1}^{n}\sum_{j=1}^{n}(W_{ij})} \quad ; \quad S^2 = \sum_{i=1}^{n}\frac{(X_i - \overline{X})^2}{n} \qquad (3.2)$$

Where X_i and X_j are the observed value of the region i and region j respectively. W_{ij} is the matrix of spatial weights.

If $I(d) > 0$ it shows the existence of positive spatial correlation which implies that there is global spatial pattern.

If $I(d) < 0$ it shows the existence of negative spatial correlation which implies that there is no global spatial pattern.

Overtime if the Moran's I show an increase than it means that spatial agglomeration of RTD would become increasingly intense overtime. The interpretation is reversed if overtime the value of I would not have shown significant increase (Zhang & Zhang, 2022).

3.2.2. Section 2: Drivers of Rural Transformation Development

3.2.2.1. Description of variables

The definition of main variables used in the study are described under this section. The study aims to explore the impact of multiple drivers on the index of rural transformation; hence we describe here how these variables are constructed.

Table 3.4 contains the drivers of RTD taken in the study.

Table 3.4 Description of Drivers

Variable	**Description**
Irrigation	It is taken as Share of irrigated farmland, measured as a % of irrigated areas of the total sown area; $$\text{Share of irrigated farmland} = \frac{\text{irrigated area}}{\text{total sown area}} * 100$$ Since, there are different sources of irrigation which includes canal, tube wells, canal and tube well and therefore, the share of irrigated farmland is developed at three levels i.e. share of irrigated farmland by canal, share of irrigated farmland by tube wells, share of irrigated farmland by canal and tube wells. The increasing share of irrigated area in a district is expected to have positive relationship with rural transformation (Rijsberman (2003), Pinstrup & Shimokawa (2006) and DeJong et al., (2021).
Education	*Education* driver is taken as the number of the year of schooling of rural population having age 15 or more. More years of schooling reflects the better quality of labor. The data for this variable is taken from PSLM for 2004, 2009, 2014 and 2019. The consideration of age is important, so that we can look at the level of education of those rural population who are at their working age and are part of labor force. And later their role in rural transformation could be studied.
Credit	Agriculture formal credit consists both the farm and production credit given to the agricultural sector measured in billion Pakistani rupees.

Variable	Description
	The data has been taken from State bank of Pakistan reports.
Climate	For climate change, maximum temperature is taken which is measured in degree Celsius. The data is taken from Pakistan meteorology department. It is the average annual maximum temperature.
Infrastructure	For infrastructure two variables have been used. One is percentage share of rural population satisfied with road facility, and percentage share of rural population satisfied with banking facility. The data has been taken from PSLM, various rounds.

3.2.2.2. Econometric Model

The study has employed the spatial econometric approach to see the impact of multiple drivers on RTDI. For this purpose, there is a need to select the appropriate model that can capture the spatial spillover effects along with the direct effects. Spatial econometrics is a wider discipline under which spatial aspects of the data are studied specifically in the context of regional variations attributed to various regional structures (Anselin & Rey, 2010; Lesage, 2015; Arogundade et al., 2022). Tobler (2004) presents the first law of geography which states that things interact with each other, but two items that are close together are more likely to do so than two objects that are far apart. The availability of localized data, together with the spatial statistics techniques now pre-programmed into a variety of statistical software tools, poses the question of how this closeness may be modelled into economic analyses.

Theoretical Rationale for Spatial Dependence

In this study, the spatial econometric technique has been adopted which is both a statistical choice and a representation of established economic theories linking the spatial dependence with development outcomes.

The new economic geography and regional science literature highlight that economic activities are spatially interdependent due to agglomeration economies, mobility of factors, and market integration (Krugman, 1991; Fujita, Krugman & Venables, 1999). In the context of RT these interdependencies arise naturally because districts are not isolated units rather they are connected through flows of labor, goods, technology, irrigation and infrastructure networks.

District-level drivers of transformation (irrigation, agricultural credit, infrastructure, education, and income) can generate spillover effects that extend beyond their own boundaries (Anselin, 1988; Elhorst, 2014). For example, improved irrigation systems in one district may enhance productivity in its neighboring districts through shared water channels. Access to credit, irrigation and better infrastructure in one location can stimulate better cropping practices and non-farm employment in surrounding areas. Localized interdependencies across administrative boundaries are further enhanced due to uneven design and implementation of provincial and district-level policy interventions. It implies that spatial linkages cannot be ignored otherwise it may lead to biased and inefficient econometric estimates (LeSage & Pace, 2009). This concern has been well taken care of in this study and it has been ensured that RTDI is analyzed within a comprehensive framework capturing economic, social and policy driven spillovers across districts. In this way, it will not only strengthen the empirical validity but also policy relevance of the findings will be ensured.

Specification of Spatial Dependence

Since we have developed the theoretical foundation for spatial interdependence in last section now, we need to select the most appropriate econometric specification for the study. In the context of RT, spatial dependence may manifest in several ways:

Spatial lag (SAR): Outcome-driven spillovers can affect neighboring districts. It may happen via labor movement, market integration, or knowledge diffusion.

Spatial dependence in explanatory variables: Drivers of RT may themselves spill over across the district boundaries. It, implies that the explanatory variables may themselves are spatially interdependent.

Spatial error (SEM): This specification can capture the correlated disturbances, but it fails to describe the essential channels of policy or infrastructural interaction across cross-section units.

Given the dual pathways of outcome-level and driver-based spatial spillovers in rural transformation, the Spatial Durbin Model (SDM) with time fixed effects emerges as the most comprehensive and flexible specification. The SDM integrates both endogenous dependencies in the outcome variable and exogenous spillovers from explanatory variables, making it well-suited to capture the structural and policy-driven interactions across districts (Pace & LeSage, 2008). Moreover, simulation evidence suggests that SDM yields unbiased coefficient estimates even when the true data-generating process follows a spatial lag or error model, unlike simpler specifications (LeSage & Pace, 2009)

3.2.2.3 Construction and Selection of Spatial Weight Matrix

Examination of spatial dependency includes spatial weights as a vital element. They enable the creation of spatially explicit variables and are a crucial component in the generation of spatial autocorrelation statistics (Anselin and Rey, 2014). Various weight matrices are suggested by literature, including Rook and Queen contiguity weights. The presence of a shared edge connecting two spatial units serves as the rook criterion's definition of neighbors. Neighbors are defined as spatial units sharing a shared edge or vertex by the queen criterion, which is a little more comprehensive. Because of this, the number of neighbors according to the queen criterion are always be at least as much as for the rook criterion (Anselin, 1988; Anselin, 2002).

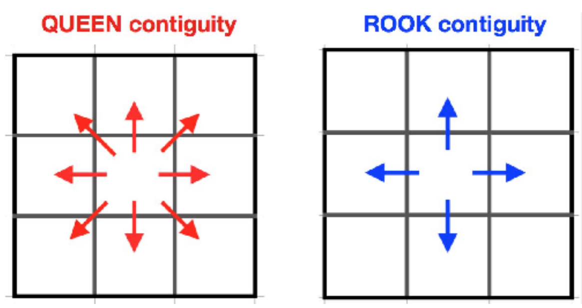

Figure 3.2: Weight Matrix

In practice, except from the simplest of circumstances, it is impossible to calculate the spatial weights from the geometry of the data by eye examination or manual computation. Explicit spatial data structures must be used to handle the placement and layout of the polygons in order to determine whether two polygons are adjacent. The spatial weights feature of various soft wares like GeoDa and arc GIS are used to do this. In this study we have used GeoDa for this purpose.

3.2.2.4 Spatial Autocorrelation Test

Before building the spatial model, there is a pretest to examine the spatial autocorrelation in the dataset using Global Moran's I (Bivand, 2004; Cao et. al., 2019 and Moura & Fonseca, 2020). Once the data's spatial autocorrelation would be detected than multivariable model could be developed (Floch & Saout, 2011).

3.2.2.5 Selection of Model

(i) In order to choose the appropriate model, we use Likelihood ratio Test (LR Test). It helps to choose that whether spatial autoregressive model (SAR) is nested model of SDM or not. The Null hypothesis of the test is SAR is nested model of SDM.

(ii) If SDM is selected then AIC and BIC criteria is used to further select the variant of model under SDM.

3.2.2.6 Dynamic Spatial Durbin Model (DSDM)

After proving that SAR and SEM are not nested model of SDM, then we may proceed with using DSDM. This model can estimate the lag spatial dependency (in both dependent and independent variables) and also it can estimate the spatial spillovers (Elhorst et al., 2014). Such model is essential here because the districts' geographical aspects can affect the estimates through endogenous, exogenous and error components (Anselin & Rey, 2010; Huang et al., 2022). Also, DSDM overcome the challenge of biased and inefficient coefficients (Tang, 2022). The model in its generic form is written as follows (Equation 3.3) (Belotti et al, 2017):

$$y_t = \tau y_{t-1} + \varphi W y_{t-1} + \rho W y_t + X_t \beta + W X_t \theta + \mu + \varepsilon_t \tag{3.3}$$

Where y_t is dependent variable, y_{t-1} is lag dependent variable, W is spatial weight matrix, τ coefficient for lagged dependent variable, φ coefficient for spatial lag of

y_{t-1}, ρ coefficient for the spatial lag of y_t, X_t is for explanatory variables, WX_t is spatial lag of exploratory variable, μ is fixed/random effect term, ε_t is error term.

Each driver in the model (from the matrix of explanatory variables X_t) exhibits an interaction with the stage dummy at the time of empirical analysis. For stages thresholds are defined on the basis of difference in maximum and minimum values (dx=maximum-minimum) where the stage 1 indicates the value less than min+dx/3, stage 2 is recognized for the values lies between min+dx/3 and min+2dx/3, finally the transformation is regarded in stage 3 if it crosses the limit of min+2dx/3 (Abedullah, 2023). In our case, we have three stages of rural transformation, implying that there are two stage dummies (symbolized as S2 and S3 for stage 2 and stage 3 respectively) by considering stage 1(S1) as a base. If the coefficient of a driver in interaction with S2 is positive (negative) and significant then it implies that contribution of that specific driver in S2 is higher (lower) in rural transformation as compared to stage 1 (base category). Similarly, if the coefficient at S3 is positive and greater than the coefficient at S2 then it implies that the contribution of the specific driver in rural transformation is higher at S3 than S1 and S2 (and otherwise).

3.2.3. Section 3: Cross Sectional Spatial Heterogeneity of Rural Transformation Development

3.2.3.1. Geographically Weighted Regression (GWR)

Spatial econometrics is very diverse field and the choice of models depends on the scope of the study and its objectives. Here we are interested in learning the presence of cross sectional spatial heterogeneity on non-smoothness in the spatial relationship. For meeting this purpose GWR is a good choice, because it quantifies the heterogeneity of the spatial data relationships. It does it through local weighted regression analysis for each included location and produce such estimates that vary across spatial units (Brundson et al., 1998; Lu et al., 2020). It is significantly better than global regression (Leyk et al., 2012). The model can be written as (equation 3.4):

$$y_i = \alpha_0(v_i, w_i) + \sum_{j=1}^{J} \alpha_j(v_i, w_i)\, x_{ji} + \varepsilon_i \tag{3.4}$$

y_i dependent variable at district i.

x_{ji} Independent variables j at district i.

$\alpha_0(v_i, w_i)$ intercept at district i which depends on geographical coordinates (v_i, w_i)

$\alpha_j(v_i, w_i)$ coefficient of independent variables at district i, it vary across space based on coordinates (v_i, w_i)

Adaptive bandwidth has been used in the study in order to run GWR using the ArcGIS software. Bandwidth is helpful in deciding the number of neighborhoods (Harris et al., 2010).

3.2.4. Section IV Impact of Rural Transformation on per capita Agriculture Income

3.2.4.1. Description of Variables

In order to see the impact of rural transformation on per capita agriculture income, it is important to first see how we measure the per capita agriculture income. It is measured as follows:

per capita agriculture income = district level agriculture income/rural population

District level agriculture is not given hence it is calculated using the product of per acre contribution into acre of land in a district. Furthermore, per acre contribution is calculated by dividing the total agriculture income (without livestock) by the total agriculture land of Pakistan. This is repeated for each included year of the study. Ultimately, all this practice gives the per capita agriculture income at district level for 2004, 2009, 2014 and 2019.

CHAPTER IV

RESULTS AND DISCUSSION RURAL TRANSFORMATION DEVELOPMENT

4.1. Introduction

This section is based on the results and discussion of PCA weights, its equations and exploratory spatial data analysis. Extent, patterns and clusters have been identified and presented accordingly.

4.2. Principal Component Analysis (PCA)

A holistic approach has been adopted to measure the rural transformation development. Three elements/domains with five indicators[13] have been selected to construct the rural transformation development index (RTDI). These indicators have been standardized to ensure that variables with different scales or units are treated equally in the analysis. By standardizing, the variables transform to have zero mean and unit standard deviation. The standardization makes the analysis more meaningful and also it prevents the variables with larger scale from dominating the PCA results.

To proceed with the PCA, factor loadings are calculated. These loadings are selected to ensure that the factors derived from these loadings remain uncorrelated. These loadings also indicate that how much each variable contributes to the formation of each principal component. The first factor loadings absorb maximum possible variations coming from the input variables, subsequent factor loadings then absorb the remaining variation left from first factor. In this study, the first factor is utilized to construct the index (Table 4.1) as followed by Alesina & Perotti (1996); Ali et al.,

[13] The indicators of RTDI are share of high-valued agriculture, share of livestock, share of non-farm employment, urbanization and land use intensity.

(2013). Using these selected first factor loadings the weights has been assigned to the five indicators in order to create a composite index i.e., RTDI. In this study the PCA is adopted with a purpose to assign unequal weights to the all indicators and then to ultimately see that which indicator contributes more to determine the overall rural transformation in districts of Pakistan.

Each negative indicators are multiplied with -1 before proceeding (Long et al., 2011; Ohlan, 2016). The weight of each indicator is calculated by dividing the respective factor loading with the sum of loadings, the exercise is repeated for each year in order to capture year-specific variations and trends that may not be evident when aggregating data across multiple years. The standardized values of each indicator are then multiplied to the weights as following Equations in order to have RTDI for each year.

$$RTDI_{2004} = \left(0.3511 * RT1_{crops}\right) + \left(0.3675 * RT1_{livestock}\right) + (0.0622 * RT2) + (0.008 * urbanization) + (0.2111 * land\ intensity) \tag{4.1}$$

$$RTDI_{2008} = \left(0.3185 * RT1_{crops}\right) + \left(0.3592 * RT1_{livestock}\right) + (0.1201 * RT2) + (0.0648 * urbanization) + (0.1374 * land\ intensity) \tag{4.2}$$

$$RTDI_{2014} = \left(0.3449 * RT1_{crops}\right) + \left(0.6375 * RT1_{livestock}\right) - (0.3453 * RT2) - (0.0677 * urbanization) + (0.4307 * land\ intensity) \tag{4.3}$$

$$RTDI_{2019} = \left(0.2767 * RT1_{crops}\right) + \left(0.1690 * RT1_{livestock}\right) + (0.3368 * RT2) + (0.1806 * urbanization) + (0.0369 * land\ intensity) \tag{4.4}$$

Table 4.1. PCA weights for each time unit

Unit	Elements/Domains	Weights (2004)	Weights (2008)	Weights (2014)	Weights (2019)
RTDI	Agriculture Production	0.7186	0.6777	0.9824	0.4457
	Employment Structure	0.0622	0.1201	-0.3453	0.3368
	Population Structure	0.008	0.0648	-0.0677	0.1806
	Land Use pattern	0.2111	0.1374	0.4307	0.0369

If we look at the weights to the all elements of the RTDI, it is seen that agriculture production contributes more in the district-level rural transformation in each period of our study, making it primary indicator of the index. The contribution of other dimension varies in each period, even for human resources it became negative in 2014[14], while the weight of agriculture production increased tremendously. It can be linked to the aftermath of 2010 floods which severely damages the agriculture, infrastructure, livestock and irrigation in Punjab, Sindh and KPK (Dorosh et al., 2010). In response, the efforts to recover accelerated rural transformation speeds up in terms of agriculture specialization and mechanization. Government policies were pro-agriculture and initiatives such as Kissan package of 2015 for provision of interest free loan played a pivotal role in supporting these developments (Hussain et al., 2022).

[14] Theoretically, in PCA, the sign of a loading is arbitrary and only reflects the direction of correlation with the principal component. The negative coefficients indicate that during 2014, districts with relatively higher values of non-farm employment and urbanization tended to be associated with lower values of the dominant component captured by PCA.

Since, these reforms are largely centered on farming so they also reflected in the increased weight of land use patterns. By 2019, as agriculture became more mechanized and labor shifted to the non-farm sector, the weight of the non-farm sector rose significantly to indicate rural transformation.

Moreover, PCA weights reflect the relative contribution of an indicator in explaining the overall variation in index rather than its economic importance alone. A decline in PCA weight does not imply a decline in the significance of the livestock sector. In the context of Pakistan, the livestock sector has remained an important component of agricultural GDP and has shown considerable growth over time. However, during the last decade, greater inter-district variation emerged in other dimensions of RT, particularly non-farm employment and urbanization. As PCA assigns weights according to the contribution of each indicator in explaining total variance, the relative weight of livestock declined as these dimensions became more influential in differentiating districts.

From a theoretical perspective, this finding is consistent with the literature on rural transformation, which suggests that as economies progress through different stages of transformation, structural shifts in employment, urbanization, and diversification increasingly characterize the transformation process. Thus, the declining livestock weight reflects changing patterns of inter-district variation and the multidimensional nature of rural transformation rather than a reduction in the economic importance of the livestock sector.

4.3 Exploratory Spatial Data Analysis (ESDA)

Upcoming sub-sections contain the ESDA analysis for the objective one of the study.

4.3.1. Rural Transformation Development Level

In this section rural transformation level of the included districts is discussed. Firstly, it is seen that what was the level of transformation is in year 2004 and then in 2019 (Appendix A). These years are compared to analyze the overtime change in the level of rural transformation. Furthermore, in order to see the improvement overtime, the difference of RTDI is calculated and graded. In order to differentiate the rural transformation across districts, the RTDI is classified into five categories as discussed in Table 4.2. These ranges are based on mathematical and statistical standards as: Low = (Minimum value, Mean-0.5SD), Intermediate Low = (Mean-0.5SD, Mean), Medium = (Mean, Mean+0.5SD), Intermediate High = (Mean+0.5SD, Mean+SD), High = (Mean+SD, Maximum value). The ranges of the different grades defined according to the above mentioned rule and respective parameters (mean and standard deviation) for year 2004 and 2019 are as follows (Table 4.2).

Table 4.2. Ranges for categories of rural transformation level

Categories	Score range for RTDI 2004	Score range for RTDI 2019	Score range for ∆RTDI
	Mean=0.88, SD=0.39	Mean=0.83, SD=0.35	Mean=-0.04 SD=0.47
Low	(0.15, 0.69)	(0.11, 0.66)	(-1.65, -0.28)
Intermediate low	(0.69, 0.88)	(0.66, 0.83)	(-0.28, -0.04)
Medium	(0.88, 1.08)	(0.83, 1.01)	(-0.04, 0.20)
Intermediate high	(1.08, 1.27)	(1.01, 1.18)	(0.20, 0.43)
High	(1.27, 2.14)	(1.18, 1.56)	(0.43, 1.03)

4.3.2. Extent of Regional Rural Transformation

Differentiated extent of rural transformation development level has been observed across all included districts of Pakistan. There are 28 districts which remain in the "low" category of rural transformation with respect to ∆RTDI (score ranges are given in Table 4.2); 13 districts fall in the category "intermediate low"; 15 districts in "medium" category; 20 lies in the "intermediate high" category and lastly 16 districts are in "high" rural transformation category (Table 4.3).

Table 4.3. Districts graded with respect to ∆RTDI

Districts	∆RTDI	Grades of ∆RTDI	Districts	∆RTDI	Grades of ∆RTDI
Kalat	-1.65285	low	Mardan	0.035774	medium
Shaheed Sikandarabad	-1.65285	low	Chakwal	0.050534	medium

Districts	ΔRTDI	Grades of ΔRTDI	Districts	ΔRTDI	Grades of ΔRTDI
Kasur	-0.84986	low	Attock	0.071008	medium
Mastung	-0.82646	low	Sheikhupura	0.081182	medium
Lodhran	-0.81466	low	Nankana Sahib	0.081182	medium
Khanewal	-0.76615	low	Charsadda	0.08221	medium
Batagram	-0.75412	low	Abbottabad	0.083923	medium
Sahiwal	-0.69638	low	Hangu	0.115773	medium
Ziarat	-0.66301	low	Jhelum	0.118789	medium
Kohistan Lower	-0.65226	low	Leiah	0.154609	medium
Barkhan	-0.60506	low	D. I. Khan	0.202997	intermediate high
Bhakkar	-0.58534	low	Mandi Bahauddin	0.204358	intermediate high
Vehari	-0.54529	low	Haripur	0.214947	intermediate high
Swat	-0.51315	low	Shikarpur	0.223189	intermediate high
Shangla	-0.4869	low	Buner	0.243626	intermediate high
Khushab	-0.4596	low	Sialkot	0.251953	intermediate high
Okara	-0.4532	low	Mirpur Khas	0.262272	intermediate high
Toba Tek Singh	-0.44372	low	Umer Kot	0.262272	intermediate high
Badin	-0.43182	low	Khairpur	0.273192	intermediate high
Sargodha	-0.41826	low	Jaffarabad	0.280922	intermediate high
Muzaffarabad	-0.36441	low	Sohbatpur	0.280922	intermediate high
Loralai	-0.35856	low	Gujrat	0.307047	intermediate high
Duki	-0.35856	low	Mansehra	0.315443	intermediate high
Rahim Yar Khan	-0.33048	low	Tor Ghar	0.315443	intermediate high
Sibi	-0.31764	low	Sukkur	0.3217	intermediate high

Districts	ΔRTDI	Grades of ΔRTDI	Districts	ΔRTDI	Grades of ΔRTDI
Harnai	-0.31764	low	Upper Dir	0.37063	intermediate high
Malakand	-0.29547	low	Jacobabad	0.379218	intermediate high
Pakpattan	-0.29466	low	Faisalabad	0.398069	intermediate high
Tharparkar	-0.26756	intermediate low	Kohat	0.403124	intermediate high
Mianwali	-0.24256	intermediate low	Nowshera	0.424353	intermediate high
Thatta	-0.2259	intermediate low	Ghotki	0.436162	high
Sujawal	-0.2259	intermediate low	Hyderabad	0.511652	high
Multan	-0.20473	intermediate low	Matiari	0.511652	high
Swabi	-0.19409	intermediate low	Tando Allahyar	0.511652	high
Narowal	-0.18916	intermediate low	Tando Muhammad Khan	0.511652	high
Bahawalnagar	-0.16949	intermediate low	Gujranwala	0.51173	high
Hafizabad	-0.14778	intermediate low	Lakki Marwat	0.522297	high
Nasirabad	-0.13979	intermediate low	Bannu	0.529932	high
Dadu	-0.13979	intermediate	Rawalpindi	0.532243	high

Districts	ΔRTDI	Grades of ΔRTDI	Districts	ΔRTDI	Grades of ΔRTDI
		low			
Jamshoro	-0.13979	intermediate low	Lower Dir	0.554984	high
Rajanpur	-0.11145	intermediate low	Tank	0.555781	high
Chiniot	-0.03255	medium	Chitral Lower	0.571986	high
Jhang	-0.03255	medium	Larkana	0.602504	high
Sanghar	-0.0281	medium	Kambar Shahdad Kot	0.602504	high
Bahawalpur	-0.02071	medium	Peshawar	0.970524	high
Dera Ghazi Khan	0.019817	medium	Karak	1.030641	high

It is worth mentioning here that the pace of rural transformation from 2004 to 2019 implies that how fast they transform overtime. It does not necessarily means that the districts which are graded as "high" with respect to ΔRTDI also have high index value in some particular year and the district which are graded "low" are all have low value in start and end of period of analysis. Moreover, it is important to understand that if the high pace maintains in coming years too then it is possible that index value of the districts also shown a high stage at a particular point in time. The extent of RTDI over 2004-2019 is also visualized from following maps (Table. 4.1).

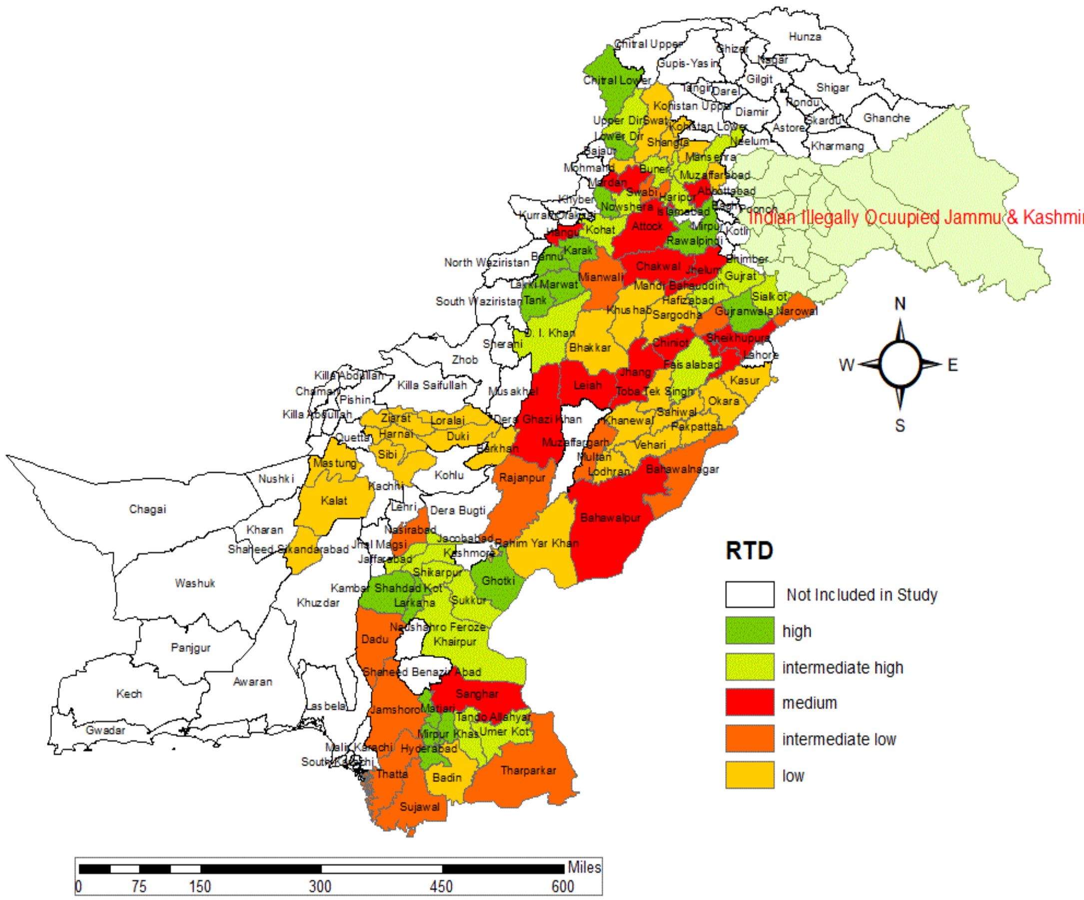

Fig. 4.1. Map showing Rural transformation development level across districts of Pakistan overtime (2004-2019)

Overall, in Pakistan it is evident that rural transformation is not uniform rather it represents large inter-district disparities (Table. 4.1). The coefficient of variation (CV) is also calculated for year 2004 and 2019 which shows some signs of convergence. The value of CV is 44.32% in 2004 whereas it shows a decline in 2019 and becomes 42.17%. However, by looking at the clusters in the map (Table. 4.1) it is further implies that the convergence is not uniform, with certain regions still exhibiting distinct patterns of rural transformation. The existence of higher inter-district variation in rural development highlights the need for tracking the forces which govern growth dynamics across Pakistan. It further implies that homogenous set of policies for all Pakistan are inappropriate rather the effective solution for the regional development needs to be multidimensional with keen focus on district level characteristics.

4.3.3. Global Pattern of Regional Rural Transformation level

In order to visualize the pattern in regional rural transformation development level, spatial autocorrelation using the Global Moran's I is seen. The global spatial correlation is positive and highly significant which implies that there exists the form of clustering in the dataset. Since it appears non-random so we can proceed further with spatial analysis. The Global Moran's I value has increased by 47.16% which indicates a stronger spatial clustering in 2019 compared to 2004 (Table 4.4). Spatial pattern of the data has become more pronounced, with similar values being more closely grouped (geographically concentrated) together over time.

Table 4.4. Global Moran'I value of RTDI

Time	Global Moran's I	E(I)	Z(I)	P(I)
2004	0.2856	-0.0057	6.45	0.0000
2019	0.4203	-0.0057	9.40	0.0000

E(I): Expected Moran's I under spatial randomness; Z(I): Standardized test statistic (z-score); P(I): Probability value indicating statistical significance

To further understand the pattern, the Global Moran I for ∆RTDI overtime is also calculated. The value for the overtime difference is also significant (Table. 4.2) and high and suggests an extremely strong spatial pattern in the change between 2004 and

2019. It indicates that the spatial changes between these two years are highly patterned, showing a notable shift in how values are distributed over space.

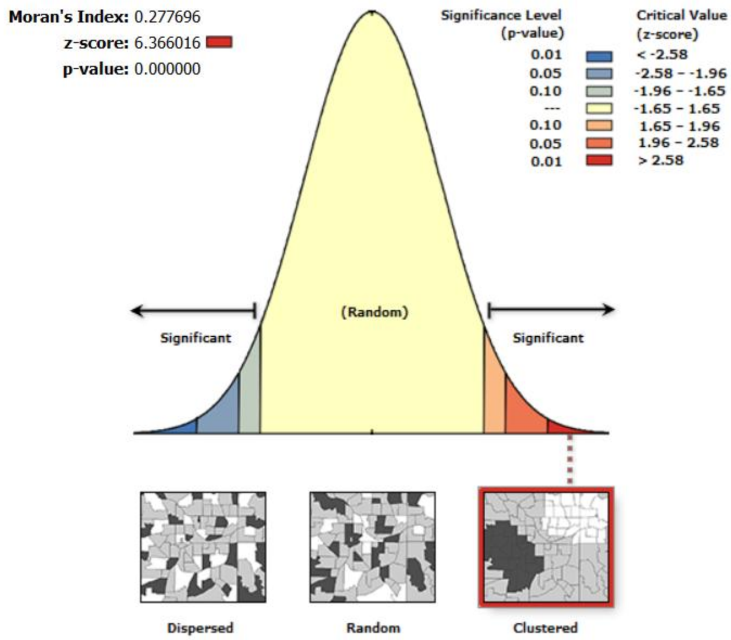

Fig. 4.2 Global Spatial Autocorrelation of ΔRTDI

4.3.4. Local Patterns/Clusters

Now we examine and identify the specific clusters in the pattern of RTD. In this way we have marked the foundation for spatial regression analysis in upcoming sections where the drivers responsible for these spatial lags are identified.

- One of the clusters categorized as having "low" rural transformation over time has been identified in Punjab, comprising the districts of Kasur, Okara, Sahiwal, Pakpattan, Toba Tek Singh, Khanewal, Vehari, and Lodhran. Among these, Kasur and Lodhran experienced a significant reversal. Both of them shows transitioning from a high level of rural transformation in 2004 to a low level in 2019. This decline is primarily attributed to a reduced share of high-value crops in these districts along with an increased emphasis on low-value crops such as wheat and rice. Rest of the districts within the cluster were initially at an intermediate-low level of rural transformation in 2004 and further declined to a low level by 2019, collectively placed in “low-level" RT category. Faisalabad is being the interesting case; it lies in the vicinity of low-performing cluster but stands out as an exception. Faisalabad falls into the "intermediate-high" category due to significant progress in its non-farm employment over the period of time. It is highlighting the potential influence of localized economic dynamics and infrastructure in driving differential transformation patterns within the region.

- Another “low” category cluster has been identified in the province of Baluchistan. This cluster has districts namely Kalat, Shaheed Sikandrabad, Mastung, Ziarat, Barkhan, Loralai, Duki, Sibbi and Harnai. Among these, Ziarat, Loralai, and Duki have historically exhibited high levels of RT due to their prominent fruit cultivation (especially apples) and other high-valued horticultural produce. However, due to minimal changes in agricultural and economic practices over time, these districts are now falling into the low-level transformation category in terms of change dynamics. Kalat has entered this cluster primarily due to an increased focus on low-value crops (such as grains) over time, reflecting a shift away from high-valued agricultural production. Mastung, Barkhan, Sibbi, and Harnai have transitioned from intermediate-high to medium rural transformation categories over time, indicating a slower pace of development. As per our anlaysis, this change is indicated by a decrease in urbanization.

- An “Intermediate low” cluster is present there in Sindh (Figure 4.1). This cluster has districts namely Dadu, Jamshoro, Thatta, Sajawal and Tharparker. These districts exhibit limited progress in RT, which is indicated by a consistently low and declining share of high-valued crops, reduced land-use intensity, and minimal urbanization. The persistent underperformance across these indicators collectively places them in this "Intermediate Low" category.
- A "Medium" category cluster in Punjab comprises of Jhang, Chiniot, Layyah, and Dera Ghazi Khan. Jhang and Chiniot are primarily rural in nature and are known for being among the largest wheat producers in Punjab, they have displayed a medium pace of transformation. However, a notable increase in the share of non-farm employment over time has supported their placement in this category. Layyah also demonstrates a medium pace with improvements in indicators such as the share of livestock and high-value crops. Despite these gains, the district shows limited progress and remains predominantly rural with slow urbanization and declining off-farm employment. Dera Ghazi Khan contributes to this cluster through its rising share of high-value crops (cotton, sugarcane, and oil crops), which sustain its position in this category.
- Another "Medium" category cluster has been identified in Punjab (Figure 4.1). This cluster comprises the districts of Attock, Chakwal, and Jhelum, each demonstrating a moderate level of RT driven by distinct yet interconnected indicators. Attock is primarily an agricultural district cultivating wheat and

peanuts but it shows significant progress through a rising share of non-farm employment, indicating a diversification of its economic base. Chakwal stands out for its increasing share of high-value crops (sugarcane, fruits, and vegetables), alongside a substantial contribution from livestock products. Jhelum is characterized by both urban and rural dominance and has shown improvement in land use intensity over time, along with a growing share of high-value agriculture and livestock production. These districts reflect a balanced progression in RT, forming a cohesive cluster with shared attributes. In close proximity to this cluster lies Rawalpindi which categorized as "high" in RT. Unlike its neighboring districts, Rawalpindi benefits significantly from advanced urbanization and a robust rise in non-farm employment, placing it in a higher category. Its strategic location and urban-rural integration have fostered diverse economic activities, contributing to its sustained high performance. This contrast highlights the role of urbanization and economic diversification in accelerating rural transformation within the same region (Abedullah et al, 2023).

- An “Intermediate high” cluster of Sindh is made up of Jacobabad, Shikarpur, Sukkar and Khairpur. Jacobabad and Shikarpur are placed in this category largely due to their increasing share of livestock production, reflecting a gradual shift towards more diversified agricultural activities. For sukkar, the paced accredited to increase in share of non-farm employment. District Khairpur actually changes its category from “low” in 2004 to “intermediate low” in 2019, but the pace is fine enough to make it fall in the “intermediate high" category overtime. Khairpur demonstrates consistent improvement across all indicators.

- Another cluster belonging to the same pace of transformation i.e., intermediate high, is in Punjab. Mandi bahuddin, Sialkot and Gujrat form this cluster. All of three districts have this pace accredited to rising share in non-farm employment overtime. They also have a close neighborhood district Gujranwala which is in "high" category by pace, which is again indicated by rising share of non-farm employment along with urbanization.
- "High" paced cluster has been identified in KPK, comprises of Karak, Bannu, Lakki Murwat and Tank. These districts have transitioned from a low to a high category over time, reflecting their accelerated pace of rural transformation. This significant rise in their index values is indicated by the increasing share of non-farm employment across these areas.

Districts Faisalabad, Rawalpindi, and Ghotki can also be used as structural reference points for seeing spatial heterogeneities. Faisalabad is an example of balanced transformation, where high-yielding agricultural intensity coexists with a robust non-farm textile industrial sector. In contrast, Rawalpindi represents a service-led transformation frontier, where close proximity to the federal capital, high literacy rates, and advanced urban agglomeration pull labor directly into the tertiary sector, bypassing traditional agro-dependent phases. Ghotki presents an alternative structural model characterized by capital-intensive industrial enclaves (fertilizer and power plants) operating within a rigid, traditional cash-crop agrarian economy. Comparative spatial analysis against these three benchmarks reveals that lagging districts in South-Central Punjab and Balochistan often suffer from a missing middle; they lack either the aggressive non-farm labor capitalization seen in Faisalabad or the urban-service infrastructure characteristic of Rawalpindi.

4.4 Conclusion

This chapter examines the extent and pattern of RTD across districts of Pakistan using ESDA. Firstly, index have been developed using the five most prominent indicators of RTD which are share of high-valued agriculture, share of livestock, share of non-farm employment, urbanization and land use intensity. The index has been constructed using Principal Component Analysis (PCA) and is computed separately for each year included in the study to capture year-specific variations in the weights of the indicators. If we look at the weights to the all elements of the RTDI, it is seen that agriculture production contributes more in the district-level rural transformation in each period of our study, making it primary indicator of the index. Based on the index, the classification of districts into five categories reveals that a large number of districts remain in the low and intermediate stages, indicating slow structural progress.

The Global Moran's I result confirm strong and increasing spatial clustering, suggesting that similar levels of transformation are geographically concentrated. Local cluster analysis further highlights distinct regional patterns, with low-performing clusters concentrated in parts of Punjab and Balochistan, while high and rapidly transforming clusters are observed in KPK and selected districts of Punjab and Sindh. These patterns are strongly linked to variations in cropping structure, employment diversification, land use intensity and Urbanization. Overall, the findings emphasize that RT in Pakistan is uneven and spatially dependent. So, there is a need for region-specific and targeted policy interventions rather than uniform national strategies.

CHAPTER V

RESULTS AND DISCUSSION-DRIVERS OF RURAL TRANSFORMATION DEVELOPMENT

5.1. Introduction

A very comprehensive and detailed analysis is upcoming on drivers of RTD, their direct and indirect relationships, their spatial temporal dependencies, and understanding the behavior of the drivers in varying stages.

5.2. Descriptive Statistics

Summary statistics of the included variables is presented in Table 5.1. Average value of the RTDI is 0.81 and average household size across all included districts is 8 which is quite high. On average 65% of the rural population who are having access to roads are satisfied with the facility whereas 91% are those satisfied with banking facility. Average Maximum temperature in Pakistan is 44.91 degree Celsius. The average years of schooling of rural population is quite low (3.62 years), perhaps it is because this value represents the average over all districts at four points in time, covering a period of about 15 years. Nonetheless, this indeed represents the low level of education in rural communities which varies between 1.16 to 7.58, demonstrating that average schooling is below 10 years. This situation is primarily due to low investments in education-related infrastructure, especially in rural areas, and the socio-cultural constraints in sending children to school. The share of irrigated farmland from all sources (i.e., canal, tube well and both) shows that there are districts with 100% of the areas being irrigated, but yet there are districts with few or no irrigation. This indicates the uneven distribution of water facilities across districts of Pakistan.

Table 5.1 Descriptive Statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
RTDI	312	0.81	0.43	-0.04	2.65
Household Size	312	7.79	1.39	4.39	12.39
Share of rural population satisfied by road facility (%)	312	65.14	20.97	10.15	98.79
Share of rural population satisfied by banking facility (%)	312	91.01	13.30	19.17	100.00
Maximum Temperature (degree celsius)	312	44.91	2.79	38.50	51.00
Education of rural population (number of years of schooling)	312	3.62	1.32	1.16	7.58
Share of irrigated farmland through canal (%)	312	34.2	40.5	0	100
Share of irrigated farmland through tube well (%)	312	19.3	36.5	0	100
Share of irrigated farmland through canal & tube well (%)	312	17.8	29.9	0	100
Farm Credit (billion PKR)	312	4.11	7.02	0.00	54.51

5.3. Statistical Analysis

Statistical analysis conducted for objective two is part of this section.

5.3.1. Selection of Spatial Weight Matrix

As already mention in early discussion that, spatial model required the definition of spatial weight matrix. The matrix in helpful in understanding the local dependencies and it further affect the estimations of the model (Anselin, 2007). In our analysis we have proximity of geographical contiguity identified by polygons. Hence we choose the *queen contiguity* which includes both edges and corners as neighbors. These weights have been constructed in GeoDa software and then imported into the STATA software for proceeding the spatial analysis. Row normalization has been done in STATA and weights are set to align with the rest of panel data. Row normalization of the spatial weight matrix ensures that each row sums to 1, which standardizes the influence of neighboring units in the spatial analysis. This step prevents any one neighbor from disproportionately affecting the model's results, allowing for a more balanced and accurate estimation of spatial dependencies.

5.3.2. Spatial Autocorrelation Test Result

Moran's, I value for each year is positive and highly significant[15] (Table 5.2) which implies that there exists the form of clustering in the dataset. Since it appears non-random so we can proceed further with spatial analysis.

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[15] If $I(d) > 0$ it shows the existence of positive spatial correlation which implies that there is global spatial pattern.
If $I(d) < 0$ it shows the existence of negative spatial correlation which implies that there is no global spatial pattern.

Table 5.2 Global Moran's I value of RTDI

Time	Global Moran's I	E(I)	Z(I)	P(I)
2004	0.2856	-0.0057	6.45	0.0000
2009	0.1976	-0.0110	2.72	0.0066
2014	0.1255	-0.0110	1.77	0.0759
2019	0.4203	-0.0057	9.40	0.0000

5.3.3. Selection of Model results

According to p-value the null hypothesis based on the results of LR test (LR-SDM-SAR) has been rejected (Table 5.3) and the Spatial Durbin model (SDM) has been selected to proceed.

Table 5.3. Results of the LR Test for Model Selection

Test Statistic	Degrees of Freedom	P-Value
19.78	9	0.02

Now next it is important to see that which dynamic spatial durbin model (DSDM) to use in order to interpret the findings of the study (the results of all models are reported in Appendix B). The decision is based on both econometric and theoretical reasoning. For econometric reasoning we see the AIC and BIC value for appropriate model selection. Since the model with lower AIC and BIC is selected so in our case hence we proceed with DSDM with time-fixed effects. Theoretically, DSDM with time fixed effects is better suited to the Time-Based PCA approach (the RT index is constructed for each year separately), where the primary goal is to capture temporal changes across districts while accounting for spatial dependence and temporal dynamics simultaneously. Time fixed effects controls for unobserved temporal variations that affect all districts equally. These unobserved temporal variations include: economic policies, climate changes, or general shifts in rural development patterns.

Table 5.4. AIC and BIC Criterion

Criterion	DSDM with Random effect	DSDM with spatial fixed-effects	DSDM with time-fixed effects	DSDM with spatial and time fixed-effects
AIC	177.06	63.67	51.23	164.07
BIC	319.29	198.42	185.99	298.82

5.3.4. Dynamic Spatial Durbin Model Results

Empirical analysis is based on the results of DSDM with time fixed effects using queen contiguity weighted matrix.

The coefficient of lag dependent variable i.e. L. RTDI is statistically significantly positive which indicates that the level of rural transformation achieved in one period continues to influence the transformation process in the subsequent five-year period. Since the panel dataset consists of five-year intervals (2004, 2009, 2014, and 2019), therefore the lagged dependent variable captures the persistence of RTD over a medium-term period rather than an annual effect. This finding is theoretically consistent with the nature of RT, which is a gradual and path-dependent process involving structural changes in agricultural production, employment patterns, urbanization, and land use. Such changes require time to materialize and therefore their effects are expected to persist across medium-term intervals.

In table 5.5 ρ is the coefficient of spatial lag of dependent variably. The value of ρ is also positive and significant, implying that RTDI in one district correlates the RTDI in its neighboring districts (Ahmad, 2011). L. WRTDI is the spatial lag of the temporal lag, it measures the influence of a neighboring region's lagged dependent variable on the current dependent variable in the focal region. A significant coefficient of 0.24 indicates that on average a 1unit increase in the RTDI in neighboring regions in the previous time period leads to a 0.24 unit increase in the current period's RTDI in the focal region. It highlights the presence of temporal spillover effects across neighboring regions, suggesting that historical developments or improvements in one region positively impact adjacent regions over the period of time. Such findings emphasize the importance of considering both spatial and temporal dynamics in policymaking and regional planning in order to foster collaborative growth and development across the country.

Table 5.5 Results of DSDM

Variables	**Value**
L. RTDI	**0.13****
L. WRTDI	**0.24****
Main (X)	
Farm Credit S2	-0.0014
Farm Credit S3	-0.0148
Education of rural population S2	0.0407***
Education of rural population S3	0.0926**

Variables	Value
Share of irrigated farmland through canal S2	0.0015***
Share of irrigated farmland through canal S3	0.0311***
Share of irrigated farmland through tube wells S2	0.0025*
Share of irrigated farmland through tube wells S3	0.0102***
share of irrigated farmland through canal & tube wells S2	0.0031**
share of irrigated farmland through canal & tube wells S3	0.0054***
Temperature	-0.0117
Rural Household size	-0.0120
Share of rural population satisfied by road facility (%)	-0.0001
Share of rural population satisfied by banking facility (%)	-0.0013
WX (Spatial Spillovers)	
Farm Credit _S2	-0.0124**
Farm Credit _S3	0.0207
Education of rural population S2	-0.0045
Education of rural population S3	-0.0578
Share of irrigated farmland through canal S2	0.0015**
Share of irrigated farmland through canal S3	0.0102
Share of irrigated farmland through tube wells S2	-0.0030
Share of irrigated farmland through tube wells S3	-0.0029
share of irrigated farmland through canal & tube wells S2	0.0066*
share of irrigated farmland through canal & tube wells S3	0.0046
Temperature (^{O}C)	0.0066
Rural Household size	0.0248
Share of rural population satisfied by road facility (%)	0.0053
Share of rural population satisfied by banking facility (%)	-0.0016
ρ	0.12**

Variables	Value
sigma2_e	0.11***
No. of Observations	234
No. of Districts	78

Note: *** denotes significant at 1%, ** at 5% and * at 10%.

There are three stages of RT taken in this study, implying that there are two stage dummies (symbolized as S2 and S3 for stage 2 and stage 3 respectively) by considering stage 1(S1) as a base. Drivers studied for their association with RDTI at S2 and S3 with S1 as base category. Also, the coefficients of explanatory variables are presented in table for direct effects and spatial spillovers (indirect effects). Our first driver, credit, appeared insignificant at both S2 and S3 in comparison to S1. This may happen due to the poor existence of supporting factors. Credit alone may not do much wonders but along with efficient markets, better social capital, and the understanding of how to effectively utilize it and where to allocate it, all these factors collectively enhance the benefits of credit (Hussain & Taqi, 2014). These findings are not consistent with the only other study on credit and regional rural transformation in Pakistan by Abedullah & Shujaat (2024). However, this discrepancy may arise due to differences in how the dependent variable is measured. Abedullah & Shujaat (2024) focused on individual aspects of RT while this study employs a composite index of RT, capturing a broader and more aggregated perspective. It is probably diluting the direct impact of credit on specific dimensions of transformation. Interestingly, the spillover effects of credit at S2 are statistically significantly negative. The negative spillover effect does not imply that credit is harmful. Rather, it suggests that increased credit availability in one district may attract productive resources, investment, technology, and economic opportunities towards that district, creating regional imbalances. Consequently, neighboring districts may experience relatively slower rural transformation, resulting in a negative spatial spillover effect. This reflects uneven regional development rather than a direct adverse impact of credit itself.

Our results indicate that *education* has a significant positive association with RTDI, implying that as the number of years of schooling increases it enhances rural transformation. Education works through multiple channels, better education encourages farmers to continue farming and use the land more intensively as it helps to increase farm productivity through better understanding of technology, more information, and better interaction with input-output markets (Stiglbauer & Weiss, 2000). With education it is also more likely that rural population invest in livestock for meat and milk which is a profitable source. When agriculture production increases, it increases the farm household income as well (Panda, 2015). On the other hand, education also works as a push and pull factor which lead people to move from farm to off-farm employment. Education increases the ability to perform different activities which appears in terms of the high opportunity cost of trained labor which the agriculture sector cannot afford to pay (Muhammad et al., 2012). This increases the probability to get better job in the non-farm sector (Agarwal & Agarwal, 2017) and may encourages urbanization in some case. The expansion of non-farm activities contributes significantly to household income growth (Yang, 2004). Education can produce negative attitudes towards manual tasks or working in the fields. It can also raise aspirations for white-collar jobs and create dissatisfaction with traditional occupations like farming (Agarwal & Agarwal, 2017; Ahmad et al., 2020). Motiram

& Singh (2012) believed that education is seen as a way of escaping agriculture rather than as being complementary to good farming. All of these channels affect the indicators of RTDI positively and hence justified the positive coefficient. The magnitude of the positive effect varies with S2 and S3.

Our empirical results demonstrate that 1-year increase in schooling could lead to an increase in the RTDI by 0.04 units for the districts in their S2 whereas at the S3 the value of coefficient increases and become 0.09. The contribution of education at S3 of rural transformation is more pronounced than the contribution at S2. It further implies that the districts that are at higher stages of rural transformation have more intervening factors. These factors like technological advancement, better policy implementations etc. may assist and contribute to the entire process and enhance the impact of education. On average, education fails to have any spillover effects, as the coefficient of education appears insignificant.

Our results from the models having irrigation related variables (Model 3 & 4) indicate that *irrigation* has a significant positive association with RTDI, implying that as the share of irrigated farmland increases it enhances rural transformation. The positive and significant relationship remains irrespective of the source of irrigation i.e. canal, tube well and canal tube well. It is observed that if the districts are at the S2 of rural transformation then 1% increase in *share in irrigated farmland through canal* is associated with an increase in RTDI by 0.15% whereas at the S3 the percentage increase to 3.11 (here the coefficients have been multiplied to 100 in order to interpret them in percentages). It clearly demonstrates that the contribution of irrigation is higher at higher stages, making it an important driver to RTD. If the source of irrigation is tube well then the it is associated with 0.25% and 1.02% increase in RTDI with S2 and S3 respectively. Similarly, if the area irrigated through canal tube wells increases then the RTDI increases by 0.31% and 0.54% respectively in S2 and S3. Our results further reveals that the contribution of canal irrigation is highest compared to other sources of irrigation which is comparatively expensive. These findings clearly produce empirical and quantitative evidence that at higher stages the productivity of irrigation increases and associated with RTD through multiple channels. Firstly, with better irrigation farmer shifts towards high-valued crops (which are sensitive to water availability) and they also adopt modern management practices along with water conserving technologies. The findings are consistent with Rijsberman (2003), Pinstrup & Shimokawa (2006) and DeJong et al., (2021). Secondly, with enhancement in crop yield and farm income, the reliance on agriculture labor reduces which spares the labor for non-farm sector (Abraham, 2023) and also some may move to urban areas and hence rural transformation identifies through urbanization (Singhal & Bains, 2018). Also, the rural population started to allocate their resources differently and start prioritizing the other income generating activities as well like rearing livestock (Abraham, 2023). Thirdly, with better irrigation land is used more intensively and its productivity enhances, hence it changes the land use pattern identifies as transformation development (Liangije, 2017). The irrigation also expected to have the spatial spillovers for neighboring district's transformation, but in our results they only appear in S2 for the case of canal irrigation. It makes sense because canal irrigation system happened to the spatially connecting various districts, hence the provisions and utilization of water further depends on indigenous policies and water usage rights. Also the similar spillover has been seen in the case of canal tube well irrigation, again in S2.

Lastly, in the model the drivers such as maximum temperature, the share of people satisfied with road facilities, and banking facilities show no significant spatial association on average for the study period. This lack of statistical significance could be attributed to several reasons. First, the effects of these variables might be too small to reach significance. Second, their impacts could vary across regions, with positive effects in some areas and negative effects in others, effectively canceling each other out when averaged. A future study may be conducted to understand these complex relationships and regional variations with a focus on spatial heterogeneities.

Sigma2e is the variance of the residuals. Its value is significant in the model which demonstrates the goodness-of-fit. This result validates the robustness of the model specifications and also provides confidence in the findings.

5.3.5 Discussion

The findings from the DSDM underscore the fact that rural transformation in Pakistan is a process shaped both by temporal persistence and spatial interdependence. The significance of the lagged dependent variable reveals that the improvements in RT during the subsequent previous period continue to reinforce current developments. It also highlights the path-dependent nature of the transformation. Similarly, the positive effect of the spatially lagged lag suggests that progress in one district not only benefits itself but also spills over to neighboring districts over the period of time. Such persistence emphasizes the importance of coordinated and regionally integrated development strategies rather than fragmented and district-specific interventions.

Considering the shared trajectories of neighboring districts while making the policies can create mutually reinforcing growth patterns essential for rural development planning.

The results of our analysis show the limited and inconsistent role of farm credit. Direct effects across both S2 and S3 are insignificant, while spillover effects at S2 are negative. It implies that increased credit availability in one district may crowd out opportunities for surrounding areas. This weak performance of credit is not entirely surprising given that financial resources alone are unlikely to drive transformation without the presence of supporting conditions like market access, social capital, financial literacy, and efficient allocation of loans. Credit may have tendency to transform only when embedded in an enabling environment that could provide technical guidance, transparent allocation mechanisms, and linkages with value chains. Policies such as the Kissan Card program should therefore not be viewed in isolation but rather as part of a broader framework that strengthens capacity for productive utilization of credit and ensures balanced and transparent disbursement across districts. Credit will continue to fall short of its transformative potential without these complementary conditions

In contrast, education stands out as one of the strongest and most consistent drivers of RT in our model, with positive and highly significant results at both S2 and S3 . The effect is more pronounced in districts at advanced stage of RT, implying that education potentially interacts with other enabling factors such as technology, infrastructure, and policy environment to magnify its impact over time. In a system, education can contribute through multiple pathways, on the one hand it may enhance farm productivity by improving access to knowledge and adoption of new technologies, encouraging diversification into profitable activities such as livestock, and on the other hand it may enable labor mobility into higher-paying non-farm jobs. Education also helps raise aspirations and facilitates entry into urban employment, which in turn drives structural shifts in the rural economy. These results provide a strong rationale for prioritizing investment in rural education infrastructure, with a particular focus on vocational and technical training that could bridge agricultural skills with non-farm opportunities. However, the absence of significant spillover effects suggests that the benefits of education remain localized within districts, and thus policies must directly target lagging regions to ensure more equitable outcomes.

Another critical driver that consistently shows a significantly positive relationship with transformation is irrigation. The results confirm that irrigation is an input for agricultural production and also a structural catalyst for reshaping rural economies. Canal irrigation, tube wells, and combined canal-tube well systems all contribute positively to RT They have demonstrated a larger impact in those districts which are at advanced stages of development. Canal irrigation also exhibits spatial spillovers in S2 which reflects the interconnected nature of canal systems across the districts. This calls for strong governance and collective management of irrigation resources to ensure equitable and efficient distribution of water. In order to sustain these gains, there is a need of Investments in rehabilitation of canal systems, modernization of infrastructure, and promotion of water-saving technologies such as drip irrigation and laser leveling. The findings also suggest that better irrigation allows farmers to shift toward high-valued crops, adopt modern management practices, and intensify land use. Interestingly, other drivers such as temperature, household size, satisfaction with roads, and access to banking services do not show significant results. Although their impacts may not be large or consistent enough to appear in aggregate analysis but still they could matter in region-specific contexts where local dynamics differ. This reinforces the need for policies that are sensitive to regional heterogeneity rather than applying uniform solutions nationwide.

In a nutshell, the evidences from the study suggests that education and irrigation form the two pillars of rural transformation in Pakistan. Credit requires an enabling environment to be effective. The presence of spatial and temporal spillovers indicates that policies must be regionally coordinated and long-term in outlook. Stage-specific policies are essential, early-stage districts may require basic infrastructure and access, whereas advanced-stage districts will further be benefitted from technological upgrading, skill development, and market integration. By embedding the successful drivers into coherent and integrated framework, policymakers can foster inclusive and sustainable rural transformation. Such RT will not only strengthen agriculture but also diversifies rural livelihoods and links them more effectively to non-farm opportunities.

CHAPTER VI

RESULTS AND DISCUSSION-CROSS SECTIONAL SPATIAL HETEROGENIETY

6.1. Introduction

This chapter aims to analyze the cross-sectional spatial heterogeneity in RTDI across districts of Pakistan for year 2019. It further examines how the effects of key determinants, including education, irrigation, credit, and household characteristics, vary across space. The analysis provides insights into the factors responsible for regional differences in RTD.

6.2. Geographically Weighted Regression

Following are the local parameters of the GWR model. These has been estimated using the ArcGIS software (Table 6.1).

Table 6.1 Local Parameters of GWR

Parameter	Value
Neighbors	30
Residual Squares	1.7371
Effective Number	22.7953
Sigma	0.2797
AICc	56.6677
R2	0.6588
Adjusted R2	0.3238

The model uses 30 neighbors for calibration, with a residual sum of squares of 1.7371, indicating the overall fit of the model. The effective number of parameters is 22.7953, which accounts for the model's complexity. The sigma value of 0.2797 represents the model's standard deviation, and the AIC value of 56.6677 suggests a reasonably well-fitted model for the given data. The R^2 value of 0.6588 indicates that approximately 66% of the variance in the dependent variable is explained by the model, while the adjusted R^2 value of 0.3238 accounts for the number of predictors and the effective degrees of freedom, highlighting the localized nature of the relationships explored through the GWR approach.

Fig. 6.1 illustrates the spatial heterogeneity in the influence of various factors on Rural Transformation Development (RTD) in 2019, as captured through the distribution of positive and negative Geographically Weighted Regression (GWR) coefficients for each factor. The results reveal significant spatial variation in the strength and direction of relationships which highlights the localized nature of these influences. The education factor demonstrates a predominantly positive influence, 77% of the districts are showing a positive relationship with RTDI and only 23% exhibiting a negative relationship. Positive relationship varies slightly across different irrigation sources. The share of irrigated farmland through canals (I2) shows a 68% positive relationship., Other irrigation measures also shows positive coefficients (I3 and I4 have 74% and 69% respectively). Credit exhibits a more balanced distribution, 55% of regions displaying a positive relationship and 45% negative. Interestingly, household size (HHsize) has a predominantly negative relationship with RTD, 69% of regions showing a negative coefficient. Larger household sizes might impose resource constraints or limit diversification opportunities which hinders rural transformation in many districts.

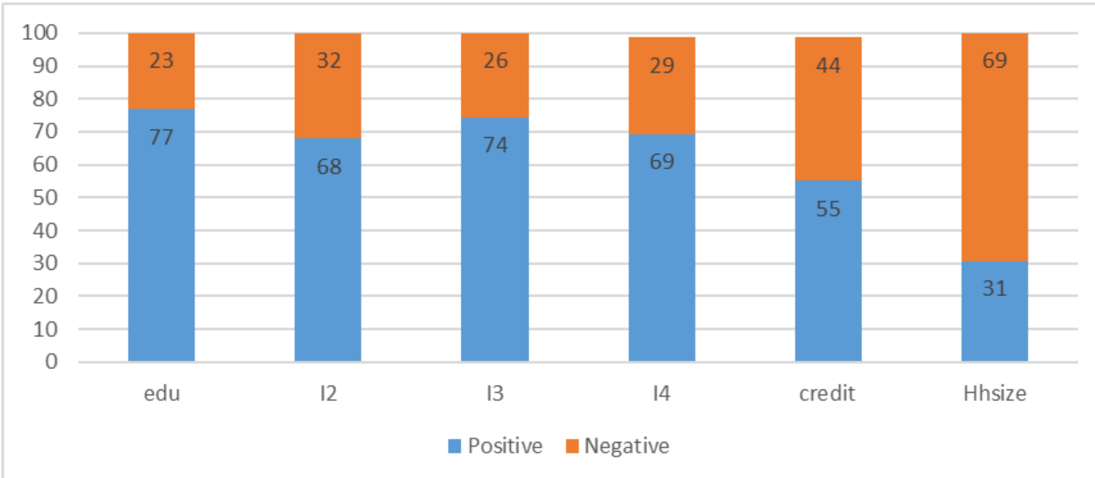

Fig. 6.1 Positive and negative values of regression coefficient for each included factor

6.3. Analysis of Effects

This section analysis the various factors explaining the cross sectional heterogeneity.

6.3.1. Education Factor

Education for rural transformation is about positive changes in rural communities (Bansal, 2018). Development economists agree that fair access to education and learning is crucial for long-term progress and sustained development. Inequality in education may lead to asymmetrical growth of the economy (Jamal, 2014). Educational crisis at national and rural levels happens mainly due to distributional issues; in developing countries, most of the educational resources are diverted towards the urban areas of the country; secondly, there exists an incompatibility between the school teachings and the real-life needs of the rural population; thirdly educational policies also neglected the learning needs of the children and adults of the rural population (UNESCO, 2001).

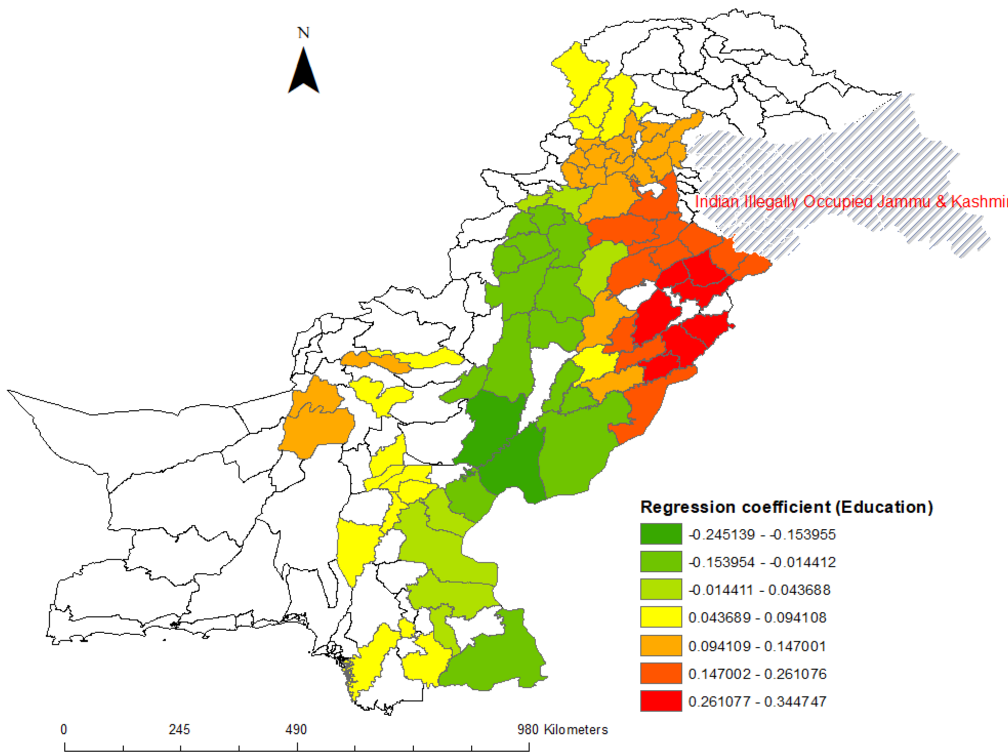

Fig. 6.2 Distribution of Regression Coefficient of Education

By looking at the Fig. 6.2, it is seen that the positive values are concentrated mostly in upper Punjab, KPK and some parts of Sindh. Whereas there are districts where education is not playing its positive role. Pakistan spends less than 2% of GDP on education (World Bank, 2022) which is quite low but still government of Pakistan is motivated to achieve SDG Goal 4[16] by bringing improvement in quality of education, removal of discrimination, investment in education related infrastructure etc. Overall, the current literacy rate in Pakistan is 62% whereas rural literacy rate is 54% against

[16] Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all

the urban literacy rate which is 77.3 %(GoP, 2022-23). Poor natural resource endowment[17], infrastructure[18] & institutional deficiency[19], socio-cultural barriers and human development deficiencies[20] are the key obstacles that might be the reason that education yield uneven gains.

These findings are somewhat aligned with the findings of the PSLM report 2019-20. According to the report, a detailed analysis of education in Punjab in 2019 shows significant disparities among districts, with Rawalpindi ranking the highest and Rajanpur at the bottom. Out of the 36 districts in Punjab, 19 districts have better education standards (PSLM, 2019), Abbottabad district in KP stands out for having the best educational indicators compared to other districts in the province. The recent stats for Sindh are quite alarming because out of the 29 districts of Sindh only 10 districts (Karachi at the top) are slightly better than the rest of the 19 districts in terms of the level of education (PSLM, 2019). Baluchistan faces substantial educational challenges compared to the other provinces. According to the PSLM (2019) report, not a single district in Baluchistan achieved a classification of "very good" in terms of education quality. In fact, the report highlights that 23 out of the 28 districts in Baluchistan are in a critical state of education, urgently requiring interventions to bring about substantial improvements in the education sector. Hence, the contribution of education in the process of rural transformation is expected to be lowest in Baluchistan given these educational disparities and challenges.

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[17] Shortage of farmland and water, unfavorable climatic and ecological conditions

[18] Poor roads and irrigation system, insufficient power provision etc.

[19] Lack of access to credit, political obstacles in labor mobility, absence of social safety nets

[20] Poor quality of primary and secondary education, lack of vocational and technical education, lack of appropriate skills

6.3.2. Irrigation Factor

6.3.2.1. Canal Irrigation Factor

Fig. 6.3 depicts the spatial distribution of canal irrigation and its influence on Rural Transformation Development (RTD), as captured through GWR coefficients. The results demonstrate that districts with a well-established canal irrigation system exhibit predominantly positive coefficients. It indicates a strong positive relationship between canal irrigation and RTDI in these districts.

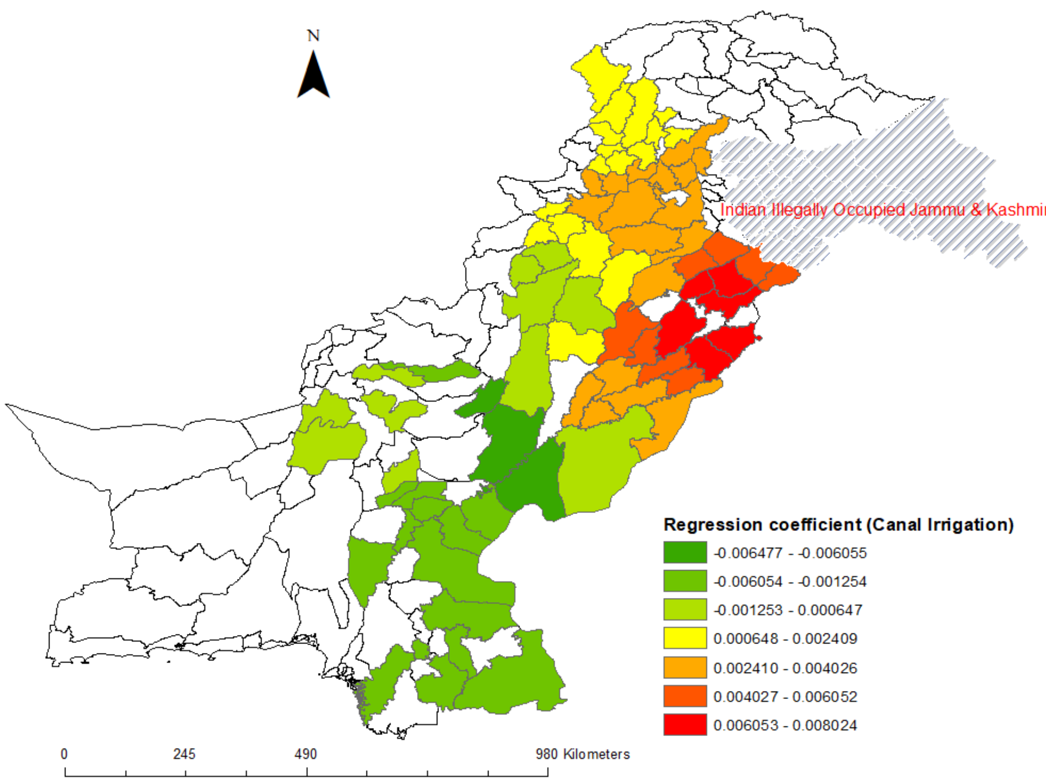

Fig. 6.3 Distribution of Regression Coefficient of canal irrigation

Punjab emerges as the region with the highest concentration of positive coefficients, because it is well-known for its extensive and efficient canal irrigation network. Canal irrigation plays a significant role in enhancing agricultural productivity and also it is helpful in cultivation of high-valued crops. It serves as a good support for rural transformation. When such reliable water resources facilitate the modern farming practices then it ultimately leads to increased farm income and better livelihoods. Similar positive coefficients have also been seen for KPK. Spatial distribution of these coefficients identifies that how important canal irrigation as a driver for rural transformation, especially in areas with water scarcity and agriculture dependence. We also seen in Fig. 6.3 the areas with negative coefficients. These areas highlight the inefficient water management, inequitable distribution of water, or dependence on irrigation sources other than canal irrigation.

6.3.2.2. Tube well Irrigation Factor

The distribution of water based on tube wells is shown in Fig. 6.4. This factor has shown a more positive concentration overall. About 74% association of GWR coefficient has been seen for the districts in 2019. It shows the rapidly growing importance of tube well irrigation as an alternative water source in those areas where canal irrigation is insufficient or unreliable.

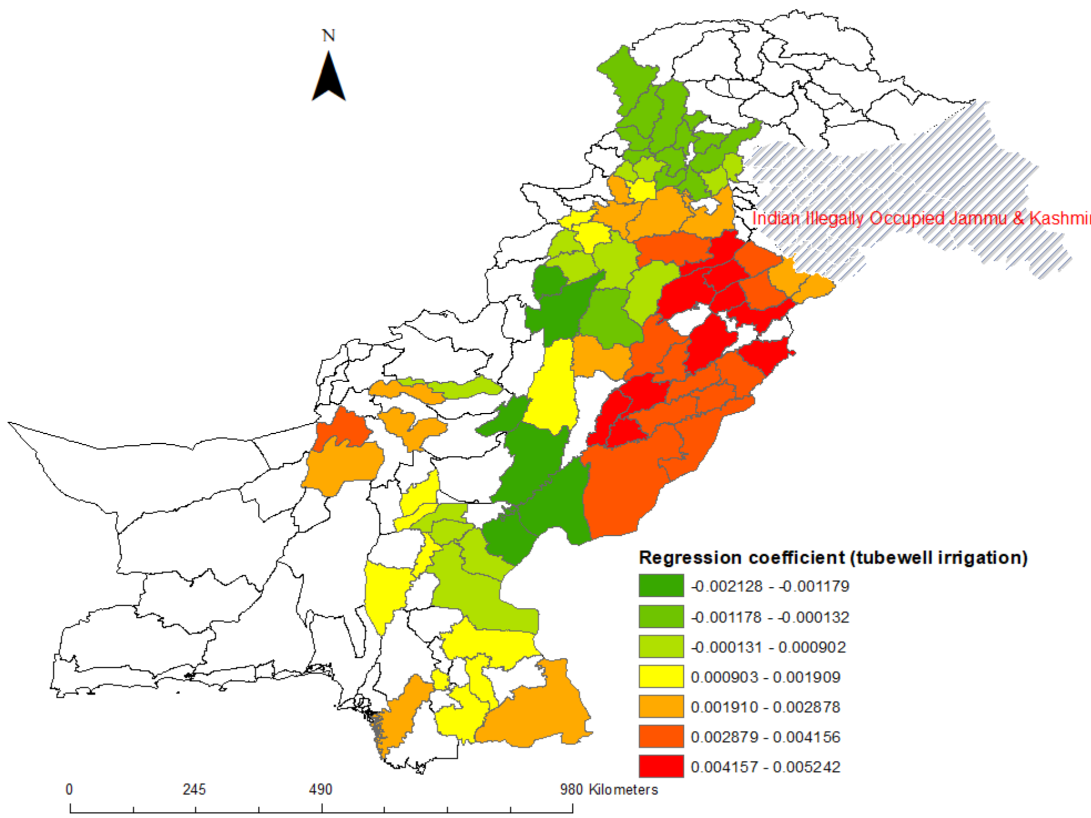

Fig. 6.4 Distribution of Regression Coefficient of tube well irrigation

With the wider adoption of tube wells, the farmers are acquiring more control over the availability of water. So now they can grow more water-intensive and high-valued crops. The positive coefficients are more evident in water scarce areas, now tube wells are mitigating that shortage and enhancing the agricultural productivity in those areas. However, there exists a genuine concern about the depletion of ground water and water sustainability. The tube well water usage has to be handled through appropriate policy measures and resource management strategies in order to conserve the water.

6.3.2.3. Canal-Tubewell Factor

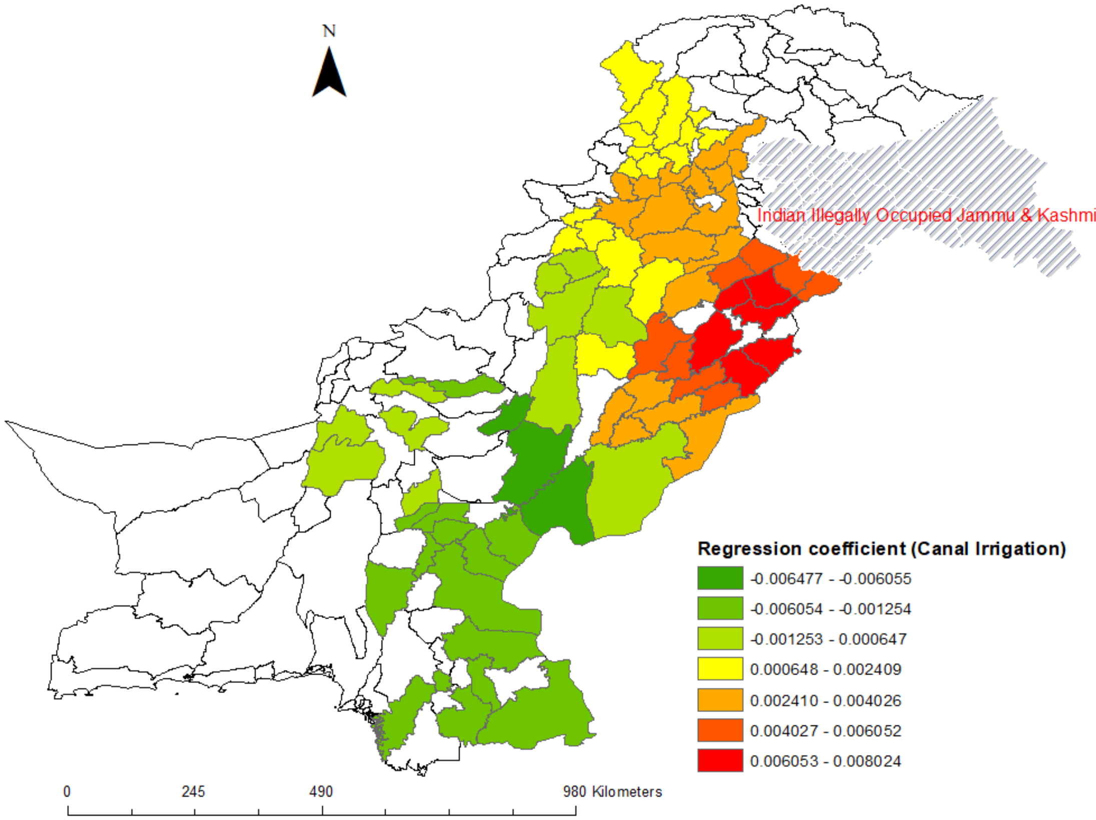

Fig. 6.5 Distribution of Regression Coefficient of Canal Tube well irrigation

The canal tube well factor has shown positive coefficients in those areas where both of these facilities are available and has been in use alternatively. The synergy between these two alternative water resources ensures the water availability particularly in the period of canal water scarcity. Hence, the agriculture activities are not affected and remained enabled.

6.3.3. Credit Factor

As seen in Fig. 6.6, multiple districts have positive coefficients for credit in 2019. There exists spatial heterogeneity across districts. The districts with higher positive coefficients have better access to credit facilities. Credit availability ensures the farmers and rural populations to invest in productive activities that could enhance economic outcomes and may drive transformation.

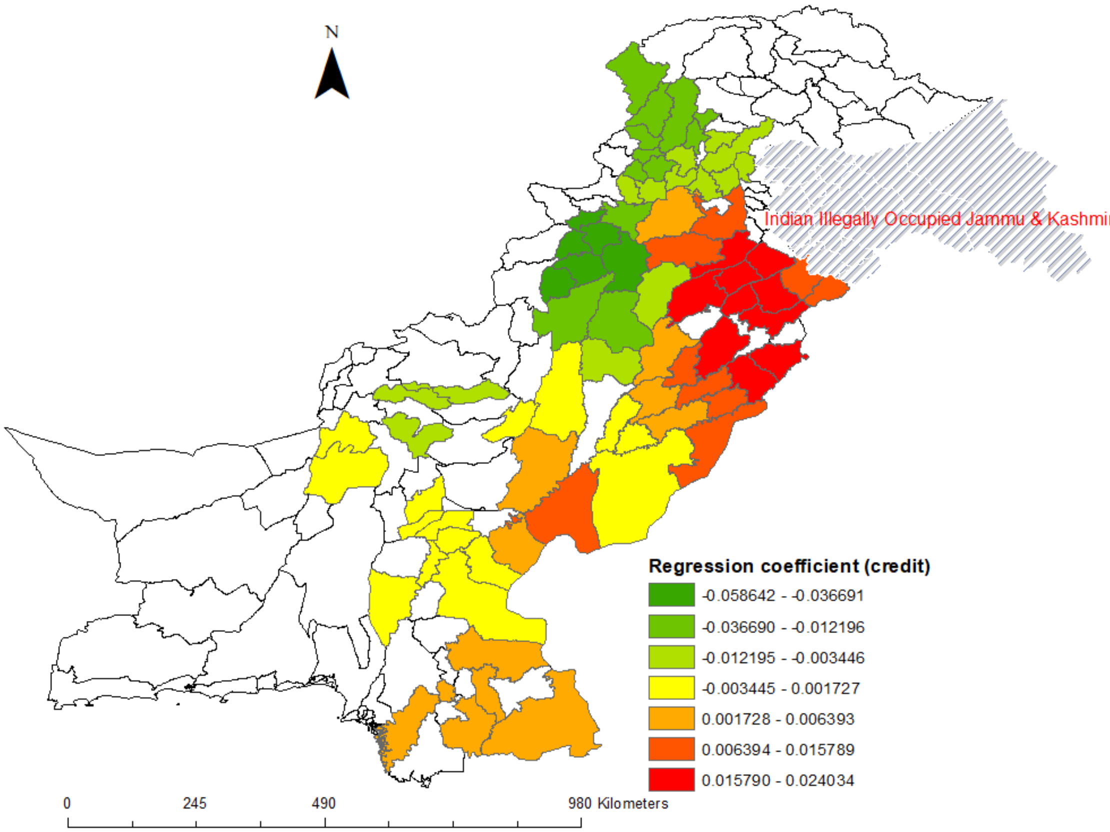

Fig. 6.6 Distribution of Regression Coefficient of credit

Table 6.2 has shown that the disbursement of credit has been improved over time much and hence have good impact on RTD.

Table 6.2 Disbursement of Credit

Year	Punjab	Sindh	KP	Balochistan	National
Farm Credit (Million Rs.)					
2008	213,386	76,288	7,585	3,055	300,314
2014	398,364	85,632	9,434	291	493,721
2019	679,761	178,909	26,665	6,697	892,032
Off Farm Credit (Million Rs.)					

Year	Punjab	Sindh	KP	Balochistan	National
Farm Credit (Million Rs.)					
2008	12,283	7,089	1,409	154	20,934
2014	47,741	12,545	1,844	95	62,225
2019	218,173	46,546	8,438	1,046	274,203

Source: Farm Credit data is taken from State Bank of Pakistan for farm-credit and Microfinance Network Pakistan for non-farm credit

6.3.4. Household Size Factor

The GWR analysis for household size reveals that 69% of the districts exhibit a negative relationship between household size and Rural Transformation Development (RTD) in 2019. This suggests that larger household sizes in most regions may be linked to resource dilution or dependency burdens, which can hinder economic progress and transformation. However, some districts in Khyber Pakhtunkhwa (KPK) show positive coefficients, indicating that in these areas, larger households might contribute positively to RTD, potentially through diversified income sources and shared labor etc.

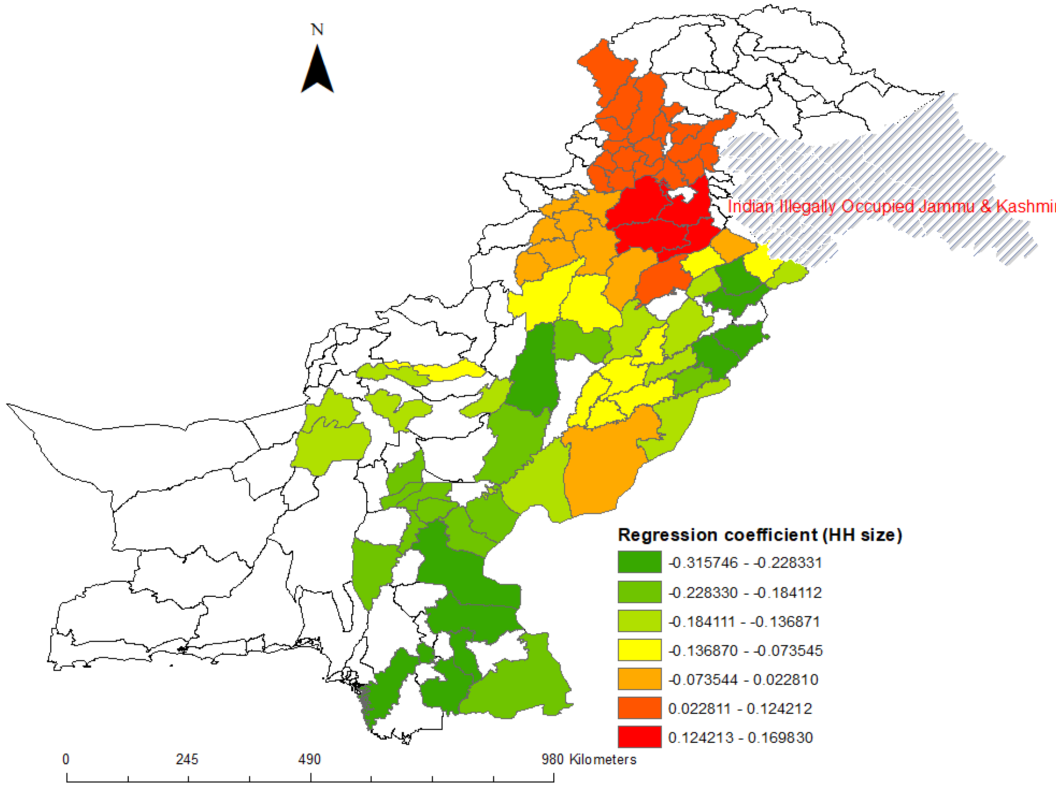

Fig. 6.7 Distribution of Regression Coefficient of Household size

6.4. Discussion

In this section, we reclassify the clusters identified in Section 4 using the 2019 cross-sectional RTDI data. While the GWR analysis has highlighted spatial heterogeneities across Pakistani districts, it is essential to link these variations with the clusters. This approach allows us to pinpoint which factor coefficients exert a stronger influence within each cluster.

The GWR analysis for 2019 reveals marked spatial heterogeneities in the determinants of RTD across Pakistan. These localized coefficient patterns can be linked with the clusters identified in Section 4 of the study. In those clusters that belong to Low category, the education factor exhibits weak or even negative coefficients. It reflects the insufficient educational infrastructure and low literacy levels are the factors associated with this category. Not only education but both canal and tube well irrigation also display limited positive effects in the districts belonging to low category., It further suggest severe deficiencies in water management and infrastructure. By looking at the Credit factor, it is seen that its access is modest in these districts. Consistently negative impact of large household sizes is seen in these districts which indicates that resource dilution further hampers local development. Policy should prioritize improving educational facilities, rehabilitating canal systems, expanding credit opportunities, and implementing targeted family planning and support programs in order to address household constraints.

Referring to the Intermediate-Low cluster there is modest progress in RTD. Education shows slightly improved coefficients compared to the Low category cluster. Tube well irrigation emerges as the more influential water resource in this cluster. This factor shows the higher concentrations of positive coefficients. Credit access is somewhat better in the regions belonging to this cluster, but still it is insufficient to fully drive transformation. For these districts, policies should focus on bridging educational gaps alongside enhancing sustainable tube well practices and gradually expanding canal networks. Strengthening tailored credit products and financial inclusion measures would further support development.

In the Medium cluster a transitional phase of RTD has been seen. Here, in this cluster the positive effects of education are becoming more pronounced. Both canal and tube well irrigation also demonstrate significant positive impacts. The credit factor also registers stronger, more consistent positive influences, indicative of improved financial service penetration. Although the negative impact of large household sizes persists but less dominant, so it reflects improved per capita resource allocation. In these districts, the focus should be on consolidating gains by continuing investments in quality education, optimizing irrigation practices through technological upgrades, and further expanding credit facilities to promote entrepreneurship and agricultural innovation. Monitoring household dynamics and providing targeted support will help sustain the momentum of transformation.

Districts in the Intermediate-High cluster are on the verge of advanced RTD. In these areas, education emerges as a key driver. Education factor shows a high positive coefficients underscoring its central role in transformation. Canal irrigation exhibits a strong positive relationship, reflecting the benefits of well-developed water infrastructure that supports modern agricultural practices. The robust positive effects of credit indicate that financial services are well-integrated, bolstering economic outcomes. Although larger household sizes still exert some negative influence, their impact is relatively mitigated, likely due to better income distribution and more efficient resource management. Policymakers in these districts should focus on sustaining high-quality educational programs, modernizing canal systems further, and enhancing the diversity and depth of financial services. Additional targeted socio-economic interventions are needed to address the residual negative impacts of large households and push these districts toward even higher levels of transformation.

Finally, the High cluster represents the pinnacle of RTD. In these regions, education exhibits exceptionally high positive coefficients, affirming its role as the foremost driver of transformation. Canal irrigation consistently yields strong positive impacts, supported by efficient, well-maintained systems that underpin agricultural productivity. Credit is readily accessible and effectively integrated into local economies, further promoting development. The adverse effects of large household sizes are notably minimal in these areas, as higher incomes and efficient resource allocation help mitigate potential drawbacks. For districts in the High cluster, policy focus should shift toward sustaining achievements and ensuring long-term sustainability. This can be achieved through continued innovation and investment in education, modernization of irrigation infrastructure with an emphasis on advanced technologies, and the promotion of sophisticated financial products tailored to dynamic economies. Even minor challenges, such as the residual negative effects of household size, should be managed through adaptive, evidence-based policy measures.

In summary, integrating the localized regression coefficients from the GWR analysis with the cluster-based categorization of districts reveals significant cross-sectional heterogeneity in the drivers of RTD across Pakistan. Each cluster exhibits distinct characteristics: The Low and Intermediate-Low clusters require foundational investments in education, irrigation, and credit access, while the Medium, Intermediate-High, and High clusters can build on existing strengths through refined and targeted interventions. This localized approach to policy formulation addresses regional disparities and leverages the unique potential of each district, ultimately fostering a balanced and sustainable transformation of rural areas across Pakistan.

6.5 Conclusion

The results highlight significant cross-sectional spatial heterogeneity in the drivers of RTD across districts of Pakistan. The GWR analysis reveals that the impact of key factors such as education, irrigation, credit, and household size varies considerably across regions, both in magnitude and direction. These findings emphasize the need for region-specific and targeted policy interventions rather than a uniform approach, as different districts exhibit distinct transformation dynamics.

CHAPTER VII

Results and Discussion-Impact of Rural Transformation on Per Capita Agriculture Income

7.1. Introduction

In previous chapters we have successfully identifies the drivers of rural transformation, hence in this chapter we are seeing the outcome of the rural transformation development. For the outcome variable, per capita agricultural income is chosen so that the impact of transformation stages and related socioeconomic factors on rural economic well-being can be empirically assessed.

7.2. Descriptive Statistics

Income for agriculture sector of Pakistan has increased over the time from 2004 to 2019, along with increase in the total agriculture land of Pakistan. Income level increase more sharply with a greater slope as compared to area under agriculture, which shows that the increase in agricultural income is not solely attributable to an expansion in cultivated land but rather to improvements in productivity and value generation within the sector. The steeper rise in income relative to agricultural area reflects a gradual shift towards yield enhancement, crop diversification into high-value commodities, and greater integration of technology, irrigation, and credit facilities. This widening gap between income and area trends provides empirical evidence of enhanced Total Factor Productivity, where improvements in input efficiency and technological adoption are yielding higher economic returns per hectare. This trend indicates that agricultural growth in Pakistan over the period 2004 to 2019 has been increasingly driven by intensification and structural transformation rather than extensive land use, carrying important implications for sustainable agricultural development and rural transformation.

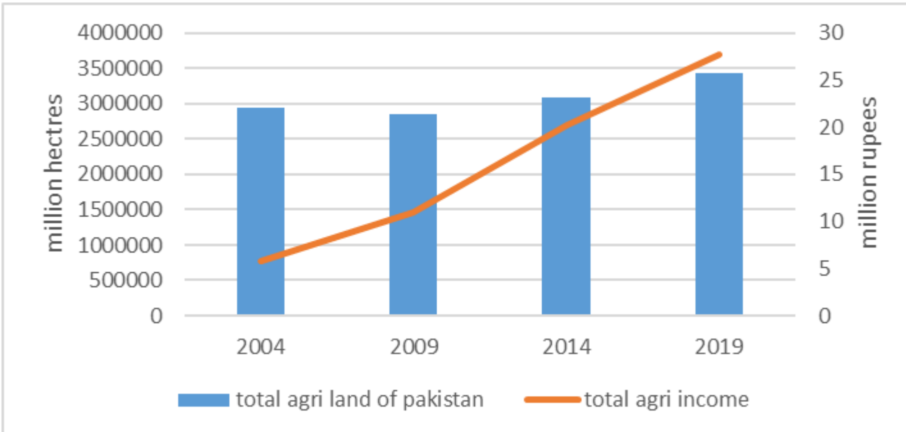

Fig. 7.1 Total agriculture land and total agriculture income of Pakistan Source: Ministry of National Food Security and Research, and State Bank of Pakistan[21]

7.3. Statistical Analysis

7.3.1. Spatial Autocorrelation Test Result

Moran's, I value for each year per capita agriculture income value is positive and highly significant (Table 7.1) which implies that there exists the form of clustering in the dataset. Since it appears non-random so we can proceed further with spatial analysis.

Table 7.1 Global Moran's I value of Per Capita Agriculture Income

Time	Global Moran's I	E(I)	Z(I)	P(I)
2004	0.4145***	-0.0057	9.10	0.0000
2009	0.4313***	-0.0057	9.41	0.0000
2014	0.4236***	-0.0057	9.25	0.0000

[21] https://www.sbp.org.pk/departments/stats/PakEconomy_HandBook/index.htm

Time	Global Moran’s I	E(I)	Z(I)	P(I)
2019	0.4300***	-0.0057	9.38	0.0000

7.3.2. Selection of Model results

According to p-value the null hypothesis based on the results of LR test (LR-SDM-SAR) has not been rejected[22] (Table 7.2) and the Spatial Autoregressive model has been selected to proceed.

Table 7.2. Results of the LR test for model selection

Test Statistic	Degrees of Freedom	P-Value
9.31	4	0.11

The Likelihood-Ratio test comparing the SAR and SDM specifications indicated that the additional spatial lags of the explanatory variables in the SDM were not statistically significant. This suggests that the more parsimonious SAR model provides an adequate fit for the data. Moreover, the SAR model captures the core spatial dependence through the spatial lag of the dependent variable, while the inclusion of dynamic lags (dlag) ensures that intertemporal persistence and diffusion effects are also accounted for. Thus, the SAR with time fixed effects is both statistically justified and consistent with the panel structure of the data. It can effectively capture the spatial interdependence in rural incomes. SAR will model the spillover effects of income levels across the included districts and avoids over-parameterization by excluding unnecessary spatial lags of the independent variables. This feature aligns with the parsimonious principle of model selection.

[22] Ho: SAR is nested model of SDM.

7.3.3. Dynamic Spatial Autoregressive Model (DSAR) with time-fixed effects Results

This section presents the results of empirical analysis based on the results of DSAR for time fixed effects using queen contiguity weight matrix. The coefficient of lag dependent variable i.e. L. Agri-Income appears to be statistically significantly positive. It implies that the subsequent past per capita agricultural income has a strong link with income in next period. It is indicating path dependence in rural economies. It means that those districts which historically have higher income will sustain and amplify these gains over time.

The negative and significant coefficient for the spatial lag of lagged per capita agricultural income i.e. L.WAgri-Income implies negative spillovers across districts. In other words, higher agricultural income in neighboring districts is associated with a reduction in income in the reference district. This could be due to competition for markets, labor migration, or input substitution effects.

The coefficients for RTDI at S2 and S3[23] is providing is associating rural transformation and per capita agriculture income. Stage 2 dummy has the coefficient value 0.14. Since it is a log-linear specification, so a value 0.14 will be translated into an income differential of around 15% higher per capita rural income in comparison to districts of Stage 1. Similarly, Stage 3 dummy has a coefficient of 0.43 which when translated implies a 54% higher per capita agriculture income for the districts of this stage in comparison to districts of stage 1. These findings are an empirical

[23] There are three stages of RT taken in this study, implying that there are two stage dummies (stage 2 and stage 3 respectively) by considering stage 1 as a base.

confirmation of what we expected theoretically, districts enjoy substantial gains in their income as they progress through the successive stages of RT.

The results in Table 7.3 are also highlighting the contribution of socioeconomic factors in determining the rural incomes. Education coefficient has a statistically significant positive value of 0.03. Though the value in quite modest in terms of magnitude but it indicates that those districts with a better-educated rural population tend to have higher per capita incomes. The result aligns with the theory of human capital which says that education adds positively to human capital which in turn helpful in improvement of agricultural productivity, facilitates in adoption of modern technologies and also extend the access to non-farm employment opportunities.

The coefficient of farm credit is negative and significant with value–0.03, which is unexpected but policy-relevant. Theoretically, credit access linked to higher income but the empirical results of the study says other way around. It could be explained through various channels and factors. It may happen that credit is channelized towards non-productive uses or the borrowers might face debt servicing burdens, in both situations potential returns of credit might outweigh from agriculture investment. Credit markets of Pakistan are mostly skewed in favor of large landowners whereas the smallholders remained credit constrained, because of this uneven distribution of credit its utilization might not be translated into broad-based productivity gains. It identifies the need of targeted and well monitored rural credit schemes that could ensure their supportive role in agricultural transformation and rural income growth.

The spatial autoregressive coefficient (ρ) is 0.04 but statistically insignificant. It indicates that there is no strong evidence of contemporaneous spatial dependence in per capita agriculture incomes across districts. This suggests that the current per capita income level of a district is not directly influenced by the current income levels of its neighboring districts.

Table 7.3 Results of DSAR

Variables	**Coefficient**
L. Agri-Income	1.58***
L. WAgri-Income	-0.40***
RTDI stage 2	0.14***
RTDI stage 3	0.43***
Education of rural population	0.03**
Farm credit	-0.03***
ρ	0.04
sigma2_e	0.11***
No. of Observations	234
No. of Districts	78

Note: *** denotes significant at 1%, ** at 5% and * at 10%.

The estimated error variance (σ^2_e) is 0.107 and it is statistically significant at the 1% level It confirms the presence of unexplained variation in per capita rural income across included districts. The relatively modest magnitude of this estimate indicates that the explanatory variables[24] included in the model account for a substantial share of the variation, although some degree of unobserved heterogeneity persists. This finding highlights the importance of incorporating fixed effects, particularly time-specific effects, to control for omitted but time-invariant district-level characteristics that may otherwise bias the results.

[24] Detailed summary statistics (mean, median, and standard deviation) for the independent variables analyzed in this chapter are provided in Chapter 5, Table 5.2

7.3.4. Discussion

The empirical findings of this study, derived from the dynamic spatial autoregressive model with time fixed effects, provide valuable insights into the dynamics of per capita agriculture incomes in Pakistan. The significantly positive coefficient of lagged agricultural income demonstrates the persistence of income over time, with past per capita agricultural income exerting a strong influence on current income levels. This reflects path dependence in rural economies, where historically better-off districts tend to sustain and amplify their income advantages. In the policy context, agricultural strategies during this period emphasized productivity growth through subsidies on inputs such as fertilizers and machinery, as well as targeted programs like the Benazir Tractor Scheme introduced in 2009–10. While these interventions may have reinforced productivity gains in relatively resource-rich districts, they also contributed to persistent disparities, as poorer or less connected districts benefitted less from such schemes (Government of Pakistan, 2009). The evidence of strong temporal persistence in incomes suggests that agricultural policies during the period often favored continuity of growth in already better-performing districts, rather than enabling lagging regions to catch up.

The negative and significant coefficient of the spatial lag of lagged agricultural income indicates that higher past income in neighboring districts is associated with reduced income in the reference district. This points towards competitive spillover effects, where districts compete for limited markets, labor, and inputs, resulting in a crowding-out effect rather than mutually reinforcing growth. This dynamic resonates with the uneven distribution of agricultural development projects in Pakistan. Following the 18th Amendment in 2010, agriculture became a provincial subject, leading to greater variation in the reach and effectiveness of policies across provinces. Evidence from World Bank assessments shows that many productivity-enhancing projects, such as those related to value chain development and irrigation modernization, were concentrated in better-performing regions with stronger institutional capacities (World Bank, 2023). This uneven implementation may have intensified regional disparities and explains why some districts benefitted at the expense of their neighbors, reinforcing the observed negative spillover effects.

The analysis of rural transformation stages provides further support for the argument that structural change is central to rural income growth. Districts in Stage 2 of transformation recorded, on average, 15 percent higher per capita agricultural income than those in Stage 1, while Stage 3 districts enjoyed nearly 54 percent higher income. These findings confirm that rural transformation—through diversification, improved infrastructure, and integration into non-farm activities—translates into tangible economic benefits. Policy documents such as the Draft Food Security and Agriculture Policy of 2013 emphasized the importance of value addition, market access, and sustainable agricultural practices, but progress was inconsistent across districts due to weak provincial implementation (Government of Pakistan, 2013). Where transformation-supportive measures, such as rural infrastructure investments or extension reforms, were more effectively enacted, incomes rose substantially, highlighting the uneven but powerful role of transformation in shaping rural prosperity.

Education emerges as another significant driver of rural incomes, with results showing a positive though modest effect. Districts with better-educated rural populations experience higher per capita incomes, which is consistent with the argument that education enhances human capital, facilitates technology adoption, and improves access to non-farm opportunities. During the period under review, the Government of Pakistan increased allocations to education in successive budgets, particularly after 2010, but the rural education system remained underdeveloped. Agricultural extension systems, which could bridge the gap between education and productivity improvements, have historically been weak and fragmented (Khan et al., 2016). This explains why the effect of education, though significant, is relatively small in magnitude. Nonetheless, the results reinforce the idea that human capital development remains a critical but underutilized lever for boosting rural incomes.

In contrast, the results reveal a surprising and policy-relevant finding regarding farm credit, which shows a negative and statistically significant relationship with per capita rural income. Rather than contributing to income growth, higher levels of credit are associated with declining incomes. This finding resonates with longstanding critiques of Pakistan's rural credit system. Although credit disbursement increased significantly during the period, rising from Rs. 168 billion in 2005–06 to over Rs. 600 billion by 2017–18 (State Bank of Pakistan, 2018), much of this lending was captured by larger landowners and often diverted to non-productive uses. Smallholders, who constitute the majority of farmers, remained credit constrained due to lack of collateral and high transaction costs. Research shows that when credit is not effectively targeted or monitored, it can exacerbate debt burdens without translating into productivity gains (Malik et al., 2011). The negative association found in this study underscores the inefficiencies of Pakistan's rural credit markets and the urgent need for reforms that ensure equitable access and effective utilization.

Finally, the spatial autoregressive coefficient (ρ) is positive but statistically insignificant, indicating that contemporaneous spatial dependence in agricultural incomes is weak or absent. In practical terms, the current income of a district is not significantly influenced by the current income of neighboring districts once lagged income, rural transformation stages, and socioeconomic drivers are accounted for. This finding stands in contrast to the significant negative effect of the spatial lag of lagged income, suggesting that spatial dynamics in Pakistan's rural economy are primarily historical and competitive in nature, rather than contemporaneous and mutually reinforcing. This reflects the policy environment of the period, where interventions often had delayed or uneven impacts. For example, investments in irrigation infrastructure or rural roads may take years to influence neighboring districts, while immediate gains tend to remain localized. The absence of contemporaneous spillovers suggests that policies designed to promote rural transformation should emphasize spatial inclusivity and regional complementarity, ensuring that benefits are not confined to specific districts at the expense of others.

Taken together, the discussion of these results highlights the close alignment between empirical evidence and Pakistan's agricultural policy environment from 2004 to 2019. Policies during this period intermittently supported productivity growth and transformation but often reinforced existing disparities due to uneven implementation and limited inclusiveness. Education contributed positively but modestly, reflecting systemic weaknesses in rural schooling and extension systems, while farm credit underperformed due to structural inefficiencies and elite capture. The findings point to the need for policy reforms that not only enhance productivity but also ensure equitable spatial distribution of benefits, strengthen human capital, and improve the targeting of financial resources to smallholders. Such measures would better align future agricultural policy with the objectives of sustainable rural transformation and inclusive income growth.

7.4. Conclusion

This chapter concludes that the RTD in Pakistan is a dynamic process. It is driven by intensification and structural shifts rather than simple land expansion. The results confirm that the impact of irrigation, technology, and credit becomes significantly more pronounced as districts progress through stages of transformation. The empirical evidence from the SAR model identifies strong spatial interdependencies. Results suggest that development in one district creates positive spillover effects for its neighbors. Policy interventions should prioritize localized resource efficiency and regional connectivity for the sake of sustainable growth. The transition toward high-valued agriculture and non-farm integration will serve as a critical pathway for increasing rural incomes and reducing regional disparities across districts of Pakistan.

CHAPTER 8

CONCLUSIONS

Rural transformation is a holistic process of change which this study aims to capture comprehensively at the regional level for the case of Pakistan. The analysis aims to firstly see extent and pattern of RTD from 2004 to 2019 period. The whole analysis is carried out on 92 districts across four provinces of Pakistan. Rest of the districts have been excluded either due to data unavailability of data or less suitability of a certain districts for the study. The analysis aligning the first objective reveals substantial heterogeneity of RTDI pattern across districts. District level index of RT have been categorized on the basis of pace of transformation into low, intermediate low, medium, intermediate high, and high development levels. Among the elements of index, agriculture production is the most crucial factor influencing overall RT. ESDA reveals the positive value of Global Moran's I, it implies spatial pattern of data are pronounced with similar values being more closely grouped together over time. Moreover, the analysis of local clusters belonging to different categories reveals distinct patterns of RT across provinces. Low-performing clusters of Sindh and Baluchistan are reflecting the challenges indicated by declining shares of high-valued crops, and slow urbanization. Intermediate low performing cluster of Sindh is indicated by low land use intensity. Medium-paced clusters from Punjab are indicated by the rising share of high valued agriculture and livestock production along with gradual urbanization. Intermediate High and High category clusters from Punjab, Sindh and KPK are marked by rising share of non-farm employment. These findings provide valuable insights into the spatial dynamics of RTD at the regional level

The second objective of the study is to see what actually drives this process of transformation. Since the study already establishes on the spatial characteristics of the RTDI while looking at the extent and pattern, so moving forward requires a serious focus on the spatial dimensions. For this second objective the study employs a DSDM with time-fixed effects and a queen contiguity weight matrix to examine the direct and spillover effects of drivers on RTDI across the same 92 districts of Pakistan. The results show that RTDI in the subsequent previous period significantly influences the current RTDI which implies the temporal persistence. Spatial spillover effects are also evident from the results of the model in which one district correlates positively with neighboring districts in terms of RTDI. As far as drivers are concern, education emerges as a significant driver and its impact appears to be more pronounced at higher stages (S3). Education has multifaceted role in improving farm productivity, in enabling non-farm employment, and fostering urbanization. Irrigation also plays a pivotal role as a driver of transformation. It contribution also increases at advanced transformation stages. Among the three variables of irrigation, canal irrigation demonstrates the highest impact. Also canal-tube well systems exhibit spatial spillovers at S2 which highlights the interconnected nature of water resources. Away from expectations, the farm credit shows no direct effect on RTDI rather it exhibits negative spillovers at S2. It ispotentially due to inefficient allocation or competition for resources. Other drivers like temperature, road facilities, and banking access, remain insignificant on average. The findings emphasize the significance of targeted interventions in education sector, irrigation infrastructure, and regional collaboration for the sake of rural transformation.

In its third objective, the analysis demonstrates model robustness and the explanatory power of included variables through spatial heterogeneity. This cross section spatial heterogeneity has been measured through GWR for included drivers for the year 2019. The findings from GWR indicate that while education and irrigation consistently show a positive association with RTDI in most districts but their magnitude and significance differ spatially. For 2019, credit also appeared to be very important. The credit disbursement has been increasing overtime, so its positive impacts are also becoming prominent.

This study contributes to the broader discourse on RT by moving beyond a linear growth narrative. It highlights the complex, non-linear stages of development within a developing country context. The study provides a unique methodological framework for understanding how regional spillovers affect economic outcomes. Though this study is primarily empirical but it extends the existing theoretical discourse on RT by validating the Huang (2018) segmentation within the socio-economic landscape of Pakistan. The study extends that rural transformation is not a uniform process rather it is subject to spatial interdependencies. Similar is suggested by New Economic Geography theory. This research contributes a spatial dimension to the Lewis Model through spatial autocorrelation and cluster analysis. It shows that cropping patterns and structural shifts are heavily influenced by a district's proximity to developed neighbors. However, certain limitations must be regarded while interpreting these findings. Firstly, the analysis is primarily based on secondary district-level data, which may not fully capture intra-district household variations or informal non-farm activities. Secondly, the SAR model effectively identifies spatial inter-dependencies but the study has data limitation. It uses the available time-series data only which constrains the ability to track long-term longitudinal shifts across several decades. Mentioning the limitations is important because these will be actually helpful for any future research.

Policy Recommendations: Effective policy interventions will be those that will be well aligned with the specific category and stage of transformation and the significance of the contributing driver in the whole process.

- The districts which are at their S1 and performing quite low are also resource constraint districts. Instead of pushing them for immediate high-value crop shifts, the priority should be on identifying their structural constraints and to overcome those constraints. Policies should focus on infrastructure and, reliable primary education in order to stabilize subsistence farming before attempting commercialization in S2.
- Most of the districts which are at their S2 are in the phase of transition and belong to medium clusters. Such districts are better off, have basic foundations but struggles with efficiency. For these district, the Policy should prioritize strengthening institutional support through targeted agricultural credit and localized extension services. It will help farmers in transition toward initial commercialization and input optimization for S3.
- The districts that belong to S3 are well-endowed for agriculture and have a rapidly growing non-farm sector. They should be further supported by investment in value chains, cold storage and export certifications, such a policy will maximize their comparative advantage.

- Since the spatial dependencies has been identified in the SAR model so cluster-based development is essential. Regional planning should be in such a way that district boundaries could allow high-performing districts to play their role as engines of growth for their lagging neighboring districts
- Provincial Irrigation Departments may design irrigation projects using cross-district frameworks, explicitly leveraging the positive spatial spillovers where water investments in one district naturally accelerate development in neighboring ones.
- Replicate the Faisalabad Model for rural industrialization by Scaling up small industrial estates directly inside lagging agricultural districts, also incentivizing agro-processing units.
- Replicate the Rawalpindi Model for service-led Growth via prioritization of digital connectivity and service sector job creation especially in those districts where traditional farming cannot scale.Establish Joint District Development Authorities to empower neighboring districts within the same spatial clusters to form institutional alliances and pool cross-district budgets for shared transport, cold storage, and regional market infrastructure.

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Appendix

Appendix A: Categories of RTDI of districts in year 2004 and 2019

District	rtd2004	category2004	rtd2019	category2018	diff	Category difff
Kalat	2.142787	high	0.489936	low	-1.65285	low
Shaheed Sikandarabad	2.142787	high	0.489936	low	-1.65285	low
Kasur	1.382339	high	0.532482	low	-0.84986	low
Mastung	1.735177	high	0.908722	medium	-0.82646	low
Lodhran	1.197598	intermediate high	0.382937	low	-0.81466	low
Khanewal	0.8768478	intermediate low	0.1107	low	-0.76615	low
Batagram	1.473387	high	0.71927	intermediate low	-0.75412	low
Sahiwal	0.8095552	intermediate low	0.113178	low	-0.69638	low
Ziarat	2.067089	high	1.404081	high	-0.66301	low
Kohistan Lower	1.612355	high	0.960091	medium	-0.65226	low
Barkhan	1.578036	high	0.972979	medium	-0.60506	low
Bhakkar	1.046365	medium	0.461025	low	-0.58534	low
Vehari	0.8121681	intermediate low	0.266881	low	-0.54529	low
Swat	1.414251	high	0.9011	medium	-0.51315	low
Shangla	1.164689	intermediate high	0.677785	intermediate low	-0.4869	low
Khushab	0.886354	medium	0.42675	low	-0.4596	low
Okara	0.7932077	intermediate low	0.340006	low	-0.4532	low
Toba Tek Singh	0.7781339	intermediate low	0.334418	low	-0.44372	low
Badin	0.9812782	medium	0.549461	low	-0.43182	low
Sargodha	1.146923	intermediate high	0.728661	intermediate low	-0.41826	low
Muzaffarabad	0.5388198	low	0.174411	low	-0.36441	low
Loralai	1.693668	high	1.335106	high	-0.35856	low

Duki	1.693668	high	1.335106	high	-0.35856	low
Rahim Yar Khan	0.9841908	medium	0.653714	low	-0.33048	low
Sibi	1.160761	intermediate high	0.843121	medium	-0.31764	low
Harnai	1.160761	intermediate high	0.843121	medium	-0.31764	low
Malakand	1.429966	high	1.134492	intermediate high	-0.29547	low
Pakpattan	0.8925589	medium	0.597901	low	-0.29466	low
Tharparkar	1.360956	high	1.093396	intermediate high	-0.26756	intermediate low
Mianwali	0.8968225	medium	0.654259	low	-0.24256	intermediate low
Thatta	0.7924547	intermediate low	0.566556	low	-0.2259	intermediate low
Sujawal	0.7924547	intermediate low	0.566556	low	-0.2259	intermediate low
Multan	0.9997177	medium	0.794986	intermediate low	-0.20473	intermediate low
Swabi	1.062488	medium	0.868394	medium	-0.19409	intermediate low
Narowal	0.9270445	medium	0.737888	intermediate low	-0.18916	intermediate low
Bahawalnagar	0.5224656	low	0.35298	low	-0.16949	intermediate low
Hafizabad	0.9227737	medium	0.774994	intermediate low	-0.14778	intermediate low
Nasirabad	1.277343	high	1.137552	intermediate high	-0.13979	intermediate low
Dadu	0.8157342	intermediate low	0.675947	intermediate low	-0.13979	intermediate low
Jamshoro	0.8157342	intermediate low	0.675947	intermediate low	-0.13979	intermediate low
Rajanpur	0.7916476	intermediate low	0.680201	intermediate low	-0.11145	intermediate low
Chiniot	0.6894478	intermediate low	0.656899	intermediate low	-0.03255	medium
Jhang	0.6894478	intermediate low	0.656899	intermediate low	-0.03255	medium
Sanghar	0.6763626	low	0.648263	low	-0.0281	medium
Bahawalpur	0.5731986	low	0.552488	low	-0.02071	medium
Dera Ghazi Khan	0.4740333	low	0.493851	low	0.019817	medium
Mardan	1.00846	medium	1.044234	intermediate high	0.035774	medium
Chakwal	0.5217761	low	0.572311	low	0.050534	medium

Attock	0.589396	low	0.660404	intermediate low	0.071008	medium
Sheikhupura	0.8711811	intermediate low	0.952363	medium	0.081182	medium
Nankana Sahib	0.8711811	intermediate low	0.952363	medium	0.081182	medium
Charsadda	0.9982664	medium	1.080476	intermediate high	0.08221	medium
Abbottabad	0.748586	intermediate low	0.832509	medium	0.083923	medium
Hangu	0.7832852	intermediate low	0.899058	medium	0.115773	medium
Jhelum	0.7153233	intermediate low	0.834113	medium	0.118789	medium
Leiah	0.386983	low	0.541592	low	0.154609	medium
D. I. Khan	0.6741101	low	0.877107	medium	0.202997	intermediate high
Mandi Bahauddin	0.2939893	low	0.498347	low	0.204358	intermediate high
Haripur	0.478895	low	0.693842	intermediate low	0.214947	intermediate high
Shikarpur	1.030073	medium	1.253262	high	0.223189	intermediate high
Buner	0.431484	low	0.67511	intermediate low	0.243626	intermediate high
Sialkot	0.8557439	intermediate low	1.107697	intermediate high	0.251953	intermediate high
Mirpur Khas	0.5282652	low	0.790537	intermediate low	0.262272	intermediate high
Umer Kot	0.5282652	low	0.790537	intermediate low	0.262272	intermediate high
Khairpur	0.4815677	low	0.75476	intermediate low	0.273192	intermediate high
Jaffarabad	1.024669	medium	1.305591	high	0.280922	intermediate high
Sohbatpur	1.024669	medium	1.305591	high	0.280922	intermediate high
Gujrat	0.8661461	intermediate low	1.173193	intermediate high	0.307047	intermediate high
Mansehra	0.1496213	low	0.465064	low	0.315443	intermediate high
Tor Ghar	0.1496213	low	0.465064	low	0.315443	intermediate high
Sukkur	0.5438687	low	0.865569	medium	0.3217	intermediate high
Upper Dir	0.7351192	intermediate low	1.105749	intermediate high	0.37063	intermediate high
Jacobabad	1.059136	medium	1.438354	high	0.379218	intermediate high
Faisalabad	0.3761771	low	0.774246	intermediate low	0.398069	intermediate high

Kohat	0.6426551	low	1.045779	intermediate high	0.403124	intermediate high
Nowshera	0.7405065	intermediate low	1.164859	intermediate high	0.424353	intermediate high
Ghotki	0.2441277	low	0.68029	intermediate low	0.436162	high
Hyderabad	0.6688462	low	1.180498	high	0.511652	high
Matiari	0.6688462	low	1.180498	high	0.511652	high
Tando Allahyar	0.6688462	low	1.180498	high	0.511652	high
Tando Muhammad Khan	0.6688462	low	1.180498	high	0.511652	high
Gujranwala	0.8897658	medium	1.401496	high	0.51173	high
Lakki Marwat	0.6754216	low	1.197719	high	0.522297	high
Bannu	0.6810377	low	1.21097	high	0.529932	high
Rawalpindi	0.9041273	medium	1.43637	high	0.532243	high
Lower Dir	0.5593134	low	1.114297	intermediate high	0.554984	high
Tank	0.8853268	medium	1.441108	high	0.555781	high
Chitral Lower	0.368491	low	0.940477	medium	0.571986	high
Larkana	0.7694972	intermediate low	1.372001	high	0.602504	high
Kambar Shahdad Kot	0.7694972	intermediate low	1.372001	high	0.602504	high
Peshawar	0.5919712	low	1.562495	high	0.970524	high
Karak	0.4121042	low	1.442745	high	1.030641	high

Appendix B: Results of SDM with various models

Variables	SDM with Random effect	SDM with spatial fixed-effects	SDM with time-fixed effects	SDM with spatial and time fixed-effects
Main				
Farm Credit _S2	-0.0047**	-0.0072***	-0.0049**	-0.0068***
Farm Credit _S3	-0.0115	-0.0301	-0.0176	-0.0528
Education of rural population S2	0.0548***	0.0684***	0.0587***	0.0697***
Education of rural population S3	0.2478***	0.1056	0.2456***	0.0791
Share of irrigated farmland through canal S2	0.0017***	-0.0003	0.0016***	-0.0002
Share of irrigated farmland through canal S3	0.0089	0.0117	0.0092*	0.0173**
Share of irrigated farmland through tube wells S2	0.0033***	0.0024**	0.0032***	0.0018
Share of irrigated farmland through tube wells S3	0.0013***	0.0019***	0.0011*	0.0019***
share of irrigated farmland through canal & tube wells S2	0.0027**	0.0024	0.0025**	0.0031
share of irrigated farmland through canal & tube wells S3	0.0049**	0.0102***	0.0052***	0.0117***
Temperature	-0.0166	0.0057	-0.0155	0.0115
Rural Household size	-0.0028	-0.0005	0.0021	-0.0122
Share of rural population satisfied by road facility (%)	-0.0004	0.0010	-0.00071	0.000413

Share of rural population satisfied by banking facility (%)	0.0002	-0.0004	0.00045	0.000159
WX				
Farm Credit _S2	-0.0166***	-0.0037	-0.0162***	-0.0036
Farm Credit _S3	-0.0205	0.0250	-0.0467	-0.0188
Education of rural population S2	-0.0078	-0.0070	0.0018	-0.0016
Education of rural population S3	-0.0058	-0.0181	-0.0031	-0.0771
Share of irrigated farmland through canal S2	0.0017***	0.0017***	0.0016***	0.0022***
Share of irrigated farmland through canal S3	0.0139***	0.0066	0.0146***	0.0147***
Share of irrigated farmland through tube wells S2	-0.0004	-0.0021	-0.0004	-0.0039**
Share of irrigated farmland through tube wells S3	0.0003	0.0007	0.0001	0.0010
share of irrigated farmland through canal & tube wells S2	0.0082***	0.0105**	0.0078***	0.0132***
share of irrigated farmland through canal & tube wells S3	0.0116***	0.0235***	0.0119***	0.0274***
Temperature	0.0047	0.0141	0.0042	0.0585
Rural Household size	-0.0067	-0.0187	0.0080	-0.0480
Share of rural population satisfied by road facility (%)	-0.0005	0.0006	-0.0014	-0.00134**
Share of rural population satisfied by banking facility (%)	0.0032	0.0077*	0.0035	0.0087
rho	0.1619***	0.0867	0.1235***	0.0422
sigma2_e	0.0803***	0.0569***	0.0783***	0.055***

AIC	177.06	63.67	51.23	164.07
BIC	319.29	198.42	185.99	298.82