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# Application of MK trend and test of Sen's slope estimator to measure impact of climate change on the adoption of conservation agriculture in Ethiopia

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## ABSTRACT

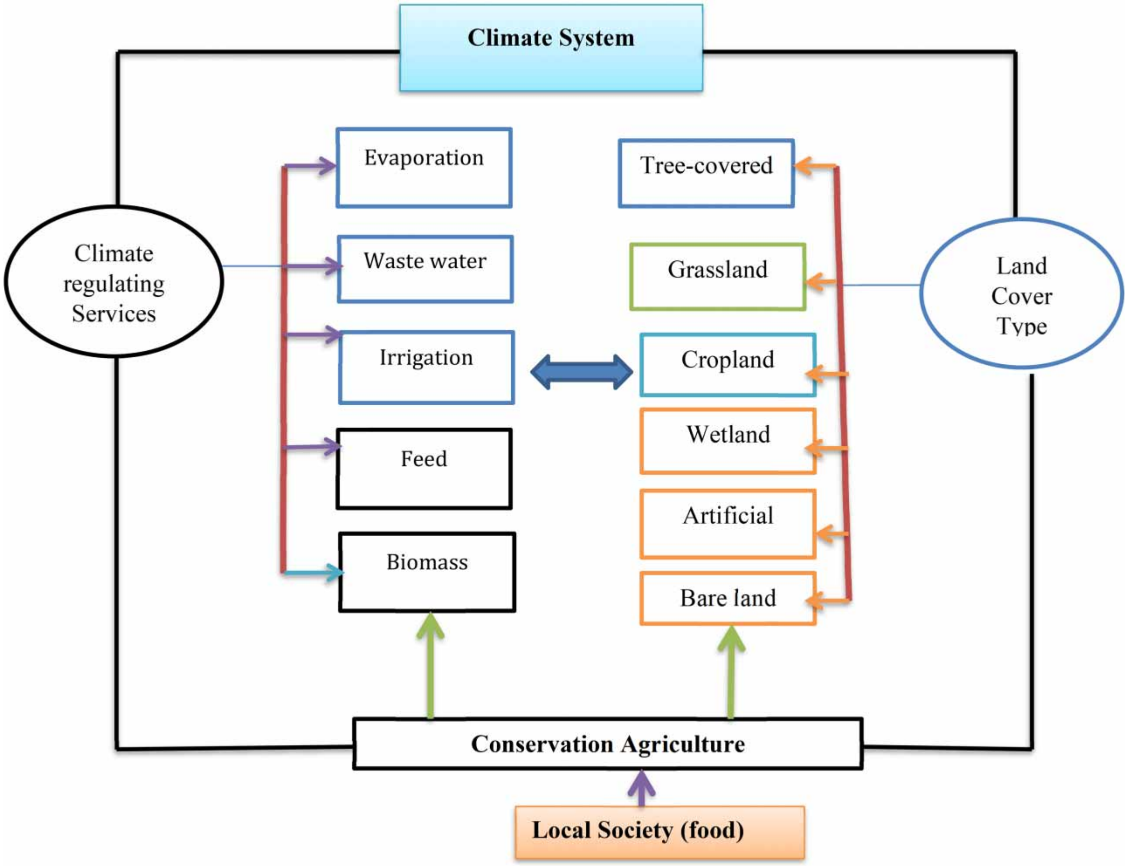
The objective of this study is to identify the adoption level of this agricultural technology affected by climate change and to confirm the relationship with conservation agriculture. The assessment was carried out using the Mann–Kendall trend test and the Sen's slope is used. The collected data were statistically analyzed by Statistical Down Scaling Model Software to compare the observed and climate model scenarios of temperature and precipitation. According to the results of the study, earth analysis of the 2001–2021 data revealed that 26.68% of the land area has improved productivity, 67.38% of the territory is stable, 5.93% of the area has degraded productivity, and 0.02% of the area has no productivity data. The study result indicated that there is variability, a decrease in rainfall, and a rise in temperature in the area. The Mann–Kendall and Sen's slope test findings for the total maximum annual rainfall reveal a *P*-value of 0.307, indicating that there is no pattern in the series or variability of rainfall and that there is a diminishing trend in the rainfall data. The study's findings may help decision-makers and water managers provide more sustainable strategies and methods for managing water resources.

**Key words:** adoption, climate change, conservation agriculture, land productivity

## HIGHLIGHTS

- Crucial information for smallholder farmers in rural regions.
- To explain how conservation agriculture might assist us to lessen the influence of events.
- It also offers a comprehensive answer to Ethiopia's major issue.
- Maintaining the cultivated land will help local residents by reducing the effects of high-intensity raindrops.
- To pinpoint the key socioeconomic elements that influence the adoption of conservation agriculture.

## GRAPHICAL ABSTRACT




## INTRODUCTION

Conservation agriculture is a crucial ecological issue impacting Earth and humans (Wilhite & Glantz 1985). It refers to water scarcity, severely impacting society's different segments, such as hydropower, agriculture, industrial, and water supply (Dracup *et al.* 1980). The crucial factors for assessing the conservation agriculture severity include period, location in absolute time, i.e., start and closure time points, areal coverage, and scale or force (Mishra *et al.* 2009). Climate and stream flow data from mountainous places have shown a pattern of increasing winter minimum temperatures over the last few decades and reduced snowfall compared to the total precipitation (Knowles *et al.* 2006). It has been indicated that decreased spring snow cover and snow depth affect summer stream flow (Rood *et al.* 2008). Studies in various countries have shown that snow significantly impacts the surface moisture accessible for runoff in the future (Maurer *et al.* 2003).

Climate change impacts are causing the biggest challenge in the world in terms of reduction in land productivity through reducing crop yield and increasing yield variability (Sehgal *et al.* 2020). This problem can be preserved by the adoption of conservation agriculture (Fleitas *et al.* 2020). Conservation agriculture is a field-level farming approach that fosters natural ecological processes to increase agricultural yields and sustainability by minimizing soil disturbance, maintaining permanent soil cover, and diversifying crop rotations (Juliana *et al.* 2020). It can also encompass natural resource management at the farm, village, and landscape scales to increase synergies between food production and the conservation and use of ecosystem services (Velu *et al.* 2020). As a context-sensitive management strategy, conservation agriculture can include diverse practices such as livestock and fodder management, improved fallows, agroforestry, watershed management, and community-protected areas (Su *et al.* 2021).

Several authors reported that conservation agriculture is an essential analysis to make long-term water management plans, particularly with regard to increasing agricultural yields and sustainability (Change 2014). In addition to this, biomass and residue data are regularly recorded and utilized for the planning and management of conservation agriculture (Hanssen et al. 2020). In this regard, a review of the literature revealed that several studies are conducted to understand the changing characteristics of flow using river flow data in developing countries, including Ethiopia (Benti et al. 2021).

Many approaches have been also proposed in the past to identify the trends in the adoption of conservation agriculture (Gabisa & Gheewala 2018). However, nonparametric approaches such as Mann–Kendall (MK) test and Sen's slope test have been preferred over parameter methods for biomass production in deserts due to the non-requirement of missing data, no-parameter estimated uncertainty, and simplified computation (Nguyen et al. 2022). The major drawback is that the significance of the test is severely affected by the presence of autocorrelation (Hu et al. 2020). Therefore, many researchers have proposed modifications to overcome the autocorrelation problem through conservation agriculture in order to increase yield (Malik et al. 2020). However, recent studies have revealed that while conservation agriculture may help us to reduce biomass phenomena such as the impact of climatic variability or land-use change (Alashan 2020), such localized variation may also result in a false trend that may impact the results of the MK test (Alhaji et al. 2018).

The other previous studies focused on the main socioeconomic factors that affect the adoption of conservation agriculture such as extension services, household head, high input cost, low input variability, possibly low biomass access, and greater size of land owned (Maina et al. 2020). There is a theoretical basis and limited empirical evidence to support the notion that climate variability affects the adoption and productivity levels of conservation agriculture. The impacts of climate change on the adoption of conservation agriculture have not been well studied (Abera et al. 2020). The variability of climate variables has a direct significant impact on the adoption of conservation agriculture (Hassen & Bantider 2020). However, there is not sufficient research to confirm this relationship as being broadly true. These relationships have not been specifically studied in adoption of the conservation agriculture practiced in Ethiopia.

The main objectives of this study were (i) to identify the long-term changes at different study areas assessing the adoption of conservation agriculture using Statistical DownScaling software; (ii) to compare the results of Statistical Downscaling software with the traditional MK and Sen's slope tests conducted in the study areas; (iii) and finally to identify whether adoption of conservation agriculture is increasing or decreasing in the study areas.

### Significance of the study

Furthermore, in order to give crucial information to smallholder farmers in rural regions, this study details how water erosion is one of the major issues with land degradation and constitutes a huge environmental hazard. The findings also helped us to explain how conservation agriculture might assist us to lessen the influence of events like climate variability or land-use change in the study areas on biomass. It also offers a comprehensive answer for Ethiopia's major issue with soil erosion brought on by excessive grazing, poor land management, and deforestation. Maintaining the cultivated land will help local residents by reducing the effects of high-intensity raindrops with high runoff potential. Additionally, it helps the smallholder farmer to pinpoint the key socioeconomic elements – extension services, family heads, high input costs, low input variability, potentially limited access to biomass, and ownership of larger tracts of land in the research areas – that influence the adoption of conservation agriculture.

## METHODOLOGY

### Description of the study areas

The study was carried out in the Dire Dawa which is found in the eastern part of Ethiopia on the border of Awash plain on the highland just at the foot slope of the Dengego mountain between 9°27′ and 9°49′N Latitude and 41°38′ and 42°19′E Longitude (Solomon et al. 2020). It is astronomically located in the eastern part of Ethiopia 515 km away from the capital Addis Ababa (Gelata et al. 2022). It has a rugged and undulating mountainous topography ranging from 1,000 to 2,260 m asl and receives a total annual rainfall ranging between 410 and 850 mm and extreme temperatures of 34.6 °C and experiences frequent droughts, dry spells, and floods (Ayalew et al. 2017). The study area covers a total area of 3,143.8 km$^2$ and has a total population of 535,000 living in 38 rural and 9 urban kebeles (smallest administrative unit) (Anley et al. 2022). Agriculture (both crop and livestock production) is the main mainstay of the economy and subsistence mixed farming constitutes 93% of the total farm households in the study area (Mehari & Belay 2017).

### Data sources

The climate data (rainfall and air temperature from 1981 to 2021) for the present study were obtained from the NASA POWER (Prediction of Worldwide Energy Resources) project. The POWER project derives its data from the following

NASA sources: World Climate Research Program (WCRP), Global Energy and Water Cycle Experiment (GEWEX), Surface Radiation Budget Project (NASA GEWEX SRB) and the Clouds and the Earth's Radiant Energy System and Assimilation Office at the Goddard Space Flight Center. Other researchers have used NASA POWER for their research and have justified its usefulness for metrological daily data to apply it in agro meteorology (Al-Adwan *et al.* 2022).

### Data analysis

The temperature and rainfall data collected over the period were analyzed using statistical methods such as Mann–Kendall and Sen's slope. Several researchers have adopted this approach to understand the trends in the temperature phenomenon (Yaouba & Dieudonné 2022).

### MK test

The MK test is used to perceive statistically significant decreasing or increasing trends in long-term temporal data (Mallick *et al.* 2021). The MK trend test is based on two hypotheses: one is null (H0) and the other is the alternative (H1) hypothesis (Gadedjisso-Tossou *et al.* 2021). The H0 expresses the existence of no trend while H1 elucidates a significant rising or declining trend in precipitation data (Agbo *et al.* 2021). On the basis of 5% significance level, if $p$-value is $<0.05$, then the alternative hypothesis is accepted which signifies the presence of a trend in the data and if the $p$-value is $>0.05$, the H0 will be accepted that denotes the absence of a trend in the data (Baig *et al.* 2021). The formula is provided by the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sign}(X_j - X_i) \tag{1}$$

where $n$ is the numbers of data points, $X_j$ and $X_i$ are annual values in years $j$ and $i$, $j > 1$ and Sign $(X_j - X_i)$ calculated using the equation:

$$\operatorname{Sign}(X_j - X_i) = \begin{cases} -1 \text{ for } (X_j - X_i) < 0 \\ \ \ 0 \text{ for } (X_j - X_i) = 0 \\ +1 \text{ for } (X_j - X_i) > 0 \end{cases} \tag{2}$$

### Test of Sen's slope estimator

This test was originally developed by Sen for the performance of checking the statistical linear relationships (Agarwal *et al.* 2021). It is used to calculate the magnitude of trends in the long-term temporal data (Agarwal *et al.* 2021). Sen's slope is considered better to detect the linear relationship as it is not affected by outliers in the data (Ray *et al.* 2021). In this study, Sen's slope is applied to calculate the magnitude of the trend for temperature and rainfall data.

The following equation is used to estimate each individual slope ($Q_i$):

$$Q_i = \frac{Y_j - Y_i}{j - 1} \tag{3}$$

where $i = 1$ to $n - 1$, $j = 2$ to $n$, $Y_j$ and $Y_i$ are data values at time $j$ and $i$ ($j > i$), respectively. If in the time series, there are $n$ values of $Y_j$, estimates of the slope will be $N = n(n - 2)/2$. The slope of the Sen estimator is the mean slope of such slopes' $N$ values. The Sen's slope is:

$$Q_{ij} = \begin{cases} \dfrac{Y_j - Y_i}{j - 1} & \text{if } n \text{ is odd} \\ \dfrac{1}{2}\left(Q\dfrac{N}{2} + Q\left[\dfrac{N+2}{2}\right]\right) & \text{if } n \text{ is even} \end{cases} \tag{4}$$

The positive ($Q_i$) indicates an increasing trend, while the negative $Q_i$ values tell us that there is a negative trend in the temporal data. The unit of Sen's slope ($Q_i$) is the slope magnitude per year.

And then SDSM software was used to compare the observed and models climate scenarios of temperature and precipitation (Shakeri *et al.* 2021). For the calibration of the model, data from 1981–2005 was used, while 2006–2021 data was used for the validation (Sunil *et al.* 2021). The statistics for checking the performance of each of the models were the R2 and RMSE (Hassan & Hashim 2021). During the calibration, the downscaled parameters from the GCM which acted as the predictors were used iteratively to select the best predictor variables for the temperature (Shakeri *et al.* 2022).

According to the methodology for determining land degradation adopted by the UN for the calculation of the sustainable development goal's (SDG) indicator 15.3.1, land productivity on the basis of remote sensing data is one of the three sub-indicators (Shakeri *et al.* 2021). Then in order to estimate the biological productive capacity of the land, the sources of all the food, fiber, and fuel that sustain humans, we focused only on land productivity indicators (Sunil *et al.* 2021). Land productivity dynamics (LPD) data are provided by the Joint Research Council (JRC) as the default data for computing the final SDG 15.3.1 indicator (Wilby *et al.* 2002).

## RESULTS AND DISCUSSION

The MK and Sen's slope trend tests were individually applied at the different stations at seasonal, monthly, and annual time frame for the period 2021 at 90, 95, and 99% confidence levels (Ali *et al.* 2019). The methods were applied on monthly, mean annual, annual maximum, and annual minimum flow. Fitness of data was evaluated using the data of both stations at a 95% level of confidence (Kuriqi *et al.* 2020). The graphical results of SDSM were used to compare the observed and models (future) climate scenarios of temperature and precipitation.

According to the result, the models are significant and the observed and future scenarios was used for the assessment of trends. Parametric methods are more reliable compared to the nonparametric method (Gameda *et al.* 2022). However, parametric methods are applicable only when the data are normally distributed (Ayele *et al.* 2021). Distribution analysis of conservation agriculture data at both stations revealed that none of them is normally distributed, which means parametric methods cannot be used for assessment of trends. Therefore, nonparametric methods (MK and ITA) were used for the assessment of trends in the present study.

The result shows us the models are significant and the observed and future scenarios are similar through the year except those of April and August rainfall values. The model slightly over/underestimates some of the peak flows. This may have resulted from input data uncertainty and the weather or flow data quality used to input the model (Ayele *et al.* 2021). Some stations have missing weather data, which were left to be estimated and filled by the weather generator.

### Land productivity

Indicators for the UN SDGs state that places are considered enhanced if their production is 'improving,' stable if it is 'stable' or 'stressed,' and 'degraded' if it is 'moderately decreasing' or 'declining.' According to the result (Table 1), earth analysis of the data from the years 2001 to 2021 revealed that 26.68% of the land area has increased productivity, 67.38% has remained stable, 5.93% has decreased productivity, and 0.02% has no productivity data. The Mann–Kendall and Sen's slope trend test of the 1981–2021 data reveals that the region experiences variability, a decrease in rainfall, and an increase in temperature. Yearly statistical error results indicate that the model performance is very good. However, it can be observed that the model overestimates and underestimates the stream flow at different times (Malik *et al.* 2021). The values were in high agreement compared to previous studies conducted in other regions of the world (Kumar *et al.* 2022). The values of the statistical indicators are in a close range to those obtained during calibration and validation.

**Table 1** | Summary of change in land productivity

| Variable | Area (km$^2$) | Percent of total land area |
|---|---|---|
| Total land area | 3,143.8 | 100.00 |
| Land area with improved land productivity | 838.61 | 26.68 |
| Land area with stable productivity | 2,118.21 | 67.38 |
| Land area with degraded productivity | 186.43 | 5.93 |
| Land area with no data for productivity | 0.53 | 0.002 |

The Sen's slope and MK trend test were individually applied to the study areas. The tests were applied at each month, annual mean, annual maximum, annual minimum, and seasonal flows for the period from the years 2001 to 2021 at 90, 95, and 99% confidence levels. The obtained results are presented in Table 2. Results show that there are positive (increasing) and negative (decreasing) trends in both stations (Ali *et al.* 2019). The highest negative trend can be seen in October while the highest positive trend can be seen in January at both stations.

Results presented in the present study are based on observed data at two locations of Dire Dawa for the period of monthly absolute maximum daily rainfall from 1981 to 2021. Conservation of agriculture at different points along a river are highly correlated to each other. The similarity in results obtained at the two stations also suggests similar trends in annual and seasonal stream flow at different locations of the Yangtze River (Ali *et al.* 2019). Therefore, the results presented in this study (Table 3) can be considered as the trends for the study areas. However, future research can be conducted with the availability of data from other locations to verify the findings of the present study. Besides, different modified versions of MK tests (Ayele *et al.* 2021) can be used to assess trends in stream flow, and the obtained results can be compared with the findings of the present study in Figure 1.

Goodness-of-fit analysis of stream flow data at all stations revealed that the normal distribution is not followed with the best fit for the assessment of trends, which recommends that the data cannot be analyzed using parametric methods (Ali *et al.* 2019). Therefore, from now, the trend assessment by using nonparametric methods is shown in Figure 2.

### MK trend test/two-tailed test (total maximum annual temperature)

The results of Mann–Kendall and Sen's slope test for the total maximum annual rainfall show a $P$-value of 0.307 which means there is no trend in the series or variability of rainfall and the negative $Q_i$ values ($-0.100$) show that there is a decrease in the rainfall data. The slope of rainfall trend analysis shows that the rainfall graph for Dire Dawa station has a negative trend ($Y = -0.001x + 60.22$) as found by another researcher. For the total maximum annual temperature, the $P$-value is 0.01 which means there is a trend in the series or the temperature will continue increasing and the positive $Q_i$ values (0.380) indicate an increasing trend.

Areas of land with increasing productivity from 2001 to 2021 are broken down by kind of land cover transition (Table 4). The productivity of the land increased from 40.00 to 84.86, 2.58 to 9.03, and 2.73 to 5.16 km$^2$ for tree-covered land, artificial land, and bare land, respectively. The productivity of the grassland and crops has decreased from 283.94 to 259.73 and 508.67 to 479.14 km$^2$, respectively. Additionally, there has been no improvement in the productivity of the land in the marsh and water bodies.

According to the result (Table 5), the tree-covered, artificial, and bare land cover show an improvement from 153.28 to 220.51, 3.87 to 9.18, and 16.16 to 18.51 with stable productivity, respectively.

By type of land cover transition, the area of land with stressed productivity (Table 6) with strained productivity, the amount of tree-covered and bare land increases from 1.29 to 1.44 and 0.00 to 0.15, respectively. With stressed productivity, the farmland, artificial land, water body, and wetlands exhibit little change. However, the productivity of the grassland has decreased from 2.73 to 2.43 due to stress.

According to the results (Table 7), tree-covered land, cropland, and artificial land all show increases with moderate declines in productivity from 0.15 to 0.23, 0.91 to 0.76, and 0.00 to 0.23, respectively. With a mild fall in production from 0.83 to

**Table 2** | Summary statistics

| Variable | Obs. | Obs. with missing | Obs. without | Minimum | Maximum | Mean | Std. deviation |
|---|---|---|---|---|---|---|---|
| Total maximum annual rainfall | 41 | 0 | 41 | 12.410 | 48.730 | 30.282 | 8.658 |

**Table 3** | Sen's slope

| Variable | Value | Lower bound (95%) | Upper bound (95%) |
|---|---|---|---|
| Slope | −0.100 | −0.378 | 0.139 |
| Intercept | 228.804 | −246.691 | 786.909 |

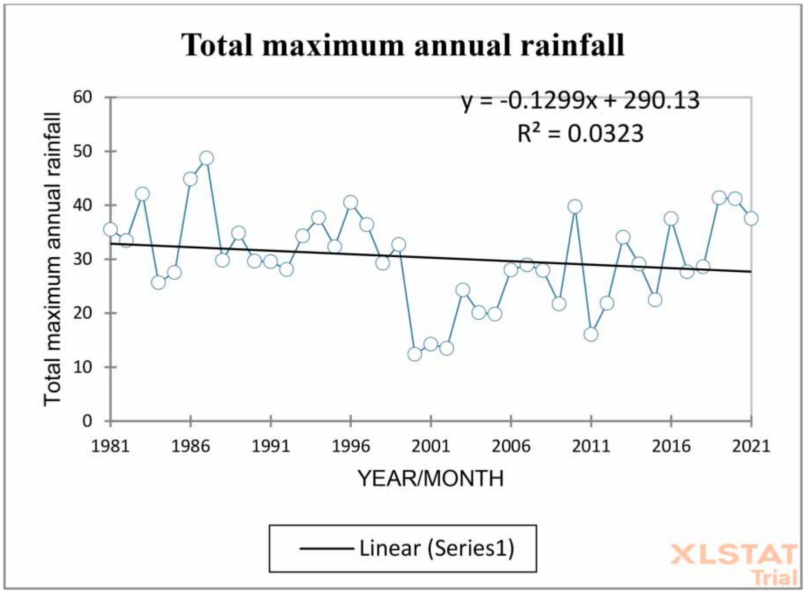



**Figure 1** | Total maximum annual rainfall.

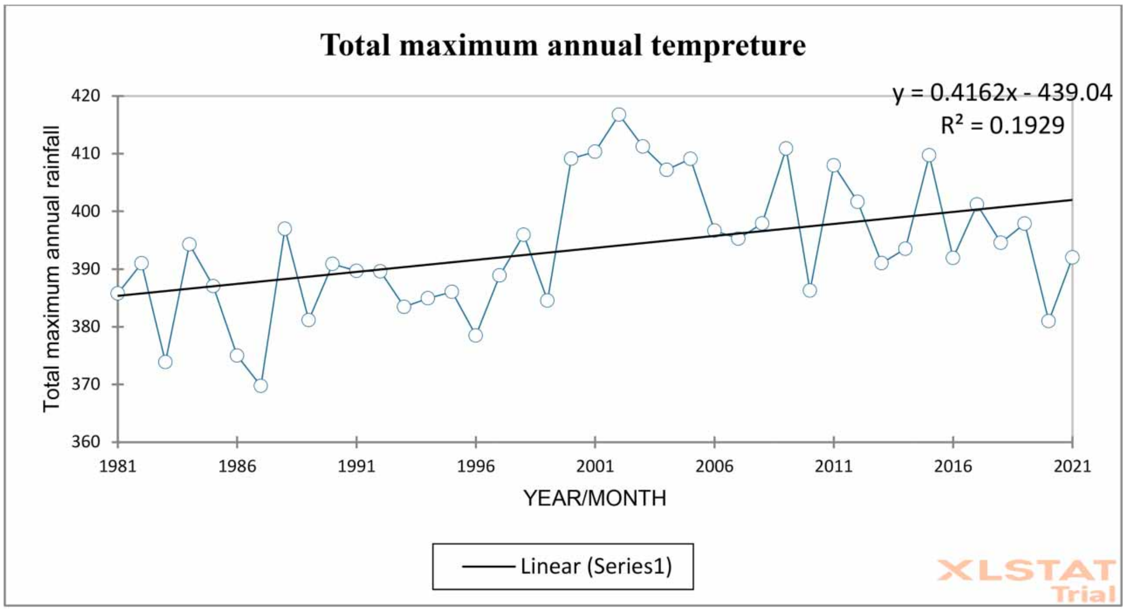



**Figure 2** | Total maximum annual temperature.

0.68 $km^2$, the grassland exhibits a reduction. Although productivity has moderately decreased, the wetland, bare land, and water body have not changed.

The above result (Table 8), the tree-covered and artificial land show an increase from 19.27 to 26.86 and 2.28 to 4.93 $km^2$ with declining productivity, respectively. The grassland and cropland show a reduction from 133.54 to 125.42 and 28.69 to 26.41 $km^2$ with declining productivity, respectively. But the wetland, bare land, and water body do not show any change with declining productivity. This is due to the variability and reduction of rainfall and increase of temperature in the region from the Mann–Kendall and Sen's slope trend test. Within a given ecosystem, primary productivity is affected by several factors,

**Table 4** | Area of land with improving productivity by type of land cover transition (km$^2$)

| Land cover type in initial year Variable | Land cover type in final year | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Tree-covered** | **Grassland** | **Cropland** | **Wetland** | **Artificial** | **Bare land** | **Water body** | **Total** | |
| | Tree-covered | 40.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 40.00 |
| | Grassland | 17.15 | 258.06 | 1.29 | 0.00 | 5.01 | 2.43 | 0.00 | 283.94 |
| | Cropland | 27.71 | 1.67 | 477.85 | 0.00 | 1.44 | 0.00 | 0.00 | 508.67 |
| | Wetland | 0.00 | 0.00 | 0.00 | 0.23 | 0.00 | 0.00 | 0.00 | 0.23 |
| | Artificial | 0.00 | 0.00 | 0.00 | 0.00 | 2.58 | 0.00 | 0.00 | 2.58 |
| | Bare land | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 2.73 | 0.00 | 2.73 |
| | Water body | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.46 | 0.46 |
| | Total: | 84.86 | 259.73 | 479.14 | 0.23 | 9.03 | 5.16 | 0.46 | 838.61 |

**Table 5** | Area of land with stable productivity by type of land cover transition (km$^2$)

| Land cover type in initial year | Land cover type in final year | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Tree-covered** | **Grassland** | **Cropland** | **Wetland** | **Artificial** | **Bare land** | **Water body** | **Total:** | |
| | Tree-covered | 153.28 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 153.28 |
| | Grassland | 54.63 | 1,400.67 | 0.61 | 0.00 | 4.17 | 6.07 | 0.00 | 1,466.15 |
| | Cropland | 12.60 | 7.89 | 450.82 | 0.00 | 1.14 | 0.00 | 0.00 | 472.46 |
| | Wetland | 0.00 | 0.00 | 0.00 | 0.30 | 0.00 | 0.00 | 0.00 | 0.30 |
| | Artificial | 0.00 | 0.00 | 0.00 | 0.00 | 3.87 | 0.00 | 0.00 | 3.87 |
| | Bare land | 0.00 | 3.72 | 0.00 | 0.00 | 0.00 | 12.44 | 0.00 | 16.16 |
| | Water body | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Total: | 220.51 | 1,412.28 | 451.43 | 0.30 | 9.18 | 18.51 | 0.00 | 2,112.21 |

**Table 6** | Area of land with stressed productivity by type of land cover transition (km$^2$)

| Land cover type in final year | Land cover type in final year | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Tree-covered** | **Grassland** | **Cropland** | **Wetland** | **Artificial** | **Bare land** | **Water body** | **Total:** | |
| **Tree-covered** | **1.29** | **0.00** | **0.00** | **0.00** | **0.00** | **0.00** | **0.00** | **1.29** | |
| | Grassland | 0.15 | 2.43 | 0.00 | 0.00 | 0.00 | 0.15 | 0.00 | 2.73 |
| | Cropland | 0.00 | 0.00 | 1.90 | 0.00 | 0.00 | 0.00 | 0.00 | 1.90 |
| | Wetland | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Artificial | 0.00 | 0.00 | 0.00 | 0.00 | 0.08 | 0.00 | 0.00 | 0.08 |
| | Bare land | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Water body | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | Total: | 1.44 | 2.43 | 1.90 | 0.00 | 0.08 | 0.15 | 0.00 | 5.99 |

such as temperature, and the availability of light, nutrients, and water. Of those, increasing temperature and rainfall variability was the most significant factor in influencing the amount of plant tissue produced every year.

## DISCUSSION

The findings show that conservation agriculture, a field-level farming strategy that promotes natural ecological processes to increase agricultural yields and sustainability by minimizing soil disturbance, maintaining permanent soil cover, and

**Table 7** | Area of land with moderate decline for productivity by type of land cover

| Land cover type in the initial year | Land cover type in the final year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Tree-covered | Grassland | Cropland | Wetland | Artificial | Bare land | Water body | Total: |
| Tree-covered | 0.15 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.15 |
| Grassland | 0.08 | 0.68 | 0.00 | 0.00 | 0.08 | 0.00 | 0.00 | 0.83 |
| Cropland | 0.00 | 0.00 | 0.76 | 0.00 | 0.15 | 0.00 | 0.00 | 0.91 |
| Wetland | 0.00 | 0.00 | 0.00 | 0.08 | 0.00 | 0.00 | 0.00 | 0.08 |
| Artificial | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Bare land | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Water body | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Total: | 0.23 | 0.68 | 0.76 | 0.08 | 0.23 | 0.00 | 0.00 | 1.97 |

**Table 8** | Area of land with declining productivity by type of land cover transition ($km^2$)

| Land cover type in the initial year | Land cover type in the final year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Tree-covered | Grassland | Cropland | Wetland | Artificial | Bare land | Waterbody | Total: |
| Tree-covered | 19.27 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 19.27 |
| Grassland | 7.21 | 125.42 | 0.00 | 0.00 | 0.91 | 0.00 | 0.00 | 133.54 |
| Cropland | 0.38 | 0.15 | 26.41 | 0.00 | 1.75 | 0.00 | 0.00 | 28.69 |
| Wetland | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Artificial | 0.00 | 0.00 | 0.00 | 0.00 | 2.28 | 0.00 | 0.00 | 2.28 |
| Bare land | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.68 | 0.00 | 0.68 |
| Waterbody | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Total: | 26.86 | 125.57 | 26.41 | 0.00 | 4.93 | 0.68 | 0.00 | 184.46 |

diversifying crop rotations, is becoming more and more popular. Additionally, future studies should take climate change projections into account in order to effectively estimate the intensity, frequency, and severity of droughts over a long time span (Ali *et al.* 2019).

Trend identification is one of the most important analyses in conservation agriculture adoption and climate change research, according to several earlier studies (Kuriqi *et al.* 2020). Our findings confirmed prior research showing that the adoption of conservation agriculture was more reliable for increasing agricultural yield in order to keep the sustainability policy for the 2023 goal (Wegari & Gelata 2021). The latter includes heavy tillage, which farmers already use to prepare the soil and clear crop wastes from agricultural fields for feed, fuel, and free grazing. Farmers till four to seven times annually.

This study demonstrated, among other things, that the goal for which water infrastructures were constructed is frequently at odds with extensive development and inefficient management of those infrastructures (Kumar *et al.* 2022). Effective management of water resources requires determining if low, medium, and high hydrological events have different trends or not in addition to establishing monotonic trends across a time range (Malik *et al.* 2021). Assumptions that may not always be accurate when considering socioeconomic aspects that influence the adoption of conservation agriculture include extension services, household head status, high input costs, low input variability, potentially limited access to biomass, and larger land ownership.

It is crucial to distinguish between the types of elements that have the greatest impact on flow alteration and availability in this study (Malik *et al.* 2021). On the other hand, the planning and implementation of the adaptation and mitigation measures that must be implemented in response to the alteration of water resources brought on by climate change and the occurrence of water scarcity events require additional time and money. The results of this study also showed that seasonality shift climate change can pose a risk to humid regions as well as desert climate zones (Ali *et al.* 2019). Consequently, more in-depth research in this area is required taking into account varied flow regimes and climates.

## CONCLUSION

Risks associated with climate change's impact on the land cover could be decreased by enhanced conservation agriculture adaptation. Therefore, when applying conservation agriculture to agricultural, water, and food policies, a proper understanding of how climate change will affect its adoption is particularly helpful. For temperature and precipitation data, this analysis used NASA POWER, together with QGIS and Trends. Earth indicators and the research area's land production were examined. The trend result indicates that the region's land productivity has declined due to variability, less rainfall, and an increase in temperature. This suggests that conservation agriculture is being used less. However, with good planning and management of agricultural systems, these dangers might be greatly diminished. When there is a shortage of water, conservation agriculture should concentrate on efficient water use and water harvesting. In these conditions, maintaining the soil cover should be given less priority, and fertilizers should be utilized to prevent soil nutrient depletion. As biomass output rises over time, more organic matters may be added to the soil to improve its ability to retain water. This will increase soil cover. As a result, it is strongly advised that purposeful action be taken to create agroecosystems, institutions, and knowledge systems that can adapt quickly to changing conditions in order to avoid interruptions to the food supply.

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## DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

## CONFLICT OF INTEREST

The authors declare there is no conflict.

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