Postprint: SDG-Oriented Analysis of Agricultural Grey Water Footprint in the Tarim River Basin

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Abstract

The Tarim River Basin, situated in the northwestern arid region, represents a critical agricultural-pastoral transitional zone in Xinjiang. Investigating agricultural non-point source pollution in this watershed is of paramount importance for advancing green and sustainable agricultural development. Grounded in grey water footprint theory and incorporating Chinese sustainable development evaluation indicators, this study quantifies the agricultural grey water footprint, agricultural grey water footprint intensity, and agricultural grey water footprint efficiency in the Tarim River Basin from 2006 to 2020, and examines their spatiotemporal variation characteristics within the SDGs sustainable development framework. The findings reveal: (1) Since 2006, the agricultural grey water footprint in the Tarim River Basin has demonstrated an overall declining trajectory, decreasing from 6.95×10^{10} m^3 (the maximum value) in 2006 to 3.96×10^{10} m^3 (the minimum value) in 2017. The grey water footprint originating from livestock husbandry accounted for an annual average proportion of 91.3% of the basin' s agricultural grey water footprint, constituting the primary source. Kashgar Prefecture exhibited the highest contribution rate to the basin' s agricultural grey water footprint. (2) The agricultural grey water footprint intensity in the Tarim River Basin declined from 4.48×10^{4} m$^3\cdot$hm^{-2} in 2006 to 1.68×10^{4} m$^3\cdot$hm^{-2} in 2017, representing a reduction of 62.5%. Subsequent to 2012, the decline in agricultural non-point source pollution became more conspicuous in Hotan Prefecture, Kashgar Prefecture, and Kizilsu Kyrgyz Autonomous Prefecture. (3) The agricultural grey water footprint efficiency in the Tarim River Basin increased from 0.6 yuan$\cdot$m^{-3} in 2006 to 4.03 yuan$\cdot$m^{-3} in 2019. During the period 2012–2020, the agricultural grey water footprint efficiency in the Tarim River Basin exhibited a certain degree of improvement, accompanied by a decrease in the number of underdeveloped regions. Accordingly, promoting integrated crop-livestock development in agricultural regions, adjusting the livestock and poultry breeding structure, and

enhancing the resource utilization of livestock and poultry manure represent key focal points for water environment improvement in the Tarim River Basin.

Full Text

Preamble

Agricultural Grey Water Footprint Analysis in the Tarim River Basin for SDGs

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Abstract: The Tarim River Basin, located in the arid region of Northwest China, serves as a critical ecotone for agricultural and pastoral resources in Xinjiang. Investigating agricultural non-point source pollution in this basin is essential for promoting green and sustainable agricultural development. This study introduces China' s sustainable development evaluation indicators into the grey water footprint theoretical framework to calculate the agricultural grey water footprint, its intensity, and its efficiency in the Tarim River Basin from 2006 to 2020, analyzing spatiotemporal patterns within the sustainable development framework. Results indicate: (1) The agricultural grey water footprint in the Tarim River Basin has generally declined since 2006, decreasing from 6.95×10^{10} m^3 (peak value) to 3.96×10^{10} m^3 (lowest value). Livestock farming accounts for 91.3% of the basin's agricultural grey water footprint annually, representing the primary pollution source, with Kashgar Prefecture contributing the highest share. (2) Agricultural grey water footprint intensity decreased from 4.48×10^{4} $m^3 \cdot hm^{-2}$ to 1.68×10^{4} $m^3 \cdot hm^{-2}$, a reduction of 62.5%, with notable declines in agricultural non-point source pollution in Hotan and Kashgar prefectures. (3) Agricultural grey water footprint efficiency increased from 0.6 yuan $\cdot m^{-3}$ to 4.03 yuan $\cdot m^{-3}$, indicating improved efficiency, though the number of underdeveloped regions remains significant. Therefore, promoting integrated crop-livestock development, adjusting livestock breeding structures, and enhancing resource utilization of livestock manure should be prioritized for water environment improvement in the Tarim River Basin.

Keywords: agricultural grey water footprint; agricultural grey water footprint intensity; agricultural grey water footprint efficiency; sustainable development goals; Tarim River Basin

Introduction

At the 2015 UN Sustainable Development Summit, the *2030 Agenda for Sustainable Development* was adopted, proposing 17 Sustainable Development Goals (SDGs) with 169 specific targets that emphasize coordinated development among economy, society, and environment. Since then, SDGs have become a key framework guiding international development. China has actively implemented these goals, integrating the 17 SDGs with its national medium- and long-term development plans to establish China' s sustainable development evaluation system.

Water resource scarcity and pollution pose significant challenges to economic development, social stability, and environmental protection. Compared with the Millennium Development Goals, the SDGs place greater emphasis on water environment issues. Goal 6, which focuses on clean water and sanitation, has become a critical international priority, with its indicators interlinked with other goals. For instance, groundwater pollution from agricultural production under Goal 2 (zero hunger) directly relates to Goal 6' s water and sanitation targets.

Following the introduction of the grey water footprint concept by Hoekstra and Chapagain, numerous scholars have integrated SDG indicators to construct evaluation systems from various perspectives. The grey water footprint represents the freshwater volume required to dilute pollutants to natural background concentrations or existing environmental water quality standards, enabling water pollution assessment from a quantitative perspective that can be compared with water consumption. Traditional water pollution evaluation methods such as single-factor index, fuzzy comprehensive evaluation, and water pollution index methods do not associate pollution with the freshwater needed for dilution. The grey water footprint addresses this gap by incorporating this water requirement into pollution assessment.

Current research on agricultural grey water footprints primarily focuses on quantification and spatiotemporal evolution characteristics, with most domestic studies concentrating on specific crops such as corn, wheat, vegetables, fruits, and cotton. However, few studies have incorporated pollution from livestock and poultry farming, potentially leading to biased results. Research scopes have covered provinces, river basins, and countries, but studies on the Tarim River Basin remain limited, particularly those integrating agricultural grey water footprints with SDG indicators. Calculating the grey water footprint from agricultural activities in the Tarim River Basin is crucial for water pollution control, ecological restoration, and promoting green agricultural sustainability. This study examines the spatiotemporal distribution of agricultural grey water footprints in the Tarim River Basin from an SDG perspective, providing scientific support for sustainable agricultural development and water resource protection policies.

1. Materials and Methods

1.1 Study Area Overview

The Tarim River Basin (73°10 -94°05 E, 34°55 -43°08 N) is China' s largest inland river basin, covering Bayingolin Mongol Autonomous Prefecture (hereafter Bayingolin), Aksu Prefecture, Kizilsu Kirghiz Autonomous Prefecture (hereafter Kizilsu), Kashgar Prefecture, Hotan Prefecture, and several divisions of the Xinjiang Production and Construction Corps (XPCC). The basin spans 102.7$×10^{4}$ km^2 and features a continental arid climate with abundant light and heat resources, serving as Xinjiang' s primary base for grain, cotton, and livestock production. As a critical agricultural-pastoral ecotone, the basin' s agricultural water consumption accounts for approximately 95% of total water use. However, intensive human activities have exacerbated water scarcity and pollution, with agricultural endogenous pollution further intensifying these challenges.

According to the *Xinjiang Statistical Yearbook* and *Xinjiang Production and Construction Corps Statistical Yearbook* (2006–2020), the basin' s annual nitrogen fertilizer application reached 4.9$×10^{5}$ t, with livestock inventories averaging 2.43$×10^{7}$ head annually.

1.2 Calculation Methods

1.2.1 Agricultural Grey Water Footprint Planting Grey Water Footprint. Planting grey water primarily dilutes nitrogen, phosphorus, and potassium from chemical fertilizers and pesticides. Unabsorbed fertilizers infiltrate groundwater or enter surface runoff through rainfall or irrigation, causing water pollution. Given nitrogen fertilizer' s dominant proportion in chemical applications and its significant pollution share, we selected nitrogen as the evaluation indicator. Since the Tarim River Basin receives minimal precipitation and relies on irrigation, nitrogen pollution primarily affects groundwater rather than surface runoff.

Using the drinking water standard that nitrogen concentration should not exceed 10 mg·L^{-1}, we adopted Cmax = 0.01 kg·m^{-3} as the maximum allowable concentration. Based on Hoekstra' s method, the planting grey water footprint is calculated as:

$$WF_{\text{pla-grey}} = \frac{\alpha \times \text{Appl}}{C_{\max} - C_{\text{nat}}}$$

where $WF_{\text{pla-grey}}$ is the planting grey water footprint (m^3), Appl is the pure nitrogen application rate (kg), α is the nitrogen leaching rate, Cmax is the maximum allowable concentration in receiving water bodies (kg·m^{-3}), and Cnat is the natural background concentration (kg·m^{-3}).

Livestock Grey Water Footprint. Livestock grey water footprint stems from manure accumulation or field application, where pollutants enter groundwater via surface runoff. Key pollutants include COD and total nitrogen (TN). We selected TN as the key indicator, focusing on cattle, pigs, horses, camels, mules, sheep, and donkeys. The nitrogen emission from livestock is calculated as:

$$\mathrm{TN}_{\mathrm{bre}} = \sum_i \mathrm{Num}_i \times \mathrm{Day}_i \times (f_i \times n_{i,f} \times \beta_{i,f} + p_i \times n_{i,p} \times \beta_{i,p})$$

where TNbre is livestock nitrogen emission (kg), Numi is the inventory of livestock type i, Dayi is the breeding days, fi and pi are fecal and urinary excretion coefficients, ni,f and ni,p are total nitrogen contents in feces and urine, and βi,f and βi,p are loss rates.

The livestock grey water footprint is then:

$$WF_{\text{ani-grey}} = \frac{\mathrm{TN}_{\mathrm{bre}}}{C_{\max} - C_{\mathrm{nat}}}$$

Total Agricultural Grey Water Footprint. The total agricultural grey water footprint combines planting and livestock components:

$$WF_{\text{agr-grey}} = WF_{\text{pla-grey}} + WF_{\text{ani-grey}}$$

1.2.2 Agricultural Grey Water Footprint Intensity and Efficiency Intensity. Agricultural grey water footprint intensity reflects pollution pressure per unit cultivated land area:

$$\mathrm{int} = \frac{WF_{\text{agr-grey}}}{\mathrm{Land}}$$

where int is intensity ($\mathrm{m}^3 \cdot \mathrm{hm}^{-2}$) and Land is cultivated area (hm^2).

Efficiency. Efficiency reflects economic benefits per unit water pollution cost, indicating agricultural development level:

$$\mathrm{eff} = \frac{\mathrm{GDP}_{\mathrm{agr}}}{WF_{\text{agr-grey}}}$$

where eff is efficiency ($\mathrm{yuan} \cdot \mathrm{m}^{-3}$) and GDPagr is agricultural gross domestic product (yuan).

1.2.3 SDGs-Oriented Agricultural Grey Water Footprint Indicators
While agricultural grey water footprint indicators are not mandatory for SDG implementation, they contribute to assessing progress toward clean water and sustainable agriculture. We established evaluation indicators linking grey water footprint metrics with SDG targets (Table 1).

1.3 Data Sources Data on nitrogen fertilizer application, livestock numbers, cultivated area, and agricultural GDP (2006–2020) were obtained from the *Xinjiang Statistical Yearbook* and *Xinjiang Production and Construction Corps Statistical Yearbook*. Livestock excretion coefficients, nitrogen content coefficients, and loss rates were sourced from *Investigation on Pollution from Large-Scale Livestock and Poultry Breeding and Prevention Countermeasures*. Following existing research, the nitrogen leaching rate α was set at 0.1, Cmax at 0.01 kg · m^{-3}, and Cnat at 0 kg · m^{-3}.

2. Results

2.1 Spatiotemporal Changes in Agricultural Grey Water Footprint

2.1.1 Temporal Trends The Tarim River Basin' s agricultural grey water footprint showed an overall declining trend from 2006 to 2020 [Figure 1: see original paper], improving water environmental quality. This decline primarily resulted from reduced nitrogen fertilizer use and decreased total nitrogen emissions from livestock. The footprint peaked at 6.95$\times10^{10}$ m^{3} in 2006 and reached its lowest point at 3.96$\times10^{10}$ m^{3} in 2017. Livestock grey water footprint dominated, accounting for 91.3% annually, while planting grey water footprint showed an increasing trend due to expanded cultivated area and rising nitrogen application.

Planting grey water footprint declined slowly from 2006–2014, then increased gradually to 0.59$\times10^{10}$ m^{3} by 2020. Livestock grey water footprint mirrored the total agricultural trend, consistently exceeding planting grey water footprint and demonstrating that basin-wide agricultural pollution is primarily driven by livestock development.

2.1.2 Spatial Patterns Under strengthened water resource and environmental policies, particularly after the 2012 State Council' s "Three Red Lines" policy and the 2015 Water Pollution Prevention Action Plan, the basin' s agricultural water pollution improved significantly. From 2006–2012, the average annual agricultural grey water footprint was 6.50$\times10^{10}$ m^{3}, with Kashgar, Hotan, and Aksu prefectures contributing most (1.25$\times10^{10}$ m^{3}, 1.24$\times10^{10}$ m^{3}, and 1.17$\times10^{10}$ m^{3} respectively) [Figure 2: see original paper]. Kashgar' s high contribution stemmed from extensive nitrogen fertilizer use and large livestock populations, particularly high-excretion cattle and horses.

From 2013–2020, the average footprint decreased to 5.47$\times10^{10}$ m^{3}. While Kashgar, Aksu, and Hotan remained the top contributors, their shares shifted to

39.35%, 21.34%, and 15.08% respectively. Notably, Bayingolin and XPCC Division 14 showed increased footprints, while all other regions decreased. Livestock grey water footprint remained dominant at 93.90% (2006–2012) and 89.57% (2013–2020), with Kashgar, Hotan, and Aksu consistently exceeding averages.

2.2 Agricultural Grey Water Footprint Intensity

2.2.1 Temporal Trends Agricultural grey water footprint intensity reflects pollution per unit cultivated area. Basin-wide intensity decreased substantially from 4.48×10^{4} $m^3 \cdot hm^{-2}$ in 2006 to 1.68×10^{4} $m^3 \cdot hm^{-2}$ in 2017, a 62.5% reduction [Figure 3: see original paper]. This improvement followed adjustments in livestock structure: although total livestock numbers rose slightly, large animals (cattle, camels, horses, donkeys) decreased from 1.80×10^{6} to 0.92×10^{6} head (a 48.86% drop), while small animals (sheep, pigs) increased minimally. Though nitrogen application rates rose from 198.23 to 288.73 $kg \cdot hm^{-2}$ (a 31.34% increase), the dominance of livestock in the total footprint ensured overall intensity reduction.

2.2.2 Spatial Patterns From 2006–2012, average intensity was 3.53×10^{4} $m^3 \cdot hm^{-2}$, with Kizilsu showing the highest intensity (9.39×10^{4} $m^3 \cdot hm^{-2}$) and XPCC Division 1 the lowest (1.05×10^{4} $m^3 \cdot hm^{-2}$). Using these extremes as reference, we classified pollution levels into five grades: severe, moderately severe, moderate, light-moderate, and light [Figure 4: see original paper]. Kizilsu was severe; Hotan moderately severe; Kashgar moderate; and Divisions 1, 2, 3, 14, Bayingolin, and Aksu light.

From 2013–2020, average intensity fell to 2.52×10^{4} $m^3 \cdot hm^{-2}$ (28.61% reduction). Kizilsu remained highest but dropped to 8.02×10^{4} $m^3 \cdot hm^{-2}$ (14.74% decrease), while Division 1 stayed lowest at 8.10×10^{3} $m^3 \cdot hm^{-2}$ (23.62% decrease). The classification shifted: only Kizilsu remained moderately severe; Hotan and Kashgar became light-moderate; all others were light pollution zones, indicating basin-wide improvement.

2.3 Agricultural Grey Water Footprint Efficiency

2.3.1 Temporal Trends Agricultural grey water footprint efficiency reflects agricultural development level and the coordination between economic growth and groundwater environmental quality. Basin efficiency increased overall from 0.6 $yuan \cdot m^{-3}$ in 2006 to 4.03 $yuan \cdot m^{-3}$ in 2019 [Figure 5: see original paper]. Planting efficiency (average 9.9 $yuan \cdot m^{-3}$) far exceeded livestock efficiency (average 1.2 $yuan \cdot m^{-3}$), with planting contributing over 85% of agricultural GDP. This disparity reflects the basin' s traditional farming-dominated structure and natural constraints favoring crop production.

2.3.2 Spatial Patterns From 2006–2012, average efficiency was 2.2 $yuan \cdot m^{-3}$, with XPCC Division 1 highest (6.6 $yuan \cdot m^{-3}$) and Kizilsu lowest (0.6

yuan · m^{-3}). Regions exceeding the average included Bayingolin, Aksu, and XPCC Divisions 1, 2, 3, and 14. From 2013-2020, average efficiency rose to 6.2 yuan · m^{-3} (183.33% growth), with Division 1 still highest (16.5 yuan · m^{-3}) and Kizilsu lowest (1.7 yuan · m^{-3}). All regions showed growth exceeding 93.20%, with Division 14 growing most dramatically at 287.97% [Figure 6: see original paper].

Using the basin' s maximum and minimum efficiency values as reference, we classified development levels into five categories: underdeveloped, less developed, moderately developed, developed, and highly developed. In 2006–2012, only Division 1 was developed; Divisions 2 and 3 were less developed; Division 14, Bayingolin, and Kizilsu were underdeveloped; and Kashgar, Aksu, and Hotan were highly underdeveloped. By 2013–2020, Division 1 became highly developed; Divisions 2 and 3 moderately developed; Division 14 developed; Bayingolin less developed; while Kizilsu, Kashgar, Aksu, and Hotan remained underdeveloped, though with improved efficiency.

3. Discussion

This study confirms that livestock manure nitrogen emissions constitute the primary source of agricultural grey water footprint in the Tarim River Basin. Huang et al. found that Xinjiang' s livestock grey water footprint creates 14 times more environmental pressure than planting. The basin' s numerous but low-scale livestock operations prevent harmless and resourceful manure treatment, causing severe water pollution. Additionally, slow integration between crop farming and livestock husbandry hinders resource utilization of agricultural waste. Zhao et al. noted that crop-livestock coupling in the Tarim River Basin remains at a primary stage, with livestock failing to leverage crop farming advantages for transitioning to circular agriculture.

Planting structure diversification from grain-dominated to cotton, fruit, and diversified grain development increased economic crops and fertilizer dependence. Yan et al. found crop yields in the basin depend heavily on fertilizer application. Despite rising nitrogen rates, improved fertilizer efficiency and livestock structure adjustments reduced total nitrogen emissions, enhancing water environment quality and advancing SDGs 6 and 2.

Post-2015, Xinjiang aligned with national SDG plans, implementing policies for planting pollution prevention and livestock waste management. The basin' s livestock industry scaled up, manure treatment standardized, and farmer organic fertilizer usage increased, reducing nitrogen application. These measures, combined with agricultural technological advances, decreased nitrogen emissions and improved ecological water environment.

Spatial disparities remain pronounced. Kizilsu, Kashgar, and Hotan show high grey water footprints but low efficiency, requiring targeted agricultural layout optimization. XPCC divisions demonstrate higher efficiency due to intensive, large-scale modern agriculture with advanced breeding and cultivation technologies, smaller livestock populations, and lower nitrogen emissions.

4. Conclusions

(1) The Tarim River Basin' s agricultural grey water footprint declined overall from 2006–2020, primarily due to reduced large livestock numbers. Livestock accounts for 91.3% of the agricultural grey water footprint, with planting contributing 8.7%. Achieving SDG targets requires optimizing livestock scale and structure while enhancing manure resource utilization and cycling. Promoting integrated crop-livestock development and circular agriculture is essential for green, sustainable development.

(2) Agricultural grey water footprint intensity decreased significantly, but spatial heterogeneity persists. Kizilsu, Kashgar, and Hotan require prioritized attention for agricultural layout optimization tailored to local conditions.

(3) Agricultural grey water footprint efficiency increased from 0.6 yuan $\cdot$ m^{-3} (2006) to 4.03 yuan $\cdot$ m^{-3} (2019), with XPCC divisions showing superior performance. The basin has preliminarily transitioned from traditional to sustainable agriculture, achieving coordinated production, living, and ecological benefits. However, the number of underdeveloped regions remains substantial, necessitating continued efforts to enhance agricultural economic development while protecting water environmental quality.

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Note: Figure translations are in progress. See original paper for figures.