

Article

Gaps between Rice Actual and Potential Yields Based on the VPM and GAEZ Models in Heilongjiang Province, China

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Abstract: Heilongjiang Province is a significant region for grain production and serves as a crucial commodity grain production base in China. In recent years, due to the threat of declining cropland quality and quantity, coupled with the increasingly prominent demand for grain, there is an urgent need to enhance rice yields in Heilongjiang Province. It is imperative to accurately identify the gaps between actual and potential grain yields and effectively implement yield-enhancing measures in regions with significant yield gaps. This study aimed to determine the rice reproductive periods of Heilongjiang Province for 2000, 2010, and 2020, estimate the rice actual yields using the Vegetation Photosynthesis Model (VPM), simulate the rice potential yields based on the Global Agro-Ecological Zones (GAEZ) Model, and then identify the rice yield gaps at the pixel level by calculating the rice absolute yield gap (AYG) and relative yield gap (RYG). Additionally, yield-enhancing measures were proposed for regions with significant yield gaps. The results were as follows. (1) The rice reproductive periods of Heilongjiang Province for 2000, 2010, and 2020 were determined as days 153~249, days 145~249, and days 137~249. (2) The mean rice actual yield and potential yields decreased by 1222 and 5941 kg ha⁻¹ during the 2000–2020 period, respectively, and the total actual and potential production increased by 3.75 and 1.70 million tons in Heilongjiang Province, respectively. (3) The rice AYG and RYG in the Sanjiang Plain region, such as Jixi City, Hegang City, and Jiamusi City were relatively large compared to other regions for the three years, and the rice yield gaps continued to decrease during the 2000–2020 period. (4) With regard to the Sanjiang Plain region with a large rice yield gap, this study proposes measures to narrow the rice yield gap by establishing ecological protection forests on cropland, transforming low- and middle-yielding fields, increasing agricultural science and technology inputs, selecting better rice cultivars, etc., which are important for ensuring food security.

Keywords: rice reproductive period; absolute yield gap (AYG); relative yield gap (RYG); yield-enhancing measures; food security



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1. Introduction

Heilongjiang Province plays a significant role in agriculture as it encompasses vast areas of the Songnun Plain, Sanjiang Plain, and Muling River-Xingkai Lake Plain, all of which are characterized by fertile black calcium soils [1]. Rice stands out as the primary grain crop cultivated in Heilongjiang Province. However, in recent years, inadequate land management practices and excessive utilization of fertilizers and pesticides have led to a significant degradation in soil quality. The once fertile black soil has progressively diminished, resulting in a substantial decline in farmland productivity. This situation poses severe constraints on the sustainable development of the agricultural economy [2]. Given the threat of diminishing cropland quality, coupled with an increasing demand for food security, there is limited potential to boost grain production by expanding cultivation

areas [3]. Therefore, it is imperative to optimize grain production capacity, enhance yields, and narrow the gaps between actual and potential yields as a viable approach to ensure sufficient grain supply and maintain a competitive edge in the global market. The disparities between crop actual and potential yields in different regions of Heilongjiang Province should be thoroughly investigated, and tailored measures to enhance yields in regions with significant yield gaps should be proposed based on local conditions, thus ensuring food security in Heilongjiang Province.

In recent years, scholars have devoted significant attention to food security, leading to extensive research on the estimation of crop actual yields, simulation of crop potential yields, and measures for reducing yield gaps [4–6]. Crop actual yields refer to the quantity of harvested grains from arable plots and are influenced by regional climate conditions, availability and quality of cropland, human inputs, as well as management constraints. The methods commonly employed to obtain grain actual yields can be categorized into statistical survey methods, statistical forecasting methods, crop growth simulation forecasting methods, and yield estimation methods based on remote sensing and GIS [7]. Statistical survey methods refer to the methods of extrapolating the total output from the survey of partial output data of the total population. For example, the statistical sampling method is commonly used. Statistical forecasting methods refer to crop yield forecasting methods based on the characteristics or behaviors of crop production systems and based on probability theory, statistics, and operational research. It is usually based on environmental conditions, agricultural production inputs, and other factors to establish a forecast model. By contrast, crop growth simulation and remote sensing yield estimation are novel techniques developed in conjunction with computer, information, and space technologies. Among these methods, remote sensing yield estimation has distinct advantages due to its broad research scope, rich data resources, and strong visual presentation [8], and has good application prospects. For crop remote sensing yield estimation, researchers have also been exploring various methods. For instance, the principle of estimating crop yields based on remote sensing statistical models involves directly utilizing spectral vegetation indices or canopy remote sensing inversion parameters to establish correlations with crop yields. This involves establishing correlations between normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and leaf area index (LAI) with crop yields [9,10], which is a straightforward and practical approach, but it may overlook certain yield formation mechanisms and pose challenges to ensuring accuracy. Therefore, the utilization of semi-mechanical models for remote sensing yield estimation has progressively gained widespread acceptance, such as the Light Use Efficiency (LUE) model initially proposed by Monteith in 1972. This model is based on physiological and ecological principles, whereby crops utilize solar energy to acquire the necessary resources for growth and development. It employs photosynthetically effective radiation absorbed by the vegetation canopy and light use efficiency to estimate gross primary productivity (GPP) or net primary productivity (NPP) through an energy balance approach, which is then translated into crop yields [7]. Currently, common LUE models include the Carnegie-Ames-Stanford Approach (CASA) model [11], Global Production Efficiency Model (GLO_PEM) [12], Eddy Covariance-Light Use Efficiency (EC-LUE) model [13], vegetation photosynthesis model (VPM) model [14]. The LUE models offer numerous advantages. First, they are user-friendly and easily operable. Second, certain parameters (such as photosynthetic effective radiation) can be acquired through remote sensing techniques, thereby reducing the need for extensive ground measurements. Third, remote sensing data have a broad coverage that can satisfy the requirements of regional-scale yield estimation and enable surface-to-point analysis, making it highly versatile in various applications.

Potential crop yields represent the maximum achievable grain yield under prevailing natural conditions (including climate, soil, terrain, etc.) and optimal levels of human inputs and management within a specific region [15,16]. Through a step-by-step correction method, models have been developed to estimate photosynthetic potential yield for optimal grain yield under solar radiation stress only [17], light-temperature potential yield for optimal

grain yield under both solar radiation and temperature stress [18], climatic potential yield for optimum grain yield under light-temperature-water stress [19], and climatic soil potential yield with increased soil condition stress [20]. In the 1970s, the Agro-Ecological Zones (AEZ) model was jointly developed by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA), which later evolved into the Global AEZ (GAEZ) model in 2002. The model offers standardized crop-related parameters and environmental matching procedures for determining the crop limitations under current climate, soil, and terrain conditions with assumed levels of inputs and management. It employs a stepwise correction approach to obtain the crop potential yield under combined effects of light, temperature, precipitation, CO₂ concentration, soil, and terrain when human input and management are at optimal levels [21,22]. The model has gained popularity as a mainstream approach for estimating potential grain yield due to its rigorous methodology, accessibility of fundamental data, and ease of computation [23–27]. Moreover, the applicability of the model in China has been extensively validated, and its relevant parameters have undergone revision [28,29].

In terms of narrowing the grain yield gaps, scholars have predominantly recommended the selection of high-yielding cultivars [30,31], improved water and fertilizer management practices [32], and increased utilization of agricultural machinery [33]. In addition, Denison argued that the improvement in potential yield comes mainly from shifting past selection for individual plant competitiveness and that identification of the minimum agronomic trade-offs caused can provide further improvements in yield potential [34]. Fischer and Connor proposed measures to remove serious institutional and infrastructural barriers faced by farmers [35].

Previous studies on grain yield have become increasingly sophisticated, resulting in improved precision and accuracy of results. However, these studies have often focused solely on either actual yield estimation or potential yield simulation without effectively integrating the two aspects. Although some studies have addressed grain yield gaps, they have primarily relied on administrative region-level statistics for actual yields and simulated potential yields within those regions (provinces, cities, or counties) to calculate the yield gap results. This failed to account for spatial heterogeneity within administrative regions. Therefore, the highlight of this study is to estimate the rice actual yields in Heilongjiang Province using the VPM model and to determine the rice potential yields under optimal levels of human inputs and management based on the GAEZ model for 2000, 2010, and 2020. Based on the two models, we can obtain rice actual and potential yields with a spatial resolution of 500 m. By comparing the rice actual yields with the potential yields, the rice yield gaps with the spatial resolution of 500 m can be obtained, which represent the yield increase space, thus realizing the spatialization of rice yield gaps in Heilongjiang Province at the pixel level. The results of this study can enhance the field of grain yield gap research and effectively capture the spatial heterogeneity of the grain yield gaps so that yield increase suggestions can be made for regions with large yield gaps according to local conditions. This is crucial in optimizing agricultural production in Heilongjiang Province, promoting efficient land use practices, and ensuring food security.

2. Materials and Methods

2.1. Study Area

In this study, Heilongjiang Province was selected as the study area. It is located in Northeast China, covering a total area of about 473 thousand km² [2] (Figure 1). The province spans longitudes ranging from 121°11′ to 135°05′ E and latitudes between 43°26′ and 53°33′ N. The landscape of Heilongjiang is characterized by “five mountains, one water, one grass, and three fields”, with a general trend of high terrain in the northwest, north, and southeast, and low terrain in the northeast and southwest [36]. Heilongjiang Province spans four major river systems, including the Heilongjiang River, Ussuri River, Songhua River, and Suifen River. The region exhibits a cold-temperate and temperate continental monsoon climate, characterized by an average annual temperature ranging from 1°C to 6°C,

annual precipitation between 500 and 1000 mm, and a mean annual relative humidity of 60~70%. In 2021, the total cropland area in Heilongjiang Province was 171.95 thousand km², accounting for 36.35% of the total area, with paddy fields accounting for 48.09 thousand km². Heilongjiang Province boasts abundant chernozem soil, rendering it a pivotal grain production hub and commodity grain base in China. Rice, as one of the primary cereal crops, is cultivated annually.

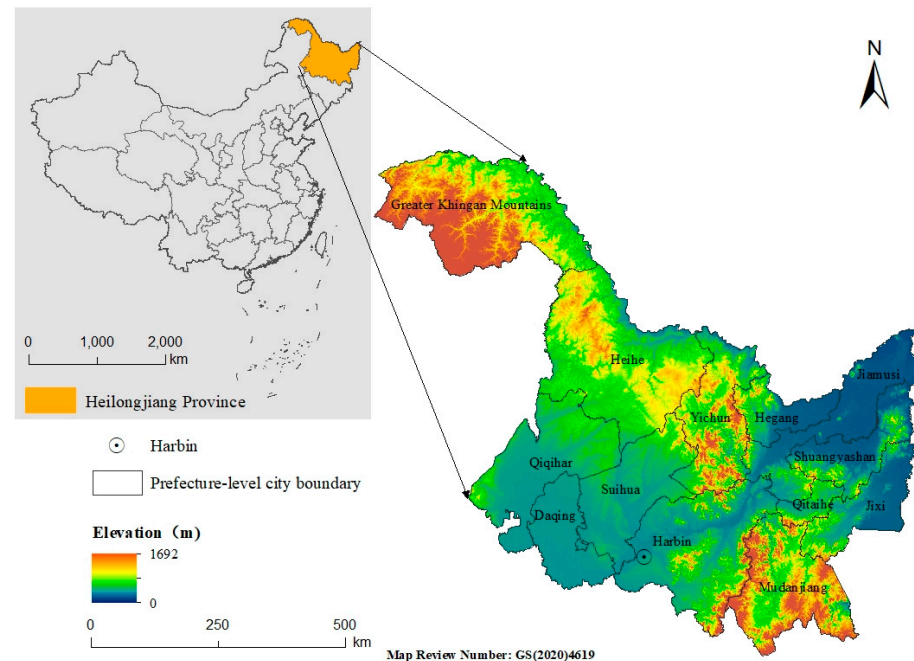


Figure 1. Location of the study area.

2.2. Data Sources and Processing

The data required for this study comprise the rice reproductive period data, land use remote sensing monitoring data, cumulative *GPP* data during the rice reproductive period, monthly climate data, and rice actual yield statistics in each prefecture-level city for 2000, 2010, and 2020, as well as soil and terrain data in Heilongjiang Province, which are shown in Table 1.

The rice reproductive period data in Heilongjiang Province in the years 2000, 2010, and 2020 were extracted from the 1 km phenological dataset of the three major national grain crops (rice, maize, and wheat) from 2000 to 2019 that was published by Zhang's research group [37]. This dataset represents the spatial distribution of different Julian days for transplanting, tasseling, and maturity of the three major grain crops in China from 2000 to 2019 with a spatial resolution of 1 km. The spatial distribution of rice transplanting and maturing Julian days in Heilongjiang Province for the years 2000, 2010, and 2019 was derived from the aforementioned dataset, and the value of the pixels with the highest number of rice transplanting and maturing Julian days in each year was used as the rice reproductive period in Heilongjiang Province in the corresponding year (with reference to the 2019 data serving as a basis for estimating the 2020 rice reproductive period). Finally, the rice reproductive periods of Heilongjiang Province for 2000, 2010, and 2020 were determined as days 153~249, days 145~249, and days 137~249.

The land use remote sensing monitoring data for 2000, 2010, and 2020 in Heilongjiang Province were acquired from the Chinese land use remote sensing monitoring dataset (with a spatial resolution of 30 m) provided by the Resource and Environment Science and Data Centre Platform of the Chinese Academy of Sciences (<https://www.resdc.cn/> (accessed on 1 June 2023)). From this dataset, the spatial distribution of the paddy field for 2000,

2010, and 2020 in Heilongjiang Province was extracted and processed into the percentage of paddy fields with a spatial resolution of 500 m.

Table 1. Data sources in this study.

Dataset	Derived Variable	Year	Original Spatial Resolution	Final Spatial Resolution	Reference URL
Rice reproductive period data	Rice_TR and Rice_MA	2000, 2010, and 2019	1 km	1 km	https://doi.org/10.6084/m9.figshare.8313530.v7 (accessed on 1 June 2023)
Land use remote sensing monitoring data	Paddy field	2000, 2010, and 2020	30 m	500 m	https://www.resdc.cn/ (accessed on 1 June 2023)
Cumulative GPP data	GPP	2000, 2010, and 2020	0.05°	500 m	https://data.casearth.cn/sdo/detail/5c19a5660600cf2a3c557ad3 (accessed on 1 June 2023)
Climate data	Mean maximum temperature, Mean minimum temperature, etc.	2000, 2010, and 2020	—	10 km	http://www.nmic.cn/ (accessed on 1 June 2023)
Rice production statistics	Rice production for each prefecture-level city	2000, 2010, and 2020	—	—	—
Soil data	Soil classes, Soil attributes, etc.	—	—	1 km	http://vdb3.soil.csdb.cn/extend/jsp/introduction (accessed on 1 June 2023)
Terrain data	Elevation, Slope, and Aspect	—	90 m	1 km	https://www.resdc.cn/ (accessed on 1 June 2023)

The cumulative GPP data for 2000, 2010, and 2020 within the rice reproductive periods in Heilongjiang Province were obtained from the global 0.05° GPP dataset based on the VPM model from 2000 to 2016 published by Xiao's research group [38]. The dataset provides global 0.05° GPP data, averaged every 8 days from 2000 to 2016 based on the VPM model, from which the data for 2000 and 2010 within Heilongjiang were extracted and resampled to 500 m. The GPP data averaged every 8 days for 2020 based on the VPM model were also shared by Xiao's research group.

The monthly climate data in Heilongjiang Province for 2000, 2010, and 2020 are seven monthly climate variables, including mean maximum temperature, mean minimum temperature, cumulative precipitation, cumulative net solar radiation, mean relative humidity, mean wind speed, and wet day frequency (number of days with precipitation exceeding 0.2 mm per month). The raw observations for the above seven climate variables were obtained from the monthly observations of 25 meteorological stations covering Heilongjiang Province in the China Meteorological Data Network (<http://www.nmic.cn/> (accessed on 1 June 2023)). Based on the DEM of Heilongjiang Province, the observations from the raw meteorological stations were interpolated to a continuous raster surface with 10 km spatial resolution using ANUSPLIN v4.2 software.

The rice production statistics for each prefecture-level city in Heilongjiang Province for 2000, 2010, and 2020 were obtained from the Heilongjiang Provincial Statistical Yearbook.

The soil data in Heilongjiang Province were obtained from the 1:1,000,000 Chinese soil database provided by the Nanjing Soil Institute of the Chinese Academy of Sciences and processed into the raster data with a spatial resolution of 1 km.

The terrain data are the DEM data with a spatial resolution of 90 m, derived from the Shuttle Radar Topography Mission (SRTM) C-band data, and further processed into slope and aspect data.

2.3. Methods

2.3.1. Estimation of Rice Actual Yields

In this study, the VPM model was used to estimate the cumulative *GPP* over the rice reproductive period in Heilongjiang Province, which was then translated into rice actual yields. The VPM model is one of the LUE models for estimating *GPP* based on remote sensing data by Xiao et al. [14], with the following Equations (1)–(4):

$$GPP = \varepsilon_g \cdot FPAR_{chl} \cdot PAR \quad (1)$$

$$\varepsilon_g = \varepsilon_0 \cdot T_{scalar} \cdot W_{scalar} \cdot P_{scalar} \quad (2)$$

$$T_{scalar} = \frac{(T - T_{min}) \cdot (T - T_{max})}{(T - T_{min}) \cdot (T - T_{max}) - (T - T_{opt})^2} \quad (3)$$

$$W_{scalar} = \frac{1 + LSWI}{1 + LSWI_{max}} \quad (4)$$

where ε_g is the light use efficiency (gC MJ^{-1}), ε_0 is the maximum light use efficiency (gC MJ^{-1}), PAR is the photosynthetically effective radiation (MJ m^{-2}), $FPAR_{chl}$ is the ratio of photosynthetically effective radiation absorbed by vegetation for photosynthesis (%), T_{scalar} , W_{scalar} , and P_{scalar} are the modulation coefficients of temperature, moisture, and crop phenology on the maximum light use efficiency, respectively, T_{min} , T_{max} , and T_{opt} are the minimum, maximum, and optimum temperatures for photosynthesis of crops, respectively, $LSWI$ is the terrestrial moisture index in each pixel during the crop reproductive period, and $LSWI_{max}$ is the maximum terrestrial moisture index in each pixel during the crop reproductive period.

The *GPP* data estimated by the VPM model for each 8-day period for 2000, 2010, and 2020 shared by Xiao's research group were directly utilized. These data were combined with the rice reproductive periods in Heilongjiang Province (days 153~249 in 2000, days 145~249 in 2010, and days 137~249 in 2020) to filter out the *GPP* within the rice reproductive periods in the corresponding years. Subsequently, this filtered *GPP* was multiplied by eight and summed together to obtain the cumulative *GPP* within the rice reproductive periods in Heilongjiang Province for 2000, 2010, and 2020 (with a spatial resolution of 500 m). However, the cumulative *GPP* in each pixel is the sum of the *GPP* obtained from various green vegetation. Therefore, to obtain the cumulative *GPP* from rice growth in each pixel, the cumulative *GPP* was obtained from rice growth in each pixel by multiplying the percentage of paddy field with a spatial resolution of 500 m for three years with the cumulative *GPP* data.

Next, the cumulative *NPP* of rice growth in Heilongjiang Province during the three-year rice reproductive period was calculated as the difference between *GPP* accumulated through vegetation photosynthesis and organic matter consumed by autotrophic respiration. The Equation (5) is:

$$NPP = GPP - Ra \quad (5)$$

where Ra is the organic matter consumed by vegetation autotrophic respiration. The ratio coefficient of organic matter consumed by autotrophic respiration to *GPP* accumulated by photosynthesis during crop growth was considered to be about 0.42 in previous studies [39]. Therefore, in this study, the Equation (6) is:

$$NPP = 0.58 \times GPP \quad (6)$$

the cumulative *NPP* during the rice reproductive periods in Heilongjiang Province for 2000, 2010, and 2020 can be determined based on the aforementioned formulas.

Next, the cumulative *NPP* during the rice reproductive periods should be transformed into rice actual yields. The Equation (7) for *NPP* and crop yields is as follows [40]:

$$NPP = 0.1 \times \left(\frac{\sum_{i=1}^N \frac{Y_i \times (1 - MC_i) \times 0.45 \frac{gC}{g}}{HI_i \times fAG_i} \times Harv_Area_i}{\sum_{i=1}^N Harv_Area_i} \right) \quad (7)$$

where *I* is the crop type within the land unit, $i = 1 \dots N$, Y_i is the yield of crop *i* within the land unit ($kg\ ha^{-1}$), MC_i is the moisture content of the harvested portion of crop *i* (%), *Harv_Area_i* is the harvested area of crop *i* within the land unit (m^2), HI_i is the harvest index of crop *i*, and *fAG* is the mass of crop *i* allocated to the aboveground part (%). In this study, where the cumulative *NPP* during the rice reproductive periods is known and the land unit is known to contain only one crop, i.e., rice, the Equation (8) for converting cumulative *NPP* to rice yield ($kg\ ha^{-1}$) is as follows:

$$Y_i = 10 \times \frac{NPP \times HI_i \times fAG_i}{(1 - MC_i) \times 0.45} \quad (8)$$

In a study by Lobell et al., the values of *MC*, *HI*, and *fAG* of rice were 9, 0.4, and 0.8 respectively [41]. Thus, we can derive the rice yields in Heilongjiang Province during the rice reproductive periods in 2000 using Equation (8) and obtain the spatial distribution with the spatial resolution of 500 m. In order to validate the accuracy of the VPM model, a linear regression analysis was performed to compare the rice actual yield in each county of Heilongjiang Province in 2000 estimated by the VPM model with the rice yield statistical data from each county of Heilongjiang Province as reported in the Statistical Yearbook. The coefficient of determination (R^2) was then calculated. After the accuracy verification of the model was passed, the rice actual yields with the spatial resolution of 500 m during the rice reproductive periods for 2010 and 2020 in Heilongjiang Province were then estimated.

We presented the spatial distribution of rice actual yields for the three years and analyzed the spatio-temporal distribution characteristics. Next, the spatial distribution of rice actual yields in 2000 and 2010, 2010 and 2020, and 2000 and 2020 were respectively compared to analyze the spatio-temporal evolution characteristics of rice actual yields during the 2000–2010, 2010–2020, and 2000–2020 periods.

2.3.2. Simulation of Rice Potential Yields

This study utilized the GAEZ model to simulate rice potential yields in Heilongjiang Province for 2000, 2010, and 2020. The AEZ model was jointly developed by the FAO and IIASA in the 1970s, which later evolved into the GAEZ model in 2002. The latest version of the GAEZ database (GAEZ v4) was developed in 2022. The model is a simple and reliable tool that provides standardized crop-related parameters and environmental matching procedures to determine the crop limitations of current climate, soil, and terrain conditions at assumed input and management levels [41]. The GAEZ model calculates the photosynthetic potential yields of crops based on crop growth parameters (such as LAI and HI) and light radiation conditions, followed by calculating the light-temperature potential yields in combination with precipitation and temperature conditions. The model then incorporates soil water limitations to calculate light-temperature-water potential yields, and then factors in agricultural hazards such as pests, diseases, and frosts to determine climate potential yields. It further combines constraints of soil and terrain conditions to estimate land potential yields. Finally, the percentage of paddy fields is taken into account to calculate the ultimate crop potential yields [21,22]. Overall, each component assumes the highest level of human input. The applicability of the model in China has been extensively validated, and its relevant parameters have undergone revision [28,29].

In this study, the variables input into the GAEZ model included the grid surfaces of 7 climate factors (mean maximum temperature, mean minimum temperature, cumulative precipitation, cumulative net solar radiation, mean relative humidity, mean wind speed,

and wet day frequency) interpolated by Anusplin v4.2 for 2000, 2010, and 2020, with the spatial resolution of 10 km, soil (soil classes, soil attributes, etc.) and terrain (elevation, slope, aspect) data with the spatial resolution of 1 km, and percentage of paddy field data with the spatial resolution of 500 m for 2000, 2010, and 2020. Finally, the rice potential yields of Heilongjiang Province for 2000, 2010, and 2020 were simulated.

We presented the spatial distribution of rice potential yields for the three years and analyzed the spatio-temporal distribution characteristics. Next, the spatial distribution of rice potential yields in 2000 and 2010, 2010 and 2020, 2000 and 2020 were respectively compared to analyze the spatio-temporal evolution characteristics of rice potential yields during the 2000–2010, 2010–2020, and 2000–2020 periods.

2.3.3. Analysis of Rice Yield Gaps

First, the Python v3.12.2 was applied to analyze the correlation between the rice actual yields of the three years estimated by the VPM model and the rice potential yields simulated by the GAEZ model to explore whether the two were consistent in high and low distribution. Subsequently, in order to characterize regional variations of rice yield gaps in Heilongjiang Province, we calculated the absolute yield gap (AYG) and relative yield gap (RYG) of rice actual and potential yields for the three years, respectively. The AYG is the absolute gap between rice potential and actual yields, while the RYG represents the multiple of potential yields relative to actual yields. Compared with the AYG, the RYG can measure rice yield gaps more accurately due to the different crop production capacities in different regions. The Equations (9) and (10) of AYG and RYG are as follows:

$$AYG = Y_{potential} - Y_{actual} \quad (9)$$

$$RYG = \frac{Y_{potential} - Y_{actual}}{Y_{actual}} \times 100 \quad (10)$$

where Y_{actual} (kg ha^{-1}) represents the rice actual yields estimated by the VPM model and $Y_{potential}$ (kg ha^{-1}) represents the rice potential yields simulated by the GAEZ model.

We analyzed the spatio-temporal distribution characteristics of the AYG and RYG for 2000, 2010, and 2020 in Heilongjiang Province, respectively, and identified the regions with large yield gaps. In order to further explore the difference between the AYG and RYG in different prefecture-level cities, we calculated the mean AYG and RYG in different prefecture-level cities of Heilongjiang Province for the three years and identified which cities had the large yield gaps.

3. Results

3.1. Rice Actual Yields in Heilongjiang Province for 2000, 2010, and 2020

3.1.1. Rice Actual Yields in 2000

The total rice actual production in Heilongjiang Province estimated by the VPM model in 2000 was 5.17 million tons. With a paddy field area of 1.47 million ha in 2000, the mean rice actual yield was calculated to be 3526 kg ha^{-1} . Analysis of the spatial distribution of rice actual yields in Heilongjiang Province in 2000 revealed higher rice actual yields in the northeastern regions compared to other regions (Figure 2). The regions exhibiting rice yields ranging from 2000 to approximately 3000 kg ha^{-1} were found in Shuangyashan City, Hegang City, and Jixi City, and in some regions, the rice yields were higher than 3000 kg ha^{-1} .

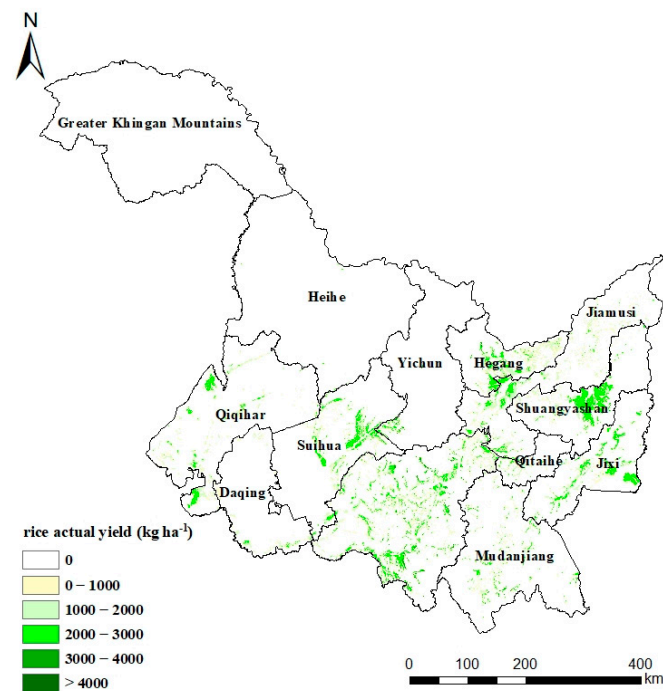


Figure 2. Spatial distribution of rice actual yields in 2000 based on the Vegetation Photosynthesis Model (VPM).

3.1.2. Accuracy Verification of the VPM Model

A linear regression analysis was performed to establish a relationship between the estimated rice actual yields and rice yields in 98 counties of Heilongjiang Province as reported in the Statistical Yearbook. The R^2 was 0.84, $p \leq 0.01$, $RMSE = 257.59 \text{ kg ha}^{-1}$, indicating a good correlation (Figure 3). Consequently, the trend in estimated rice actual yields reflected the trend in rice yields in the Statistical Yearbook. This result could be used to verify the accuracy of the VPM model.

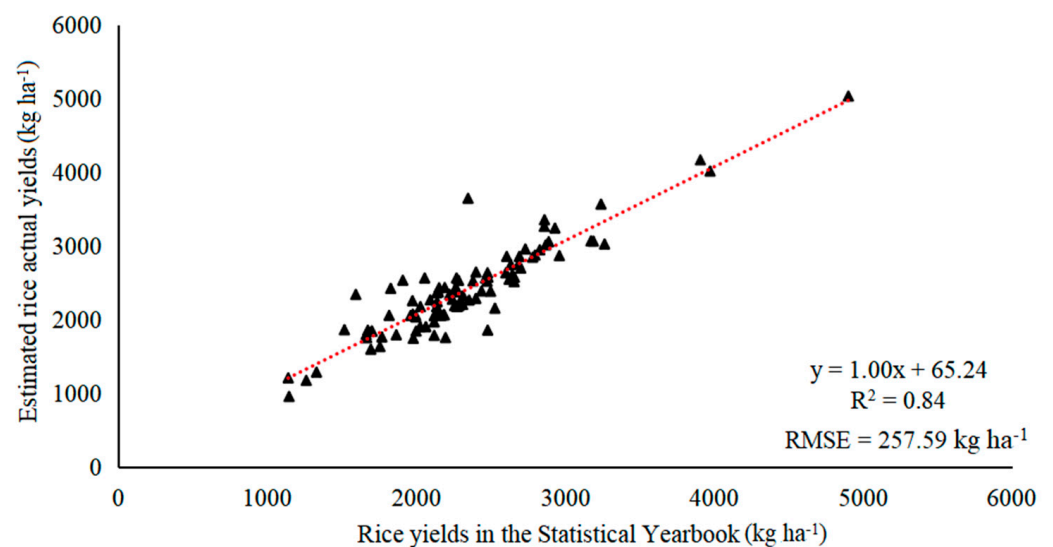


Figure 3. Comparison between estimated rice actual yields and rice yields in the Statistical Yearbook in 2000.

3.1.3. Spatio-Temporal Evolution Characteristics of Rice Actual Yields during the 2000–2020 Period

Figure 4 shows the spatial distribution of rice actual yield changes in Heilongjiang Province during the 2000–2020 period. From 2000 to 2010, the mean rice actual yield decreased by 1084 kg ha^{-1} while the total rice actual production increased by 2.49 million tons because the area of the paddy field increased by 514,700 ha (Figure 4a). The variation in rice actual yields across different regions of Heilongjiang Province was complex, with a great number of regions experiencing an increase rather than a decrease in rice actual yields. The rice actual yields increased by $1000\text{--}2000 \text{ kg ha}^{-1}$ in most regions, with the exception of the northeast of Jiamusi City and Jixi City, where the actual yield increased by more than 2000 kg ha^{-1} . Conversely, there were significant decreases in rice actual yields exceeding 2000 kg ha^{-1} in the center of Shuangyashan City and Hegang City, while most regions of Harbin City and Qitaihe City experienced a decrease of less than 1000 kg ha^{-1} .

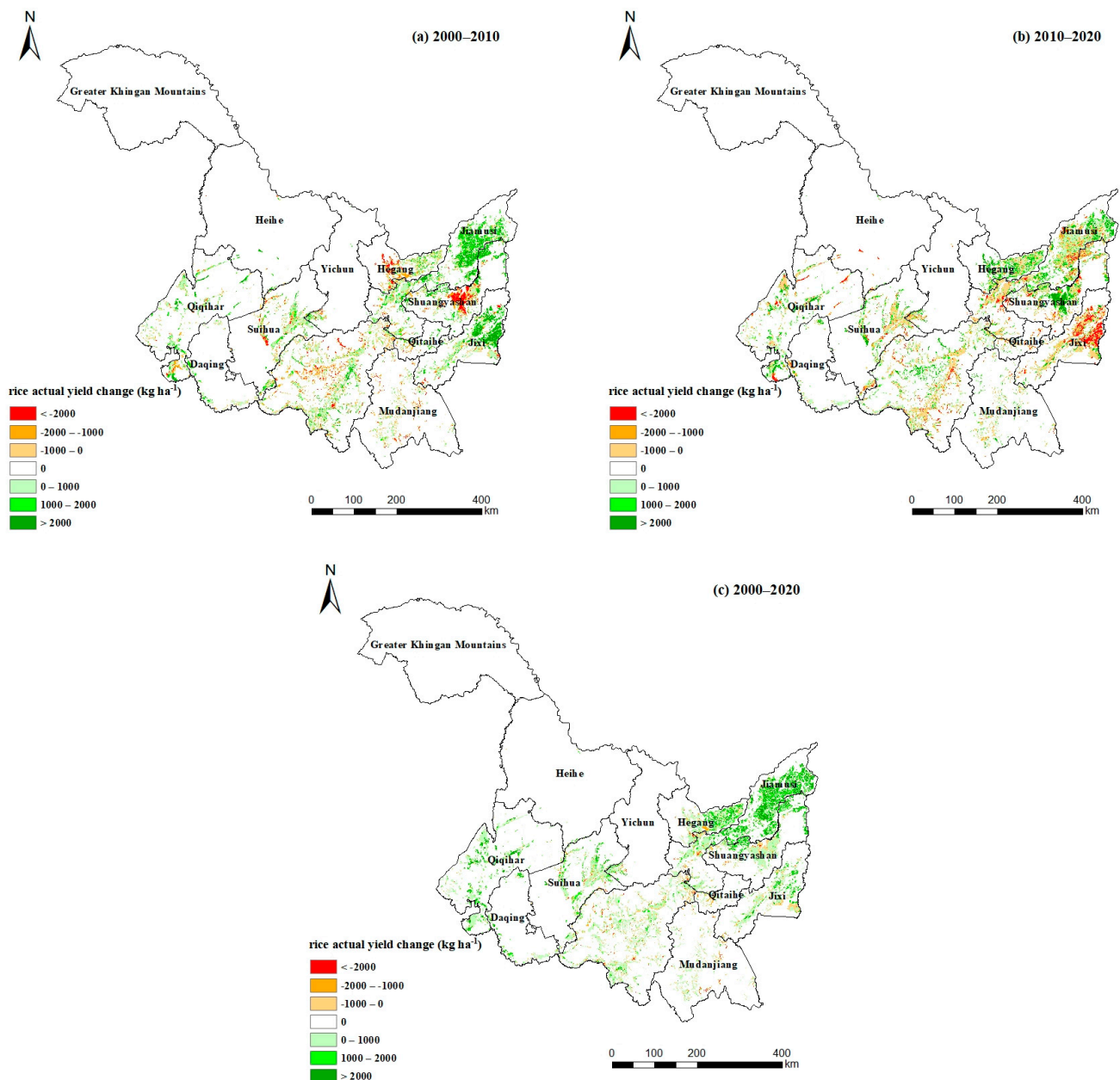


Figure 4. Spatial distribution of rice actual yield changes for the three periods.

Between 2010 and 2020, the mean rice actual yield decreased by 138 kg ha^{-1} while the total rice actual production increased by 1.26 million tons because the area of paddy fields increased by 499,900 ha (Figure 4b). Across different regions, changes in actual yield varied with more regions experiencing a decrease than an increase. In most regions, the rice actual yields decreased by less than 1000 kg ha^{-1} , but in northeastern Jixi City, the rice actual yields decreased by more than 2000 kg ha^{-1} . Conversely, in almost half of Jiamusi City, the rice actual yields increased by 1000 kg ha^{-1} , while in eastern Jiamusi City, central Hegang City, and central Shuangyashan City the rice actual yields increased by over 2000 kg ha^{-1} .

Throughout the entire time period spanning from 2000 to 2020, the mean rice actual yield decreased by 1222 kg ha^{-1} , while the total actual production increased by 3.75 million tons because the area of the paddy field increased by 1.01 million ha (Figure 4c). The rice actual yields increased in most regions of Heilongjiang Province. In Sanjiang Plain, there was a significant increase in rice actual yields, with most regions of Jiamusi and Hegang exceeding 2000 kg ha^{-1} .

3.2. Rice Potential Yields in Heilongjiang Province for 2000, 2010, and 2020

3.2.1. Rice Potential Yields for 2000, 2010, and 2020

The total rice potential production in Heilongjiang Province for 2000, 2010, and 2020 was 15.10, 18.16, and 16.81 million tons, respectively, simulated by the GAEZ model, with the paddy field area of 2.19, 2.71, and 3.21 million ha, resulting in the mean rice potential yield of 6884, 6703, and 5238 kg ha^{-1} , respectively. The spatial distribution of rice potential yields in Heilongjiang Province for the three years (Figure 5a–c) revealed that the eastern and southwestern regions exhibited relatively high yields, with most exceeding 4000 kg ha^{-1} , and some reaching as high as $6000\text{--}8000 \text{ kg ha}^{-1}$, primarily concentrated in Sanjiang Plain and Songnen Plain, such as Shuangyashan City, Hegang City, Suihua City and Jixi City. The major reason for this disparity lies in the predominant soil types of the Sanjiang Plain, which consist mainly of white slurry and meadow soils, as opposed to the Songnen Plain's predominantly black soils characterized by high organic matter content and exceptional fertility, rendering them more conducive to rice cultivation.

3.2.2. Spatio-Temporal Evolution Characteristics of Rice Potential Yields during the 2000–2020 Period

Figure 6a–c shows the rice potential yield changes in Heilongjiang Province during the three periods. From 2000 to 2010, the mean rice potential yield decreased by 180 kg ha^{-1} , while the total rice potential production increased by 3.06 million tons (Figure 6a). The northeast regions of Jiamusi City and Jixi City experienced a significant increase in rice potential yields exceeding 2000 kg ha^{-1} , whereas the centers of Shuangyashan City and Hegang City had a significant decrease in rice potential yields exceeding 2000 kg ha^{-1} . Other regions witnessed an increase ranging from 1000 to 2000 kg ha^{-1} , with some experiencing a decrease.

From 2010 to 2020, the mean rice potential yield decreased by 1465 kg ha^{-1} , while the total rice potential production decreased by 1.35 million tons (Figure 6b). In contrast to 2000–2010, the reduction in rice potential yields exceeded 2000 kg ha^{-1} in the northeast of Jixi City and Jiamusi City. Among regions with increased potential yields, most experienced an increase of less than 1000 kg ha^{-1} , while central Hegang City and central Shuangyashan City saw an increase of over 2000 kg ha^{-1} .

From 2000 to 2020, the mean rice potential yield witnessed a decline of 1646 kg ha^{-1} , while the overall potential rice production experienced an increase of 1.71 million tons (Figure 6c). The rice potential yields in most regions, such as Suihua, Harbin, Mudanjiang, and Qitaihe cities, experienced a decrease of less than 1000 kg ha^{-1} . In Shuangyashan City, the decline exceeded 1000 kg ha^{-1} . Conversely, Qiqihar and Jixi cities witnessed an increase in rice potential yields ranging from 1000 to approximately 2000 kg ha^{-1} . Moreover, the eastern region of Hegang and Jiamusi cities exhibited an even higher increase of over 2000 kg ha^{-1} .

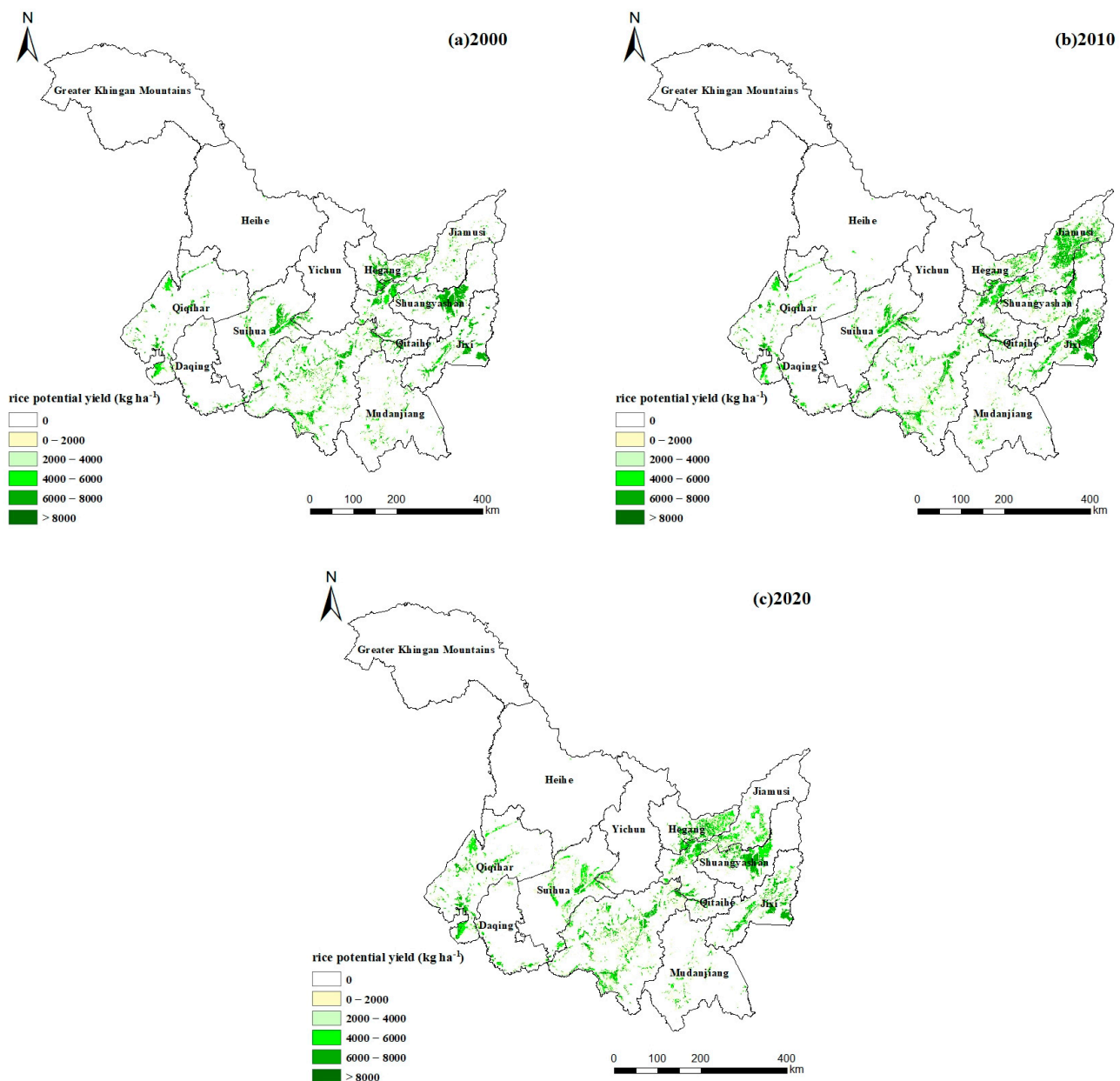


Figure 5. Spatial distribution of rice potential yields in 2000, 2010, and 2020 based on the Global Agro-Ecological Zones (GAEZ) model: (a) 2000, (b) 2010, and (c) 2020.

3.3. Rice Yield Gaps in Heilongjiang Province for 2000, 2010, and 2020

3.3.1. Correlation Analysis between Rice Actual and Potential Yields

The scatter density plots were generated to visualize the correlation between the rice potential yields ($Y_{potential}$) for the three years simulated by the GAEZ model and the rice actual yields (Y_{actual}) estimated by the VPM model (Figure 7a–c). The R^2 between the rice potential yields simulated by the GAEZ model and the rice actual yields estimated by the VPM model for the three years were 0.75, 0.70, and 0.71, respectively, indicating a good correlation between the spatial distribution of rice potential yields simulated by the GAEZ model and actual yields estimated using the VPM model. The spatial distribution of high and low rice yields simulated by the two models exhibited a relatively consistent pattern. The colors of the scatter plots represent their density, with the color bar on the right side indicating the number of data points. A higher density was observed for data points closer

to the trend line, while those further away had lower densities, suggesting a correlation between both types of yields.

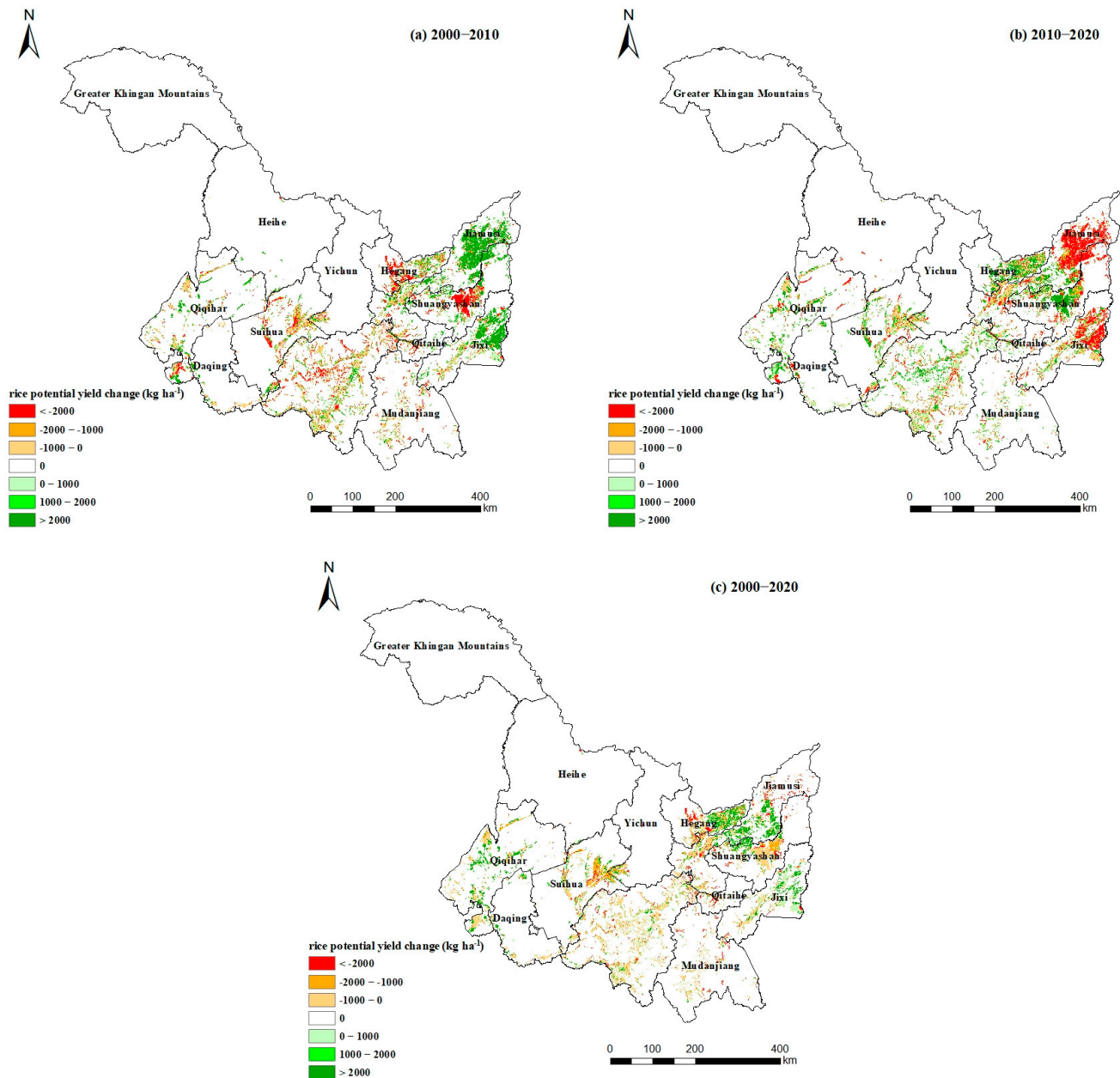


Figure 6. Spatial distribution of rice potential yield changes in Heilongjiang Province for the three periods: (a) 2000–2010, (b) 2010–2020, and (c) 2000–2020.

3.3.2. Analysis of the Rice Yield Gaps

In order to explore the gaps between the rice actual yields and potential yields, we calculated the AYG and RYG of rice actual and potential yields for the three years, respectively, and then analyzed the temporal and spatial variation characteristics of the AYG and RYG during the 2000–2010 period in Heilongjiang Province. Figures 8a–c and 9a–c show the AYG and RYG of rice actual and potential yields for the three years, respectively. It can be seen that the AYG and RYG in all regions of Heilongjiang Province were greater than 0, indicating that the rice potential yields were larger than the actual yields in Heilongjiang Province.

As can be seen in Figure 8a–c, the AYG ranged from 4000–6000 kg ha^{−1} and 6000–8000 kg ha^{−1} in most areas of Heilongjiang Province, indicating a large gap be-

tween rice actual and potential yields for the three years. In the Sanjiang Plain of the northeast, most areas were 6000~8000 kg ha⁻¹, and the AYG of rice was very large. In most areas of the southwest, it was 4000~6000 kg ha⁻¹, which was not as big as the yield gap in Sanjiang Plain, but it still had large room to increase yields.

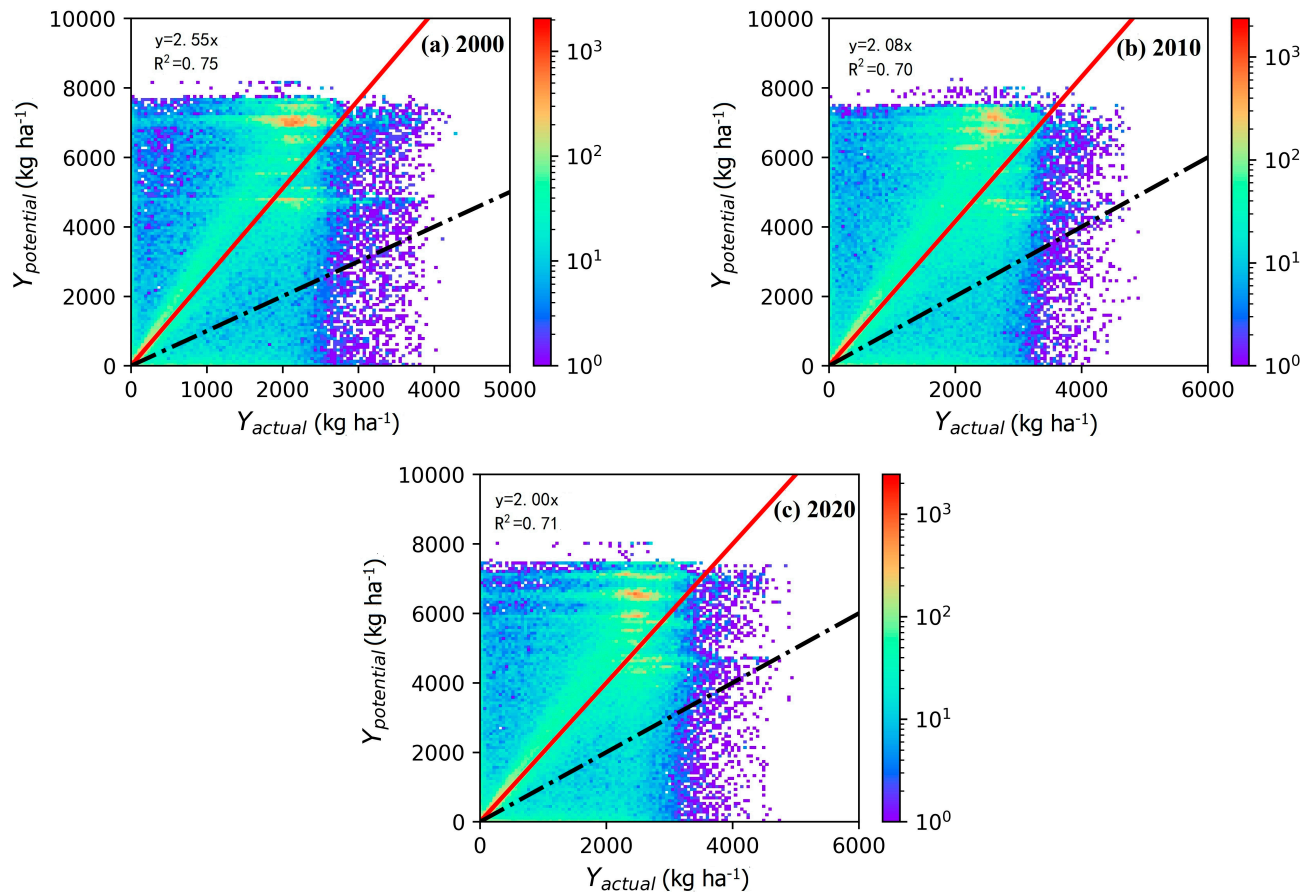


Figure 7. Correlation analysis between rice actual and potential yields for the three years: (a) 2000, (b) 2010, and (c) 2020.

However, due to the different rice production capacities in different regions and the large gap in rice potential yields, the RYG may reflect the rice yield gap in different regions more accurately than the AYG. As can be seen in Figure 9a–c, the RYG varied greatly in different regions of Heilongjiang Province. In 2000, the RYG was 200~300% in most areas, indicating that the rice potential yields were 3~4 times the actual yields, such as Hegang City, Shuangyashan City, and Jixi City in Sanjiang Plain region in the northeast, Suihua City in the middle, and Harbin City in the south. The RYG in some areas was 100~200%, indicating that the rice potential yields were approximately two to three times the actual yields, such as Qitaihe City in the southwest, and the southern part of Harbin City, as well as parts of the Sanjiang Plain region. In a small number of regions, the RYG was greater than 300%, and the difference in rice yields was even larger. In 2010, there was a smaller RYG than in 2000. The RYG in most areas was concentrated at 100~200%, indicating that the rice potential yields were 2~3 times the actual yields, such as the Sanjiang Plain area in the northeast, as well as Suihua City in the middle and Harbin City in the south. In small areas, the RYG was less than 100%, indicating that the rice potential yields were less than two times the actual yields, such as in the southern and northern areas of Qitaihe City. In 2020, the distribution of the RYG was very similar to that of 2010. The RYG was concentrated at 100~200% in most areas, such as the Sanjiang Plain region in the northeast, Suihua City in the middle, and Harbin City in the south. A few areas had an RYG of less

than 100%, such as the southern and northern parts of Qitaihe City. Overall, the rice yield gaps in Heilongjiang Province were reduced from 2000 to 2020.

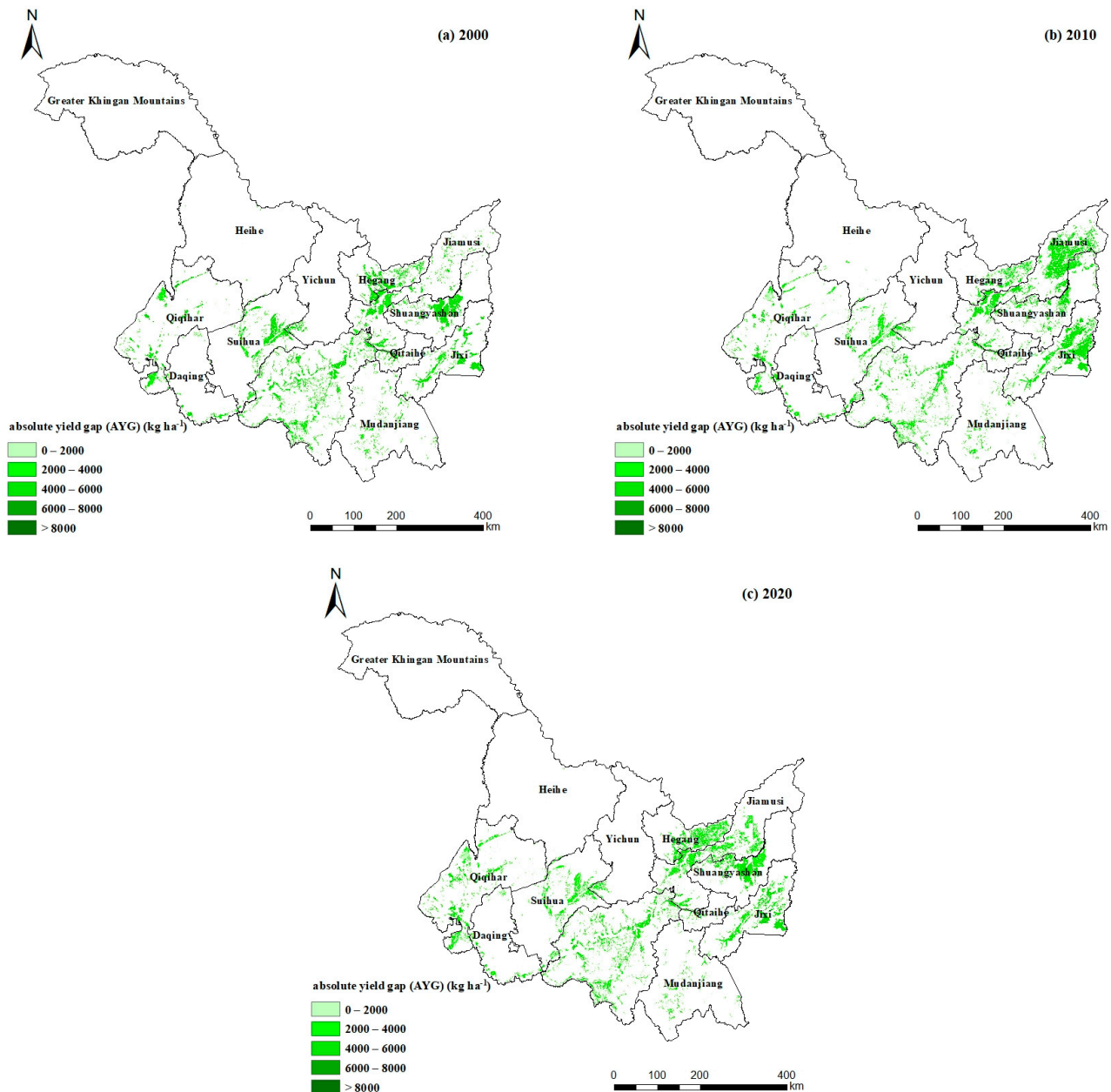


Figure 8. Absolute yield gaps (AYG) of rice actual and potential yields for the three years: (a) 2000, (b) 2010, and (c) 2020.

In order to further explore the difference between the AYG and RYG in different prefecture-level cities, we calculated the mean AYG and RYG in different prefecture-level cities of Heilongjiang Province for the three years (Figures 10 and 11). It can be seen in Figure 10 that in 2000, the AYG was larger in Hegang City, Shuangyashan City, Jixi City, and Harbin City. In 2010, the AYG was larger in Jiamusi City, Jixi City, Shuangyashan City, and Hegang City. In 2020, Hegang City, Jixi City, and Shuangyashan City had the largest AYG. Therefore, the AYG of rice in Hegang City, Shuangyashan City, and Jixi City in the Sanjiang Plain region was large for the three years, and effective measures to increase yields were urgently needed to narrow the yield gaps.

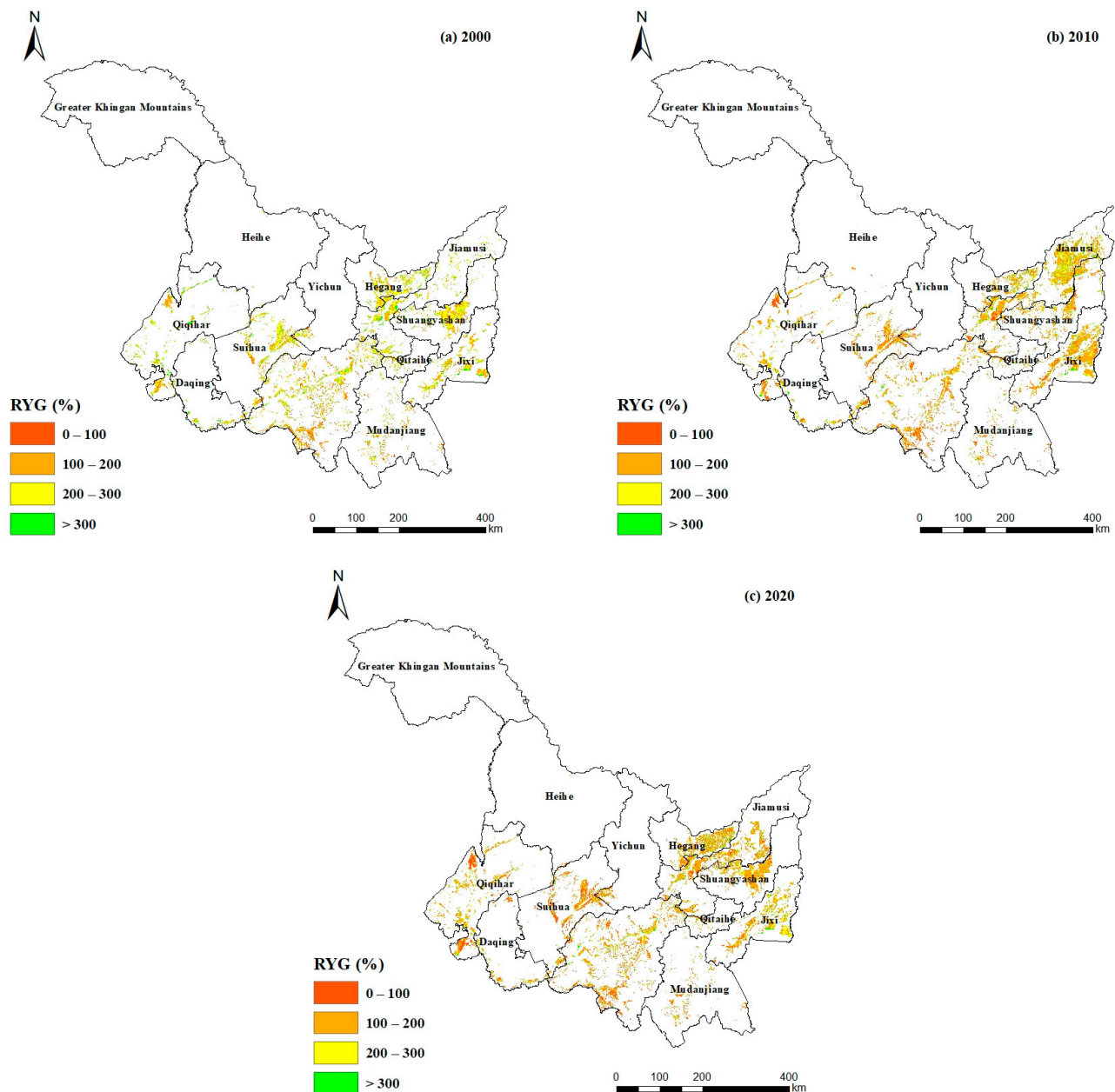


Figure 9. Relative yield gaps (RYG) of rice actual and potential yields for the three years: (a) 2000, (b) 2010, and (c) 2020.

It can be seen in Figure 11 that in 2000, in addition to the Greater Khingan Mountains, Heihe City, and Qitaihe City, the RYG of the remaining nine prefecture-level cities was higher than 400%, indicating that the rice potential yields were more than five times the actual yields, among which the RYG of Hegang City, Jiusi City and Jixi City in Sanjiang Plain region was even close to 700%, and the gaps between the rice actual yields and potential yields were very large. In 2010, the RYG of most prefecture-level cities decreased, and only six prefecture-level cities with RYG higher than 400%, among which the RYG of Hegang City, Jiamusi City, and Qitaihe City located in Sanjiang Plain region was higher than 500%. In 2020, the RYG of most prefecture-level cities continued to decrease, and only five prefecture-level cities with RYG above 400%, among which Hegang City and Jixi City in the Sanjiang Plain region had a higher RYG than other prefecture-level cities. In addition, Daqing City, located in the southwest region, also had a higher RYG (526.30%).

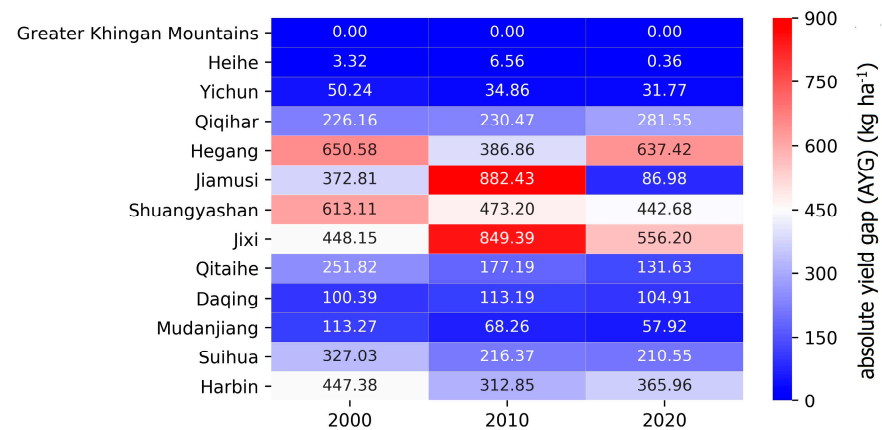


Figure 10. Absolute yield gaps (AYG) of rice actual and potential yields in different prefecture-level cities for the three years.

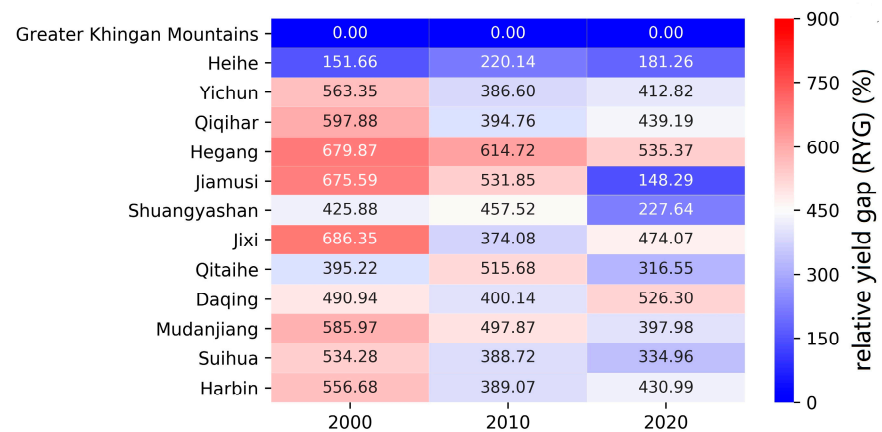


Figure 11. Relative yield gaps (RYG) of rice actual and potential yields in different prefecture-level cities for the three years.

Therefore, by exploring the AYG and RYG of different regions in Heilongjiang Province, it can be found that the rice yield gaps in the Sanjiang Plain region, such as Jixi City, Hegang City, and Jiamusi City were relatively large compared to other regions for the three years, and the rice yield gaps continued to decrease from 2000 to 2020. Although the rice actual yields in these areas were higher than in other areas, the potential yields were higher and thus the yield gaps were the highest, and there was still a large space for increasing yields.

3.3.3. Suggestions for Increasing Rice Yields

Based on the results of this study, it is evident that there is a significant disparity between the rice actual and potential yields in the Sanjiang Plain region. Although there is flat terrain, fertile soil, high production potential, and relatively high rice yields in the Sanjiang Plain region compared to other regions, and the actual and potential yield growth rates were the largest from 2000 to 2020, the rice yield gaps were large, indicating that the cropland productivity was not fully utilized. The reasons for the large yield gaps in Sanjiang Plain include land salinization and flood, extensive management of cropland, low agricultural inputs level and the extent of scientific and technological advancement in agriculture, and lack of good rice cultivars to adapt to agricultural resources and environment, etc.

First, the Sanjiang Plain region is facing a relatively severe issue of land degradation. This can be attributed to the prolonged exploitation of black soil resources. In 2016, the low and medium-yielding fields accounted for 84.3% of Heilongjiang Province, among which low-yielding fields make up 62.3% and medium-yielding ones account for 22%; this trend has been increasing every year. In contrast, high-yielding fields only constitute

15.7% [42]. There are large areas of low and medium-yielding fields in Sanjiang Plain. Furthermore, land productivity in Sanjiang Plain is also impacted by salinization. Due to the low elevation and high groundwater level in Sanjiang Plain, combined with perennial reclamation, salinization has become a serious problem. In addition, it is prone to perennial or seasonal water, prone to flood disasters [43]. However, the measures taken to address salinization and flood are inadequate. The area under salinity control in Heilongjiang Province only increased by 197,000 ha from 2000 to 2010. In 2016, the flood-prone area in Heilongjiang Province was recorded at 4.47 million ha, which slightly increased to 4.51 million ha in 2020. However, the de-flooded area decreased from 4.21 million ha to 3.41 million ha.

Second, extensive management of cropland and low agricultural input levels in Sanjiang Plain reduces crop productivity. Many high-quality croplands have not fully realized mechanized production and are still managed by small-scale farmers. The degree of intensive use of cropland is low. In addition, the Sanjiang Plain lacks good drainage facilities.

Third, the Sanjiang Plain still needs to explore better rice cultivars to adapt to the local agricultural resources and environment. According to the statistics in the China Rice Data Center (<https://www.ricedata.cn/> (accessed on 1 September 2023)), Heilongjiang Province has almost approved new rice cultivars every year and has continuously improved new cultivars since 1964, including Longjing, Beidao, and Songjing series. In 2000, 2010, and 2020, there were 8, 16, and 101 rice cultivars newly approved in Heilongjiang Province, among which 7, 12, and 89 rice cultivars were suitable for planting in Sanjiang Plain, respectively. It can be seen that Heilongjiang Province is constantly optimizing rice cultivars. This is also the reason that the rice yield gaps have gradually been narrowed since 2000. However, it is still necessary to explore better rice cultivars in the future to improve the ability of rice to resist pests, diseases, and meteorological disasters.

Therefore, this study puts forward the following suggestions to improve rice yields and narrow yield gaps in Sanjiang Plain. First of all, the establishment of ecological shelterbelts on farmland can effectively protect farmland from soil erosion and wind damage and save water resources [44]. The second suggestion is to gradually transform low and medium-yielding fields into sustainable high-yield fields. The third suggestion is to strengthen the application of agricultural science and technology, including improving the level of mechanization, realizing the modernization of production equipment, and promoting innovative technologies such as optical wave frequency agricultural intelligent controllers. Fourth, selecting rice cultivars with super high yield and disease resistance can improve the disaster resistance of rice. Fifth, we must upgrade farmland drainage and irrigation projects, and build paddy field water conservancy facilities and water conservancy projects. It can not only ensure the effective irrigation area of paddy fields, but also effectively alleviate natural disasters.

4. Discussion

4.1. Limitations of Determining the Rice Reproductive Periods of Heilongjiang Province

Although this study obtained rice yield gaps at the pixel level (with a spatial resolution of 500 m), there were still several limitations. The method used in this study to identify the rice reproductive periods of Heilongjiang Province for the three years may be inaccurate, which may lead to some errors. We used the 1 km phenological dataset of the three major national grain crops (rice, maize, and wheat) from 2000 to 2019 that was published by Zhang's research group [37] and used the value of the pixels with the highest number of rice transplanting and maturing Julian days in each year as the rice reproductive period in Heilongjiang Province and determined that the rice reproductive periods of Heilongjiang Province for 2000, 2010, and 2020 were days 153~249, days 145~249, and days 137~249. However, because of the vast territory of Heilongjiang Province and the different rice cultivars for the three years, the rice reproductive periods have strong spatial heterogeneity. Therefore, future studies should try to integrate the 1 km rice phenological data with 30 m

spatial distribution data of paddy fields to obtain the spatial distribution of 30 m rice reproductive periods to obtain more accurate *GPP* estimation results.

4.2. Limitations of Identifying the *GPP* of Rice Growth

Second, after estimating the cumulative *GPP* during the rice reproductive periods based on the VPM model, there may be some errors in extracting the *GPP* of rice growth. In this study, the global 0.05° *GPP* dataset based on the VPM model shared by Xiao's group was applied to estimate the rice actual yields in Heilongjiang Province [14,38]. Since the original resolution of this dataset was 0.05° and each pixel was almost always a mixed pixel containing multiple land cover types (such as forest and grassland) or multiple crops (such as rice, maize, and soybean), the *GPP* within each pixel was the sum of the *GPP* obtained from multiple land cover types or crops. Therefore, we need to identify the *GPP* obtained by rice from each mixed pixel. In this study, we obtained the *GPP* of rice growth by multiplying the percentage of paddy field with the *GPP* data, but it may have led to some errors in our results. Since the ε_0 , T_{min} , T_{max} , and T_{opt} of different land cover types or crops were different [45,46] and the EVI and LSWI may also differ, they may not obtain the same *GPP*. Therefore, future research should explore more accurate methods to separate the *GPP* obtained by different land cover types or crops within a mixed pixel. It might be a good way to use high spatial resolution or remote sensing data with high spatio-temporal resolution based on fusion technology to drive the VPM model and obtain higher resolution crop actual yields (such as spatial resolution of 30 m) [47].

4.3. Limitations of Applying the GAEZ and VPM Models

Third, the uncertainty of the parameters in the GAEZ model and the VPM model may cause errors in our results. When using the two models to simulate the rice actual and potential yields, it is not fully ensured that the various parameters related to rice in the two models are fully consistent with rice growth in Heilongjiang Province. For example, when using the GAEZ model to estimate the rice potential yields, many parameters of rice growth were based on the standardized coefficients from previous studies. When the VPM model was used to estimate the rice actual yields, parameters such as *GPP* were converted to *NPP*, and when *NPP* was converted to crop yields, *HI* also included empirical values from previous studies [39,41], which, to a certain extent, could not be ensured to be completely suitable for the rice growth in Heilongjiang Province. Thus, it might have led to some errors in the simulation results of rice actual and potential yields in Heilongjiang Province. In future studies, more relevant information should be reviewed, and field visits and research should be conducted to localize the crop-related parameters in the VPM model and GAEZ model to improve the accuracy of the simulation results of crop yields.

5. Conclusions

The objective of this study was to estimate the rice actual yields using the VPM model and the potential yields based on the GAEZ model in Heilongjiang Province for 2000, 2010, and 2020 and obtain the rice yield gaps, which represent the yield increase space, thus realizing the spatialization of rice yield gaps in Heilongjiang Province at the pixel level. The conclusions are described below.

From 2000 to 2020, the mean rice actual yield in Heilongjiang Province decreased by 1222 kg ha^{-1} , while the total rice actual production increased by 3.75 million tons due to the increase in paddy field area. In the same way, the mean rice potential yield in Heilongjiang Province decreased by 5941 kg ha^{-1} , while the total rice potential production increased by 1.70 million tons. The spatial variation characteristics of rice actual and potential yields during the 2000–2020 period were similar. In Sanjiang Plain, there was a significant increase in rice actual and potential yields, with most regions of Jiamusi and Hegang exceeding 2000 kg ha^{-1} .

There was a strong positive association between the rice potential yields estimated by the GAEZ model and actual yields estimated by the VPM model by calculating the R^2

between the rice actual and potential yields for the three years. By exploring the rice yield gaps of different regions and prefecture-level cities in Heilongjiang Province, it was found that although the rice actual and potential yields in Sanjiang Plain increased from 2000 to 2020, the rice AYG and RYG in Sanjiang Plain region, such as Jixi City, Hegang City and Jiamusi City were relatively large compared to other regions for the three years, and it was encouraging to observe that the rice yield gaps continued to decrease from 2000 to 2020. This study proposed measures to enhance rice yields and narrow the yield gaps in Sanjiang Plain where significant yield gaps exist. These include establishing ecological protection forests on farmland, upgrading medium and low-yielding fields, strengthening the application of agricultural science and technology, selecting better rice cultivars, and building paddy field water conservancy facilities and water conservancy projects.

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Data Availability Statement: Data are available in a publicly accessible repository that does not issue DOIs. Publicly available datasets were analyzed in this study. This data can be found at: [URL: <https://pan.baidu.com/s/1OOuaiaLOyXqYCqXl6MFYg> (accessed on 5 February 2024)/ Accession number:1234].

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