Estimating and analyzing the spatiotemporal characteristics of crop yield loss in response to drought in the Koshi River Basin, Nepal

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Received: 12 July 2021 / Accepted: 2 April 2023 / Published online: 14 April 2023
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Abstract
The quantitative assessment of crop yield loss due to drought is critical for the development of the agricultural sector to improve productivity. This study aimed to estimate and analyze the spatiotemporal patterns of crop yield loss in response to drought using the Lagrange interpolation method, wavelet analysis, and sequential Mann–Kendall test in Nepal’s Koshi River Basin, covering the mountain, hill, and Terai (low-land) regions from 1987 to 2016. The findings indicate that average crop yield loss was common after 2000, with the Terai, hill, and mountain regions experiencing the greatest loss in maize, rice, and wheat crops, respectively. The average annual rice and wheat yield losses rate were highest in the mountains, while maize yield losses were highest in the Terai. The mountain region experienced an abrupt change in wheat yield loss, showing a significant increasing trend. The hill region showed a significant increase in maize and wheat yield loss, while a decrement in rice yield loss was observed. The periodic variations of maize, rice, and wheat between 1987 and 2016 revealed significant yield loss after 2000. The characteristics of the first and second key periods for crop yield loss demonstrated a variation period, predicting that crop yield loss would either enter a high yield loss or low yield loss period shortly after 2016. The study findings provide a detailed assessment of crop yield loss at the river basin level, highlighting the urgent need to develop a crop yield loss mitigation plan in the agricultural sector.

1 Introduction
Agriculture is a sector that is particularly vulnerable to climate extremities such as drought. Despite modern technological advancements, climate and weather have always been uncontrollable factors that affect agricultural production (Lobell and Field 2007). Studies predict that, drought conditions will become more widespread and persistent in the future due to climate change (Dai 2011; Trenberth et al. 2014). Crop yield loss can occur because due to several factors, including climate, drought and crop diseases (Savary et al. 2006). Drought is a major abiotic factor that affects crop yield and is expected to impact more than 50% of the world’s arable land by 2050 (Vinocur and Altman 2005; Naveed et al. 2014). Global cereal production is estimated to decline by an average of 10.1%, with most significant impacts in Australia, North America and Europe (Lesk et al. 2016). Quantifying and analyzing crop yield loss is difficult due to its changing nature, depending on drought characteristics during different growth stages (Potopová et al. 2016; Savary and Willocquet 2014; Cerda et al. 2017; Oerke 2006).

Crop yield loss assessment measures the difference between the expected (ideal) yield and the actual yield (Nutter et al. 1993). The expected yield is the maximum yield obtained in the absence of disasters and with the best available agricultural inputs and techniques (Yu and Zhang 2009; Cerda et al. 2017). The term “actual yield” refers to the yield obtained from resources, which can be influenced
by different abiotic and biotic factors (Cerda et al. 2017; Chandio et al. 2019). Crop protection methods must evolve alongside agricultural technologies to increase crop yield and meet the future food demand caused by rising population (Oerke 2006; Van Ittersum et al. 2013). Currently, crop producing land must achieve higher yield levels especially in regions with lower than national average yield levels due to unfavorable abiotic and biotic factors, while some regions possess higher potential for crop yield (Van Ittersum et al. 2013). Consequently, under ideal conditions, there exists a yield gap (yield loss) between the current (actual yield) and theoretically achievable (expected yield). Therefore, developing comprehensive knowledge about yield loss is crucial to achieving sustainable agricultural intensification (Van Ittersum et al. 2013).

As mentioned earlier, agricultural productivity is highly vulnerable to drought as it directly affects water availability (Hanja and Qureshi 2010). Although each crop has a different threshold and level of resilience to water deficit, drought can cause yield loss if it occurs during the crop’s sensitive growth stage (Lobell and Field 2007; Lobell et al. 2011). Consequently, the drought can exacerbate agricultural losses, leading to food insecurity and famine. Tilman et al. (2011) have stated that due to the rising population, global food demand is expected to double by 2050, necessitating a 2.4% increase in crop yield per year to meet this demand. Therefore, drought-related yield loss may be a significant threat to achieving this demand in the future (Field et al. 2012). Consequently, assessing trends and detecting change point in the historical series of crop yield loss is critical to carrying out spatial and temporal scale to consider inclusive knowledge about yield loss (Kim et al. 2019).

Agriculture is a vital economic and livelihood activity in developing countries like Nepal, where more than 75% of the rural population depends on rainfed agricultural activities. Hence, any type of water hazards, such as drought is critical to their livelihood (Chapagain and Gentle 2015). Historical drought events significantly impacted agricultural productivity and livelihood support for farming communities in Nepal during the 1970s, 1980s, 1990s, and after 2000 due to uneven and insufficient precipitation (Adhikari 2018). The eastern part of Nepal was especially affected by drought during these periods, resulting in significant crop losses (UNDP and BCPR 2013). The Koshi River Basin (KRB) located in the Nepal’s eastern part, is one of the largest river basins. According to a study, the basin’s mean temperature is increasing by 0.2 °C per decade, precipitation is erratic and making it vulnerable to the drought (Shrestha et al. 2017; Chen et al. 2013). As 70% of the population in the basin relies on rainfed agriculture, changing climate impacts, especially drought, are significantly impacting the basin (Dixit et al. 2009). Several studies have been conducted in the basin on climate, water resources, and agriculture (Agarwal et al. 2014, 2016; Bharati et al. 2019; Bhatt et al. 2014; Neupane et al. 2013) but none of them have focused on time series quantification of crop yield loss, their changing trends and patterns in drought. Therefore, this study aims to (a) quantify the crop yield loss of rice, maize, wheat in different regions—mountain, hill, Terai (low land) of the basin from 1987 to 2016 (b) identify the trend and turning point of the crop yield loss in mountain, hill and Terai regions during 1987 to 2016 and (c) investigate the characteristics of crop yield loss variation at different timescales in mountain, hill and Terai regions from 1987 to 2016. The novelty of this study is to understand interannual variation and characteristics of crop yield loss and its future prediction. This study can help policymakers and stakeholders design plans for future sustainable agricultural intensification by identifying spatial temporal characteristics of agricultural losses and quantifying them.

2 Materials and methods

2.1 Study area

The Koshi River Basin is a transboundary river basin originating from the southern part of the Tibet (China) and passing through Nepal before entering the northern part of Bihar (India) (Hussain et al. 2018). It covers a total area of 87,311 km² with 33% in China, 45% in Nepal, and 22% in India. In Nepal, the basin is divided into three major regions: mountain, hill, and Terai based on the natural regionalism (Sahayogee 2017), management and for development purposes (Petley et al. 2007). The altitudinal range from 75 to 8849 m from the south to the north and covering 27 districts. The basin has a population of 40 million most of whom depend on subsistence agriculture for their livelihood (Neupane et al. 2015). The basin has total of 3.4 million hectares (ha) of arable land with maize, rice, wheat being the major food crops produced. Maize is grown on 32%, rice on 61% and wheat on 23% of the total arable land (Neupane et al. 2015). As of 2011, the KRB Nepal had a population of about 11.7 million, which was projected to increase to 13.2 million by 2017 (Hussain et al. 2018). Over 50% of the arable land in the basin relies on rainfall making it sensitive to rainfall variations. Low rainfall can lead to water shortages, which directly affect agriculture and water dependent livelihood.

2.2 Data

2.2.1 Agricultural data

For the purpose of this study, data on the total annual yield of maize, rice, and wheat were collected from the 16 districts in the KRB, Nepal spanning a period of 30 years from 1987...
to 2016. The data were collected from the Ministry of Agriculture and Livestock Development, Government of Nepal. The collected data were considered to be the actual crop yield data and were subjected to further analysis to calculate the expected yield during the period from 1987 to 2016.

### 2.2.2 Climate data and drought identification

In this study, monthly data on minimum temperature, maximum temperature, and precipitation data from 23 meteorological stations that cover the selected 16 districts in the KRB, Nepal (Fig. 1). The data span a period of 30 years from 1987 to 2016 and were obtained from the Department of Hydrology and Meteorology, Government of Nepal. The raw climate data were analyzed to identify drought in the KRB using the commonly used Standardized Precipitation Evapotranspiration Index (SPEI) method developed by Vicente-Serrano et al. (2010). R software (SPEI package version 1.7) was used to apply the SPEI method (R Core Team 2020).

To calculate SPEI, monthly precipitation and temperature data are required. Monthly temperature is further used to estimate monthly potential evapotranspiration (PET). The difference between precipitation and PET provides the climatic water balance, which is used to calculate SPEI. In this study, we used Hargreaves method to calculate PET (Hargreaves and Samani 1985) which has been successfully applied in Nepal in previous studies (Aadhar and Mishra 2017; Dahal et al. 2016, 2021; Bhatt et al. 2014; Penton et al. 2016; Hamal et al. 2020).

SPEI index values were calculated at different time-scales (1 to 12-month lags) for the growing season months of maize (March-August), rice (June-November) and wheat (November–May) from 1987 to 2016. The growing seasons for these crops were identified based on literature and verified through the field visit (Nayava...
et al. 2009; Paudyal et al. 2001; Ghimire et al. 2012). The SPEI values in each region were obtained by averaging the SPEI-values at each meteorological station for the crop growing seasons at 1 to 12-month lags to identify drought (Hamal et al. 2020; Liu et al. 2018; Potop et al. 2014). The drought categories defined by McKeel et al. (1993) and Vicente-Serrano et al. (2010) are illustrated in Table 1.

### 2.3 Lagrange interpolation method

Celik (2018b) defines interpolation as a mathematical function used to estimate data for unavailable measured data values from the set of measured values. Interpolation techniques have various applications, including in the agriculture (Celik 2018a). In this study we employed Lagrange interpolation method to calculate the expected yield of maize, rice, and wheat in the mountain, hill and Terai regions of KRB, Nepal (Jeffreys et al. 1999; Celik 2018a; Yu and Xiu 2007). The Lagrange interpolation method was first published by Waring in 1779, rediscovered by Euler in 1783 and published by Lagrange in 1795 (Jeffreys et al. 1999). The detail procedures of Lagrange interpolation method are as follows:

Consider \( x_1, x_2, \ldots, x_n \) are the data in the time series, with their corresponding values \( y_1, y_2, \ldots, y_n \) with function \( y = f(x) \) and a polynomial \( p(x_i) = f(x_i); i = 0,1,2, \ldots, n \). The polynomial equation can be written as follows:

\[
p(x) = a_0 + a_1x + a_2x^2 + \ldots + a_nx^n \tag{1}
\]

for given \((n + 1)\) data points there are \( x_0, x_1, \ldots, x_n \). For \( i = 0, 1, 2, \ldots, n \) at \((n + 1)\) number of points are illustrated as follows:

\[
L_i(x) = \frac{(x-x_0)(x-x_1)(x-x_{i+1})(x-x_{i+2})\ldots(x-x_n)}{(x_i-x_0)(x_i-x_1)(x_i-x_{i+1})(x_i-x_{i+2})\ldots(x_i-x_n)} \tag{2}
\]

These polynomials are known as the Lagrange polynomials for \( x_0, x_1, \ldots, x_n \) points with \( n^{th} \) degree and its sum is given as follows:

\[
p(x) = f_0L_0(x) + f_1L_1(x) + f_2L_2(x) + \ldots + f_nL_n(x) \tag{3}
\]

The polynomial \( p(x) \) is expressed as below and is known as the Lagrange interpolation

\[
p(x) = \sum_{i=0}^{n} f_iL_i(x) \tag{4}
\]

The Lagrange interpolating polynomial (LIP) of \( p(x) \) which has \((n-1)\) degree is passing through the \( n \) points \((x_1, y_1 = f(x_1)), (x_2, y_2 = f(x_2)) \ldots, (x_n, y_n = f(x_n))\), and is expressed as:

\[
f(x) = \sum_{j=0}^{n} f_j \prod_{k=1}^{n} \frac{x - x_k}{x_j - x_k} \tag{5}
\]

The equation can be written as:

\[
f(x) = \frac{(x-x_2)(x-x_3)\ldots(x-x_n)}{(x_1-x_2)(x_1-x_3)\ldots(x_1-x_n)} y_1 + \frac{(x-x_1)(x-x_3)\ldots(x-x_n)}{(x_2-x_1)(x_2-x_3)\ldots(x_2-x_n)} y_2 + \ldots + \frac{(x-x_1)(x-x_2)\ldots(x-x_{n-1})}{(x_n-x_1)(x_n-x_2)\ldots(x_n-x_{n-1})} y_n \tag{7}
\]

### 2.4 Estimation of expected crop yield and crop yield loss

Actual crop yield refers to the yield obtained after accounting for the effects of meteorological hazards, farm inputs, and other agricultural technological inputs, while expected crop yield refers to the yield that can be achieved when there are no meteorological hazards (such as drought) and all of the favorable conditions required to attain maximum (expected) crop yield (Chandio et al. 2019). In this study, we estimated the expected yield of maize, rice, and wheat in the mountain, hill and Terai regions of the KRB, Nepal. First, we used the SPEI values to identify the years free meteorological hazards during the growing seasons of maize, rice, and wheat in each region from 1987 to 2016. SPEI-values ranging from -0.99 to 0.99 were considered normal (hazards-free) growing seasons for that year. The SPEI values less than -0.99 indicate drought conditions whereas higher than 0.99 indicate wet conditions (Table 1). Second, the maximum crop yield observed in the normal years from 1987 to 2016 was considered as the expected crop yield, assuming that the maximum yield is always expected and can be attained only if there is no hazards and all favorable conditions such as farm and agricultural inputs, are present. The Lagrange interpolation method

| Table 1 Drought categories based on the SPEI values |
|-----------------------------------------------|
| SPEI Value | Categories |
|---------------------|------------|
| Above 0      | No drought |
| 0 to -0.99    | Near normal |
| -1 to -1.49   | Moderate drought |
| -1.50 to -1.99| Severe drought |
| -2 and less   | Extreme drought |
was used to calculate expected yield for the remaining years between 1987 and 2016. The positive difference between expected yield and actual yield indicates a loss of yield.

### 2.5 Sequential Mann–Kendall test

The Sequential Mann Kendall test is a rank based non-parametric test used to detect potential abrupt change point in a timeseries of \( x_i \) (Sneyres 1990; Mohsin and Gough 2010). It involves analyzing the rank values \( y_i \) of all the terms in time series \( x_1, x_2, x_3, \ldots, x_n \) to be analyzed. The magnitude of \( y_i = 1, 2, 3, \ldots, n \) is compared with \( y_j \), where \( y_j = 1, 2, 3, \ldots, i - 1 \). For each comparison, cases where \( y_i > y_j \) are counted and represented by \( n_i \). The MK rank statistic \( t_i \) is therefore expressed as (Bonfils 2012):

\[
t_i = \sum_{j=1}^{i} n_i
\] (8)

When there is no monotonic trend under the null hypothesis, \( t_i \) has normal distribution with expected value of \( E(t_i) \) and the variance \( \text{var}(t_i) \) is:

\[
E(t_i) = \frac{i(i-1)}{4}
\] (9)

---

**Fig. 2** The actual and expected yield of maize, rice, and wheat in the mountain, hill and Terai regions of Koshi River Basin, Nepal, from 1987 to 2016
Based on above assumption, the sequential values of standardized variables known as \( u(t_i) \) statistic index is estimated for each of the test static variable \( t_i \) is:

The forward sequential statistic, \( u(t_i) \) is calculated by using the original time series data \( x_1, x_2, \ldots, x_n \) and the backward sequential statistic, \( u'(t_i) \) are estimated using the same process but starting from the end of time series. While estimating \( u'(t_i) \) the timeseries data is rearranged so that the last series values come to the first \( (x_1, x_2, \ldots, x_n) \).

The sequential Mann Kendall test provides the identification of approximate beginning of a developing trend. When \( u(t_i) \) and \( u'(t_i) \) curves are plotted, the intersection of these curves at certain point during the time interval shows the potential turning point. This point represents the approximate beginning of a developing trend. The intersection of the curves indicates that the number of increasing and decreasing values in the time series are equal at that point, suggesting a potential change in the direction of the trend. It is also important to note that the intersection of the \( u(t_i) \) and \( u'(t_i) \) curves does not necessarily mean that a trend has already started (Hanif et al. 2022). Rather, it suggests that a trend may be developing, and further analysis is required to confirm the trend (Hekmatzadeh et al. 2020; Shahid 2011). If this intersection occurs within \( \pm 1.96 \) (5% significance level) of the standardized statistic then a significant change at time interval is supposed. If at least one value of the standardized variable is greater than the chosen significance level, the null hypothesis is rejected.

### 2.6 Wavelet analysis

Wavelet analysis is a useful tools for studying multi-scale analysis in various research field (Torrence and Compo 1998). This method allows for the analysis of multiple time scale features of a signal sequence by scaling and translating mathematical functions. It reflects local
Estimating and analyzing the spatiotemporal characteristics of crop yield loss in response to variations characteristics in time series data and has the capacity to identify turning points. In comparison to Fourier transform, this analysis is more effective in studying non-stationary time series data.

Torrence and Compo (1998) defined wavelet analysis by considering \( \varphi(t) \) as a square-intangible function which is \( \varphi(t) \in L^2(R) \) if its Fourier transform \( \mathcal{F}(\omega) \) satisfies the admissibility condition:

\[
C_{\varphi} = \int_{-\infty}^{\infty} |\mathcal{F}(\omega)|^2 d\omega < \infty
\]

(12)

Then, \( \varphi(t) \) is called basic wavelet or the mother wavelet. The wavelet function \( \varphi(t) \) must be scaled and translated to get a continuous wavelet (Labat 2010).

\[
\varphi_{a,t}(t) = \frac{1}{\sqrt{a}} \varphi\left(\frac{t-t}{a}\right), a, t \in R, a > 0
\]

(13)

For any function \( f(t) \in L^2(R) \), its continuous wavelet transform is defined as:

\[
W_f(a, \tau) = \frac{1}{\sqrt{|a|}} \int_{R} f(t) \varphi\left(\frac{t-t}{a}\right) dt = \langle f(t), \varphi_{a,t}(t) \rangle
\]

(14)

where \( a \) is a scale factor, \( \tau \) is time factor, \( W_f(a, \tau) \) is the wavelet coefficient.

Morlet wavelet function is given by:

\[
\varphi_{0}(\eta) = \pi^{-\frac{1}{4}} e^{i\omega_0 \eta} e^{-\frac{\eta^2}{2}}
\]

(15)

Table 3  The annual rate of maize, rice, and wheat yield loss in the mountain, hill, and Terai regions of Koshi River Basin, Nepal, from 1987 to 2016

| Year | Mountain MYLR (%) | RYL R (%) | WYLR (%) | Hill MYLR (%) | RYL R (%) | WYLR (%) | Terai MYLR (%) | RYL R (%) | WYLR (%) |
|------|-------------------|-----------|----------|--------------|-----------|----------|----------------|-----------|----------|
| 1987 | 0.00              | 20.72     | 15.42    | -6.12        | 29.69     | -1.05    | 2.14           | 25.62     | -5.53    |
| 1988 | 14.30             | 13.02     | 15.15    | -6.83        | 19.79     | 0.00     | 13.24          | 4.23      | 0.96     |
| 1989 | 16.03             | 7.00      | 10.81    | -3.24        | 10.01     | 5.62     | 3.06           | 4.41      | -1.99    |
| 1990 | 18.95             | 6.24      | 13.87    | -7.81        | 9.51      | 6.33     | 3.99           | 1.16      | 0.00     |
| 1991 | 12.66             | 0.00      | 14.43    | -7.46        | 0.00      | 10.96    | 0.00           | 0.00      | 4.12     |
| 1992 | 13.59             | 4.89      | 16.93    | -3.04        | 13.01     | 18.36    | 2.82           | -3.55     | 9.20     |
| 1993 | 17.25             | 10.41     | 12.47    | 0.00         | 26.83     | 21.56    | 0.00           | 8.21      | 28.43    |
| 1994 | 18.46             | 18.68     | 8.68     | 12.01        | 19.51     | 15.92    | 2.05           | 0.56      | 15.14    |
| 1995 | 17.83             | 22.42     | 8.31     | 12.28        | 19.13     | 18.96    | 13.88          | 15.05     | 16.00    |
| 1996 | 18.21             | 17.40     | 14.51    | 16.48        | 18.12     | 20.76    | 10.66          | 7.71      | 17.26    |
| 1997 | 18.52             | 16.70     | 9.25     | 20.88        | 16.92     | 19.02    | 13.50          | 6.00      | 14.61    |
| 1998 | 15.18             | 16.18     | 0.00     | 21.00        | 15.98     | 17.94    | 15.70          | 7.39      | 17.97    |
| 1999 | 21.37             | 13.43     | 22.89    | 19.95        | 12.68     | 23.55    | 20.78          | 16.80     | 22.77    |
| 2000 | 19.23             | 10.75     | 8.17     | 18.03        | 11.74     | 17.21    | 15.93          | 2.95      | 11.71    |
| 2001 | 16.67             | 8.94      | 1.46     | 19.02        | 10.56     | 16.81    | 24.72          | 0.00      | 10.00    |
| 2002 | 21.41             | 17.97     | 3.77     | 25.65        | 10.10     | 16.18    | 20.38          | 3.79      | 8.57     |
| 2003 | 14.44             | 8.44      | 0.00     | 14.62        | -0.08     | 7.40     | 20.73          | 2.74      | 5.68     |
| 2004 | 17.01             | 8.55      | 2.61     | 19.40        | 0.46      | 0.00     | 23.94          | -4.07     | 0.00     |
| 2005 | 15.79             | 2.47      | 3.54     | 22.20        | 0.00      | 4.01     | 30.06          | -2.19     | 2.12     |
| 2006 | 16.37             | 13.47     | 13.74    | 18.88        | 2.97      | 11.98    | 30.75          | 5.94      | 8.10     |
| 2007 | 12.73             | 23.44     | 16.97    | 18.50        | 3.80      | 19.71    | 36.09          | 16.94     | 1.73     |
| 2008 | 5.64              | 20.30     | 18.22    | 14.09        | 3.89      | 19.15    | 38.84          | 9.42      | 2.87     |
| 2009 | 6.70              | 20.40     | 40.19    | 13.28        | 6.96      | 30.80    | 42.06          | 6.97      | 9.88     |
| 2010 | 16.38             | 24.45     | 40.30    | 12.60        | 11.87     | 31.17    | 42.58          | 15.12     | 6.78     |
| 2011 | 2.36              | 13.85     | 28.83    | 11.66        | 11.98     | 4.51     | 40.47          | 9.61      | 8.00     |
| 2012 | 3.65              | 0.00      | 32.61    | 0.00         | 5.62      | 0.00     | 20.87          | -2.02     | 7.15     |
| 2013 | 2.84              | 26.97     | 28.19    | 18.12        | 5.31      | 2.70     | 13.88          | 9.73      | 3.00     |
| 2014 | 0.00              | 0.37      | 29.62    | 4.80         | 4.62      | 4.70     | 0.00           | 0.00      | 0.75     |
| 2015 | 6.03              | 0.45      | 28.43    | 1.46         | 0.00      | 0.00     | 41.56          | 10.28     | 0.00     |
| 2016 | 3.99              | 7.33      | 26.90    | 0.00         | 11.89     | 1.26     | 30.24          | 12.02     | 8.99     |

MYLR: Maize Yield Loss Rate; RYL R: Rice Yield Loss Rate; and WYLR: Wheat Yield Loss Rate
where, \( w_0 \) is the non-dimensional frequency.

Wavelet variance is obtained by taking an integral of the square of wavelet coefficients in the same time domain

\[
\text{Var}(a) = \int_{-\infty}^{\infty} |W_j(a, \tau)|^2 d\tau
\]  

(16)

Wavelet variance processes with scale \( \tau \) can get map of wavelet variance which reflects the distribution of fluctuations with timescales in time series (Miao et al. 2012). Detail is explained in (Torrence and Compo 1998).

3 Results

3.1 Expected crop yield and crop yield loss in the KRB

Figure 2 presents a graphical representation of the actual and expected yields of maize, rice, and wheat in the mountain, hill, and Terai regions of KRB, Nepal, from 1987 to 2016. Overall, the graph showed an increasing trend in both yields over time. However, there were obvious year-to-year variations in the actual yield for all crops.
Notably, sharp fluctuations were observed in the Terai region's maize yield after 2010 and the hilly region's rice yield before 1993. Table 2 provides normal years with their respective maximum yields from 1987 to 2016 for all crops in the regions based on SPEI values.

In the mountain region, the Lagrange interpolation polynomial for maize, rice, and wheat followed a first-order polynomial, indicating a linear increase in expected yield from 1987 to 2016. Wheat showed a sharp linear increasing trend in the region, followed by maize and rice, which had a slight increasing trend. The difference between expected and actual maize yield was observed to be greater from 1989 to 2007, and again in 2010 (Fig. 2a). For rice yield, the gap was greatest between 1991 and 2012, with the smallest in 2005. (Fig. 2b). The yield gap between expected and actual wheat yield was smaller from 1987 to 1998, and it steadily increased after 2005. Lower and higher yield gaps represent lower and higher yield losses, respectively.

From 1987 to 2016, the expected maize and rice yields in the hill region of KRBl followed a second order polynomial, while wheat yield followed a third order polynomial with a non-linear increment (Table 2). Actual maize yield was slightly higher than the expected yield during the years 1987 to 1992 (Fig. 2d). After 1992, the gap between expected yield and the actual yield widened, and the size of the gap fluctuated with the fluctuating actual yield. Prior to 1995, the expected rice yield in this region was not obvious (Fig. 2e). However, during this period, the yield gap between expected and actual was observed greatest in 1987 and 1993. After 1995, the expected yield increased in accordance with the increasing actual yield trend. As a result, the yield gap has shrunk in comparison to before 1995. Figure 2f depicts the yield gap between expected and actual wheat yield. The wheat yield gap was greatest in 2009 and 2010, indicating significant yield loss.

Similarly, the LIP for expected maize, rice, and wheat yield in the Terai region followed a second order polynomial from 1987 to 2016, indicating a non-linear increment (Table 2). The actual maize yield showed a sharp increase in 2014, resulting in a widening gap between expected and actual yield (Fig. 2g). Consequently, the yield gap was greatest from 2006 to 2011, 2015, and 2016. From 1987 to 2016, the yield gap between expected and actual rice yield fluctuated (Fig. 2h). In 1987, 1995, 1999, 2007 and 2010, the yield gaps were noticeably larger. Between 1987 and 2016, the expected wheat yield in the Terai region showed sharp increase (Fig. 2i). The actual yield is also increasing, with fluctuations over several years. Therefore, the yield gap between expected and actual yield has been observed to be greater in several years, including 1993, 1999, and 2009.

The analysis reveals that the crop yield loss was highest after 2000. The highest maize yield loss occurred in 2002, with the mountain region losing 429 kg/ha and the hill region losing 611 kg/ha, while the Terai region lost 1977 kg/ha in 2015. The highest rice yield loss occurred in 1987 in the hill (979 kg/ha) and Terai (578 kg/ha) regions, and in 2013 in the mountain region (624 kg/ha). For wheat, the highest yield losses occurred in 2010 in the mountain (853 kg/ha) and hill (823 kg/ha) regions, while the Terai region experienced a loss of 519 kg/ha in 1993. The average pattern of yield loss was Terai > hill > mountain for maize, hill > mountain > Terai for rice, and mountain > hill > Terai for wheat.

Table 3 presents the annual yield loss rates for maize, rice, and wheat from 1987 to 2016. The Terai region showed the highest annual yield loss rate for maize (42.58%), while the hill region showed the highest loss rate for rice (29.69%) and the mountain region for wheat (40.3%) (Table 3). Furthermore, after 2000, there was an increase in the frequency of years with a higher yield loss rate (> 20%) for all the crops in regions. Specially, from 2007 to 2010 and 2009 to 2016, the yield loss rate for rice and wheat in the mountain region was greater than 20% and 25% respectively. The hilly region showed a wheat yield loss rate greater than 30% in 2009 and 2010, while the Terai region showed a maize yield loss rate was greater than 20% from 2001 to 2012 and again from 2015 to 2016.

Between 1987 and 2016, the average maize yield loss rate was highest in the Terai region at 19.16 kg/ha, followed by the mountain region at 12.79 kg/ha and the hill region at 10.01 kg/ha. For rice, the average yield loss rate was highest in the mountain region at 12.51 kg/ha, followed by the hill region at 10.43 kg/ha and the Terai region at 6.36 kg/ha. The average yield loss rate for wheat was highest in the mountain region at 16.21 kg/ha, followed by the hill region at 12.18 kg/ha and the Terai region at 7.81 kg/ha. During the period of 1987 to 2016, the highest maize yield loss rates were observed in the Terai region at 42.58% in 2010, in the hill region at 25.65% in 2002, and in the mountain region at 21.41% in 2002. Similarly, the highest rice yield loss rates were observed in the mountain region at 26.97% in 2013, in the hill region at 29.69% in 1987, and in the Terai region at 25.62% in 1987. For wheat, the highest yield loss rates were observed in the mountain region at 40.3% in 2010, in the hill region at 31.17% in 2010, and in the Terai region at 28.43% in 1993.

Overall, the average yield loss rate of rice and wheat from 1987 to 2016 followed the pattern of mountain > hill > Terai, while maize followed the pattern of Terai > mountain > hill. During the period, the highest maize yield loss rate was observed in the Terai region, the highest rice yield loss rate in the hilly region, and the highest wheat yield loss rate in the mountain region. Similarly, in 1987, the hill and Terai regions had the highest rice yield loss rate. The highest maize yield loss rate was observed in 2002 in the mountain and hill regions, while the highest wheat yield loss rate was observed in the mountain and Terai regions in 2010.
### 3.2 Abrupt changes of annual crop yield loss

Identifying the point at which crop yield loss occurs is crucial in providing better interpretation and more accurate crop yield prediction. Figure 3 illustrates the abrupt changes points in the annual crop yield loss timeseries data from 1987 to 2016. During this period, there were abrupt changes in the inter-annual variation of the crop yield loss in the mountain, hill, and Terai regions of the KRB. Figure 3a shows the abrupt changes in maize yield loss that occurred between 2013 and 2015, indicating a decreasing trend in the mountain region. Figure 3b suggests an intersection in rice yield loss in the mountain region in 1994, 2004, 2006, 2012, 2013, and 2014. The intersection showed a trend of both increasing and decreasing yield loss. Figure 3c shows the increasing trend of wheat yield loss in the mountain region since 2009, with a significant trend beginning in 2013 (P < 0.05).

According to Fig. 3d, the intersection for maize yield loss in the hill region was observed in 1993, with a significant increasing trend noticed after 1995 (P < 0.05). Furthermore, Fig. 3e demonstrates an abrupt change in rice yield loss in the hill region in 1990, 1992, and 1998. After 1998, the change exhibited a decreasing trend with statistically significant after 2002 (P < 0.05). Figure 3f illustrates an abrupt change in wheat yield loss that occurred in the hill region in 1988 and 2015. The change in 1988 displayed an increasing trend that remained significant after 1990 until 2004.

Figure 3g showed an abrupt change in maize yield loss in the Terai region in 2000, along with an increasing trend. Moreover, Fig. 3h indicated the intersection point for a short, increasing trend in Terai rice yield loss, which occurred in 2010 and 2011. Lastly, Fig. 3i portrays an abrupt change in wheat yield loss in the Terai region in 2014, with a slight decreasing trend.

The overall results indicate that crop yield losses in the mountain, hill, and Terai regions of KRB fluctuated significantly between 1987 and 2016, with most of the changes occurring after 2000. The mountain region experienced an abrupt change in 2009, followed by a significant increase in wheat yield loss after 2013. In the hill region, maize, rice, and wheat yields showed abrupt changes and a significant trend. After 1993, maize yield losses increased, with a significant rise after 1995. Rice yield loss intersected in 1990, 1992, and 1998, followed by a decreasing trend after 1998, which became significant after 2002. Wheat yield loss experienced abrupt changes in 1988 and 2015, with a significant upward trend between 1990 and 1999.

### 3.3 Wavelet analysis of crop yield loss

#### 3.3.1 Analysis of wavelet transform

The real contour map of the wavelet coefficient illustrates the periodic variation of crop yield loss (maize, rice, and wheat) in different timescales (1 to 16 years) based on time series data from 1987 to 2016. Figures 4a, e, i, 5a, e, i, and 6a, e, i depict the real part of the yield losses in the mountain, hill, and Terai from 1987 to 2016. The pink zone represents the highest yield losses, the blue zone represents the lowest yield losses, and the other colors represent the intermediate level of loss.

Figures 4a, e, and i demonstrate that in the mountain region, maize yield losses varied from 4 to 12 years, rice yield loss varied from 4 to 16 years, and wheat yield loss varied from 8 to 16 years. The 4–12-year scale showed over 3 cycle oscillations, while the 10–16-year and 8–16-year scales displayed two cycle oscillations. Maize yield losses were high in 1990–1992, 2007–2008, and 2011–2012, while rice yield losses were high in 1987–1989, 1998–2001. Similarly, wheat yield losses were high in 1998–2003, 2007–2012. Low maize yield periods occurred in 1987–1989, 1993–1994, 2009–2010, 2013, 2014–2015. Low rice yield periods were observed in 1991–1995, 1999–2000, 2003–2005. Additionally, low wheat yield periods occurred in 2005–2006 and 2013–2014.

In the hill region, the loss of maize yield showed variation across timescales ranging from 4–7 years and 12–16 years. Rice yield loss varied across timescales of 9 to 15 years, while wheat yield varied across timescales of 10 to 16 years. These trends are illustrated in Figs. 5a, e, and i. The oscillations on the 4–7-year scale were over 1 cycle, while those on the 12–16-year scale were over 2 cycles. Similarly, there were one and two oscillations on the 9–15-year scale and 10–16-year scale, respectively.

The periods of high maize yield loss were 2010–2011 and 2014–2015 on the 4–7-year timescale, and 1987–1988 and 1997–1999 on the 12–16-year timescale. For rice yield, the periods of high loss were 1987–1990 and 1993–2000, while for wheat yield, they were 1999–2003 and 2008–2012. On the other hand, the periods of low maize yield loss were 2012–2013 (4–7-year timescale), 1991–1994, and 2001–2004 (12–16-year timescale), and 2004–2007 and 2013–2016. For rice yield, the periods of low loss were 1991–1994, and for wheat yield, they were 2004–2007 and 2013–2016.

In the Terai region, maize yield loss varied across timescales ranging from 10 to 16 years, rice yield loss varied across timescales of 11 to 16 years, and wheat yield loss varied across timescales of 7 to 16 years, as depicted in Figs. 6a, e, and i. There were 2 cycle oscillations on the 10–16-year
Fig. 4 Wavelet coefficient contour map (a, e and i), wavelet variance diagram (b, f and j), major periodic oscillation at different timescale of maize, rice and wheat yield loss in the mountain region of the KRB, Nepal.
scale, 3 cycle oscillations on the 11–16-year scale, and over 3 cycle oscillations on the 7–16-year scale.

The periods of high maize yield loss were 1998–2003, 2008–2012, and 2011–2012. For rice yield, the high loss periods were 1987–1990, 1997–2001, and 2007–2011. Similarly, for wheat yield the high loss periods were 1987–1991, 1992–1996, 1999–2003, and 2009–2014. The low maize yield loss periods were observed in 2004–2007 and 2013–2016, low rice yield loss periods were observed in 1992–1995, 2003–2005, and 2013–2014; and low wheat yield loss periods were observed in 1989–1992, 1997–1999, 2005–2007, and 2013–2016.

Overall results of the wavelet transform analysis indicate that maize yield loss varied in two timescales (4–7-year and 12–16-year) in the hill region, one timescale in the mountain (4–12-year), and one timescale (10–16-year) in the Terai region, over a 16-year period from 1987 to 2016. In contrast, rice and wheat yield losses varied in one timescale across all three regions over the same period.

From 1987 to 2016, the mountain and Terai regions experienced several years of high maize yield loss until 2012, while the hill region experienced high yield loss until 2015. The mountain region experienced a high rice yield loss period until 2001, the hill region until 2000, and the Terai region until 2011, during the same period. Similarly, a high wheat yield loss period was observed in the mountain and hill regions until 2012 and in the Terai region until 2014 from 1987 to 2016.

### 3.3.2 Analysis of wavelet variance and periodic features

The wavelet variance figures provided a visualization of the wave energy distribution with respect to the timescale (year) of the crop yield loss time series in different regions of KRB, Nepal. This analysis allowed for the identification of key periods in the development process of a yield loss series. The annual crop yield loss series had two obvious peaks, as shown in Figs. 4b, f, and j for mountain crops; 5b, f, and j for hill crops; and 6b, f, and j for Terai crops. The highest peak value observed at a particular timescale reflects the strongest cycle oscillation of that timescale and represents the first key period of crop yield loss variation. For instance, in the mountain region, the highest peak value observed at timescale-8 for the maize corresponds to the strongest first key period of yield loss from 1987 to 2016. The second peak value
Fig. 5 Wavelet coefficient contour map (a, e and i), wavelet variance diagram (b, f and j), major periodic oscillation at different timescale of maize, rice and wheat yield loss in the hill region of the KRB, Nepal.
corresponds to the second dominant period from 1987 to 2016. This demonstrates that the fluctuation of these two periods governs the variation features of the annual crop yield loss over the study time domain.

Based on the wavelet variance test results, Fig. 4c-d, g-h and k-l illustrate the wavelet coefficient process of the two-key period (timescale) of the crop yield loss time series evolution for the mountain region. Figure 5c-d, g-h and k-l show the same for the hill region while Fig. 6c-d, g-h and k-l show it for the Terai region. Table 4 summarizes the average period and variation characteristics in the evolution process of annual crop yield loss in the mountain, hill, and Terai regions over different timescales. The distribution characteristics of crop yield loss time series from 1987 to 2016 in the entire study domain are uneven and show significant localization characteristics. The variation process of high and low yield loss under different timescale features is distinct and closely related to timescale. Thus, the crop yield loss time series in all regions have two key timescale periods.

Based on the results of the wavelet variance and periodic feature analysis, it was observed that the first main period of maize and wheat yield loss varied for the mountain and Terai regions, while for rice yield loss the first main period was the same (11-year timescale). The characteristics of these timescales played an important role in determining the high and low yield loss variation trends in the crops of the KRB regions. Using these scale characteristics, it is possible to predict that the crop yield loss may enter the high yield loss or low yield loss period in a short time after 2016.

4 Discussion

In this study, we aimed to estimate and analyze the yield loss of maize, rice and wheat in the mountain, hill and Terai regions of KRB from 1987 to 2016. To do so, we first calculated the yield loss by estimating the expected crop yield using the Lagrange interpolation method. Then, we identified the year in which abrupt changes in yield loss occurred during the time series. Finally, we analyzed the periodic variation of crop yield loss time series data in different timescales, and determined the key periods in the development process of the crop yield loss series.
Fig. 6 Wavelet coefficient contour map (a, e and i), wavelet variance diagram (b, f and j), major periodic oscillation at different timescale of maize, rice and wheat yield loss in the Terai region of the KRB, Nepal.
4.1 Analysis of crop yield loss in the KRB, Nepal

According to our study, the highest yield loss for maize, rice, and wheat occurred after 2000 in KRB from 1987 to 2016. This loss could be attributed to the frequent occurrence of moderate and severe droughts in the basin during this period, as reported by Dahal et al. (2021). Our analysis found that the average maize yield loss was the highest in the Terai region followed by the hill and mountain regions, while the rice yield loss was the highest in the hill region followed by the mountain and Terai regions. For wheat, the average yield loss rate was highest in the mountain region followed by the hill and Terai regions. These losses were found to be related to spring, summer, and winter droughts prevalent in the Terai, hill, and mountain regions of the KRB, respectively, as reported by Dahal et al. (2021).

Similar findings were reported by Joshi (2018), who noted that droughts in the eastern and central regions of Nepal in the 1990s (1992, 1994, and 1997) and 2000s (2002, 2008, 2009, 2012, and 2013) caused significant crop loss of approximately 0.385 million Metric Ton. Our results showed that the average yield loss rate for rice and wheat was mountain > hill > Terai, while maize was Terai > mountain > hill. The higher yield loss rate characteristics observed in the study can be attributed to several factors, including the lack of agricultural intensification, adequate precipitation, and farming inputs, which can result in low yield and exacerbate food insecurity (Joshi et al. 2012). Inappropriate technologies for rainfed agriculture and limited accesses to modern technology to minimize loss rate from abiotic factors such as drought are major constraints for low rice yield (Tripathi et al. 2019). The higher maize yield loss in the Terai region may be attributed to the use of inappropriate seed varieties in the changing climate, which can increase food insecurity and profit loss. Therefore, selecting hybrid maize varieties may be appropriate for reducing yield loss in the Terai conditions (Ghimire et al. 2016). Meanwhile, the higher wheat yield loss in the mountain region could be attributed to sowing conditions, varietal selection, and varying climatic conditions such as drought (Thapa et al. 2020). Our findings showed that the mountain’s wheat loss was 40.2% which is slightly lower than Thapa et al. (2020) findings of 50–62% for the entire Nepal. Overall, these findings highlight the need for appropriate technologies, varietal selection, and access to modern farming inputs to minimize crop yield loss and reduce food insecurity in KRB.
4.2 Abrupt change in crop yield loss

Our study focused on analyzing the yield loss of maize, rice, and wheat in the mountain, hill, and Terai regions of the KRB from 1987 to 2016. Our findings revealed a series of yield losses in all three regions during this period. We conducted an abrupt change analysis of these losses to understand the pattern of change over time.

We found a significant increase in wheat yield loss in the mountain and hill regions. There was a significant increase in maize yield and a decrease in rice yield in the hill region. The increase wheat yield loss observed in mountain in 2009 could be attributed to the winter droughts of 2008 and 2009, which reduced national wheat yield by 14.5% (WFP 2009). Similarly, the wheat yield loss change observed in the hill region in 1988 and 2015 and the significant increasing loss trend between 1990 and 1999 could be attributed to various abiotic factors such as drought and hailstone (Pandey et al. 2020). The significant decrease in winter precipitation (10.9 mm/decade) in the hill region during 1987 to 2017 may also have contributed to yield loss (Dahal et al. 2021). Similarly, the scarcity of improved seed varieties, inefficient water use, and a lack of climate resilient farming techniques were also found to contribute to wheat yield loss as discussed by Chatrath et al. (2007). In the hill region, maize yield loss was observed in 1993 and showed a significant increase after 1995. Maize is sown in the rainfed condition in the hill region (Nayava 2010). The obvious poor distribution of precipitation in the 1990s (particularly in 1992, 1994 and 1997) in the eastern and central regions of Nepal may have contributed to a significant increase in maize yield loss in the region (Joshi 2018). Rice yield loss intersected in 1990, 1992, 1998 and a decreasing trend was observed after 1998, becoming significant after 2002. The decreasing trend of rice yield loss may be due to improved technologies. Rice is cultivated without irrigation in terraced lands in the hill region, and several crop management practices and drought-tolerant varieties have been introduced to reduce the potential threat of yield loss due to abiotic stresses (Adhikari et al. 2015). Similarly, drought tolerant rice varieties introduced after 2001, and chemical fertilizers usage may have reduced rice yield losses in the hill region after 2002 (Bhandari 2017).

4.3 Wavelet analysis of crop yield loss

The wavelet transform analysis was conducted to investigate the variation of maize, rice, and wheat yield loss at different timescales in the KRB’s mountain, hill, and Terai regions between 1987 and 2016. The results of the wavelet variance and periodic features analysis revealed two dominant periods that control the changes in crop yield loss over the entire time domain. The coefficient's process line depicts the high and low yield loss periods at different timescales. Table 3 presents the timescale, variation period (in years), and number of cycles observed for the two dominant periods for maize, rice, and wheat yield loss in all KRB regions. These findings can be used to project the next peaks of the dominant period timescale after 2016, as shown in Table 5.

The next peaks of the 11-year timescale (maximum first dominant period) for rice yield loss (all regions) and maize yield loss may occur around 2019 and 2026 in the Terai region. Similarly, the next 5-year timescale peaks (maximum second dominant period) for rice yield loss (mountain) and wheat yield loss may occur around 2019 and 2022 in the Terai region. For wheat yield loss in the mountain region, the next peaks to occur in 2023 and 2026, and for rice yield loss in the hill region, the next peaks to occur in 2017 and 2020.

5 Conclusion

In this study, we analyzed the spatial and temporal patterns of maize, rice, and wheat yield loss in the KRB region Nepal between 1987 and 2016. Our analysis revealed that the average crop yield loss (kg/ha) followed a pattern of Terai > hill > mountain for maize; hill > mountain > Terai for rice, and mountain > hill > Terai for wheat. This pattern became more significant after 2000. Similarly, the average yield loss rate for rice and wheat followed a mountain > hill > Terai pattern, while the maize yield loss rate was found to be Terai > mountain > hill pattern. We observed an abrupt change in the mountain wheat yield loss in 2009, and the trend has been increasing significantly since 2013. In the hill region, the abrupt change in wheat yield loss occurred in 1988 and 2015, with a significant increasing trend observed between 1990 and 1999. Similarly, the abrupt change in maize yield loss in the hill region was observed in 1993 and it significantly increased after 1995. Despite abrupt changes in rice yield loss in the hill region in 1990, 1992, and 1998, our analysis showed a decreasing trend in rice yield loss since 2002.

Between 1987 and 2016, the wavelet analysis revealed periodic variation in maize, rice, and wheat yield loss in the KRB region. The analysis showed that high maize yield loss years were observed until 2012 in the mountain and Terai regions and until 2015 in the hill region. Similarly, high rice yield loss was
observed until 2001 in the mountain, 2000 in the hill and until 2011 in the Terai region. Likewise, high wheat yield loss was observed until 2012 in the mountain and hill regions and until 2014 in the Terai region. The wavelet variance and periodic features analysis showed that the first key period of the maize and wheat yield loss differed between the mountain and Terai regions, but not for rice yield loss. The 11-year timescale was identified as the first critical period in all regions and the characteristics of these timescales played a significant role in the high and low yield loss variation trend in the crops in the KRB regions. Based on these characteristics scale, it can be predicted that the crop yield loss will enter a high or low yield loss period shortly after 2016.

The study results indicate that there were significant yield losses in maize, rice, and wheat crops in the KRB regions of Nepal from 1987 to 2016. The study also showed that the yield loss varied across different timescales during this period, and predicted the occurrence of high or low yield loss after 2016 based on the observed patterns. These findings are of great importance to agriculturalists, agronomists, and policy makers who can use this information to develop interventions to reduce yield losses, conduct economic analyses, and plan for future technical measures to increase productivity.

Acknowledgements This study was funded by the Chinese Academy of Sciences (CAS) Overseas Institutions Platform Project (Grant No. 131C11KYSB20200033) and the National Natural Science Foundation of China (NSFC) and International Center for Integrated Mountain Development (ICIMOD) (NSFC-ICIMOD) Joint Research Project (Grant No. 4166114038). We would like to express our gratitude to the Department of Hydrology and Meteorology and Ministry of Agriculture and Livestock Development (Government of Nepal) for providing the raw data for this study.

### Table 4 Analysis results of crop yield loss timeseries characteristic in the different time scales

| Region  | Crop  | Timescale | Variation period/year | Cycle Times | Crop yield loss variation trend after 2016 | Reference |
|---------|-------|-----------|-----------------------|-------------|------------------------------------------|-----------|
| Mountain | Maize | 8 | 6 | 5 | Enter high yield loss period | Figure 1c |
|         |       | 4 | 3 | 10 | Progressively entering high yield loss period | Figure 4d |
|         | Rice  | 11 | 7.5 | 4 | Progressively entering high yield loss period | Figure 4g |
|         |       | 5 | 3.75 | 8 | Enter low yield loss period | Figure 4h |
|         | Wheat | 12 | 7.5 | 4 | Enter high yield loss period | Figure 4k |
|         |       | 5 | 3.3 | 9 | Enter low yield loss period | Figure 4l |
| Hill    | Maize | 6 | 4.28 | 7 | Progressively entering low yield loss period | Figure 5c |
|         |       | 4 | 2.72 | 11 | Enter low yield loss period | Figure 5d |
|         | Rice  | 11 | 7.5 | 4 | Enter low yield loss period | Figure 5g |
|         |       | 5 | 3 | 10 | Enter low yield loss period | Figure 5h |
|         | Wheat | 13 | 10 | 3 | Enter low yield loss period | Figure 5k |
|         |       | 6 | 3.75 | 8 | Enter high yield loss period | Figure 5l |
| Terai   | Maize | 11 | 7.5 | 4 | Progressively entering high yield loss period | Figure 5c |
|         |       | 3 | 3.33 | 9 | Enter high yield loss period | Figure 5d |
|         | Rice  | 11 | 7.5 | 4 | Enter high yield loss period | Figure 5g |
|         |       | 6 | 4.28 | 7 | Enter low yield loss period | Figure 5h |
|         | Wheat | 9 | 6 | 5 | Enter low yield loss period | Figure 5k |
|         |       | 5 | 3.75 | 8 | Enter low yield loss period | Figure 5l |

### Table 5 Projection of the two dominant periods of crop yield loss timeseries characteristic in the different time scales

| Region  | Crop  | Timescale | Variation period/year | Number of Cycle | Next peak after 2016 |
|---------|-------|-----------|-----------------------|-----------------|---------------------|
| Mountain | Maize | 8 | 6 | 5 | 2017 and 2023 |
|         |       | 4 | 3 | 10 | 2017 and 2020 |
|         | Rice  | 11 | 7.5 | 4 | 2019 and 2026 |
|         |       | 5 | 3.75 | 8 | 2019 and 2022 |
|         | Wheat | 12 | 7.5 | 4 | 2019 and 2026 |
|         |       | 5 | 3.3 | 9 | 2023 and 2026 |
| Hill    | Maize | 6 | 4.28 | 7 | 2022 and 2026 |
|         |       | 4 | 2.72 | 11 | 2020 and 2022 |
|         | Rice  | 11 | 7.5 | 4 | 2019 and 2026 |
|         |       | 5 | 3 | 10 | 2017 and 2020 |
|         | Wheat | 13 | 10 | 3 | 2017 and 2027 |
|         |       | 6 | 3.75 | 8 | 2019 and 2022 |
| Terai   | Maize | 11 | 7.5 | 4 | 2018 and 2026 |
|         |       | 3 | 3.33 | 9 | 2023 and 2026 |
|         | Rice  | 11 | 7.5 | 4 | 2019 and 2026 |
|         |       | 6 | 4.28 | 7 | 2022 and 2026 |
|         | Wheat | 9 | 6 | 5 | 2017 and 2023 |
|         |       | 5 | 3.75 | 8 | 2019 and 2022 |
Author contributions All authors contributed to this study. The first draft of the manuscript was written by Nirmal Mani Dahal and all authors revised and provided feedbacks on the manuscript. All authors read and approved the final manuscript. The details of contribution are as follows:

Conceptualization: Nirmal Mani Dahal, Donghong Xiong, Nihili Neupane; Methodology: Nirmal Mani Dahal, Su Zhang; Formal analysis and investigation: Nirmal Mani Dahal; Writing—original draft preparation: Nirmal Mani Dahal; Writing—review and editing: Nihili Neupane, Yong Yuan, Baojun Zhang, Yiping Fang, Wei Zhao, Yanhong Wu, Wei Deng; Funding acquisition: Donghong Xiong, Yanhong Wu, Wei Deng; Resources: Donghong Xiong; Supervision: Donghong Xiong.

Funding This study was funded by the Chinese Academy of Sciences (CAS) Overseas Institutions Platform Project (Grant No. 131C11KYSB20200033) and the National Natural Science Foundation of China (NSFC) and International Center for Integrated Mountain Development (ICIMOD) (NSFC-ICIMOD) Joint Research Project (Grant No. 41661144038).

Data availability Not applicable.

Code availability Not applicable.

Declarations

Ethics approval All authors comply with the guidelines of the journal Theoretical and Applied Climatology.

Consent to participate All authors agreed to participate in this study.

Consent to publication All authors agreed to the publication of this study.

Conflict of interest We have no conflict of interest to declare.

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