

Article

Crop Water Footprints in the Manas River Basin: Trends, Drivers, and Futures

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Abstract

The management and efficient use of water resources are crucial to the sustainable development of agriculture in arid regions. The Manas River Basin faces severe water shortages due to its arid climate and heavy reliance on irrigation water. Therefore, based on water footprint theory, this study comprehensively utilized the CROPWAT model, pathway analysis, and CMIP6 data to construct an integrated “assessment–driving–prediction” framework for crop water footprints, with the aim of revealing the evolution patterns and driving mechanisms of water footprints in river basins. The results showed that the cultivated area of crops in the Manas River Basin exhibited a nonlinear expansion trend from 1990 to 2020, with a total increase of 143.56% over the 30-year period. Among all crops, cotton occupied the largest cultivated area, accounting for 60.34% of the total. During the study period, the crop water footprint, crop blue water footprint, and crop green water footprint in the Manas River Basin showed overall upward trends, increasing by $1.07 \times 10^9 \text{ m}^3$, $1.04 \times 10^9 \text{ m}^3$, and $3.0 \times 10^7 \text{ m}^3$, respectively. Total agricultural machinery power and per capita grain production are the main factors influencing changes in crop water footprint. Under future climate scenarios, the crop water footprint in the Manas River Basin is projected to follow the order SSP2-4.5 > SSP5-8.5 > SSP1-2.6. By 2100, the crop water footprint under the SSP2-4.5 scenario is expected to increase by 37.01% relative to 2020, posing substantial challenges to agricultural water resource management in the basin. In contrast, the crop water footprint under the SSP1-2.6 scenario remains relatively stable, indicating a more sustainable development pathway.

Keywords: water footprint; driving forces; prediction; climate change; Manas River Basin



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1. Introduction

Agriculture is the largest sector of global freshwater withdrawals, accounting for more than 70% of global water use [1]. Over-irrigation not only exacerbates water scarcity but also induces a series of environmental problems, including soil salinization, groundwater overexploitation, and agricultural non-point source pollution, thereby threatening food security and regional sustainable development [2–4]. Northwest China is located in the

arid and semi-arid regions of the country. Although its water resources account for only 10% of the national total, the region produces 12% of China's grain, forming a distinctive agricultural production pattern characterized by "low water availability but high grain output" [5]. In recent years, the expansion of irrigated agriculture, adjustments in crop planting patterns, and the intensifying impacts of climate change have further aggravated the imbalance between agricultural water supply and demand in this region [6–8]. Existing studies have mainly focused on the current status of regional agricultural water-use or single-period water footprint assessments [5,9]; however, the long-term evolution, driving mechanisms, and future projections of crop water footprints in the arid regions of Northwest China remain insufficiently understood. Therefore, developing an integrated research framework to reveal the historical changes, dominant drivers, and projected trends of crop water footprints in river basins across this region is essential for supporting the optimal allocation and sustainable management of agricultural water resources.

The application of water footprints has become one of the key methods for guiding regional agricultural water resource management, providing a clear indication of regional water resource carrying capacity [10]. Crop water footprint is an important indicator for assessing water consumption in agricultural production. Based on the type of water source, crop water footprint can be divided into blue water footprint and green water footprint. The blue water footprint represents the amount of irrigation water consumed during agricultural production, whereas the green water footprint represents the amount of effective precipitation consumed to support crop growth [11,12]. The development of crop water footprint research can be summarized as follows: in early studies, the concept of virtual water was introduced, laying the foundation for the concept of water footprint [13]. Subsequent studies defined the concept of water footprint and distinguished blue, green, and gray water footprints [10]. From 2009 to 2016, based on water footprint theory, increasing attention was paid to water footprint assessments at the global scale, including estimates of the water footprints of major crops and analyses of virtual water trade. Meanwhile, research on the water footprints of specific crops in different regions was further explored, highlighting the impacts of local climatic conditions and crop management practices on water footprints [14,15]. Recent studies since 2016 have begun to focus on the decomposition of driving factors to gain a deeper understanding of the mechanisms underlying changes in crop water footprints [6].

Water footprint research has expanded the scope of traditional water resource assessments and provides an important method for quantitatively revealing the relationship between production and consumption activities and water use. In recent years, water footprint research has continued to evolve across multiple scales, including global, regional, watershed, and product levels. Studies in this field have revealed patterns of water use from various perspectives, such as virtual water trade, the spatial distribution of water resources, crop planting patterns, consumption patterns, and the economic benefits of agricultural products [13,16–18]. Related studies indicate that countries around the world need to adopt appropriate water consumption and water trade models to achieve the sustainable management of global water resources. Between 1996 and 2005, the global average annual water footprint was approximately 908.7 billion m³, of which green water, blue water, and gray water accounted for 74%, 11%, and 15%, respectively. Agricultural production accounted for 92% of the total, and approximately 20% of the water footprint stemmed from the production of exported goods, with international virtual water flows reaching 2320 billion m³ [19]. At the same time, as water footprint calculation methods continue to improve, the focus of research has gradually shifted from simple water footprint assessment to the analysis of driving mechanisms. Methods such as the STIRPAT model [20], index decomposition [21], structural decomposition [22], and artificial neural

networks [23] have been widely used to identify the natural and anthropogenic drivers of changes in water footprints. Overall, existing research has provided an important foundation for understanding the spatiotemporal evolution and driving mechanisms of water footprints [24,25]. However, most studies remain focused on historical water footprint estimation and attribution analysis, and relatively few studies have predicted changes in crop water footprints under the combined effects of future climate change and adjustments in crop cultivation areas. This limitation is particularly evident in the arid inland river basins of Northwest China, where a comprehensive research framework that integrates historical assessment, identification of driving mechanisms, and future scenario projection remains lacking. Although this issue has attracted increasing attention, related research is still in its early stages, and quantitative analyses of future water footprints are urgently needed.

To address the limited understanding of future changes in crop water footprints in arid inland river basins, this study takes the Manas River Basin as the study area and constructs a comprehensive “assessment–driving–projection” analytical framework for crop water footprints. This framework systematically elucidates the evolution patterns of crop water footprints from both historical and future perspectives. First, the CROPWAT model was used to estimate crop water footprints during the historical period and identify their long-term trends. Second, based on the multicollinearity test, path analysis was applied to identify the direct and indirect effects of natural and human factors on changes in crop water footprints. This method has significant advantages in exploring the complex relationships between water footprints and environmental factors. By calculating direct and indirect effect coefficients, it clearly illustrates the pathways and intensity through which each independent variable influences the dependent variable, thereby overcoming the limitations of traditional methods in quantifying comprehensive impacts [26]. Finally, by combining future climate scenarios with changes in crop cultivation areas, this study predicts crop water footprint trends under different SSP–RCP scenarios.

The Manas River Basin is located in the arid region of Northwest China, where agriculture is highly dependent on irrigation. Water scarcity and its uneven spatial and temporal distribution have become key factors limiting the sustainable development of agriculture in the region. In this study, we fully considered the United Nations Sustainable Development Goals (SDGs), particularly Goal 6 (Clean Water and Sanitation), Goal 13 (Climate Action), and Goal 2 (Zero Hunger), to address the key challenges associated with unsustainable crop water management in arid regions. The objectives of this study are as follows: (1) to analyze the evolution of crop cultivation patterns and crop water footprints in the Manas River Basin from 1990 to 2020; (2) to analyze the driving factors of crop water footprints; and (3) to predict crop water footprints based on different future climate scenarios and changes in cropping patterns. As a typical agricultural region in an arid zone, the Manas River Basin provides a representative case for establishing an “assessment–driving–prediction” research framework. This framework systematically reveals the evolution patterns and driving mechanisms of crop water footprints from both historical and future perspectives, thereby providing a scientific basis for agricultural water resource management and sustainable development.

2. Materials and Methods

2.1. Study Area

The Manas River Basin is situated in the hinterland of the Eurasian continent and represents a typical arid region in Northwest China. The basin lies at the northern foot of the Tianshan Mountains in Xinjiang and along the southern margin of the Junggar Basin, extending between 43°50′–45°58′ N and 84°42′–86°33′ E (Figure 1). The total area of the basin is approximately 3.4×10^4 km², and it contains six rivers, including the Manas,

Bayingou, Jingou, Taxi, and Ningjia rivers, among others [27]. The topography of the basin is characterized by higher elevations in the east and south and lower elevations in the west and north, with elevation varying substantially from 241 m to 5146 m. The region has a typical temperate continental arid climate, characterized by scarce precipitation and intense evaporation. The average annual precipitation is approximately 115–200 mm, the average annual temperature is approximately 4.7–5.7 °C, and the long-term average evapotranspiration can reach 1500–2100 mm. The Manas River Basin considered in this study is primarily defined based on agricultural statistics and administrative boundaries, consisting of three main administrative areas: Shihezi City (it only refers to its county-level administrative division), Manas County, and Shawan City. The basin exhibits marked spatial heterogeneity: the southern mountainous region primarily serves as the runoff-generating area, the oasis plains are the core zones of agricultural production and irrigation water use, and agricultural activities are relatively limited in the northern desert region. Therefore, the crop water footprint calculations in this study primarily reflect the overall water consumption patterns of agricultural production areas in the Manas River Basin.

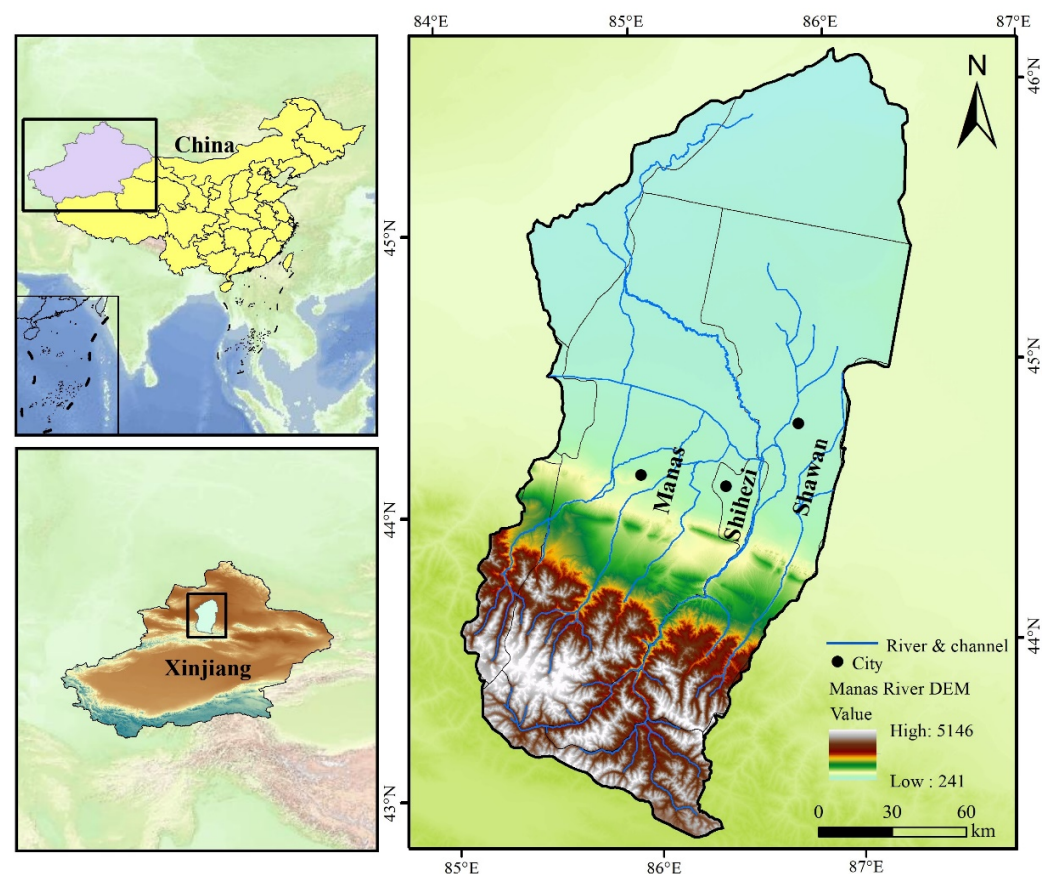


Figure 1. Location and overview of the study area.

2.2. Data Sources

The meteorological data used in this study were obtained from the daily surface meteorological dataset for China provided by the National Meteorological Information Centre (<http://www.nmic.cn/>) (accessed on 13 January 2026). This dataset includes key meteorological parameters, such as temperature (°C), relative humidity (%), average wind speed (m/s), sunshine duration (h), and precipitation (mm), as well as geographical information, including longitude, latitude, and altitude. In addition, data on sown areas, crop yields, economic indicators, demographic statistics, and agricultural production were obtained from the Xinjiang Statistical Yearbook, the Statistical Yearbook of the Xinjiang Production

and Construction Corps and the Shihezi Statistical Yearbook. All data cover the period from 1990 to 2020. The sowing dates and growth stages of each crop were determined primarily based on field surveys conducted in Shihezi City, Manas County, and Shawan City. The survey participants included more than one hundred farmers with many years of planting experience and agricultural technicians. The interviews mainly focused on the typical sowing periods and the duration of the main growth stages of ten crop types. The interview results were organized and cross-checked, and representative sowing dates and growing seasons for each crop were determined based on local agricultural production conditions. These parameters were then used as input data for the CROPWAT 8.0 model. Parameters such as K_c and root depth were mainly derived from FAO recommendations and relevant literature [6,8,28]. Owing to the limited availability of long-term and continuous crop parameter data at the annual and subregional scales, fixed parameters were used for the same crop type in this study. The relevant crop parameters are listed in Table S1. This study focuses on the water footprints of ten major crops: rice, wheat, maize, cotton, beans, oilseeds, vegetables, fruits, potatoes, and alfalfa. The future SSP–RCP scenario data were obtained from the National Aeronautics and Space Administration (NASA) (<http://www.nccs.nasa.gov>) (accessed on 28 January 2026).

2.3. Research Methods

The research workflow is shown in Figure 2. First, crop, meteorological, and soil data for the Manas River Basin were collected and organized. CROPWAT 8.0 was then used to calculate the blue water footprint, green water footprint, and total crop water footprint in the study area during 1990–2020, and the Mann–Kendall test was applied to analyze their variation characteristics. Second, based on the collected meteorological, agricultural, and socioeconomic factors, path analysis was used to identify the drivers of crop water footprint changes. Finally, three climate scenarios from the CMIP6 models, namely SSP1-2.6, SSP2-4.5, and SSP5-8.5, were selected to project future changes in the crop water footprint of the study area.

2.3.1. Calculation of the Crop Water Footprint

The crop water footprint refers to the total amount of water consumed by a crop throughout its entire growth cycle, comprising blue, green, and gray water footprints. This study focuses primarily on consumptive water resource use in crop production within the Manas River Basin, with an emphasis on analyzing the spatiotemporal evolution, driving mechanisms, and future trends of the green and blue water footprints. The green water footprint and blue water footprint reflect crop consumption of precipitation and irrigation water, respectively, and are important indicators for assessing agricultural water-use structure and water resource dependence in arid regions. In contrast, the gray water footprint mainly reflects the pressure on the aquatic environment caused by agricultural pollutant emissions. Accurate calculation of the gray water footprint requires long-term and continuous data on crop fertilizer application, pollutant runoff parameters, background pollutant concentrations, and corresponding water quality standards. Owing to the lack of relevant data for the Manas River Basin, the gray water footprint was not included in the quantitative analysis of this study. Therefore, unless otherwise specified, the term “crop water footprint” in this study refers to the sum of the green water footprint and the blue water footprint. The calculation of crop water footprints was conducted with reference to the Water Footprint Assessment Manual, using the CROPWAT 8.0 model developed by the Food and Agriculture Organization (FAO) of the United Nations to calculate the crop

water footprints of ten major crops in the Manas River Basin, namely rice, wheat, maize, cotton, beans, oilseeds, vegetables, fruits, potatoes, and alfalfa:

$$CWF = CWFB + CWFG \quad (1)$$

where CWF refers to the crop's total water footprint (m^3), and $CWFB$ and $CWFG$ represent the crop's blue water footprint and green water footprint, respectively (m^3).

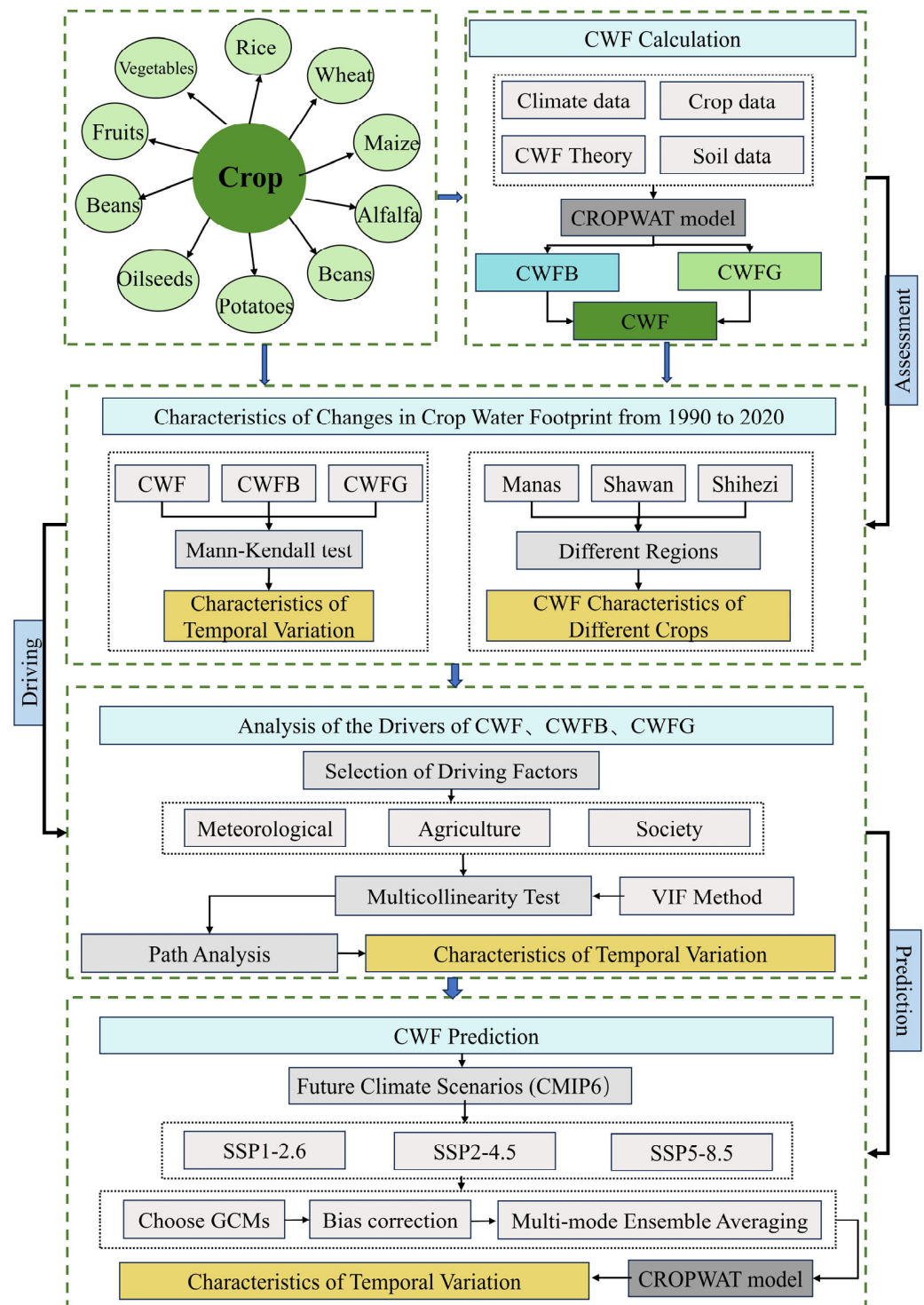


Figure 2. Flowchart of this study. Note: CWF, crop water footprint; CWFB, crop blue water footprint; CWFG, crop green water footprint.

The CWFB and CWFG are calculated by multiplying the crop's blue water and green water consumption (cumulative evapotranspiration during the growing season) by the crop's planting area. The formulas are as follows:

$$CWFB = 10 \times ET_{blue} \times A \quad (2)$$

$$CWFG = 10 \times ET_{green} \times A \quad (3)$$

where ET_{blue} and ET_{green} represent blue and green water evapotranspiration (mm) during the crop growing season, respectively; the constant coefficient 10 is used to convert water depth (mm) to water volume per unit land area (m^3/hm^2); and A represents the crop planting area (hm^2).

$$ET_{blue} = \max(0, ET_c - P_{eff}) \quad (4)$$

$$ET_{green} = \min(ET_c, P_{eff}) \quad (5)$$

where ET_c represents evapotranspiration during the crop growing season (mm), and P_{eff} represents effective precipitation (mm). Refer to the P_{eff} calculation methods commonly used in Xinjiang [6]. Calculations were performed using the formula recommended by the USDA Soil Conservation Service. This method is a commonly used approach for estimating effective rainfall within the CROPWAT 8.0 model and is suitable for watershed-scale studies where long-term, continuous, and measured effective rainfall data are unavailable.

$$P_{eff} = \begin{cases} P \times \frac{125-0.6 \times P}{125} & P \leq 250/3 \\ \frac{125}{3} + 0.1 \times P & P > 250/3 \end{cases} \quad (6)$$

$$ET_c = K_c \times ET_0 \quad (7)$$

where P (mm) represents monthly precipitation; K_c is the crop coefficient (dimensionless); and ET_0 (mm) represents reference crop evapotranspiration, calculated using the Penman-Monteith formula.

Field surveys indicated that sandy loam is the predominant soil type in the major agricultural production areas of the Manas River Basin. The soil parameters used in the CROPWAT 8.0 model were primarily determined based on the measured physical properties of soils in the oasis agricultural zones of the study area. Key parameters included field capacity (FC), wilting point (WP), and soil bulk density. Based on these parameters, the effective soil moisture content was calculated and used as a critical input for soil water balance calculations in the CROPWAT 8.0 model.

2.3.2. Path Analysis

Path analysis is a modeling method based on multivariate linear regression equations and is used to analyze linear relationships between multiple independent variables and a dependent variable. In path analysis, the directional relationship between an independent variable and the dependent variable is quantified by the path coefficient; this coefficient is used to measure the influence of the relationships among correlated variables and can be used to evaluate both the direct and indirect effects of independent variables on the dependent variable. Accordingly, path coefficients can be classified into direct path coefficients, indirect path coefficients, and total path coefficients. To ensure the reliability of the path analysis results, tolerance and the variance inflation factor (VIF) were used to test for multicollinearity among the explanatory variables [29]. Multicollinearity refers to strong correlations among explanatory variables, which may lead to unstable model parameter estimates and affect the interpretation of the effects of individual driving factors; in general,

a smaller tolerance value and a larger VIF value indicate stronger multicollinearity; when $VIF < 10$, no serious multicollinearity is considered to exist among the explanatory variables. Considering both climatic and anthropogenic factors, this study selected seven indicators as independent variables: precipitation (X1), temperature (X2), relative humidity (X3), sunshine duration (X4), total mechanical power (X5), total population (X6), and per capita grain output (X7). Multicollinearity analysis of the seven selected influencing factors was conducted using IBM SPSS Statistics 27.0 software (Table S2). The results showed that the tolerance values of all independent variables were greater than 0.1 and that all VIF values were less than 10, indicating the absence of severe multicollinearity among the variables and satisfying the basic requirements for path analysis. Furthermore, the linearity test indicated that the explanatory variables and the dependent variable generally exhibited an approximately linear relationship; the standardized residuals ranged from -1.650 to 1.834 , with a mean close to 0 and a standard deviation of 0.876 ; and the residual histogram closely approximated a normal distribution, suggesting that the model residuals essentially satisfied the normality assumption.

Based on the fundamental principles of path analysis, we assume that the dependent variable has the following linear relationship with its independent variables:

$$Y = k_{1y}X_1 + k_{2y}X_2 + k_{3y}X_3 + \cdots + k_{py}X_p \quad (8)$$

In the equation, the independent variables are $X_1, X_2, X_3 \dots X_p$; the dependent variable is Y ; and the correlation coefficient between the independent and dependent variables is k_{iy} .

Path analysis is a method based on multiple regression that decomposes the correlation coefficient k_{iy} between an independent variable X_i and the dependent variable Y into two components: the direct effect of X_i on Y , and the indirect effect of X_i on Y mediated by other independent variables X_j . The theoretical equation for path analysis is as follows:

$$\begin{cases} b_1 + k_{12}b_2 + k_{13}b_3 + \cdots + k_{1p}b_p = k_{1y} \\ k_{21}b_1 + b_2 + k_{23}b_3 + \cdots + k_{2p}b_p = k_{2y} \\ \cdots \\ k_{p1}b_1 + k_{p2}b_2 + k_{p3}b_3 + \cdots + b_p = k_{py} \end{cases} \quad (9)$$

where k_{ij} is the correlation coefficient between the two independent variables X_i and X_j ; b_i represents the direct path coefficient between X_i and Y , which is a standardized partial regression coefficient; and the effect of independent variable X_i on Y via another independent variable X_j is denoted by $b_i k_{ij}$, which is known as the indirect path coefficient. When multiple independent variables influence a single dependent variable, it is necessary to consider their indirect path coefficients. These can be calculated using Formula (10), as follows:

$$k_{iy} = b_i + \sum_{j \neq i} b_j k_{ij} \quad i = 1, 2, \dots, n \quad (10)$$

where the correlation coefficient k_{iy} between the independent variables X_i and Y is equal to the sum of the direct path coefficient b_i and the indirect path coefficients; that is, path analysis considers the interrelationships among the various variables.

2.3.3. Methods for Predicting Crop Water Footprints Under Different Future Scenarios

(1) Selection and Processing of Climate Models

Future meteorological data provide the basis for projecting crop water footprints. This study used CMIP6 GCM data provided by NASA to quantitatively assess changes in crop water footprints under different future scenarios in the Manas River Basin. First, after fully considering the availability of long-term time-series data for five meteorological factors,

namely maximum temperature, minimum temperature, relative humidity, wind speed, and precipitation, and based on previous studies in the relevant regions, four GCMs with strong simulation performance and high consistency with historical meteorological data in the basin were selected: ACCESS-ESM1-5, CanESM5, CMCC-ESM2, and MRI-ESM2-0. Next, bias correction was performed on the selected climate model data. Finally, ensemble averaging was applied to the multi-model data, and the results were evaluated (Table 1). This method has been widely used in future climate modeling [30,31]. Previous studies have shown that considerable errors may occur when local sunshine duration is estimated from solar radiation values derived from GCMs. Because sunshine duration is mainly affected by the Earth's rotation, solar altitude, latitude, and cloud cover, its interannual and interdecadal variations are relatively small. The average correlation coefficient (R) between the monthly mean sunshine duration over the past 21 years and that over the past 10 years was 0.998, with a root mean square error (RMSE) of 0.380 and a standard deviation ratio of 0.939. In addition, to further assess the influence of assumptions regarding future sunshine duration on crop water footprint projections, this study, following previous research methods [32,33], established four perturbation scenarios, namely $\pm 5\%$ and $\pm 10\%$ changes in sunshine duration. Under the SSP1, SSP2, and SSP5 scenarios, these scenarios were used to systematically evaluate the sensitivity of crop water footprint projections for different periods from 2030 to 2100 to changes in sunshine duration (Table S3). The sensitivity analysis showed that, under different future climate scenarios, crop water footprints generally responded weakly to changes in sunshine duration, with sensitivity coefficients ranging from 0.02 to 1.47. Although the sensitivity coefficients varied across certain years and scenarios, the changes in crop water footprints under the four perturbation scenarios were relatively small, and the future direction and overall trend of change remained largely unchanged. Therefore, this study used the monthly mean sunshine duration from 2000 to 2020 as the future monthly sunshine duration in the analysis.

Table 1. Evaluation results of GCM ensemble averages and observations in the Manas River Basin.

Assessment of GCM Mean Results	Highest Temperature	Lowest Temperature	Relative Humidity	Wind Speed	Precipitation
R	0.979	0.966	0.933	0.854	0.440
RMSE	3.023	3.853	5.752	0.321	11.834
Ratio of standard deviations	0.980	0.967	0.989	1.137	0.461

(2) Estimates of Population and Planting Area in the Study Area

Future changes in the regional crop water footprint will be primarily influenced by crop water requirements and cropland area under the SSP–RCP scenarios. To improve the accuracy of future crop area projections, this study drew on the System Dynamics (SD) model, which has been widely used in land-use and agricultural system research in Xinjiang [34,35], to develop a simulation framework for future crop structure in the Manas River Basin. The model comprehensively considers socioeconomic and climatic conditions under three development scenarios, namely SSP1, SSP2, and SSP5, and incorporates factors such as changes in crop yields, policy orientation, population dynamics, and land-use changes. Linear or nonlinear equations were used to characterize the interactions among these variables, thereby simulating the dynamic changes in crop cultivation areas within the basin under different climate scenarios. To test the applicability of the model, historical crop cultivation area data from 2010 to 2020 were input into the model for simulation and validation. The results showed that the relative errors between the simulated and observed cultivation areas for all crop types did not exceed 10%, indicating that the system dynamics

model developed for the Manas River Basin has good simulation accuracy and can be used to predict changes in crop cultivation areas under various future climate scenarios.

3. Results

3.1. Analysis of Crop Cultivated Structure

As shown in Figure 3, the cultivated area of crops in the Manas River Basin exhibited a nonlinear increasing trend from 1990 to 2020. Over the 30-year period, the total cultivated area increased by 287,956.64 hm², corresponding to an overall increase of 143.56%. The cultivated areas in different regions of the basin also showed significant upward trends. During the study period, Shawan City had the largest cultivated area, with a multi-year average of 86,499.07 hm², followed by Manas County, with an annual average of 50,446.54 hm². Shihezi City had the smallest cultivated area, with a long-term average of only 4657.85 hm².

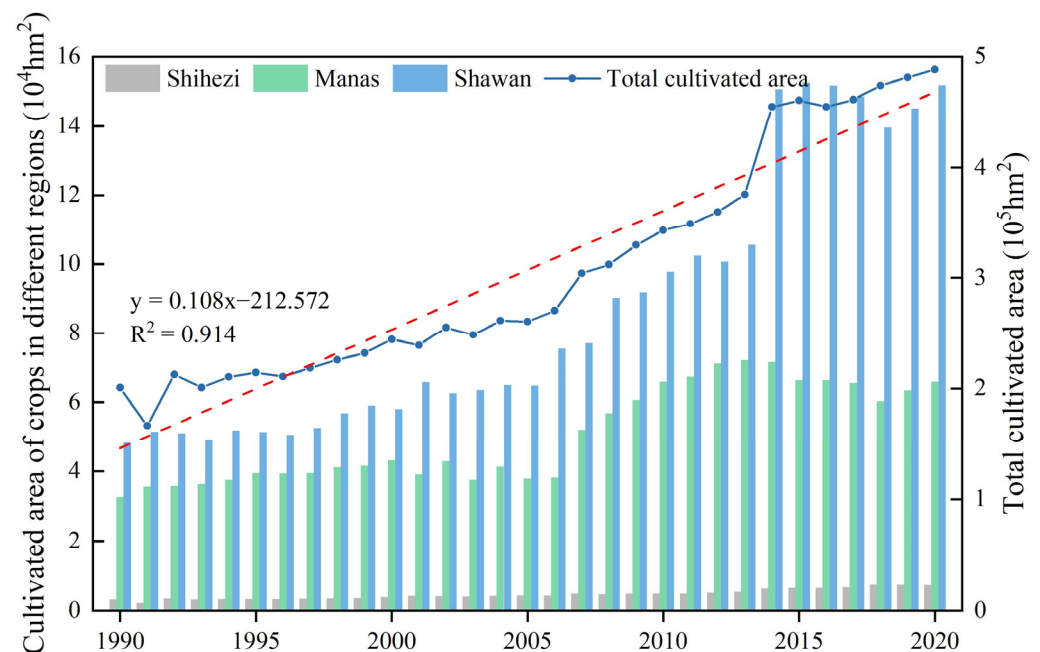


Figure 3. Changes in planting area in the Manas River Basin from 1990 to 2020.

As shown in Figure 4, the cultivated areas of different crops in the Manas River Basin exhibited diverse changing patterns from 1990 to 2020. Among them, the total cultivated area of food crops, including rice, wheat, maize, beans, and potatoes, showed an overall fluctuating downward trend. In 2006, it decreased to a minimum of 22,150.24 hm², followed by a clear upward trend from 2007 to 2015, reaching a peak of 63,901.60 hm² in 2015; from 2016 to 2020, the cultivated area of food crops declined slightly; and by 2020, it had decreased by 29.74% compared with 1990. Changes in the total cultivated area of food crops in the study area were mainly influenced by wheat and maize. However, the reduction in wheat cultivated area far exceeded the increase in maize cultivated area, resulting in an overall decline in the cultivated area of food crops. In contrast, the total cultivated area of cash crops, including cotton, oilseeds, vegetables, fruits, and alfalfa, showed a relatively consistent upward trend and reached a peak of 190,700.39 hm² in 2020. Over the 30-year period, the total cultivated area of cash crops increased by 156,732.69 hm², primarily driven by the expansion of cotton cultivation. From 1990 to 2020, the total power of agricultural machinery in the study area increased from 208,300 kW to 1,270,700 kW, and the effective irrigated area increased by 131.10%, indicating that improvements in agricultural mechanization and irrigation conditions provided important support for large-scale and intensive cotton cultivation [36]. The average annual cultivated areas of different crops in the study

area ranked as follows: cotton > wheat > maize > vegetables > oilseeds > beans > alfalfa > potatoes > fruits > rice. Among these crops, cotton had the largest cultivated area, with an annual average of 84,102.33 hm², accounting for 60.34% of the total cultivated area, wheat and maize had average annual cultivated areas of 18,996.92 hm² and 17,619.11 hm², respectively, whereas the cultivated areas of the remaining crops were all below 10,000 hm². Rice had the smallest average annual cultivated area, at only 164.67 hm².

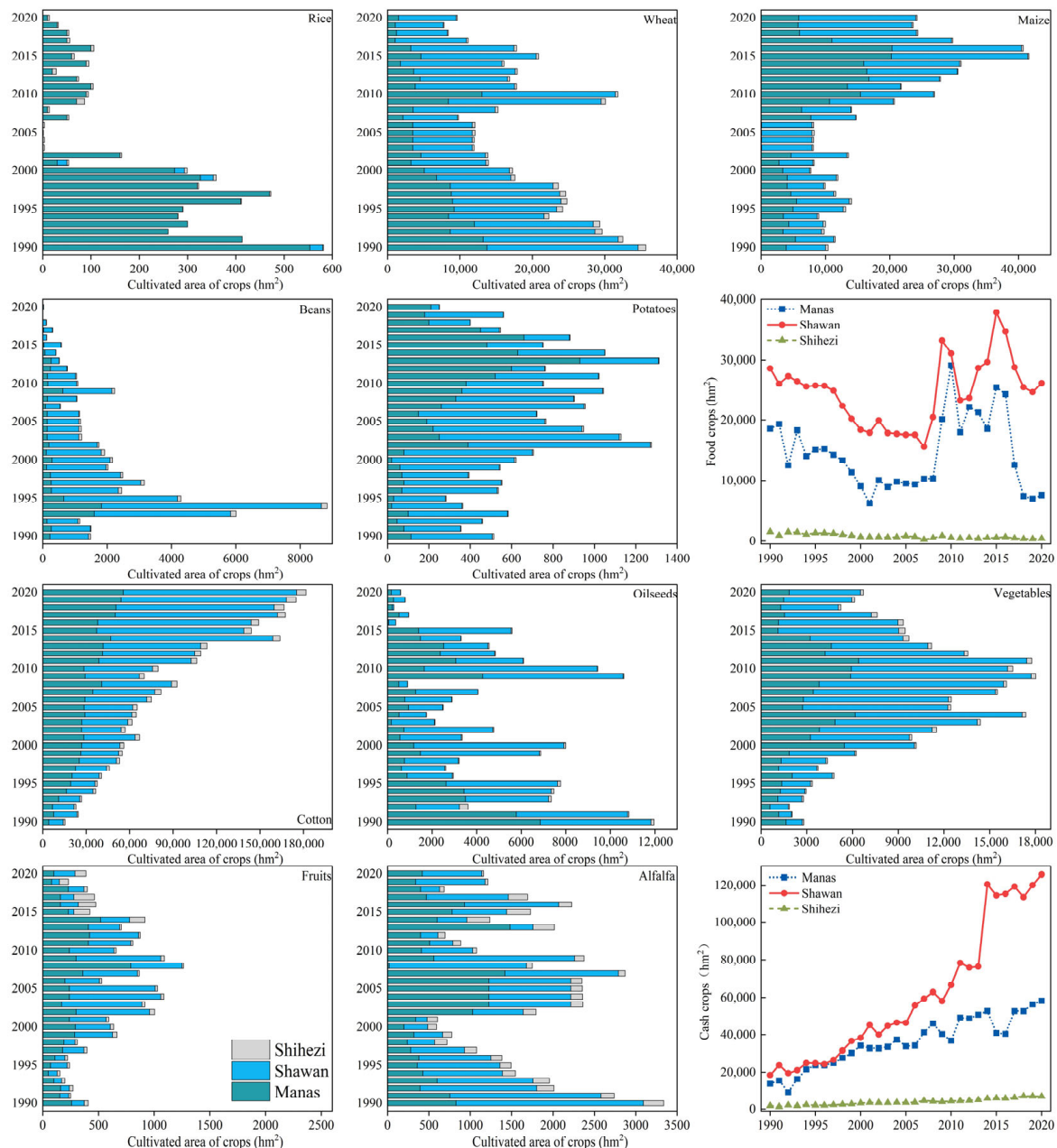


Figure 4. Planting area of various crops in the Manas River Basin from 1990 to 2020.

As shown in Figure 5, the cultivated area and crop types differed across regions of the Manas River Basin. The average annual cultivated areas of both food crops and cash crops followed the order Shawan City > Manas County > Shihezi City, with Shawan City being the largest production area for both crop categories. In Shawan City and Shihezi City, cash crops accounted for more than 50% of the total cultivated area, indicating that the crop structure in these two regions was dominated by cash crops. In contrast, in Manas County, the cultivated area of food crops was slightly larger than that of cash crops.

Overall, regional differences in crop cultivated area and crop composition may lead to variations in agricultural water use. Therefore, this study further examines agricultural water consumption for different crops across regions by analyzing their water footprints.

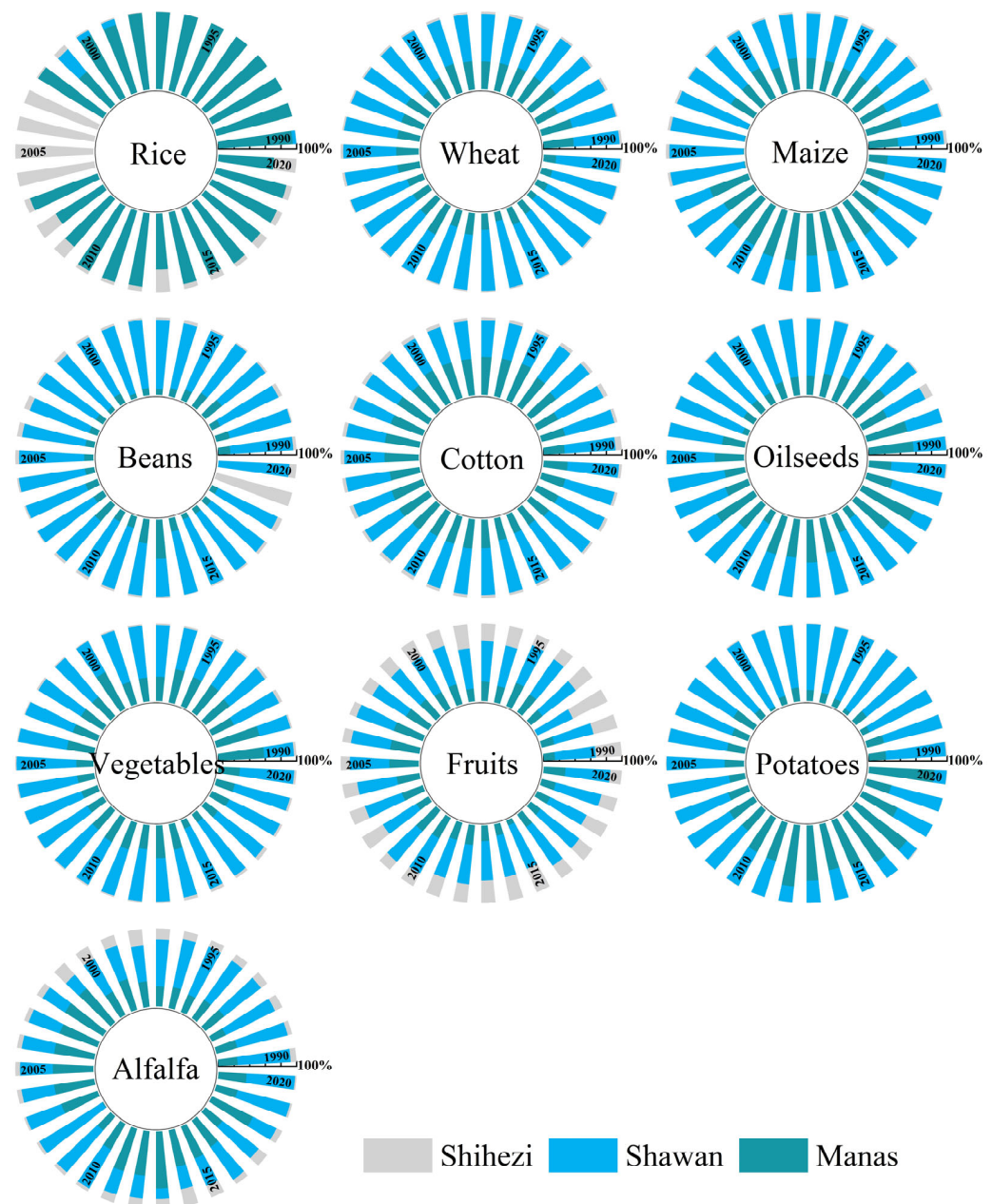


Figure 5. Proportional share of planting area for various crops in the Manas River Basin from 1990 to 2020.

3.2. Analysis of Changes in Crop Water Footprint Characteristics

As shown in Figure 6, the crop water footprint generally exhibited a fluctuating upward trend from 1990 to 2020. During the study period, the crop water footprint increased by 234.89% and reached a peak of $1.59 \times 10^9 \text{ m}^3$ in 2014. This peak was mainly attributed to the relatively large cultivated areas of crops such as cotton and maize in that year, together with climatic conditions that increased crop evapotranspiration and further raised crop water requirements. To further analyze the effects of cultivated area and climate change on the increase in the crop water footprint, this study applied a two-factor decomposition method to decompose changes in the crop water footprint

into area effects and ETc effects. The results showed that changes in cultivated area accounted for 98.52% of the increase in the crop water footprint, making it the dominant driver, whereas the ETc effect accounted for 1.48%, indicating that changes in climatic conditions also contributed to the increase by affecting crop evapotranspiration per unit area. Based on the Mann–Kendall test results for the crop water footprint in the study area from 1990 to 2020 (Figure 6), the UF value remained greater than 0 after 1990 and exceeded the significance threshold starting in 1995, indicating a significant upward trend in the crop water footprint during the study period. The UF and UB curves for the crop water footprint intersected around 2004, suggesting that a trend change may have occurred at that time. After 2004, the upward trend in the crop water footprint further strengthened. The inter-annual variation in the crop blue water footprint in the Manas River Basin was similar to that of the total crop water footprint, with both showing fluctuating upward trends. The crop blue water footprint increased from $3.61 \times 10^8 \text{ m}^3$ in 1990 to $1.40 \times 10^9 \text{ m}^3$ in 2020, representing a total increase of $1.04 \times 10^9 \text{ m}^3$, and it also peaked in 2014. According to the Mann–Kendall test results, the UF value of the crop blue water footprint also increased continuously during the study period and intersected with the UB curve around 2004, indicating that a trend change in the crop blue water footprint may have occurred around that time. This suggests a high degree of consistency between the total crop water footprint and the crop blue water footprint in terms of changing trends and the timing of inflection points. In contrast, although the crop green water footprint showed an overall upward trend during the study period, it exhibited more pronounced interannual fluctuations. From 1990 to 2020, the crop green water footprint increased by $3.0 \times 10^7 \text{ m}^3$, corresponding to an overall increase of 32.37%. Before 1993, the UF value of the crop green water footprint was less than 0, indicating a declining phase; from 1993 to 2006, the UF value showed a fluctuating upward trend; around 2006, the UF and UB curves intersected within the ± 1.96 significance interval, indicating that an inflection point in the crop green water footprint occurred around 2006 according to the Mann–Kendall test; and after 2006, the crop green water footprint showed an overall steady upward trend.

Changes in crop water footprints are influenced by both water requirements per unit area and cultivated area. As shown in Figure 7, the annual average blue water footprints of major crops in the Manas River Basin followed the order cotton ($5.33 \times 10^8 \text{ m}^3$) > maize ($9.50 \times 10^7 \text{ m}^3$) > wheat ($8.22 \times 10^7 \text{ m}^3$) > vegetables ($4.51 \times 10^7 \text{ m}^3$) > oilseeds ($3.09 \times 10^7 \text{ m}^3$) > beans ($6.83 \times 10^6 \text{ m}^3$) > alfalfa ($4.59 \times 10^6 \text{ m}^3$) > potatoes ($2.60 \times 10^6 \text{ m}^3$) > fruits ($2.27 \times 10^6 \text{ m}^3$) > rice ($1.76 \times 10^6 \text{ m}^3$). Among these crops, cotton had the largest blue water footprint, mainly because of its large cultivated area and high irrigation water requirement. During the study period, the blue water footprint of cotton increased from $9.69 \times 10^7 \text{ m}^3$ to $1.18 \times 10^9 \text{ m}^3$, while that of maize increased from $5.10 \times 10^7 \text{ m}^3$ to $1.24 \times 10^8 \text{ m}^3$, indicating that these two crops were the main contributors to the increase in the basin's blue water footprint. In addition, the blue water footprints of fruits and vegetables also showed upward trends, primarily due to the expansion of their cultivated areas, driven by socioeconomic demand and adjustments in crop structure within the basin. The blue water footprints of fruits and vegetables increased by $2.25 \times 10^7 \text{ m}^3$ and $2.58 \times 10^5 \text{ m}^3$, respectively. In contrast, the blue water footprints of the remaining crops showed downward trends. Over the past 30 years, the blue water footprint of wheat decreased by $7.07 \times 10^7 \text{ m}^3$. This decrease was mainly attributable to the reallocation of water and land resources toward crops with higher economic returns, such as cotton, fruits, and vegetables, under the background of water resource constraints and agricultural restructuring, which led to a decline in the cultivated area of food crops such as wheat. As shown in Figure 8, the ranking of the an-

nual average green water footprints of different crops in the Manas River Basin from 1990 to 2020 was consistent with that of the blue water footprints. The green water footprints of cotton, maize, vegetables, and fruits all showed upward trends, with cotton exhibiting the largest increase, increasing by $7.91 \times 10^7 \text{ m}^3$ over the 30-year period. The green water footprint of maize increased by $7.26 \times 10^7 \text{ m}^3$. In contrast, the green water footprints of rice, wheat, beans, oilseeds, potatoes, and alfalfa all showed downward trends, with wheat and oilseeds experiencing the most significant reductions, decreasing by 58.71% and 94.74%, respectively. As shown in Figures 7 and 8, the regional contributions to the blue and green water footprints of different crops showed a consistent pattern, following the order Shawan City > Manas County > Shihezi City.

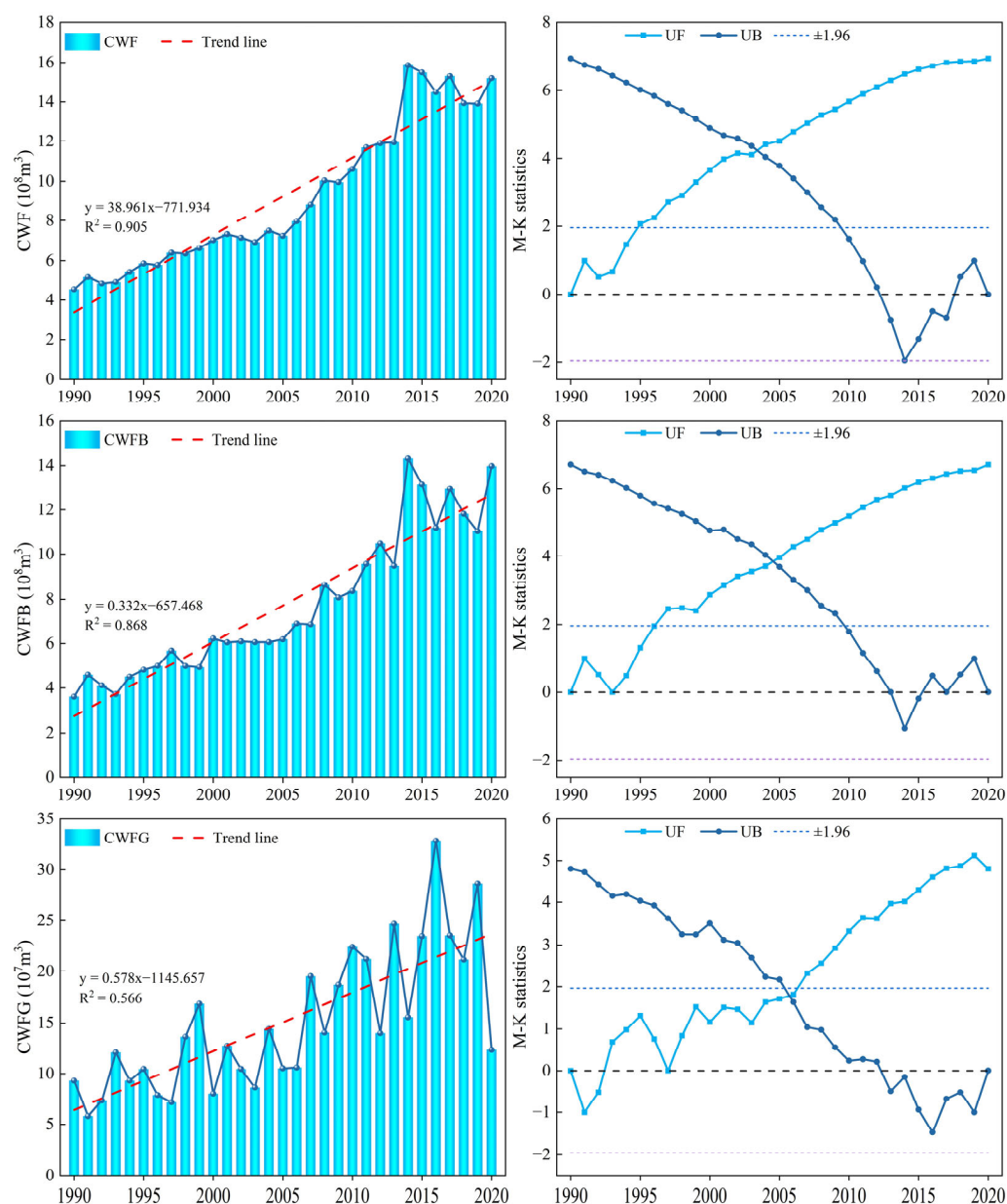


Figure 6. Changes in crop water footprint in the Manas River Basin from 1990 to 2020 and Mann–Kendall statistical test analysis.

3.3. Driving Factors Analysis of Crop Water Footprint

According to Table 2, the effects of different factors on the total crop water footprint in the Manas River Basin varied. In terms of direct path coefficients, total mechanical

power had the strongest direct effect, with a coefficient of 0.642, followed by per capita grain output, with a coefficient of 0.321; this indicates that both factors had relatively strong positive effects on changes in the total crop water footprint. Among the natural factors, average relative humidity and sunshine duration showed negative effects, with direct path coefficients of -0.154 and -0.129 , respectively. Average temperature showed a positive effect, with a coefficient of 0.099, whereas the direct path coefficient of annual precipitation was -0.026 , indicating that its direct effect was relatively weak. Based on the indirect path coefficients, total mechanical power not only had a strong direct effect but also exerted strong indirect effects through total population and per capita grain output, with indirect path coefficients of 0.417 and 0.501, respectively. This suggests a strong coupling relationship among total mechanical power, population size, grain production level, and agricultural production scale. In terms of total path coefficients, total mechanical power and per capita grain output had the highest values, at 1.319 and 0.856, respectively, indicating that these two factors were the main factors associated with changes in the total crop water footprint.

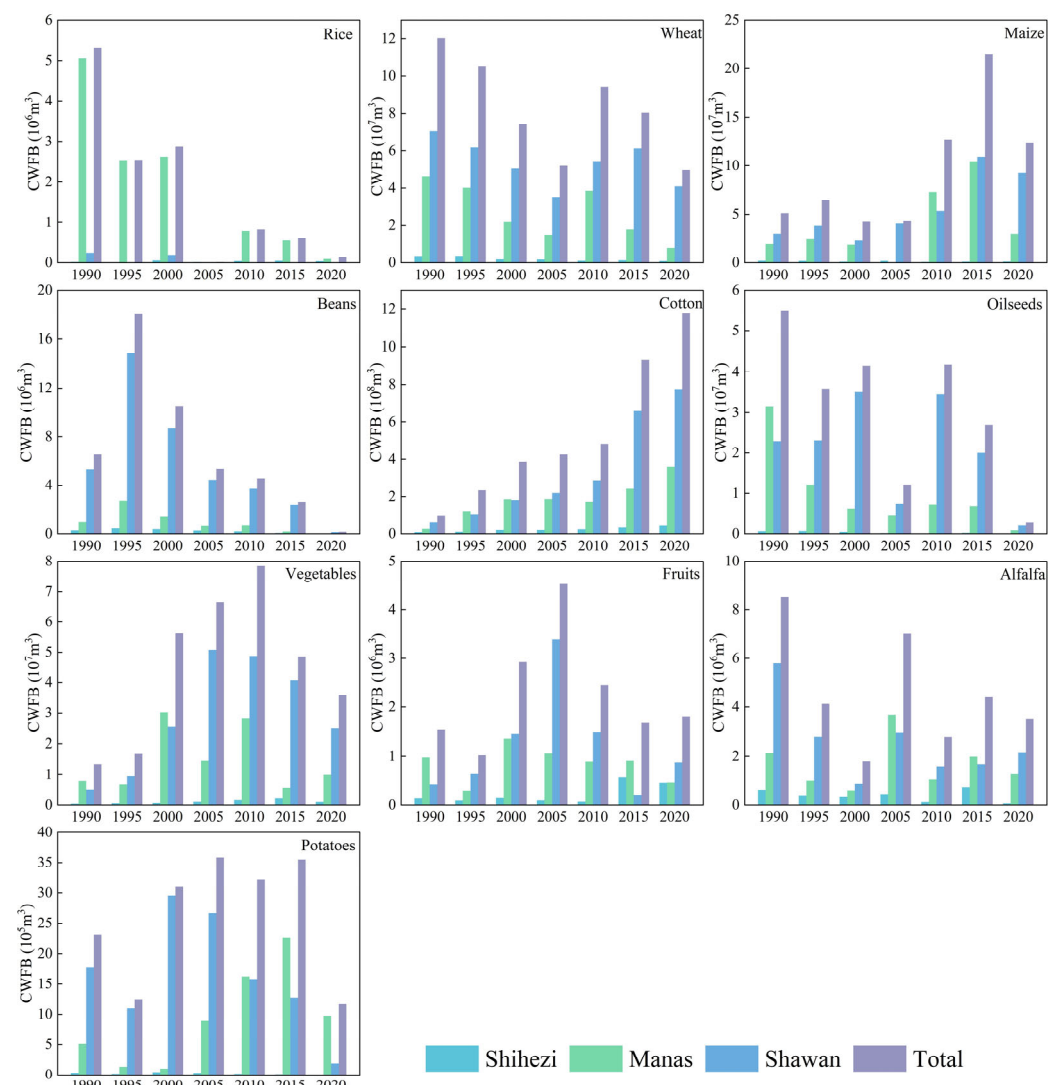


Figure 7. Blue water footprint of different crops in the Manas River Basin from 1990 to 2020.

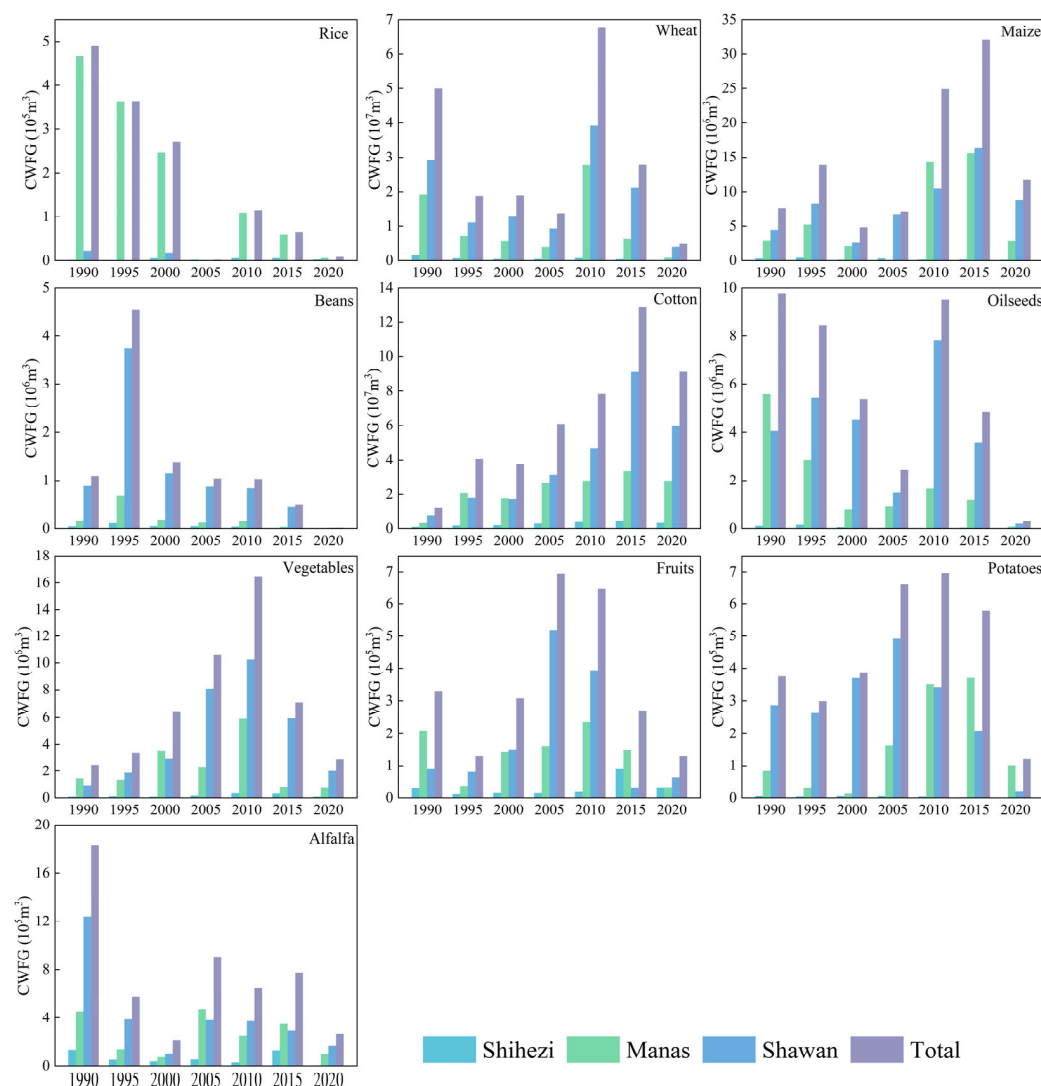


Figure 8. Green water footprint of different crops in the Manas River Basin from 1990 to 2020.

Table 2. Analysis of drivers of crop water footprint.

Factor	DPC	IPC							TPC
		X1→ CWF	X2→ CWF	X3→ CWF	X4→ CWF	X5→ CWF	X6→ CWF	X7→ CWF	
X1	−0.026	—	0.005	−0.019	0.007	−0.002	−0.006	−0.007	−0.048
X2	0.099	−0.019	—	−0.007	−0.041	0.025	−0.017	−0.002	0.038
X3	−0.154	−0.112	0.011	—	0.050	0.047	0.034	0.026	−0.097
X4	−0.129	0.036	0.053	0.042	—	0.051	−0.014	0.013	0.053
X5	0.642	0.049	0.161	−0.197	−0.254	—	0.417	0.501	1.319
X6	−0.093	−0.022	0.016	0.020	−0.010	−0.060	—	−0.084	−0.234
X7	0.321	0.088	−0.005	−0.055	−0.033	0.251	0.289	—	0.856

As shown in Table 3, for the crop blue water footprint, total mechanical power and per capita grain output had relatively strong positive effects in terms of direct path coefficients, with values of 0.630 and 0.262, respectively. Among the natural factors, annual precipitation, average relative humidity, and sunshine duration all showed negative effects, with direct path coefficients of −0.132, −0.159, and −0.118, respectively. This indicates that increases in precipitation and humidity may reduce crop dependence on irrigation water to some extent. Based on the indirect path coefficients, total mechanical power exerted strong indirect

effects through total population and per capita grain output, with coefficients of 0.410 and 0.492, respectively. Its influence mechanism was generally consistent with that of the total crop water footprint. In terms of total path coefficients, total mechanical power and per capita grain output had relatively high values, at 1.295 and 0.698, respectively, indicating that both factors had substantial effects on changes in the crop blue water footprint.

Table 3. Analysis of drivers of the blue water footprint of crops.

Factor	DPC	IPC							TPC
		X1→ CWFB	X2→ CWFB	X3→ CWFB	X4→ CWFB	X5→ CWFB	X6→ CWFB	X7→ CWFB	
X1	−0.132	—	0.025	−0.096	0.037	−0.010	−0.032	−0.036	−0.243
X2	0.095	−0.018	—	−0.007	−0.039	0.024	−0.016	−0.002	0.037
X3	−0.159	−0.115	0.011	—	0.052	0.049	0.035	0.027	−0.100
X4	−0.118	0.033	0.049	0.038	—	0.047	−0.013	0.012	0.048
X5	0.630	0.048	0.158	−0.193	−0.249	—	0.410	0.492	1.295
X6	−0.020	−0.005	0.003	0.004	−0.002	−0.013	—	−0.018	−0.050
X7	0.262	0.072	−0.004	−0.045	−0.027	0.205	0.236	—	0.698

The effects of different factors on the crop green water footprint in the Manas River Basin also varied (Table 4). In terms of direct path coefficients, total mechanical power, per capita grain output, and annual precipitation showed relatively strong positive effects on the crop green water footprint, with coefficients of 0.508, 0.503, and 0.475, respectively. In contrast, total population and sunshine duration showed negative effects, with coefficients of −0.409 and −0.143, respectively. Unlike the crop blue water footprint, annual precipitation had a positive effect on the crop green water footprint, indicating that increased precipitation can enhance effective rainfall supply during the crop growth period, thereby increasing the contribution of green water resources to crop water consumption. Based on the indirect path coefficients, total mechanical power, total population, and per capita grain output showed relatively clear indirect path relationships. In addition, annual precipitation exerted a notable indirect effect through average relative humidity, with an indirect path coefficient of 0.345. In terms of total path coefficients, per capita grain output, total mechanical power, and annual precipitation had relatively high values, at 1.341, 1.044, and 0.876, respectively, indicating that these three factors were the main factors associated with changes in the crop green water footprint.

Table 4. Analysis of drivers of crop green water footprints.

Factor	DPC	IPC							TPC
		X1→ CWFG	X2→ CWFG	X3→ CWFG	X4→ CWFG	X5→ CWFG	X6→ CWFG	X7→ CWFG	
X1	0.475	—	−0.091	0.345	−0.133	0.036	0.114	0.131	0.876
X2	0.089	−0.017	—	−0.006	−0.037	0.022	−0.015	−0.001	0.034
X3	−0.085	−0.062	0.006	—	0.028	0.026	0.019	0.015	−0.054
X4	−0.143	0.040	0.059	0.047	—	0.057	−0.016	0.015	0.058
X5	0.508	0.039	0.128	−0.156	−0.201	—	0.330	0.397	1.044
X6	−0.409	−0.098	0.070	0.090	−0.045	−0.266	—	−0.369	−1.027
X7	0.503	0.138	−0.008	−0.087	−0.052	0.393	0.453	—	1.341

Note: DPC, direct path coefficients; IPC, indirect path coefficients; TPC, total path coefficients.

3.4. Projections of Future Crop Water Footprints Under Different Scenarios

Estimating the crop water footprint in the Manas River Basin can effectively reflect future agricultural water consumption during crop growth and provide a reference for

agricultural water allocation in the basin. As shown in Figure 9, among the three future SSP–RCP scenario combinations, the crop water footprint under the SSP1-2.6 and SSP5-8.5 scenarios exhibited a trend of first increasing and then decreasing. Under these two scenarios, the crop water footprint in the Manas River Basin is projected to peak in 2060, increasing by $1.49 \times 10^8 \text{ m}^3$ and $1.81 \times 10^8 \text{ m}^3$, respectively, compared with 2020, corresponding to growth rates of 9.82% and 11.92%. This indicates that crop water demand in the basin will continue to increase over the next 30–40 years. As shown in Figure 9, the trends in the crop blue water footprint and crop green water footprint in the Manas River Basin under the SSP1-2.6 and SSP5-8.5 scenarios were generally consistent with those of the crop water footprint. By the end of this century, under the SSP1-2.6 and SSP5-8.5 scenarios, the crop blue water footprint in the Manas River Basin is projected to decrease by $1.11 \times 10^8 \text{ m}^3$ and $6.15 \times 10^6 \text{ m}^3$, respectively, compared with 2020. In contrast, the crop green water footprint is projected to increase by $4.79 \times 10^7 \text{ m}^3$ and $5.58 \times 10^7 \text{ m}^3$, respectively. Notably, under both the SSP1-2.6 and SSP5-8.5 scenarios, the total population is projected to first increase and then decrease in the future, which may significantly affect the extent of reduction in crop cultivated area. In addition, greenhouse gas emissions under different scenarios may influence precipitation and temperature, thereby affecting effective rainfall and crop water consumption. The SSP2-4.5 scenario is classified as a medium radiative forcing scenario and is associated with relatively high social vulnerability, substantial global temperature increases, and concerns regarding energy and food security. Under this scenario, population growth accelerates and cultivated land area expands substantially, leading to an increase in agricultural water use. As shown in Figure 9, the crop water footprint in the Manas River Basin shows a continuous upward trend under the SSP2-4.5 scenario, reaching a maximum value of $2.08 \times 10^9 \text{ m}^3$ by 2100, which represents an increase of 37.01% compared with 2020.

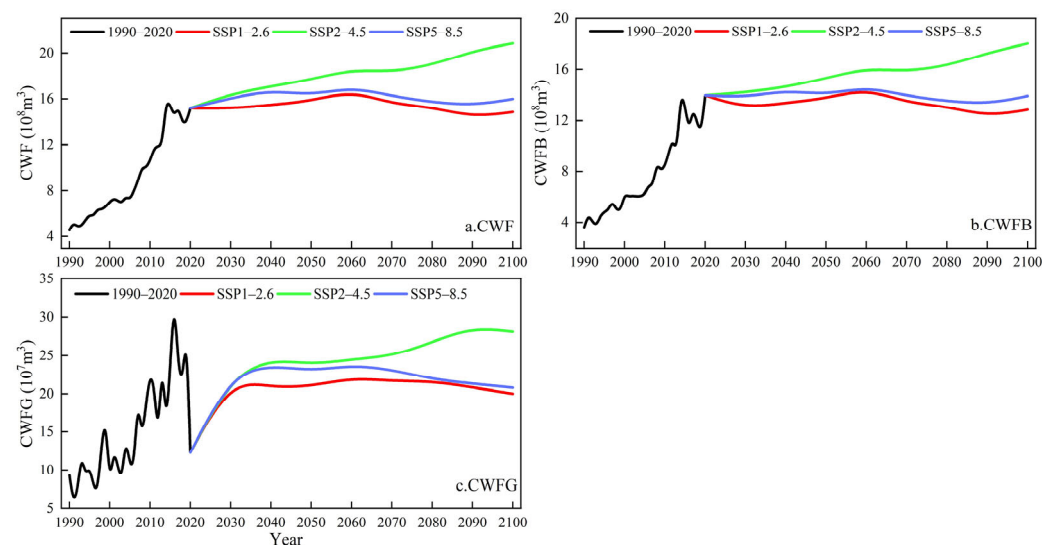


Figure 9. Temporal changes in crop water footprints under historical and future scenarios: (a) CWF, crop water footprint; (b) CWFB, crop blue water footprint; and (c) CWFG, crop green water footprint.

Overall, under the three future climate scenarios, the crop water footprint in the Manas River Basin followed the order $\text{SSP2-4.5} > \text{SSP5-8.5} > \text{SSP1-2.6}$. This difference was mainly attributable to the combined effects of anthropogenic factors and climatic conditions, with changes in agricultural production scale and cultivated area being the dominant drivers. As a result, the crop water footprint under the SSP1-2.6 and SSP5-8.5 scenarios remained at relatively low levels overall and is projected to reach $1.486 \times 10^9 \text{ m}^3$ and $1.598 \times 10^9 \text{ m}^3$, respectively, by the end of this century. Although the SSP5-8.5 scenario projects a substantial

increase in temperature, which may increase crop water requirements per unit area, the crop water footprint under this scenario remains lower than that under SSP2-4.5 because of the projected declines in population size and crop cultivated area after 2060.

4. Discussion

4.1. The Mechanism of Changes in Crop Water Footprint Is Revealed

This study compares the crop water footprint results for the Manas River Basin with those of existing studies in the arid regions of Northwest China. Zeng et al. reported that the blue water footprint in the Heihe River Basin was significantly higher than the global and Chinese averages, indicating that agricultural production in arid inland river basins generally faces substantial pressure due to its dependence on irrigation water [37]. Previous studies have shown that the agricultural water footprint in Xinjiang has generally increased, with the blue water footprint accounting for the largest share, with an average proportion of 90.19% [6]. Li et al. found that the blue water footprint has long been the dominant component of the crop water footprint in Xinjiang, accounting for approximately 78% of the total, with cotton, maize, and wheat being the major contributors [28]. Wang et al. reported that blue water accounted for as much as 94.71% of the water footprint of grain production in the Tarim River Basin, whereas green water accounted for only 5.29%, further demonstrating the high dependence of crop production in Xinjiang on irrigation water resources [38]. The results of this study showed that the crop water footprint in the Manas River Basin exhibited an overall fluctuating upward trend from 1990 to 2020. The blue water footprint accounted for a multi-year average of 83.41%, which was significantly higher than that of the green water footprint, and water-intensive crops such as cotton made a substantial contribution to the total crop water footprint. Overall, the results of this study are generally consistent with previous studies in Xinjiang in terms of changing trends, dominant water footprint components, and major contributing crops. This consistency indicates that the crop water footprint estimates for the Manas River Basin derived using the CROPWAT model are reasonable and reliable.

The underlying mechanism is mainly related to the trend of “warming and humidification” in Xinjiang, together with the continuous expansion of cultivated area driven by human activities. Changes in the crop blue water footprint were the primary cause of the increase in the crop water footprint, which can be attributed to the following three aspects. First, large-scale farmland reclamation in the basin was strongly driven by government policies. As one of the key regions on the northern slope of the Tianshan Mountains in Xinjiang, the Manas River Basin is an important area for agricultural cultivation and economic development. Therefore, changes in cultivated area in this region are particularly susceptible to human activities. Since the implementation of the reform and opening-up policy in 1980, the basin has successively adopted land policies centered on the house-hold contract responsibility system and a land management model combining centralized and decentralized management. After 2000, with the implementation of the basin’s Ninth Five-Year Plan and the Western Development Strategy, urbanization and industrialization advanced rapidly. Socioeconomic conditions improved substantially, a large number of people migrated into the area, and the demand for agricultural land became increasingly urgent [39]. These strategies provided financial support for agricultural cultivation, promoted the development of water conservancy infrastructure, and accelerated advances in crop cultivation techniques [40,41]. These policy measures contributed to a significant improvement in agricultural productivity across the basin. In addition, the level of agricultural mechanization in the basin has increased markedly in recent years, providing an important driving force for regional arable land reclamation. By reducing the costs of land reclamation and agricultural production, improving cultivation efficiency, and

facilitating land transfer and large-scale farming operations, agricultural mechanization has effectively enhanced the economic feasibility of arable land development [42]. Second, the development of water conservancy projects improved water resource utilization efficiency in the basin and thereby enhanced agricultural productivity. The Manas River Basin is located in the arid region of Northwest China, where water resources are a key factor limiting agricultural development. Similarly to most arid regions, the basin relies heavily on irrigated agriculture, with agricultural water use accounting for 90% of total annual water consumption and surface water utilization reaching 96% [43]. Since 1990, the basin has begun to develop water-saving drip irrigation technology, which has not only mitigated soil salinization but also overcome the limitations of traditional agricultural irrigation and drainage techniques, thereby improving agricultural water-use efficiency in the basin [44]. Around 1990, with the completion of reservoirs such as the Second Anji Lake Reservoir and Jiahezi Reservoir, as well as the strengthening of irrigation management, water resources in the basin became more abundant [45]. Consequently, large-scale land reclamation occurred during this period, and natural oasis areas were gradually transformed into artificial oasis areas. Third, changes in crop cultivation patterns contributed to the increase in the crop blue water footprint in the basin. Changes in the blue water footprints of wheat, maize, and cotton, as the main crops in Xinjiang, have an important influence on the crop blue water footprint of the basin. Consistent with the findings of Xiaoyu Zhang et al. [6], the results of this study indicate that maize and cotton are the primary contributors to the crop blue water footprint. Cotton, as a major cash crop in Xinjiang, has experienced changes in crop water-use intensity in recent years under the influence of local policies and socio-economic development demands. These changes have led to adjustments in the cropping structure within the basin, resulting in a gradual decrease in wheat cultivated area and a continuous increase in cotton and maize cultivated areas (Figure 4). This indicates that regional agricultural production has shifted from relatively lower-water-use crops toward higher-water-use crops. Because cotton and maize are more dependent on irrigation water throughout their growth cycles, their blue water consumption per unit area is significantly higher than that of wheat. Therefore, changes in crop cultivation patterns have directly increased the average water-use intensity of the agricultural production system [5]. Furthermore, the cultivated area of water-intensive crops has continued to expand at the expense of relatively water-saving crops, leading to an increase in total agricultural blue water consumption. In addition, under the influence of the “warming and humidification” trend in Xinjiang, precipitation in the Manas River Basin has increased. This directly increased the crop green water footprint and further contributed to the overall upward trend in the crop water footprint.

4.2. Crop Water Footprint Predicting to Promote Sustainable Water Resource Management

Current research on water footprints remains largely focused on investigating their driving mechanisms. Various mathematical and physical methods, including exponential decomposition and structural decomposition in traditional factor decomposition approaches, as well as widely used stochastic regression models and artificial neural network models [21–23], have been applied to reveal the underlying causes of changes in water footprints and to identify problems in water resource utilization. In addition, numerous scholars have conducted extensive research on the spatiotemporal variations in crop water footprints and the different water requirements of various crops during their growth stages, aiming to establish crop cultivation structures based on the rational use of water resources [14,46]. Water footprints have also been widely used in water scarcity analysis and risk assessment, thereby providing a framework for evaluating the impacts of virtual water flows on water resources [47,48]. However, although previous studies have mainly

focused on the historical evolution and application of water footprints, how the crop water footprint will change under global climate change remains a key scientific question that has not yet been fully addressed.

Although this issue has attracted widespread attention, related research is still in its early stages, and projecting future water footprints in arid regions remains an urgent challenge. To address this scientific issue, this study constructs an “assessment–driving–prediction” framework tailored to arid regions, aiming to systematically elucidate the evolution of the crop water footprint from both historical and future perspectives and thereby better support the United Nations Sustainable Development Goals (SDGs). Based on the analysis of the crop water footprint and its driving factors during the historical period, this study projected crop water footprints under different future climate scenarios. The results showed significant differences in the crop water footprint of the Manas River Basin under different future climate scenarios (Figure 9). Specifically, under the three future climate scenarios, the crop water footprint in the Manas River Basin followed the order $SSP2-4.5 > SSP5-8.5 > SSP1-2.6$. The $SSP1-2.6$ scenario represents a sustainable development pathway, which is consistent with the findings of Man Li et al. in arid regions [7]. Owing to inherent errors and uncertainties in initial conditions, single climate models often introduce considerable uncertainty into simulation results. In contrast, ensemble simulations based on multiple climate models generally outperform most individual models [31]. Therefore, this study selected CMIP6 climate model data applicable to the arid regions of Northwest China, applied ensemble averaging, and used the resulting data as meteorological inputs. Furthermore, by fully considering the impact of future climate change on crop cultivated areas, this study projected the future crop water footprint of the basin, thereby improving the rationality of the results and providing a methodological framework for future water footprint projections in other regions.

4.3. Recommendations for Agricultural Development in the Watershed Based on Crop Water Footprint

Overall, agricultural development in the Manas River Basin has remained generally stable; however, given the limited total water resources in the region, uncertainties and risks remain for future development. Economic development remains an important objective for the Manas River Basin in western China; therefore, before further promoting basin development, properly balancing agricultural development and water resource availability has become a critical issue that urgently needs to be addressed. As shown in Figure 6, the crop water footprint in the Manas River Basin has shown an upward trend over the past 30 years, mainly driven by changes in cultivated area. Therefore, optimizing the crop structure is a key strategy for addressing this increasing trend. Such optimization should be guided by the water resource carrying capacity of the basin as a fundamental constraint, with a focus on reducing the proportion of water-intensive crops, expanding the cultivation of water-saving crops, and promoting coordinated regional economic development. Specifically, while ensuring regional food security and agricultural economic stability, the expansion of water-intensive crops such as cotton and maize should be appropriately controlled, and the cultivation of low-water-use or drought-tolerant crops should be increased; planting dates and irrigation schedules should also be adjusted according to crop water requirements and changing climatic conditions. At the same time, the breeding and promotion of drought-tolerant crop varieties with high water-use efficiency should be strengthened, and unified water resource allocation and agricultural water quota management at the basin scale should be enhanced to promote coordination between agricultural production and water resource carrying capacity. In addition, further development of irrigation technologies can improve crop water-use efficiency and reduce the crop blue water footprint in the basin. Agricultural development in the Manas River Basin is highly

dependent on irrigation, with agricultural water use accounting for approximately 90% of total annual water consumption. Therefore, modern water-saving irrigation technologies, particularly drip irrigation, should be further promoted, together with integrated water and fertilizer management, precision irrigation, soil moisture monitoring, and digital field management. These measures can reduce evaporation, seepage, and water losses associated with traditional flood irrigation and inefficient water distribution, thereby lowering the blue water consumption intensity of crop production. Based on future crop water footprint projections under climate change scenarios, the basin is expected to face severe water resource pressure under the SSP2-4.5 scenario. Therefore, under this scenario, priority should be given to the development of water-saving agriculture, optimization of crop management, and regulation of population and agricultural production scale to address the impacts of future climate change on agricultural water use. Under the SSP1-2.6 and SSP5-8.5 scenarios, the crop water footprint of the basin is projected to remain relatively stable by the end of this century, and water resource pressure is expected to be relatively low; however, to achieve sustainable regional development, it remains necessary to vigorously promote eco-efficient agriculture.

4.4. Research Limitations and Future Considerations

In this study, an “assessment-driving-prediction” research framework for crop water footprints was established at the basin scale to analyze changes in the crop water footprint of the Manas River Basin from both historical and future perspectives. However, several limitations should be acknowledged to facilitate the practical application of this framework. First, this study considered only the crop green water footprint and crop blue water footprint, while the gray water footprint was not included in the calculations. Estimating the gray water footprint requires long-term, crop-scale, and spatially consistent data on fertilizer application rates, pollutant leaching coefficients, background pollutant concentrations, and regional water quality standards. Owing to the lack of relevant data for the Manas River Basin, this study was unable to provide a reliable estimate of the gray water footprint. Therefore, the results of this study primarily reflect water resource consumption during crop production and do not fully represent the overall water pressure caused by agricultural production. Given the high use of chemical fertilizers in crop cultivation in Xinjiang, excluding the gray water footprint may lead to an underestimation of agricultural water resource pressure. Future research should further integrate fertilization data and water quality monitoring data to incorporate the gray water footprint into the crop water footprint assessment system, thereby providing a more comprehensive understanding of the combined impacts of agricultural production in arid regions on water consumption and water pollution. Second, projections of future crop water footprints rely on GCM climate data, and the ability of GCMs to simulate climate variables at the regional scale directly affects the projection results. In arid and semiarid regions, precipitation is generally more difficult to simulate than temperature because of its low total amount, uneven spatiotemporal distribution, and frequent localized and sudden precipitation events [7,31]. In the GCM evaluation results presented in this study, the precipitation correlation coefficient was 0.44, indicating that the selected model ensemble still showed some deviations in representing precipitation changes in the Manas River Basin. Errors in precipitation simulation may be further propagated into future projections of the crop green water footprint, crop blue water footprint, and total crop water footprint, thereby affecting the accuracy of quantitative estimates of the crop water footprint. In addition, this study used historical monthly mean sunshine duration to represent future sunshine conditions and conducted a sensitivity analysis. The results showed that the overall trends in crop water footprints under the four sunshine-duration perturbation scenarios did not change

significantly, suggesting that the conclusions of this study are reasonably robust; however, this approach still cannot fully reflect the effects of future changes in solar radiation and cloud cover on crop evapotranspiration processes. Therefore, future research should further integrate high-resolution regional climate data, multi-model ensembles, and bias correction methods to improve the accuracy of precipitation projections in arid regions. At the same time, solar radiation or cloud cover data from GCM outputs should be used to improve future sunshine duration estimates, thereby reducing uncertainty in crop water footprint projections. Third, because the research data used in this study mainly consisted of aggregated statistics at the basin scale, this study did not further reveal the spatial variation in crop water footprint intensity across subregions such as Shihezi City, Manas County, and Shawan City. Future research could integrate higher-resolution cropping, irrigation, and meteorological data to analyze the spatial distribution of crop water footprints at the subregional scale within the basin. Finally, the USDA method was adopted in this study mainly to ensure methodological consistency with existing studies in the Manas River Basin and neighboring arid regions, thereby enhancing the comparability of the results. Owing to the lack of long-term, continuous, field-measured effective precipitation data and crop-scale irrigation data, this study was unable to further compare the effects of different effective precipitation formulas on the water footprint results. This may introduce some uncertainty into the allocation of crop green and blue water footprints. Future research could incorporate field soil moisture monitoring data to conduct sensitivity analyses of different methods for estimating effective precipitation.

5. Conclusions

To address the issue of sustainable agricultural water resources in the Manas River Basin, a drought-prone region in Northwest China, this study established an “assessment-driving-prediction” research framework for the crop water footprint and analyzed changes in the crop water footprint of the Manas River Basin from both historical and future perspectives. The main conclusions are as follows: from 1990 to 2020, the cultivated area of crops in the Manas River Basin showed a nonlinear upward trend, with a total increase of 287,956.64 hm² over the 30-year period, corresponding to an overall increase of 143.56%. Among all crops, cotton had the largest average annual cultivated area, accounting for 60.34% of the total cultivated area, followed by wheat and maize, with average annual cultivated areas of 18,996.92 hm² and 17,619.11 hm², respectively. The crop water footprint in the Manas River Basin increased from 4.54×10^8 m³ in 1990 to 1.52×10^9 m³ in 2020, showing a significant overall upward trend with an increase of 234.89%, and reached a peak of 1.59×10^9 m³ in 2014. The interannual trend in the crop blue water footprint during the study period was similar to that of the total crop water footprint, with a total increase of 1.04×10^9 m³ over the past 30 years. The crop green water footprint fluctuated considerably among years but generally showed an upward trend, with an increase of 32.37%. The factor with the greatest direct effect on the crop water footprint in the study area was total mechanical power, with a direct path coefficient of 0.642, followed by per capita grain output, average relative humidity, and sunshine duration. Notably, total mechanical power and per capita grain output also had substantial effects on both the crop blue water footprint and the crop green water footprint. Under future climate scenarios, the crop water footprint in the Manas River Basin followed the order SSP2-4.5 > SSP5-8.5 > SSP1-2.6. By 2100, the crop water footprint under the SSP2-4.5 scenario is projected to reach a maximum value of 2.08×10^9 m³, representing a 37.01% increase compared with 2020, whereas the SSP1-2.6 scenario represents a relatively sustainable pathway.

Overall, this study established an “assessment-driving-projection” research framework for crop water footprints and revealed the characteristics of crop water footprint

changes in the Manas River Basin from three perspectives: historical evolution, driving mechanisms, and future scenario projections. The findings provide a scientific basis for agricultural water resource management and sustainable development in arid regions. It should be noted that the gray water footprint was not included in the calculations in this study. The results primarily reflect green and blue water consumption and do not fully characterize the overall water resource pressure caused by agricultural production. In addition, future crop water footprint projections remain constrained by the accuracy of GCM precipitation simulations and the methods used to estimate sunshine duration. Future research should integrate gray water footprint calculations, high-resolution climate data, multi-model ensembles, and solar radiation or cloud cover data to further improve the reliability of comprehensive assessments and projections of crop water footprints in arid regions.

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