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IOP Publishing Environ. Res.: Ecol. **4** (2025) 035008 https://doi.org/10.1088/2752-664X/adf6c1

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RECEIVED
20 January 2025

REVISED
25 July 2025

ACCEPTED FOR PUBLICATION
1 August 2025

PUBLISHED
22 August 2025

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PAPER

Long-term mean climate and seasonal variability drive spatial patterns of forage production fluctuation trends across California annual grasslands

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Keywords: rangeland, forage production, climate variability, machine learning, soils, partial dependence

Supplementary material for this article is available online

Abstract

Forage production is integral to the ecological and economic functions of rangeland ecosystems worldwide and is characteristically highly variable. Understanding temporal variability and its trends in forage production are essential for sustainable resource management. This study evaluates recent long-term (2001–2018) trends in year-to-year fluctuations in forage production and identifies key factors driving spatial variability of these trends across California annual grasslands. Using annual forage production estimations at 30 m from fused remote sensing observations, we calculated coefficients of variation (CV) for 8 year moving windows to quantify interannual variability in forage production, vegetation phenology, climate, as well as other environmental factors. The trends in CVs were then assessed with Mann–Kendall tests and Sen's slope, and three random forest (RF) models were built. Results showed that more than 36% of grasslands experienced significantly increasing trends in interannual forage production fluctuations. The RF model based solely on climate variables revealed that spatial patterns of trends in temporal fluctuations of forage production were mostly driven by long-term climatic means; specifically, drier areas with a long-term mean growing season (GS) precipitation below ∼500 mm, or warmer areas with long-term mean minimum temperatures above ∼6 °C, were more likely to exhibit significant increasing trends in forage production fluctuations. Spatially, trends in the temporal variability of seasonal precipitation and late season maximum temperatures, as well as other environmental factors such as soil organic matter content and elevation, also significantly contributed to trends in forage production fluctuations, although to a lesser degree. Further analysis using a RF model with remote sensing-based phenological metrics indicated statewide trends in forage production variability were linked to trends in peak growth variability, as well as trends in the end and length of the GS. These results highlight the value of understanding year-to-year trends to inform the local, adaptive decisions that land managers must make in order to sustainably balance forage supply with livestock grazing demand.

1. Introduction

Rangelands cover nearly one-third of the US land area and support critical ecosystem services, such as food and fiber production, carbon sequestration and security, water flow regulation, and biodiversity and wildlife habitat (Havstad *et al* 2009, Jones *et al* 2018). These working lands support a diverse mix of predominantly herbaceous plants that provide forage for livestock grazing, a primary use of these landscapes. Rangelands are

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characteristically variable due to diverse climatic and biophysical factors, and this is especially the case for California's extensive and highly valued annual rangeland systems (Havstad *et al* 2007, Roche *et al* 2015, Liu *et al* 2019, 2021). Spanning ∼4 million hectares, these open annual grasslands, savannas, and woodlands provide nearly 70% of the state's livestock forage production (California Department of Food & Agriculture 2023), supporting a more than $3 billion annual cattle industry (Ostoja *et al* 2023).

Large fluctuations in forage production over both time and space are key characteristics of California's annual rangelands (Bartolome *et al* 2007, Liu *et al* 2019). This high temporal variability challenges managers' abilities to set optimal stocking rates that balance forage supply and animal demand, complicating efforts to enhance agricultural productivity while mitigating potential environmental degradation from excessive grazing. Long-term stewardship requires managers to employ adaptive strategies, using monitoring and evaluation to adjust management in response to changing conditions (Jablonski *et al* 2024). Thus, it is crucial to better understand how forage production year-to-year fluctuations are changing, along with its spatial patterns and associated drivers of these changes, in order to offer key insights for improved rangeland decision-making.

Climate plays a significant role in the temporal and spatial variability of forage production, with temperature and precipitation patterns influencing both the amount and variability of grassland forage production across different regions (Zhang *et al* 2022). In California annual rangelands, forage production has historically exhibited high temporal and spatial variability. For example, the cooler and wetter climate of northern California generally supports a longer growing season (GS), leading to higher forage accumulation compared to the southern part of the state (Hobbs and Mooney 1995). Recent studies have also shown that the specific role of precipitation in affecting year to year forage production fluctuation varies spatially: in drier regions and during drier years, the total amount of precipitation during the GS is more influential, while in wetter regions, the seasonal distribution of precipitation has a greater impact (Liu *et al* 2021).

Increasing climate variability has been documented during the past few decades in California, e.g. accelerated rapid shift between dry and wet years (Swain *et al* 2018). For example, the state experienced multi-year droughts during 2012–2016, followed by an extreme 2016–2017 wet winter. Further increases in this precipitation volatility are anticipated during the twenty-first century (Swain *et al* 2018, 2025), intensifying forage production interannual variability (Zhang *et al* 2022). Precipitation and temperature regulate vegetation phenology, influencing the start (SOS), end (EOS), and length of the GS (LOS), as well as the timing and duration of maximum photosynthesis (Wu *et al* 2011, Xu *et al* 2016, Wang *et al* 2020). Annual grasses, which dominate California's grasslands, primarily have shallow roots and can grow quickly with sufficient available water (Ren *et al* 2018). Consequently, the timing, amount, and seasonal distribution of precipitation play a critical role in forage growth and accumulation on annual grasslands (Sloat *et al* 2018, Liu *et al* 2021). Therefore, projected climate changes, including greater precipitation variability and more frequent droughts (Hoerling *et al* 2011, Wood *et al* 2021, Liu *et al* 2022), will likely further increase forage fluctuation from year to year (Zscheischler *et al* 2014). Additionally, projected higher minimum temperatures could trigger early germination and leaf unfolding (Niu *et al* 2008, Liang *et al* 2013), while warmer temperatures may accelerate ecodormancy, shortening the forage production period (Zhang *et al* 2016, Piao *et al* 2019). These conditions could also deplete soil moisture faster, leading to water stress and potentially reducing total forage production (Duan *et al* 2014).

Environmental factors such as topographical conditions and soil properties, also play important roles in influencing forage growth via microclimatic and ecohydrological regulation, especially across California annual grassland with their complex terrain and soils (Devine *et al* 2019, Liu *et al* 2021). Topography affects insolation and thus regulates the availability of photosynthetically active radiation and soil moisture, leading to variability in forage production (Beaudette and O'Geen 2009, Reed *et al* 2009). Additionally, soil properties such as soil organic matter (SOM) and texture, which critically influence soil productivity, further affect forage production. Therefore, including these environmental factors could prove critical to assessing trends in forage production fluctuation across the diverse landscape in California.

Assessing temporal fluctuations in forage production and understanding the spatial differences in these temporal patterns requires long-term datasets with large spatial coverage. Advances in satellite-based remote sensing technologies provide new opportunities to monitor vegetation dynamics and assess trends and patterns at scales relevant to rangeland management (Zhao *et al* 2015, Zu *et al* 2018, Liu *et al* 2019, 2021). Previous work has primarily focused on estimating forage production, with few studies examining how forage production varies spatially or responds to interannual climate change (Liu *et al* 2021, 2022, Zimmer *et al* 2021). However, it remains unclear whether there has been a significant trend in the fluctuation of forage production over the past decades. A comprehensive understanding of the trends and drivers of forage production year-to-year fluctuation is crucial for managers to adapt to changing conditions and develop informed management strategies.

This study aimed to assess the spatial patterns of the trends in year-to-year variability of forage production across California annual grasslands and identify their key drivers using a data-driven approach. We leveraged 18 years of annual forage production data, derived from the fusion of Landsat Analysis Ready Data (ARD) and moderate resolution imaging spectroradiometer (MODIS) collection 6 data products spanning 2001–2018 (Liu *et al* 2021). Specifically, we addressed the following questions: (1) are there significant trends in the temporal variability of forage production on California annual grasslands?; (2) Are there regional differences in forage production fluctuation trends?; (3) How do climate and environmental variables determine spatial patterns of trends in forage production fluctuations?; and (4) What phenological processes contribute to the observed trends in forage variability? We hypothesize that trends in forage production fluctuations are affected by changes in climate variability, which manifest in altering vegetation phenology such as green-up or senescence dates and peak growth. Additionally, the forage production variability trends may vary by location, influenced by local long-term mean climate, topography, and soil properties.

2. Data and methods

2.1. Study area

Our study focuses on California annual rangelands, grasslands in particular, which spans from warmer southern to cooler northern (33° N–41° N) zones, and from coast to foothills and mountain meadows (118° W–124° W) (figure 1(a)), with an elevation ranging from sea level to ∼1500 m. The study area covers four major ecoregions including Northern California Coast Ranges, Northern California Interior Coast Ranges, Central Coast Ranges, and Sierra Nevada Foothills. These ecoregions are further divided into 23 subsections based on similar ecological potentials (Cleland *et al* 2007). To eliminate any confounding impacts of post-fire recovery on forage production, we excluded areas burned during 2001–2018 based on fire records from the California Department of Forestry and Fire Protection.

California's annual grasslands are characterized by a Mediterranean climate with hot, dry summers and mild, wet winters, with the majority of rainfall occurring between November and March (Becchetti *et al* 2016). The long-term (1980–2019) mean annual precipitation ranges from around 200 mm to 1600 mm, with greater precipitation levels occurring in the north (figure 1(b)), and the long-term mean annual temperature ranges from around 7 °C–19 °C across the state's grassland. Germination of annual grasses and forbs typically begins with fall rains between October and November, followed by a slow winter growth period limited by low air temperatures and low solar radiation. Rapid growth starts with more favorable temperatures, solar radiation, and moisture conditions in late winter/early spring between February and April, with peak production occurring mid-late spring between April and June. Finally, senescence occurs when soil moisture is depleted between April and June (Larsen *et al* 2021, Liu *et al* 2022). Precipitation varies significantly from year to year in California, and forage production, which is largely impacted by precipitation patterns, exhibits higher interannual variability (Jin *et al* 2015, Larson *et al* 2021, Liu *et al* 2021, Madani *et al* 2023).

2.2. Annual forage production and remote sensing datasets

Our analysis was based on 18 years of annual forage production estimations from 2001 to 2018 at a 30 m resolution (Liu *et al* 2021). Production was estimated from remote sensing observations of Landsat every 16 days (Dwyer *et al* 2018) and MODIS on both Terra (MOD09GA) and Aqua (MYD09GA) platforms (Vermote and Wolfe 2015). The spatial and temporal adaptive reflectance fusion model (Gao *et al* 2006) was used to fuse Landsat ARD and MODIS Collection 6 datasets to obtain a continuous daily time series of normalized difference vegetation index (NDVI) and subsequently fractional absorbed photosynthetically active radiation (APAR). Forage production was then estimated as a product of daily APAR and light use efficiency, accumulated during the GS, with a high accuracy of 83% (Liu *et al* 2021). To delineate areas dominated by annual grasslands, we excluded rangeland pixels with NDVI greater than 0.3 in mid-August, when annual herbaceous plants are mostly senescent (thus low NDVI values) while trees and shrubs generally remain photosynthetically active (thus high NDVI values) (Liu *et al* 2021). The long-term mean forage production of study area is shown in figure 1(c).

To understand the trends in interannual variability (i.e. year-to-year fluctuations in annual forage production), we derived phenological metrics from the daily NDVI fused from Landsat and MODIS (Liu *et al* 2021). NDVI is strongly correlated with the absorption of photosynthetically active radiation (Kerr and Ostrovsky 2003, Wu *et al* 2017) and has been widely used to monitor vegetation cover and growth dynamics (Butt *et al* 2011, Soudani *et al* 2012, Weber *et al* 2018). We first identified the maximum NDVI (peakNDVI) for each water year from October 1 to September 30, to gauge the magnitude of peak growth. Two logistic curves were fitted to the daily time NDVI series before and after the NDVI peak date, respectively; the SOS

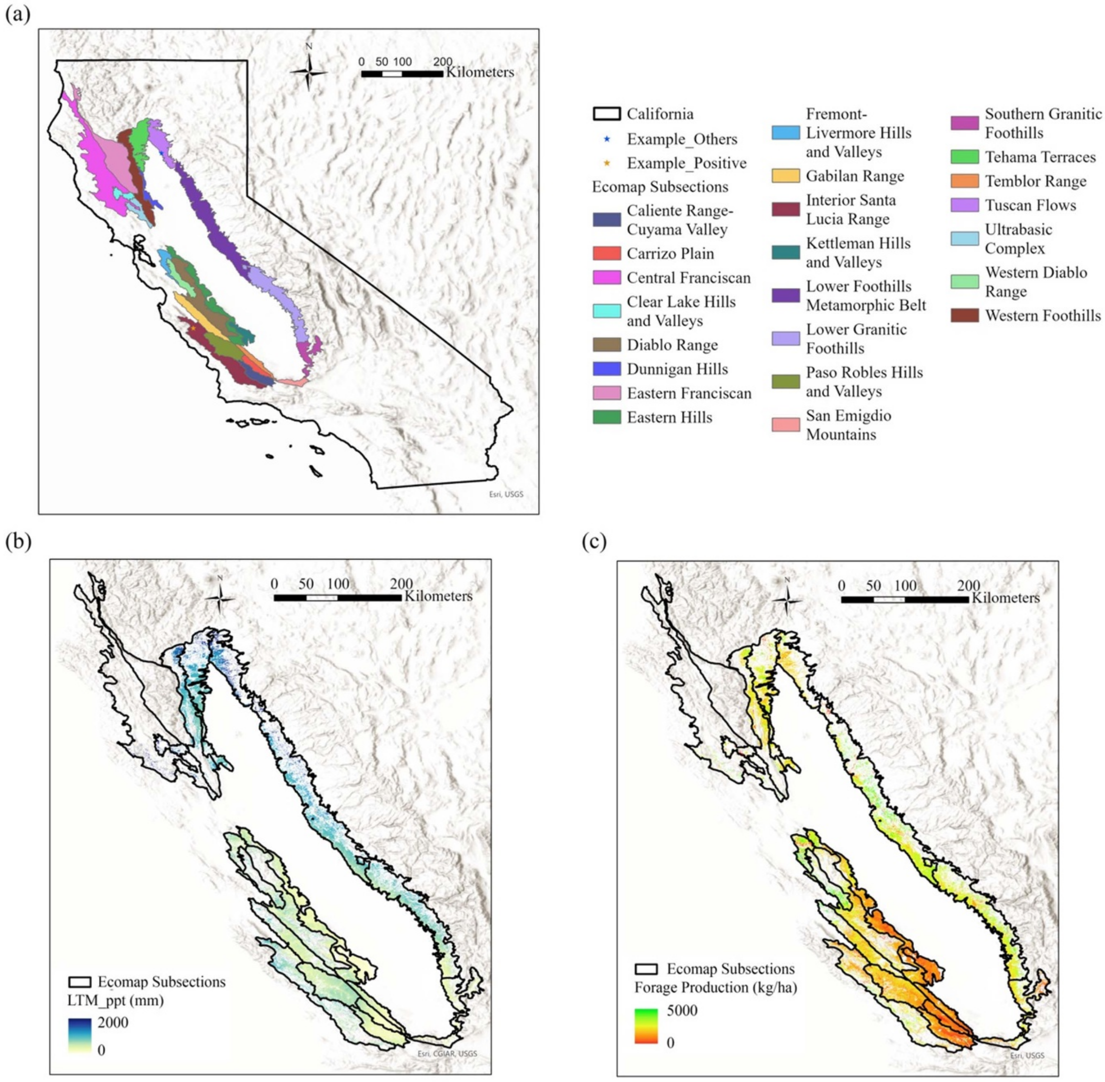

Figure 1. Study area by (a) Ecomap subsections, and distribution of (b) long-term mean annual precipitation (LTM_ppt) and (c) long-term mean forage production (forage production) across the study area. Only pixels identified as pure grass at 30 m resolution by Liu *et al* (2021) were shown here.

was then identified as the date showing the largest rate of increase, and the EOS was identified as the dates showing the largest rate of decrease, based on the curvature of the fitted NDVI curves (Liu *et al* 2021). The LOS was then calculated as the number of days between SOS and EOS.

2.3. Climate and other environmental datasets

We obtained the Daymet climate data from the National Laboratory Distributed Active Archive Center for seasonal and annual climate records during 2001–2018 (Thornton *et al* 2018). The gridded Daymet products including precipitation and temperature at a 1 km resolution were interpolated from more than 8000 meteorological stations (Thornton *et al* 2018). For this study, we calculated daily precipitation, daily mean, minimum, and maximum temperatures averaged during the GS from November to June. Additionally, seasonal climatic variables were summarized for the early season (ES: November–January), mid-season (MS: January–March), and late season (LS: April–June), based on the typical growth stage of California annual grasses, respectively (Liu *et al* 2021) (table 1). We further derived the precipitation concentration index (PCI) to quantify how evenly precipitation is distributed over a specific season, e.g. during the early, middle, late, and full GSs, respectively (Sloat *et al* 2018). The PCI was calculated using the equation (1) where p is the total monthly precipitation, for a given season from Month i_0 to Month i_1. Lower PCI values indicate a relatively uniform distribution of precipitation, i.e. rainfall spread fairly evenly throughout the time window,

$$\mathrm{PCI} = \frac{\sum_{i=i_0}^{i=i_1} {p_i}^2}{\left(\sum_{i=i_0}^{i=i_1} p_i\right)^2} * 100. \tag{1}$$

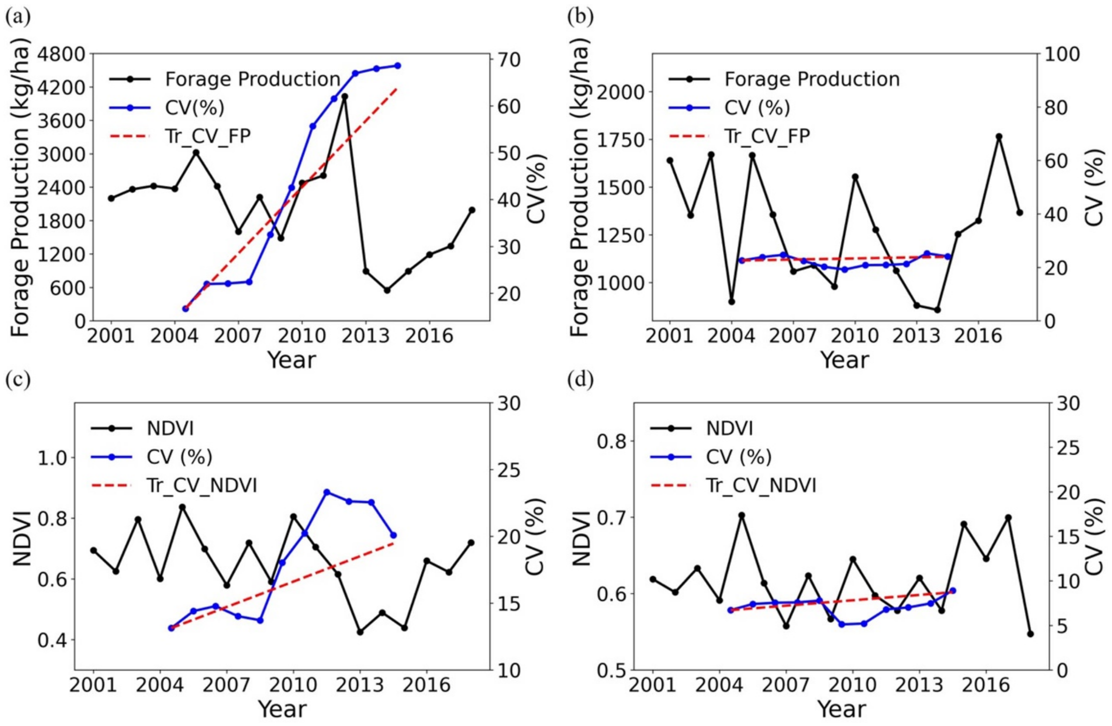

Figure 2. Examples for the original time series of both annual forage production (black line) and coefficient of variation (CV) of annual forage production during each 8-year moving window (blue line) for two selected pixels in (a) Monterey County and (b) Tehama County. Also shown are the fitted trend lines for the CV of forage production (FP) (red dashed line) (a) and (b). Similar plots are shown in the bottom panel for the corresponding annual peak NDVI (c) and (d), respectively. These two pixels illustrate cases with and without a significant increasing trend in the temporal fluctuation of forage production and peak NDVI, respectively.

We also collected data on topographical and soil properties to elucidate how these local factors potentially regulate trends in interannual forage production variability across space (table 1). We obtained elevation data from the Shuttle Radar Topography Mission (SRTM) 1 Arc-second (30 m) (Rabus *et al* 2003) and derived other topographical layers including slope and aspect. Soil properties, including SOM, water holding capacity (WHC), and soil texture as represented by percent clay (%Clay), percent silt (%Silt), and percent sand (%Sand), came from gridded Soil Survey Geographic Database (SSURGO), which aggregates USDA-NCSS soil survey data to 800 m rasters (O'Geen *et al* 2017). The soil properties have considerable impacts on the forage production fluctuations. For example, in fine textured soils, it can facilitate vegetation growth by retaining more water precipitation (Weng and Luo 2008). All climate and environmental variables were resampled to a 30 m resolution to match the spatial resolution of the remote sensing-based forage production product (Liu *et al* 2021).

2.4. Trend in forage production fluctuations and potential drivers on its spatial pattern

To quantify interannual variability in forage production, we used the coefficient of variation (CV), which is the ratio of the standard deviation (SD) to the mean value over a given period (Brown 1998). CVs were calculated over 8 year moving windows from 2001 to 2018, resulting in a total of 11 time segments (see examples in figures 2(a), (b), (c) and (d)). The 8 year duration was chosen to avoid abrupt change due to episodic events such as droughts. To evaluate the trend in interannual variability of forage production, we first applied the Mann–Kendall method, a non-parametric test, to assess statistical significance of the trend across the 11 time segments (Mann 1945, Kendall 1948). The Theil–Sen was then used to quantify the trend by estimating the slope of the Mann–Kendall test (Sen 1968). The combination of Mann–Kendall and Theil–Sen test has been widely used to analyze long-term vegetation dynamics (Jiang *et al* 2015, Gao *et al* 2020). We then classified annual grassland pixels into two categories: those with significant increasing trends in interannual variability (significant positive: slope > 0, and $p < 0.05$) and other trends (others: slope $\leqslant 0$ or $p \geqslant 0.05$) (see figures 2(a) and (b)). We focused on areas with significant increasing trends in interannual forage variability as these pose the greatest challenges for rangeland managers in adjusting stocking rates to match forage supply to animal demand. Areas without any significant trend or with significant negative trends were thus combined into the 'Others' category.

Table 1. List of variables used as predictors for classifying the trends in forage production fluctuations across the California annual grasslands with random forest (RF) models.

Predictor names	References
RF1 (Remote sensing-based model)	
Long-term mean forage production (*LTM_FP*) Trend in peakNDVI fluctuations (*Tr_CV_peakNDVI*) Trends in interannual variability in phenological dates (*Tr_SD_SOS, Tr_SD_EOS*) and growing season length (*Tr_CV_LOS*)	(Liu *et al* 2021)
RF2 (Climate-based model)	
Long-term mean climate variables during the November–June growing season (GS) (*LTM_ppt_GS, LTM_Tmin_GS, LTM_Tmax_GS*) Trends in seasonal climate variability during November–June growing season (GS) *(Tr_CV_ppt_GS, Tr_CV_Tmin_GS, Tr_CV_Tmax_GS, Tr_CV_PCI_GS)*, January–March mid-season (MS) *(Tr_CV_ppt_MS,Tr_CV_PCI_MS)*, November–January early season (ES) *(Tr_CV_Tmin_ES,Tr_CV_PCI_ES)*, April–June late season (LS) *(Tr_CV_Tmax_LS, Tr_CV_PCI_LS)*	Daymet (Thornton *et al* 2016)
RF3 (Combination of climate and environmental factors)	
All climate predictors in RF2 Topographic factors (*Elevation, Slope*) Soil properties (*SOM, WHC, %Clay, %Silt, %Sand*)	SRTM (Rabus *et al* 2003) SSURGO (O'Geen *et al* 2017)

To understand spatial patterns of trends in year-to-year forage production variability, we conducted a similar trend analysis of phenological and climate variables using the Mann–Kendall and Theil–Sen approach. For the remote sensing-based factors (table 1), we calculated trends in fluctuations of the LOS (Tr_CV_LOS) and $NDVI_{max}$ (Tr_CV_peakNDVI) based on the corresponding CV time series. Trends in fluctuations for the SOS and EOS (Tr_SD_SOS and Tr_SD_EOS, respectively) were quantified based on the SDs of the derived phenological dates (i.e. Julian Day of Year) (table 1). The selected climate variables expected to influence phenology and total forage production included precipitation; minimum and maximum temperature; and PCI for the early, middle, late, and full GSs (e.g. Tr_CV_PCI_GS, Tr_CV_PCI_ES, Tr_CV_PCI_MS, Tr_CV_PCI_LS). Similar to the trend category of forage production fluctuations, each of the trend variables discussed above were also grouped into two categories, those with significant positive trends or others.

2.5. Analyzing drivers for spatial patterns of trends in forage production fluctuation

To understand the key factors determining the spatial patterns of the trend in inter-annual forage production variability, we employed a random forest (RF) machine learning approach (Breiman 2001). The RF approach creates multiple decision trees with bootstrap samples to establish rules to link the predictors to the response variable outcomes. By combining a large set of decision trees, RF offers a more robust approach and thus has been widely used for diagnosing complex non-linear relationships and interactions of multiple predictors (Gao *et al* 2020, Li *et al* 2022). RF models can reduce bias and overfitting issues and excel at uncovering inherent relationships in datasets (Dillon *et al* 2011, Li *et al* 2022).

We built three separate sets of RF models to explain the categorical trend response variable for the forage production fluctuations (i.e. with significant positive trend or others). Each RF model used a different set of predictors (table 1). The first RF model took phenological metrics from remote sensing indices as predictors (RF1) to investigate how the observed vegetation growth changes were associated with the trends in forage production fluctuations. Trend layers included the trends in temporal variability for SOS, EOS, LOS, and peak NDVI. Annual forage production is determined by daily accumulation of APAR, which is a product of the fractional APAR (a function of daily NDVI) and solar radiation. We hypothesize that phenological dates, i.e. derived from NDVI time series, affect the annual production, and the magnitude of NDVI during the GS also contributed to the total production, by capturing the fraction of absorbed PAR. We used peakNDVI to partially represent the peak growth, which is related to annual production but is not exactly the same as annual forage production is controlled by daily accumulation of APAR (Liu *et al* 2021). We also derived the long-term mean forage production from 2001 to 2018 (LTM_FP) as another predictor, to represent the spatial heterogeneity of mean forage production, a potential driver of spatial patterns in the trends of forage production fluctuation.

Two additional models were built to evaluate the impacts of climate and its variability (RF2) and the combination of climate and other environmental variables (RF3) on trends in spatial patterns of variability in forage production. In addition to the precipitation, PCI, and temperature trend variables for the various seasons described in section 2.4, we included long-term mean precipitation (LTM_ppt), minimum temperature (LTM_Tmin), and maximum temperature (LTM_Tmax) from 1980 to 2019 to represent the spatial heterogeneity of climate (table 1). Other static layers representing environmental factors, such as topographic features (Elevation and Slope) and soil variables such as SOM, WHC, percent clay (%Clay), percent silt (%Silt), and percent sand (%Sand), were included in RF3.

For model building and evaluation, due to the large data volume at 30 m resolution, we randomly selected 30 000 samples with a minimum distance of 300 m between samples for each trend response category. For each category, 70% of the sample points were randomly selected for model training and the remaining 30% were used for validation. An ensemble of 500 decision trees (ntree) were built, and the number of randomly selected predictors at each node (mtry) was automatically optimized.

Model performance was evaluated based on the confusion matrix between the predicted and observed categorical trends in forage production fluctuations. Both the overall, producer's, and user's accuracy were quantified for each model. Variable importance was evaluated by percent increase in mean square error, which was calculated as the increase in the out of bag error when a given variable was permuted (Peciña *et al* 2021). In addition, partial dependence plots were generated to quantify how trends in forage production variability were influenced by each independent variable while holding other variables constant (Cutler *et al* 2007, Liu *et al* 2021).

3. Results

3.1. Trends in fluctuations of forage production and phenology

More than 36% of California annual grasslands, approximately 861 thousand ha, showed significant increasing trends in interannual forage production fluctuations at 30 m resolution during 2001–2018, while only ∼14% showed significant decreasing trends, with the remaining non-significant areas grouped into an 'Others' category (figures 3(a) and 4(a)). Most notably, 5 of the 23 subsections had more than 50% of their areas with significant increasing interannual variability. These areas included drier zones of the Kettleman Hills and Valleys (KHVs), Southern Granitic Foothills (SGFs), Temblor Range (TR) and Carrizo Plain (CP) subsections, as well as the Lower Granitic Foothills (LGFs) subsection with moderate mean annual rainfall. Across these 5 subsections, the areas with significant increasing interannual variability collectively accounted for more than 23.86% of the total study area.

Across the remaining annual grassland subsections, we found varying degrees of increasing forage production fluctuations. Twelve subsections, accounting for more than 44% of our study area, had between one quarter and one half of their grassland pixels showing increasing forage production fluctuations. Six subsections, occupying approximately one-third of the total study area, had less than one quarter of pixels with significant increasing trends in forage production fluctuations. For example, the Lower Foothills Metamorphic Belt subsection, located in the northeastern part of the study area, only had 23% of pixels showing significant increasing trends in fluctuations of forage production, respectively (figure 4(a)).

Trends in interannual fluctuations in peak NDVI showed similar spatial patterns to those of forage production (figures 3(b) and 4(b)). For example, the same five subsections (KHV, CP, TR, SGF, and LGF) were among the top areas with more than 50% of pixels with significant increasing trends. Moreover, more than 70% of grassland areas in TR and SGF subsections had significantly increasing fluctuations in annual peak NDVI.

Analysis of the phenological metrics showed significant trends in variability for the EOS, the LOS, and SOS in various subsections across the study area. Significant increasing trends in year-to-year fluctuations in the timing of EOS was found over more than 50% of the areas in the TR, SGF, and LGF subsections. In the LGF subsection, more than 75% of grassland areas had increasing EOS variability (figure 3(c)). Some northern subsections—including Tuscan Flows (TFs), Tehama Terraces (TTs) and Western Foothills (WFs), which accounted for ∼12% of the study area, had more than 80% of areas exhibiting significant increasing trends in LOS variability (figure 3(d)). These northern subsections (i.e., TF, TT, and WF) also had more than 75% of areas showing significant increasing trends in SOS variability (figure S1).

3.2. Spatial association of trends in phenological variability with forage production fluctuations

When only using remote sensing metrics as explanatory variables (RF1), the RF model had an overall accuracy of 70% in predicting the categorical trends in forage production fluctuations (i.e. significant positive trend or others) (table S1). Year-to-year variability in peak growth (Tr_CV_peakNDVI) was the most

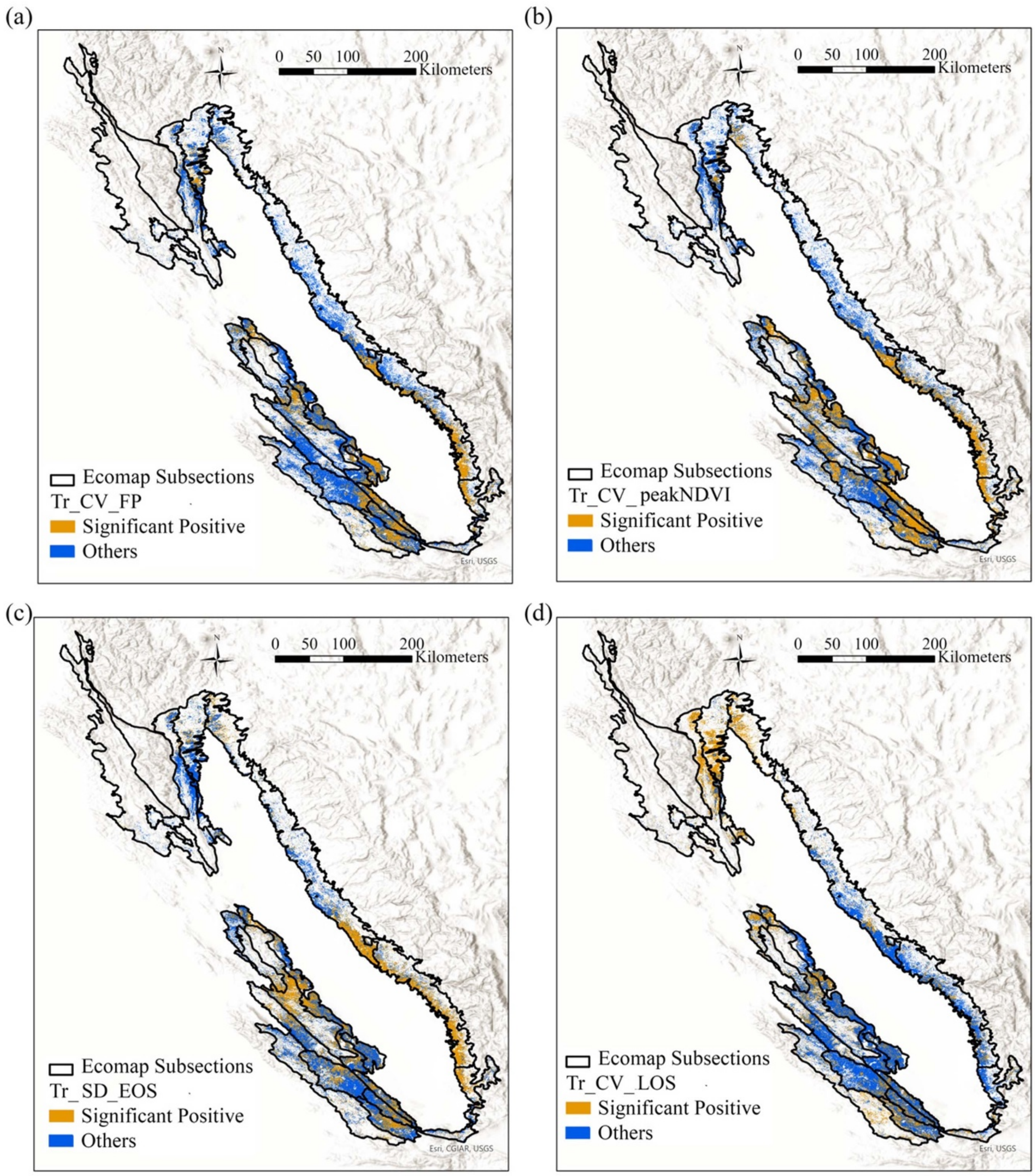

Figure 3. Distribution of grassland pixels with a significant increasing trend (significant positive) and no significant trend or negative trends (others) in temporal variability for (a) forage production (Tr_CV_FP); (b) peak NDVI (Tr_CV_peakNDVI); (c) end of growing season (Tr_SD_EOS); and (d) length of growing season (Tr_CV_LOS) across the study area.

important variable explaining spatial patterns of trends in forage production fluctuations between 2001 and 2018. Other significant factors included the trends in fluctuations for both the EOS and LOS (figure 5(a)).

Partial dependence plots showed that areas exhibiting significant increasing trends in peak NDVI (figure 6(a)), EOS (figure 6(b)), and LOS (figure 6(c)) fluctuations were more likely associated with increasing fluctuations in forage production, when all other variables were the same. In particular, trends in the variability of peak growth showed the best performance in differentiating the areas with or without significant increasing trends in forage fluctuations (figure 6(a)). For those pixels with observed increasing fluctuations in peak growth (i.e. significant positive trend), the RF1 model predicted a much higher probability (84% with a standard error of 0.65%) of increasing year-to-year fluctuations in forage production, compared to pixels with no significant or decreasing trends (Others;15 $\pm$ 0.65%); similarly, pixels with no significant or decreasing trends in peak growth had a much lower probability of experiencing increased production fluctuation (23 $\pm$ 0.58%), when all other variables were held constant (figure 6(a)). Regarding changes in phenological metrics, the predicted probability of having increasing forage fluctuations were around 75 $\pm$ 0.63% for areas with increasing trends in fluctuations in the timing of the EOS, and

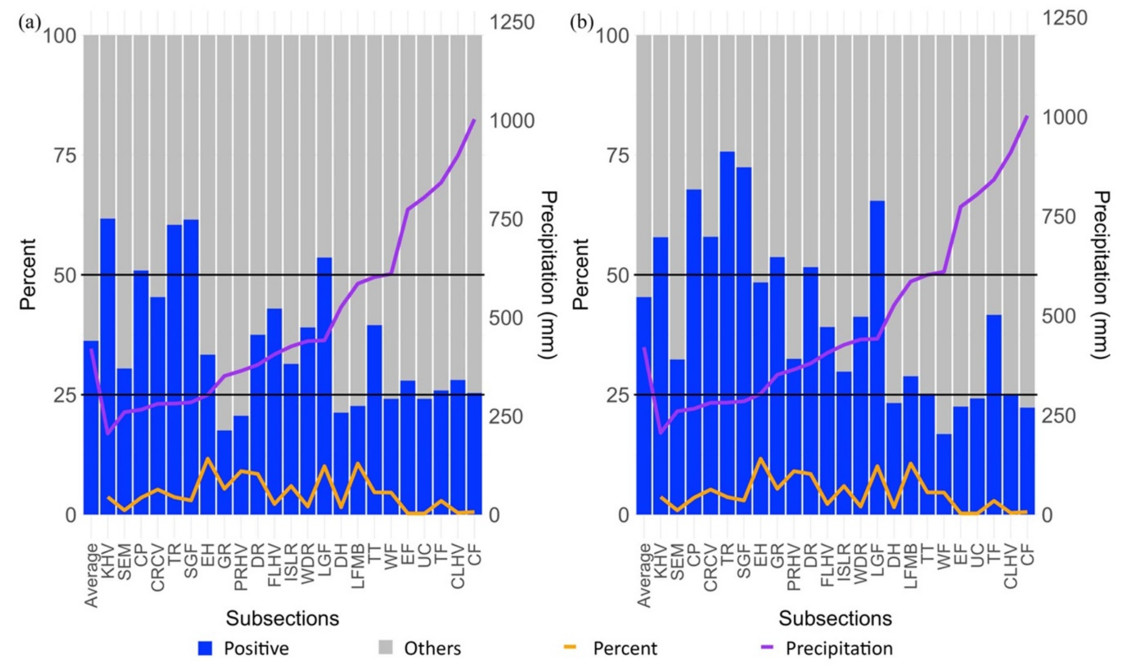

Figure 4. The percentage of annual grasslands with a significant positive trend (blue bars) of the fluctuations in (a) forage production (Tr_CV_FP), (b) peak growth (Tr_CV_peakNDVI), summarized for the study area (first column) and for each subsection ordered by the long-term mean annual precipitation (purple line, mm yr^{-1}). For reference, two black lines delineate 25% and 50% levels; and the orange line represents the percent of the total California annual grassland areas in each subsection.

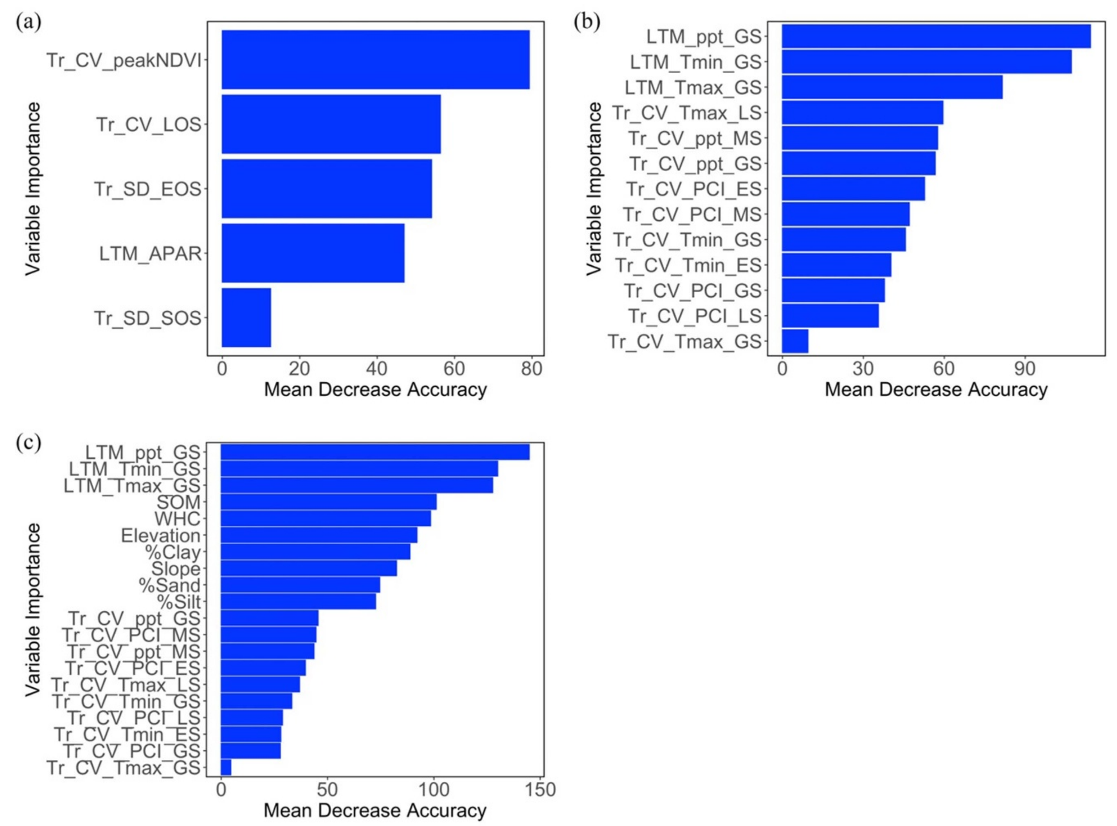

Figure 5. Variable importance based on three random forest models for predicting the probability of having significant increasing forage fluctuation, using (a) only remote sensing based phenological metrics, and long-term mean annual forage production; (b) only climate variables including long-term mean climate and trends of fluctuation of seasonal weather; and (c) the combination of climate and other environmental variables, respectively.

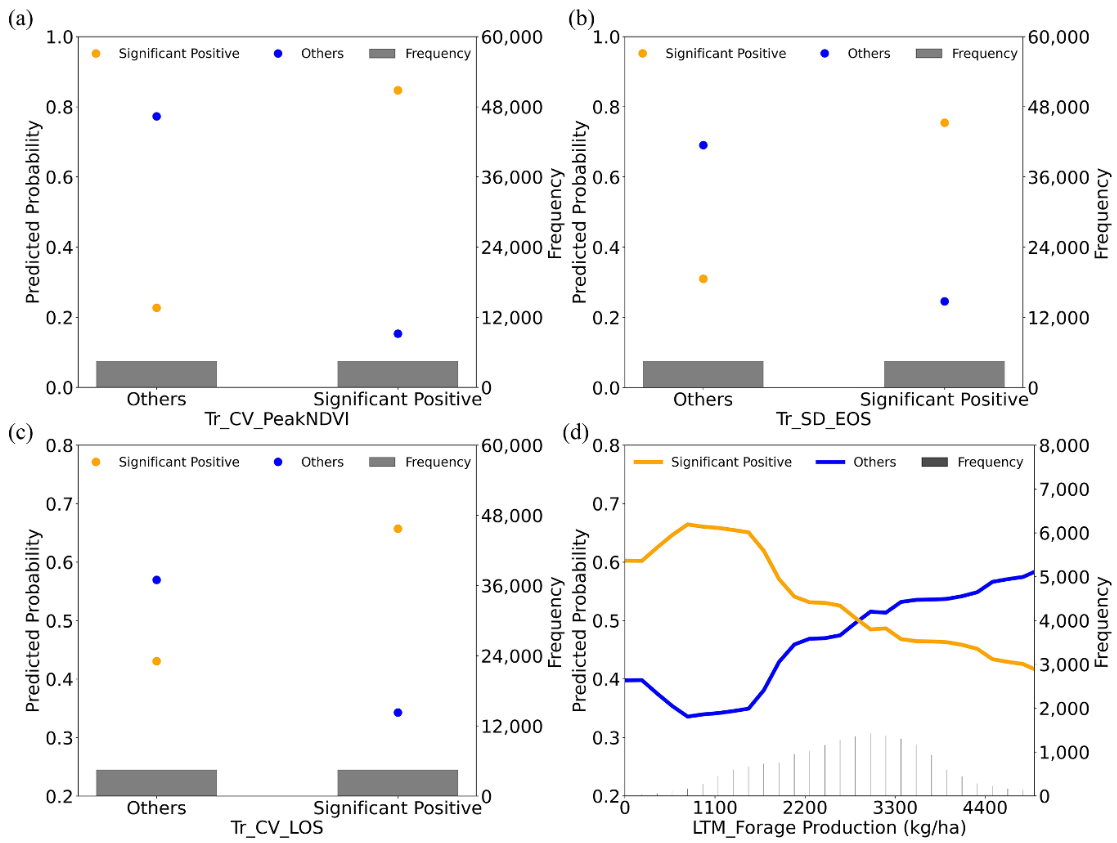

Figure 6. Partial dependence plots for fluctuation trend categories (significant positive versus others) for (a) peak NDVI (Tr_CV_peakNDVI); (b) end of growing season (Tr_SD_EOS); (c) length of growing season (Tr_CV_LOS); and (d) long-term mean forage production (LTM_FP) based on the random forest model with only remote sensing based variables. For reference, the frequency distribution of each independent variable is shown with the right *y*-axis.

$66 \pm 0.62\%$ for areas with increasing trends in fluctuations in the LOS. These probabilities were much higher than those for areas not experiencing significant fluctuations in phenology (figures 6(b) and (c)).

Finally, lower productivity areas (e.g. LTM_FP less than 1500 kg ha^{-1}) generally exhibited increasing trends in production fluctuations (figure 6(d)). The probability of having significant increasing trends in year-to-year forage production decreased rapidly over more productive sites, until LTM_FP reached 2500 kg ha^{-1}. In contrast, a site's probability of not having significant increasing trends in forage fluctuations increased with productivity across the landscape (figure 6(d)).

3.3. Impacts of climate and weather fluctuations

The RF2 model including only climate variables (long-term mean values and trends in variability) as predictors explained 71% of spatial variability in observed trends in year-to-year forage production fluctuations (see table S1 for the confusion matrix). The long-term mean climate variables during the GS (November–June), including precipitation and minimum and maximum temperature, had the highest influence in explaining the spatial variability of trends in forage production fluctuations, followed by trends in CVs of seasonal weather including mid-season precipitation, late season Tmax, GS precipitation, and PCI in early and mid-GS (figure 5(b)).

Based on the partial dependence plots from the RF2 model, the likelihood of an increasing trend in year-to-year forage production variability decreased significantly along the dry-to-wet gradient of LTM_ppt across the landscape; the opposite pattern was found along the cool-to-warm gradient of long-term mean annual minimum temperature (Tmin). Drier areas with the GS LTM_ppt less than ∼500 mm, or areas with long-term mean Tmin higher than ~6 °C tended to coincide with larger forage production fluctuations, when all other variables were held constant (figures 7(a) and (b)). Interestingly, areas with long-term mean annual Tmax lower than 20 °C were slightly more likely to experience increasing forage fluctuations, while extremely hot areas with long-term mean Tmax beyond 22 °C were less likely to do so (figure 7(c)).

The partial dependence plots also showed that the areas with significant increasing trends in variability of precipitation during the GS (Tr_CV_ppt_GS) were more likely ($55 \pm 0.47\%$) to experience increasing fluctuations in forage production (figure 7(f)). In contrast, those areas with increasing fluctuations in

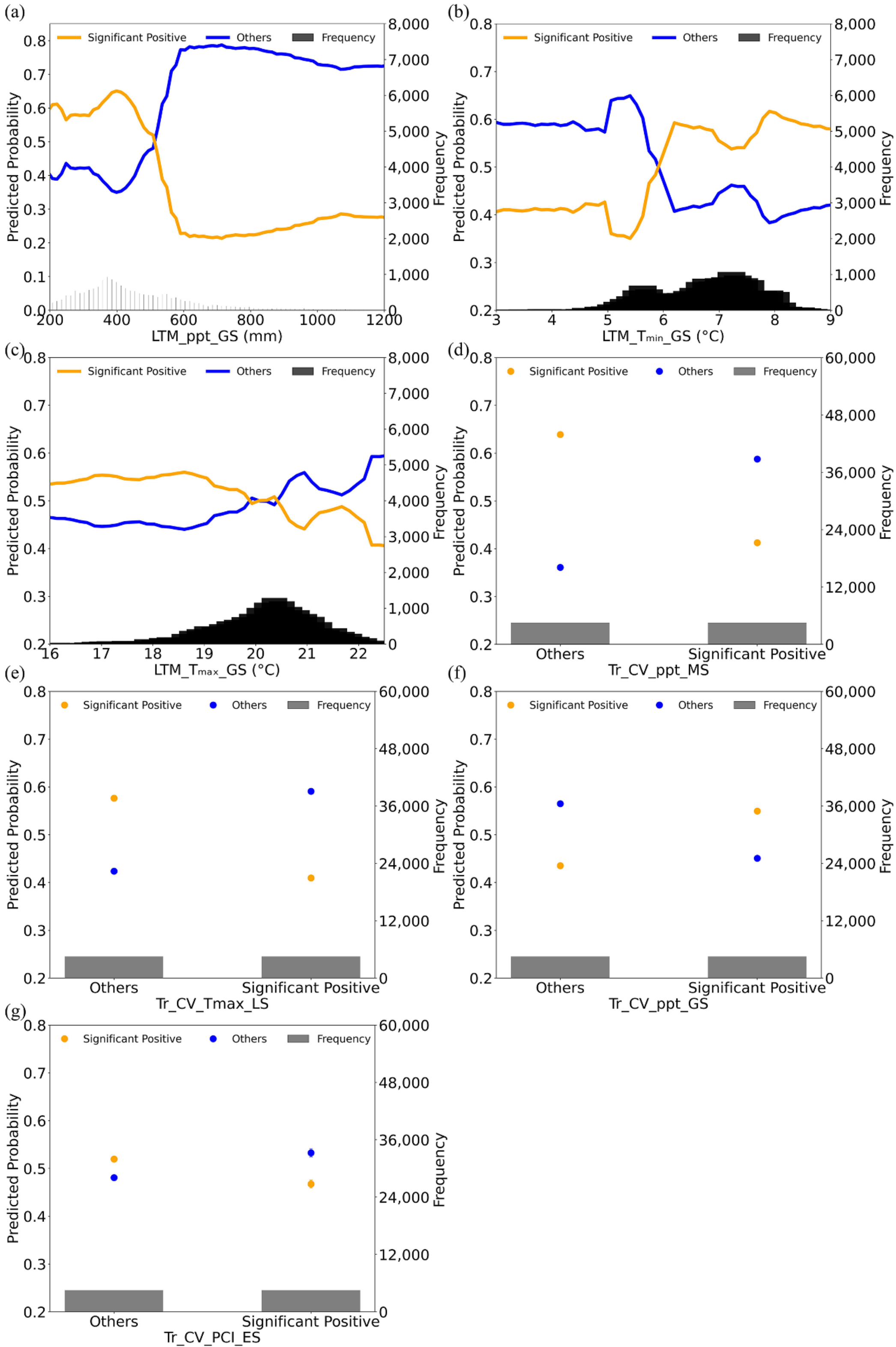

Figure 7. Partial dependence plots of the forage production fluctuation trends on top seven important climate variables, including long-term mean (a) precipitation (LTM_ppt_GS), (b) minimum temperature (LTM_Tmin_GS), and (c) maximum temperature (LTM_Tmax_GS) during the growing season; and categorical trends for fluctuations in seasonal (d) precipitation (middle season), (e) maximum temperature (late season), (f) precipitation (growing season) and (g) PCI (early season) based on the random forest model with only climate indices. For reference, the distribution of each independent variable is shown with the right *y*-axis.

mid-season precipitation (Tr_CV_ppt_MS) or late season Tmax were not likely associated with increasing forage variability (figures 7(d) and (e)). The association with the trends in PCI variability was found to be relatively small (figure 7(g)).

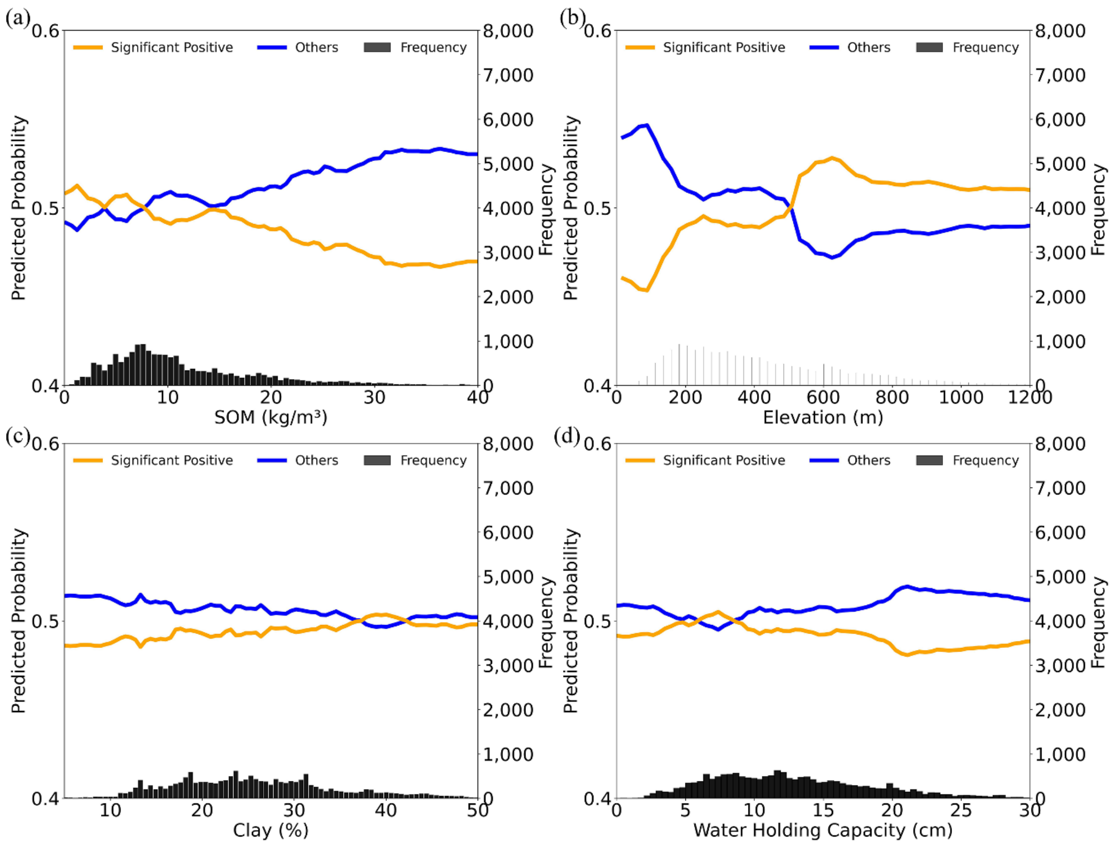

Figure 8. Partial dependence plots for (a) soil organic matter (SOM); (b) elevation (Elevation); (c) percent of clay (% Clay); and (d) water holding capacity (WHC), based on the random forest model with climate-related indices and environmental variables. For reference, the distribution of each independent variable is shown with the right *y*-axis.

3.4. Impacts of other environmental variables

Across the study area, combining other static environmental variables with climate variables in the RF model explained slightly more variance (74% versus 71%) in the spatial pattern of trends in forage production fluctuations (table S1). Similar to the RF2 model with climate-only predictors, GS LTM_ppt and temperature were dominant drivers in the RF3 model (figure 5(c)). SOM, elevation, percent of clay, WHC, slope, percent sand, and percent silt variables had relatively higher influence on forage fluctuation trends than trends in CV of precipitation and PCI (figure 5(c)). Higher SOM decreased the probability of forage fluctuation increases. However, partial dependence plots showed that trends in forage production fluctuations were much less responsive to soil and topographical factors compared to climate variables across the whole study area (figures 8(a)–(d)).

4. Discussion

Shifting climate baselines and increasing variability are expected to impact forage production in California annual grasslands, which pose considerable challenges to rangeland management decision-making. Understanding year-to-year forage production variability and anticipating its trends is crucial for rangeland managers to better navigate fluctuating conditions and ensure economic stability, animal health and production, and rangeland health over both the short- and long-term. California is known for its regional disparities in historical climate patterns and future projections (Liu *et al* 2022). Ecosystems respond to climate change at both short- and long-term scales, and annual herbaceous vegetation typically responds quickly to seasonal and interannual variations in precipitation, adjusting plant physiology, leaf growth, and senescence (Jin and Goulden 2014). This short-term 'individual-level' sensitivity, however, can be regulated by biotic constraints such as low meristem and seed densities in areas with low long-term productivity (Jin and Goulden 2014). By leveraging large sample sizes from remote sensing observations across the state over a long-time span, this study provides a comprehensive assessment of the temporal trend and spatial patterns of forage production fluctuations.

4.1. Contribution of long-term mean climate to spatial patterns of the trends in forage production fluctuations

Over California annual grasslands, forage production significantly fluctuates from year to year, mostly due to interannual variation in GS precipitation (Liu *et al* 2021, 2022). Changing precipitation patterns, rising temperatures, and weather extremes further compound production variability (Swain *et al* 2018, Gao *et al* 2022, Liu *et al* 2022). Large regional differences were reported on the sensitivity of production to climate, due to the diverse landscape and intertwining and potentially counteracting effects of seasonal temperature and precipitation regimes (Liu *et al* 2022). In this study, we found that forage production fluctuations significantly increased in >36% of California annual grasslands during the 2001–2018 period. Our machine learning analysis showed that local long-term mean climate significantly impacted spatial patterns of forage production fluctuation trends in the past two decades. This is consistent with previous work (Reeves *et al* 2014), which demonstrated that long-term precipitation and temperature significantly impacted forage production dynamics across US rangelands. More broadly, long-term climatic conditions shape ecosystem function and structure, influencing major vegetation characteristics through gradual changes in plant establishment and mortality, population density, species composition, and soil development (Guo *et al* 2012, Jin and Goulden 2014), which, in turn, likely regulate the sensitivity of plant response to short term weather variations. In particular, one study showed LTM_ppt accounted for variability in both vegetation phenology and production in Spanish grasslands (Peñuelas *et al* 2004). In California grasslands, (Liu *et al* 2021) found that the LTM_ppt amount has consistently emerged as a dominant driver of spatial variability in forage production, especially in drier ecoregions.

Our study found that the significant increasing trends in forage production fluctuations (i.e. greater variability over time) were more likely to occur in areas with LTM_ppt below 500 mm per year (figure 7(a)). Furthermore, in subsections with a significant increase in the trend of forage production fluctuations, most grassland areas experienced lower long-term mean annual precipitation compared to those where forage production fluctuations showed no significant trend. As LTM_ppt increased across the study area, greater soil moisture enhanced leaf photosynthesis and supported more vigorous vegetation growth, which can lead to more continuous and stable accumulation of forage production and reduce year-to-year fluctuations (Hui *et al* 2018). In contrast, over drier areas, forage production and its trends in variability were more sensitive to precipitation change patterns (Liu *et al* 2021, 2022), where lower precipitation combined with higher rainfall fluctuation led to larger fluctuations in forage production. This is consistent with findings from other studies, which documented that water-limited ecosystems such as rangelands are more sensitive to interannual precipitation variability (Jin and Goulden 2014, Liu *et al* 2021). The trend in variability in PCI, which represents the variations of precipitation distribution throughout the season, also affected the trends in forage fluctuation. These results align with previous work in central European grasslands (Hossain and Beierkuhnlein 2018), which demonstrated that precipitation variability can influence biomass productivity.

Temperature influences forage production and variability via effects on plant physiological processes, including germination timing during the early season (Shen *et al* 2015, Zhang *et al* 2018, Li *et al* 2019), photosynthetic rates (Hikosaka *et al* 2006, Li *et al* 2016, Meng *et al* 2017), and evapotranspiration (Kukal and Irmak 2016, Kibler *et al* 2023) during the active GS. The machine learning model showed that long-term minimum temperature significantly influences trends in forage production fluctuations. Similarly, (Liu *et al* 2021) also showed minimum temperature had strong controls on forage production, especially in wetter regions. We found that areas with LTM_Tmin below 6 °C more frequent significant increases in forage fluctuations. As LTM_Tmin rise, the probability of increasing forage production fluctuations also increases, likely due to warmer temperatures triggering germination of many plant species and stimulating growth (Cordero *et al* 2011). On the other hand, our analysis showed that areas with LTM_Tmax exceeding 20 °C had lower predicted probabilities of significant increasing trends in forage production fluctuations. This is probably because LTM_Tmax and late-season maximum temperatures can escalate evapotranspiration and soil water stress (Vermeire *et al* 2009), which can limit or even stop forage accumulation (Rigge *et al* 2013).

4.2. Role of weather variability on phenological and forage production fluctuations

We found that trends in variability of short-term weather factors also influenced spatial patterns of forage production fluctuation trends. During the study period, the study region experienced two prolonged droughts including 2007–2009 and 2012–2016 (Christian-Smith *et al* 2011, Swain *et al* 2018). Using an 8 year moving window to calculate the trends of variability in forage production has reduced the influences of the prolonged droughts or single year drought on the temporal trends of forage production fluctuation by buffering and integrating with adjacent plus and minus 4 years of different conditions. Herbaceous plants respond to changes in seasonal precipitation, and to a lesser degree temperature, through rapid adjustments in vegetation physiology, leaf growth, and phenology, resulting in forage production variability (Peñuelas *et al* 2004, Zhang *et al* 2005). Seasonal weather variation impacts manifested in the remote sensing observations as shown by the RF model using remote sensing based phenological metrics and long-term mean production as explanatory variables. In particular, trends in interannual variability in the timing of the EOS and the LOS closely mirrored the spatial patterns of forage production fluctuations, with significant increasing trends of interannual variability in these two phenological factors more likely to coincide with greater fluctuations in forage production. These findings were consistent with previous research showing that large phenological variability is especially prevalent in rangeland ecosystems, mostly driven by precipitation fluctuations (Lauenroth and Sala 1992, Tieszen *et al* 1997), and that grassland phenology, such as green-up and senescence, is primarily determined by weather conditions (Shen *et al* 2015, Liu *et al* 2021).

Although the SOS did not significantly influence forage production fluctuations, we did find that increased variability in peak growth over time played a critical role by capturing the highest increment of forage production and accumulation from the green up to the peak growth period (Meshesha *et al* 2020, Bu *et al* 2022). Additionally, long-term mean forage production, as a result of plant adaptation to local climate and physical environment, was shown to play a significant role in forage production fluctuations. Areas with lower long-term productivity tended to experience larger year-to-year fluctuations, probably because low productivity environments favor plants that can capitalize on episodic rainfall events (Jin and Goulden 2014), while the ample availability of propagules in California's annual grasslands allows for rapid response.

We recognize that extreme weather events—such as the two prolonged droughts in California from 2007–2009 and 2012–2016 (Christian-Smith *et al* 2011, Swain *et al* 2018) can also drive shifts in plant community composition, which may indirectly impact interannual variability of forage production (Cleland *et al* 2013, Shaw *et al* 2022). Future work is needed to collect more species data and map species composition from remote sensing observations, which will allow more detailed analysis on how changes in species composition regulate the sensitivity of forage production to climate change and thus production fluctuation.

4.3. Impact of topographical and soil factors on spatial variability in forage production fluctuation trends

Topographical and soil factors contributed only moderately to the trends in forage production fluctuations during our study period, which is likely because the model was trained over the whole study area, where the impacts of the spatial variability in climate and weather are more dominant. Nevertheless, SOM and elevation were the top two environmental factors influencing trends in forage production variability. Lower SOM levels (<10 kg cm^{-3}) and lower WHC contributed to significant increasing trends in forage production fluctuations, likely because lower fertility and reduced capacity to retain moisture limit vegetation growth (Fernandez-Illesca *et al* 2001, Reyes *et al* 2017, Abdallah *et al* 2021, Baldi 2021). Within individual subsections, where spatial variability of climate is smaller, local differences in soil properties—such as WHC and soil texture—may become more important in regulating year-to-year variability in forage production and thus its overall trend (Liu *et al* 2022).

4.4. Implications for rangeland management

Getting a better understanding of year-to-year variability in forage production can provide useful insights for rangeland managers, aiding in both long-term planning and short-term risk management strategies. Integrating multiple sources of information, including climate data, seasonal weather patterns, monitoring data, and local experiential knowledge, is essential for successful grazing management (Jablonski *et al* 2024). Climate-informed decision-making helps reduce uncertainty around forage availability and can enable managers to better optimize key factors—such as grazing timing, frequency, duration, and intensity—for more effective land management (Roche *et al* 2015). Our findings on the different trends in forage production fluctuation across the state can guide region-specific grazing management, e.g. helping managers better prepare for low-productivity years such as reducing grazing intensity and reserving forage in areas with higher vulnerability of low production, and therefore promote rangeland health and improve long-term better rangeland management. This is particularly important for California's rangelands, as the precipitation whiplash (dry–wet transition) is projected to increase during the twenty-first century due to global warming (Swain *et al* 2018, 2025) and consequently further increase interannual variability in forage production.

5. Conclusions

We assessed spatio-temporal patterns of fluctuations in rangeland forage production and their driving factors across California annual grasslands using long-term (2001–2018) datasets. We found interannual fluctuations in forage production have increased in more than 36% of annual grasslands. Our RF machine learning algorithm showed long-term precipitation and long-term mean minimum and maximum temperatures for the GS greatly influenced spatial patterns of trends in forage production fluctuations, and changes in seasonal weather further contributed to forage variability. These findings, highlighting the growing variability of forage production over time and across regions, emphasize the increasing need for climate-informed decision-making to support adaptive rangeland management.

For California annual grasslands, long-term mean climate plays a significant role in driving both forage productivity and its temporal variability. For example, drier regions are more likely to subject to increasing trends in forage variability, with substantial impacts on the stability of forage supply. Furthermore, in areas projected to experience warmer and drier climates in the future, variability of forage production will likely increase, which may further influence rangeland conditions and increase sensitivity to climate change. Our study results highlight how long-term mean climate (i.e. long-term precipitation and long-term mean minimum and maximum temperatures) along the short-term weather changes control the spatial patterns of the trends in forage productivity fluctuations across California annual grasslands. Droughts and heatwaves may become more frequent and more intense, while extreme wet years could lead to more grass growth. Our findings can help rangeland managers better anticipate future variability in forage production, providing insights for adapting ranch management to ensure the future viability of their operations.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary materials).

Acknowledgments

This work was supported by USDA National Institute for Food and Agriculture (NIFA) Western Sustainable Agriculture Research and Extension (SARE) program (Grant #: G373-22-W9209). This project was also supported by the USDA National Institute of Food and Agriculture, Hatch Project Number CA-DLAW-2620-H. We are also grateful for the contributions from county advisors.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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