Estimation of spatial and temporal changes in net primary production based on Carnegie Ames Stanford Approach (CASA) model in semi-arid rangelands of Semirom County, Iran Postprint

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Abstract

Net primary production (NPP) is an indicator of rangeland ecosystem function. This research assessed the potential of the Carnegie Ames Stanford Approach (CASA) model for estimating NPP and its spatial and temporal changes in semi-arid rangelands of Semirom County, Iran. Using CASA model, we estimated the NPP values based on monthly climate data and the normalized difference vegetation index (NDVI) obtained from the MODIS sensor. Regression analysis was then applied to compare the estimated production data with observed production data. The spatial and temporal changes in NPP and light utilization efficiency (LUE) were investigated in different rangeland vegetation types. The standardized precipitation index (SPI) was also calculated at different time scales and the correlation of SPI with NPP changes was determined. The results indicated that the estimated NPP values varied from 0.00 to 74.48 g C/(m2 • a). The observed and estimated NPP values had different correlations, depending on rangeland conditions and vegetation types. The highest and lowest correlations were respectively observed in Astragalus spp.-Agropyron spp. rangeland (R2=0.75) with good condition and Gundelia spp.-Cousinia spp. rangeland (R2=0.36) with poor and very poor conditions. The maximum and minimum LUE values were found in Astragalus spp.-Agropyron spp. rangeland (0.117 g C/MJ) with good condition and annual grasses-annual forbs rangeland (0.010 g C/MJ), respectively. According to the correlations between SPI and NPP changes, the effects of drought periods on NPP depended on vegetation types and rangeland conditions. Annual plants had the highest drought sensitivity while shrubs exhibited the lowest drought sensitivity. The positive effects of wet periods on NPP were less evident in degraded areas where the destructive effects of drought were more prominent. Therefore, determining vegetation types and rangeland conditions is essential in NPP estimation. The findings of this study confirmed the potential of the CASA for estimating rangeland production. Therefore, the model output maps can be used to evaluate, monitor and optimize rangeland management in semi-arid rangelands of Iran where MODIS NPP products are not available.

Full Text

Preamble

Estimation of Spatial and Temporal Changes in Net Primary Production Based on Carnegie Ames Stanford Approach (CASA) Model in Semi-Arid Rangelands of Semirom County, Iran

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Abstract

Net primary production (NPP) is a key indicator of rangeland ecosystem function. This research assessed the potential of the Carnegie Ames Stanford Approach (CASA) model for estimating NPP and its spatial and temporal changes in semi-arid rangelands of Semirom County, Iran. Using the CASA model, we estimated NPP values based on monthly climate data and the normalized difference vegetation index (NDVI) obtained from the MODIS sensor. Regression analysis was then applied to compare estimated production data with observed production data. The spatial and temporal changes in NPP and light utilization efficiency (LUE) were investigated across different rangeland vegetation types. The standardized precipitation index (SPI) was also calculated at different time scales, and the correlation between SPI and NPP changes was determined. The results indicated that estimated NPP values ranged from 0.00 to 74.48 g C/(m^2 • a). Observed and estimated NPP values showed varying correlations depending on rangeland conditions and vegetation types, with the highest correlation observed in Astragalus spp.-Agropyron spp. rangeland (R^2=0.75) with good condition, and the lowest in Gundelia spp.-Cousinia spp. rangeland (R^2=0.36) with poor to very poor conditions. The maximum and minimum LUE values were found in Astragalus spp.-Agropyron spp. rangeland (0.117 g C/MJ) with good condition and annual grasses-annual forbs rangeland (0.010 g C/MJ), respectively. According to correlations between SPI and NPP changes, the effects of drought periods on NPP depended on vegetation types and rangeland conditions. Annual plants exhibited the highest drought sensitivity, while shrubs showed the lowest. The positive effects of wet periods on NPP were less evident in degraded areas where the destructive effects of drought were more prominent. Therefore, determining vegetation types and rangeland conditions is essential for NPP estimation. The findings of this study confirmed the potential of CASA for estimating rangeland production, suggesting that model output maps can be used to evaluate, monitor, and optimize rangeland management in semi-arid rangelands of Iran where MODIS NPP products are not available.

Keywords: CASA; NPP estimation; light utilization efficiency; vegetation type; drought; rangeland condition; semi-arid rangelands

1 Introduction

Solar radiation is utilized in photosynthesis to convert carbon dioxide and water into carbon compounds including glucose and cellulose (Lammers et al., 2017), effectively storing solar energy in rangeland plants as the first trophic level of the food chain (Sainte-Marie et al., 2012). Net primary production (NPP) is defined as the amount of energy produced by plants minus the energy consumed through respiration (Lu et al., 2015). It reflects the rate of carbon assimilation (Roxburgh et al., 2005) and contributes to maintaining carbon balance in an ecosystem. NPP is determined by factors such as solar energy, temperature (Dintwe and Okin, 2018), and precipitation (Zhang et al., 2017), and is positively affected by living organisms like microbial biomass (Schimel et al., 1994).

Since direct field measurements are time-consuming and costly, models based on carbon cycle and plant structures (e.g., Biogeochemical Cycles Model (BIOME-BGC) (Kimball et al., 1997) and Dynamic Global Phytogeography Model (DOLY) (Donmez et al., 2011)), or remote sensing models based on satellite imagery (e.g., Global Production Efficiency Model (GLO-PEM) (Goetz et al., 1999), Carnegie Ames Stanford Approach (CASA) (Biondini et al., 1998; Liang et al., 2015; Bao et al., 2016; Jay et al., 2016), Simple Diagnostic Biosphere Model (SDBM) (Kaminski et al., 2002), Simple Biosphere Model (SIB) (Lokupitiya et al., 2009), and Terrestrial Uptake and Release of Carbon (TURC) model (Xia et al., 2013)), are generally used to estimate spatial and temporal changes in NPP.

Among various remote sensing models (Ruimy et al., 1994; Sun et al., 2013), CASA is a process-based model that uses remotely sensed data and climate data to estimate regional and global NPP based on light utilization efficiency (LUE) by simulating the exchange of carbon dioxide between the atmosphere and biosphere (Gao et al., 2013). Assessments of CASA at regional and global scales have shown that the model can not only estimate NPP but also examine the effects of land degradation at different stages on phenology (Dieguez and Paruelo, 2017; Rafique et al., 2017). LUE is defined as the photosynthetic efficiency of plants at converting solar radiation into organic matter (Zhang et al., 2015) and is affected by energy distribution. It is the main component of

CASA and determines the accuracy of estimated NPP (Dong et al., 2015). The optimal LUE of plants is determined by their physiological and phenological conditions, and stresses in temperature and changes in soil moisture can decrease photosynthetic efficiency (Nemry et al., 1999). According to available evidence, LUE is maximized under optimal environmental conditions and may be influenced by factors including temperature, humidity, pests and diseases, soil nutrients, and genetic and morphological characteristics of plants like leaf area index (LAI). Hence, different plant types have different LUE values (Fischer et al., 2014), which are individually determined by the difference between observed and estimated NPP (Yu et al., 2005).

Rangeland condition is defined as the current state of a particular vegetation community in comparison to some perceived potential (Stoddart et al., 1975), playing an important role in determining NPP of different vegetation types in a rangeland. For instance, NPP may be decreased by livestock grazing and reduced leaf area (Yu et al., 2018). Plant-available soil moisture can be greatly reduced by soil degradation and erosion (Biondini et al., 1998). Numerous investigations have suggested that drought, increased temperature, topography, and livestock grazing greatly affect changes in NPP of rangeland ecosystems (Chen et al., 2012; Jiang et al., 2015; Sha et al., 2017). In many rangelands of semi-arid regions, precipitation is considered a major determinant of plant production at different time scales, and large fluctuations in NPP can be observed in these areas due to changes in drought and precipitation patterns (Jafari and Bakhshandehmehr, 2013). Consequently, studies on NPP are important for natural resource management in rangelands.

Population growth and land use changes lead to rangeland degradation, which in turn causes erosion, flooding, and desertification, ultimately decreasing NPP levels at regional and global scales (Chen et al., 2017; Ardö et al., 2018). Currently, the four-factor approach is one of the most widely used methods for rangeland assessment and monitoring (Hadian et al., 2019), which categorizes rangeland condition into four levels: good, fair, poor, and very poor.

Due to topographic conditions and the presence of Alborz and Zagros mountain ranges, Iran has a diverse climate at the national scale, ranging from hyper-arid to wet (Kehl, 2009). There are a wide range of vegetation types and rangeland conditions in the country, resulting in NPP values that change not only with time but also with geographical and anthropogenic variations. These changes are more pronounced in semi-arid areas of Semirom County, Iran. In fact, because of topography and land use conditions, different vegetation types in semi-arid rangelands of Zagros have different NPP values. Drought periods also affect plant production (Khatibi et al., 2017), but these effects vary depending on plant species. Moreover, temperature fluctuations caused by elevation levels in the area directly affect the phenology and production of potential plants (Dannenberg et al., 2015).

In Iran, the most widely used technique for measuring rangeland production is probably the double sampling technique (Bonham, 2013). However, despite its wide application, this ground-based technique can only provide detailed data at relatively fine scales and fails to adequately cover large areas necessary for rangeland measurement and monitoring. In addition, currently available satellite products of rangeland production such as MOD17A3H are labeled with "no data" or have zero values in most of the arid and semi-arid lands of Iran. To our knowledge, no studies have assessed the capability of remote sensing and modeling techniques for production mapping in the rangelands of Iran. Therefore, it is essential to examine the potential of models based on remotely sensed data in mapping and monitoring rangeland production. The specific aims of this research were: (1) to evaluate the capability of CASA for NPP mapping across a range of different vegetation types in the semi-arid rangelands of Semirom County, Iran; (2) to analyze the spatial and temporal changes of NPP at a seasonal scale within a single year (2016); and (3) to monitor NPP changes at an annual scale from 2002 to 2016. In addition, since the levels and changes of NPP are affected by drought and wet periods, the trend of NPP changes in relation to precipitation was also investigated using the standardized precipitation index (SPI).

2.1 Study Area

The study area is located in the rangelands of Semirom County (30°42′–31°51′N, 51°03′–51°17′E), Isfahan Province, Iran. This area has a semi-arid climate with mean annual precipitation of 420 mm, with most precipitation occurring in winter and less in summer. Available temperature records from 2002 to 2017 indicate an annual average temperature of 13.6°C (IRIMO, 2016). Altitude in the area is relatively high, ranging from 1707 to 4393 m a.s.l., with peaks in the Zagros Mountains. Due to the large altitudinal range and human activity influences, there are numerous vegetation types and a range of conditions in the rangelands (Hadian et al., 2013). In recent years, grazing and other activities such as the construction of the Hana Dam and land use changes have degraded existing rangelands, especially those around agricultural lands in Semirom County. It has been reported that NPP in the study area ranges from 10.00 to 46.00 g $C/(m^2 \cdot a)$, depending on vegetation type and rangeland condition (Feizi, 2018).

2.2 Field Measurements

We used the following equation to calculate the sampling area by taking into account the resolution (250 m$\times$250 m) of the Moderate Resolution Imaging Spectroradiometer (MODIS):

$$A = (P + L)^2$$

where A is the sampling area (m^2); P is the pixel resolution (m) of the MODIS bands used for NDVI calculation (250 m$\times$250 m); and L is the acceptable error (pixel) (McCoy, 2005). The MODIS sensor obtains data at different spatial resolutions including 250 m (bands 1-2), 500 m (bands 3–7), and 1000 m (bands 8–36) with wavelengths from 0.41 to 14.40 m.

The conditions of rangelands in Semirom County were evaluated using a four-factor method and related forms (Khaleghi and Aeinebeygi, 2016). In this method, rangeland condition was calculated as the sum of scores for soil factor (0–20), vegetation cover (0–10), vegetation composition (0–10), and plant vigor and vitality (0–10). Scores of <20, 21–30, 31–37, 38–45, and >45 indicate very poor, poor, fair, good, and excellent conditions, respectively (Friedel, 1991). Accordingly, the conditions of rangelands in Semirom County were categorized as very poor, poor, fair, and good.

During field investigation, we identified a total of 12 vegetation types. Astragalus spp.-Bromus spp. (As-Br.F and As-Br.P) and Astragalus spp.-Daphne spp. (As-Da.F and As-Da.P) exhibited two conditions (poor and fair) in different parts of the study area. Thus, NPP was measured in 14 vegetation types (Table 1). A total of 30 sampling sites were designed for each vegetation type. Vegetation cover (in percentage) in an area of 500 m$×500mwasdeterminedusing8plots(10m×10meach)(Khajeddin,1995),andthetotalproductionofallplantsp m quadrat (Fig. 1 [Figure 1: see original paper]) (Yeganeh et al., 2014).

2.3 Climate and Satellite Data

Meteorological data including monthly temperature, precipitation, and solar radiation during 2002–2016 were obtained from regional meteorological offices of all weather stations in the study area. We used the Angstrom-Prescott equation to calculate solar radiation based on total solar radiation recorded at synoptic weather stations (Alamdari et al., 2013). The SPI was calculated with the SPIEXE program at 1-, 2-, 3-, 6-, 9-, and 12-month intervals (ending in May of each year) during 2002–2016 to determine the effect of drought on vegetation growth (Lloyd-Hughes and Saunders, 2002; Ji and Peters, 2003). NPP values at 30 sampling sites for each vegetation type and rangeland condition were separately averaged to compare with annual SPI at 1-, 2-, 3-, 6-, 9-, and 12-month intervals during the study period (Fig. 2 [Figure 2: see original paper]).

Satellite data were extracted from NASA' s Earth Observing System (EOS) and NASA' s Land Processes Distributed Active Archive Center (LP DAAC) (https://earthexplorer.usgs.gov). MODIS 16-day NDVI products were used to calculate required parameters for CASA. Seasonal variations of NPP from 21 March to 13 September in 2016 (Table 2) as well as annual NPP values during 2002–2016 were estimated using the average of two MODIS 16-day NDVI products by the same method described by Yu et al. (2009) and Yuan et al. (2016).

2.4 Estimation of NPP Using the CASA Model

Climate factors (including precipitation, temperature, and solar radiation), NDVI images, absorbed photosynthetically active radiation (APAR; MJ/m^2) at 400–700 nm, and land use/land cover maps (Feizi, 2018) were used to simulate NPP by the CASA model (Hua et al., 2014). Since NPP values differed among vegetation types, NPP was separately calculated for each vegetation type. The relationships between observed and estimated NPP at sampling sites were then evaluated using regression analysis and the coefficient of determination. Equations 2–16 were used in the CASA model, and Figure 3 [Figure 3: see original paper] described the modeling process for estimating NPP.

$$NPP(x,t) = APAR(x,t) \times \varepsilon(x,t)$$

$$APAR(x,t) = FPAR(x,t) \times SOL(x,t) \times 0.5$$

where NPP is net primary production (g C/(m^2 • a)); APAR is absorbed photosynthetically active radiation (MJ/m^2);   is light utilization efficiency (g C/MJ); FPAR is the fraction of APAR (MJ/m^2); and SOL indicates total solar radiation (MJ/m^2).

In the equations below, FPAR_{min} and FPAR_{max} values are 0.001 and 0.950, respectively (Potter et al., 1999). We obtained FPAR according to the following equations, and the obtained α was 0.447 (the mean value of $FPAR_1$ and $FPAR_2$) (Yu et al., 2009):

$$FPAR(x,t) = FPAR_{\min} + \alpha \times (FPAR_{\max} - FPAR_{\min})$$

$$FPAR(NDVI)(x,t) = \frac{(NDVI)(x,t) - (NDVI_{\min})}{(NDVI_{\max}) - (NDVI_{\min})}$$

$$FPAR(SR)(x,t) = \frac{(SR)(x,t) - (SR_{\min})}{(SR_{\max}) - (SR_{\min})}$$

$$SR(x,t) = \frac{1 + (NDVI)(x,t)}{1 - (NDVI)(x,t)}$$

$$T_\varepsilon(x,t) = 0.0005 \times T(x,t)^2 - 0.0005 \times T(x,t) + 1$$

$$T_\varepsilon(x,t) = \frac{1}{1 + \exp[0.2 \times (T_{\text{opt}} - 10 - T(x,t))]} \times \frac{1}{1 + \exp[0.3 \times (-T_{\text{opt}} - 10 + T(x,t))]}$$

$$W_\varepsilon(x,t) = 0.5 + 0.5 \times \frac{E(x,t)}{E_p(x,t)}$$

$$E_p(x,t) = E_0(x,t) \times \left[\frac{R(x,t)}{R_{\max}} + \frac{I(x,t)}{I_{\max}}\right]$$

$$I(x,t) = \sum_{i=1}^{12} \left(\frac{T_{\mathrm{ai}}(x,t)}{5}\right)^{1.514}$$

$$E_0(x,t) = 16 \times \left(\frac{10 \times T(x,t)}{I(x,t)}\right)^a$$

$$\varepsilon(x,t) = \varepsilon_{\max} \times T_\varepsilon(x,t) \times W_\varepsilon(x,t)$$

where D is a coefficient extracted from NDVI; is light utilization efficiency (g C/(MJ)) and _{max} represents radiation power at maximum APAR (g C/MJ); T_ $_1$ is the temperature (°C) at which the plant can perform photosynthetic activities; T_ $_2$ is the temperature (°C) at which the plant can efficiently use light; W_ is the water stress coefficient (K_s), which determines the moisture level affecting efficient radiation use and depends on the plant' s ability to maintain soil moisture (mm); T_{opt} is the monthly temperature (°C) when NDVI reaches its highest value in a certain area in one year; *E*, *E_p*, and *E_0* represent regional, potential, and local potential evapotranspiration (mm), respectively; R is net solar radiation (W/m^2); I is the annual heat index (Rohli and Vega, 2013); and *T_{ai}* is monthly temperature when air temperature ranges from 0.0°C to 26.5°C.

After calculating the above-mentioned parameters, NPP maps of the study area were produced, and the slope of NPP (g C/(m^2 · a)) changes during 2004-2007 (the wet period) and 2013-2016 (the drought period) was determined using the following equation (Zhou et al., 2015):

$$\mathrm{Slope} = \frac{n \times \sum_{i=1}^n i \times NPP_i - \sum_{i=1}^n i \times \sum_{i=1}^n NPP_i}{n \times \sum_{i=1}^n i^2 - \left(\sum_{i=1}^n i\right)^2}$$

where n is the interval studied and i shows the year number (i.e., 1 for the first year, 2 for the second year, and so on).

2.5 Light Utilization Efficiency (LUE) Calculation

In this study, we determined LUE based on thermodynamic laws and the ratio of NPP to APAR (Eq. 18). The LUE value was considered as the slope of the line in the regression relationship between APAR (x) and observed NPP (y) (Pan et al., 2009).

3.1 Assessment of the CASA Model and Estimation of NPP

Evaluation of the CASA model in different vegetation types revealed lower annual NPP values in rangelands with poor and very poor conditions than in those with good and fair conditions. Except for rocky areas in the southern parts of the study area, annual NPP values were lower and degradation levels were higher in areas with lower altitudes. Agricultural lands and areas around Semirom County exhibited low NPP values, possibly due to rangeland degradation.

Data on harvested plants in each vegetation type (measured at 30 sampling sites) were used to evaluate CASA efficiency in NPP estimation. Observed and estimated NPP values were significantly correlated (R^2=0.95; Fig. 4a [Figure 4: see original paper]), indicating that the CASA model was capable of predicting almost all variations in NPP across sampling sites. Despite a wide range of vegetation types and different dominant plant species in the region, correlations between observed and estimated NPP values for all rangeland conditions (very poor to good) were significant at the 0.01 level (R^2 values of 0.36–0.80). In general, estimated NPP values in the region ranged between 0.00 and 74.48 g C/($m^2 \cdot a$) in 2016 (Fig. 4b).

Observed NPP values of 37.00 and 34.00 g C/($m^2 \cdot a$) were recorded in As-Br vegetation type with fair and poor conditions, respectively. The Astragalus spp.-Agropyron spp. (As-Ag) vegetation type showed the highest NPP amount (46.00 g C/($m^2 \cdot a$)), while the annual grasses-annual forbs (An.gr-An.fo) type had the lowest NPP value (10.00 g C/($m^2 \cdot a$)). NPP was relatively high (40.00 g C/($m^2 \cdot a$)) in Daphne spp.-Astragalus spp. (Da-As) type with poor condition. Furthermore, degraded vegetation types and very poor rangelands (e.g., Gundelia spp.-Cousinia spp. (Gu-Co) and Sophora spp.-Launaea spp. (So-La)) had lower NPP values (18.00 and 19.00 g C/($m^2 \cdot a$), respectively) compared to other shrublands. Generally, NPP values differed based on vegetation cover and type. Accordingly, different observed NPP values were obtained for Astragalus spp.-Acantholimon spp. (As-Ac; 32.00 g C/($m^2 \cdot a$)), As-Da.F (27.40 g C/($m^2 \cdot a$)), Astragalus spp.-Cousinia spp. (As-Co; 29.23 g C/($m^2 \cdot a$)), Astragalus spp.-Psathyrostachys spp. (As-Ps; 29.97 g C/($m^2 \cdot a$)), Euphorbia spp.-Hertia spp. (Eu-He; 18.78 g C/($m^2 \cdot a$)), and Artemisia aucheri (Ar.au; 29.00 g C/($m^2 \cdot a$)).

The correlation between observed and estimated NPP values depended on vegetation types and rangeland conditions (Fig. 5 [Figure 5: see original paper]). As-Ag and Gu-Co types had the highest (0.75) and lowest (0.36) correlation coefficients, respectively. Under similar rangeland conditions, An.gr-An.fo type showed a higher correlation coefficient compared to perennial plants. As-Br and As-Da rangelands with fair condition showed higher correlations between observed and estimated NPP values than those with poor condition. In general, higher correlations were observed in rangeland areas with good condition. However, serious rangeland degradation and high spatial heterogeneity decreased the correlation between observed and estimated NPP values and the accuracy of the CASA model. In fact, remote (inaccessible) areas were healthier than grazed lands. Both NPP and LUE of vegetation types used by livestock were low in rangelands near agricultural and residential areas as well as in rangelands with very poor condition. Due to high spatial heterogeneity in these areas, lower correlations existed between observed and estimated NPP values (Fig. 5).

LUE values, used to evaluate photosynthesis potential of different vegetation types, depended on vegetation types and rangeland conditions (Fig. 5). As-Ag rangelands with good condition had the highest LUE (0.117 g C/MJ), and An.gr-An.fo rangelands with poor condition had the lowest LUE (0.010 g C/MJ). As-Br rangelands in fair condition had higher LUE values than those in poor condition. Generally, under poor rangeland condition, grass vegetation types showed higher LUE values than shrub vegetation. Moreover, Da-As (shrub form) had larger LUE values compared to bushlands (Fig. 5).

Based on 16-day MODIS composites, plant growth in the study area began in late March due to regional climate changes. Regional NPP values ranged from 0.00 to 10.49 g $C/(m^2 \cdot a)$ in March and 0.00 to 0.09 g $C/(m^2 \cdot a)$ in September (Fig. 6 [Figure 6: see original paper]). Production showed an increasing trend during 21 March–24 May, with maximum increase observed during 8–24 May. A significant reduction in NPP (0.00–0.82 g $C/(m^2 \cdot a)$) occurred during 24 May–9 June, and the parameter reached values of 0.00–0.09 g $C/(m^2 \cdot a)$ on 13 September.

Comparison of 16-day NPP and digital elevation model (DEM) maps revealed that NPP values depended on temperature conditions at the beginning of the growing season, with plant growth initially starting from areas with lower altitudes. NPP values varied depending on area condition at different times of year, meaning that topography greatly influenced the spatial distribution of NPP. In March and April, NPP values in rangelands located in plains (0.00–10.49 g $C/(m^2 \cdot a)$ on 22 April; Fig. 6c) were higher than values in rangelands located in highlands. With temperature rise in May, NPP increased at highlands and reached values of 0.00–21.92 g $C/(m^2 \cdot a)$ for the whole study area during late May (Fig. 6e). However, with the beginning of the dry season and considerable temperature increase, NPP values sharply declined to 0.00–0.82 g $C/(m^2 \cdot a)$ on 9 June (Fig. 6f). Under such conditions, highlands were more productive than plains. In addition, growth of different vegetation types decreased from highlands (lower temperature and higher humidity) to plains (higher temperature and lower humidity) and reached zero by late September.

In terms of spatial distribution, the western and southern parts of the study area generally had higher NPP values. During the growing season, rain-fed and agricultural lands had higher NPP values compared to grazed rangelands. Meanwhile, rocky parts of the southern region had very low NPP values. Moreover, due to rangeland degradation, reduced NPP values were observed in the vicinity of Semirom County.

3.2 Relationship Between NPP Changes and SPI

The correlation between SPI and NPP changes depended on vegetation types and rangeland conditions (Table 3). For As-Br and As-Da vegetation types with either poor or fair condition, higher correlations between SPI and NPP changes were detected in rangelands with fair condition than in those with poor condition. Among different vegetation types, NPP changes in An.gr-An.fo type had the greatest correlation (R^2=0.86) with 1-month SPI (SPI1). The correlation coefficients of NPP change with 2-, 3-, 6-, 9-, and 12-month SPI were 0.83, 0.34, 0.24, 0.14, and 0.14, respectively, showing sharp decreases in 6-, 9-, and 12-month periods. Rangelands in very poor condition (So-La and Gu-Co) had the lowest correlation with SPI, and the effect of short-term precipitation was more profound in these areas.

Larger changes were observed in As-Ag rangelands with grass-shrub composition and good condition than in rangelands with similar composition (As-Br) and fair condition. The effect of drought on NPP changes was low in degraded areas with very poor condition (Gu-Co and So-La). Drought during the growing season differentially affected various vegetation types and rangeland conditions, with degraded vegetation types being most sensitive to precipitation changes during the growing season. Generally, under the same rangeland conditions, shrub-bush (Da-As) plants were less sensitive to precipitation changes than bushes. In poor rangelands, 3-month SPI (SPI3) caused greater NPP changes in bushes than in annual plants. The correlation of NPP changes with SPI was higher in As-Br type (bush-grass form) than in bush types. Due to lack of precipitation in June, July, August, and September, the correlations of NPP changes with 9- and 12-month SPI were completely identical. Moreover, in all vegetation types, the correlation between NPP changes and 1-month SPI was significant at the 5% level. The correlations were significant at the 1% level in bush-grass types (As-Br and As-Ag) and annual plants (An.gr-An.fo) with good and fair conditions.

3.3 NPP Changes During Drought and Wet Periods

We calculated NPP changes during drought (2013–2016) and wet (2004–2007) periods based on SPI (Fig. 7 [Figure 7: see original paper]). During the 4-year wet period (2004–2007), NPP showed an average increase of 0.75 g C/($m^2 \cdot a$) in the study area, with the magnitude of changes depending on vegetation types and rangeland conditions. During this period, NPP of An.gr-An.fo and the dominant shrub type (Da-As) showed the highest (2.01 g C/($m^2 \cdot a$)) and lowest (0.52 g C/($m^2 \cdot a$)) levels of increase, respectively. Furthermore, NPP changes were larger in bush-grass type than in bush type (Fig. 7).

Total NPP in all studied vegetation types decreased by an average of 1.03 g C/($m^2 \cdot a$) within the 4-year drought period (2013–2016). The highest reduction (1.73 g C/($m^2 \cdot a$)) was observed in An.gr-An.fo, while the lowest reduction (0.25 g C/($m^2 \cdot a$)) occurred in shrub-bush type (Da-As). NPP reductions were more pronounced in very poor rangelands than in poor and fair rangelands. Although NPP of rangelands around residential areas did not show significant increase during the wet period (2004-2007), it had a more profound reduction (3.00 g $C/(m^2 \cdot a)$) during the drought period (2013-2016).

4 Discussion

The results showed that the CASA model was very reliable and had great potential for studying spatial and temporal dynamics of NPP in the semi-arid rangelands of Semirom County, Iran. Our research demonstrated a 95% correlation between observed and estimated NPP values over the whole study area. Since CASA operates based on exact determination of LUE values (Yu et al., 2009) and accurate estimation of LUE, the high accuracy can be attributed to the appropriate number of sampling sites, exact classification of rangeland conditions and vegetation types, and appropriateness of sampling size relative to study extent.

According to correlations between observed and estimated NPP values, the NPP map did not have similar accuracy in all vegetation types. Despite small LUE values, observed NPP in An.gr-An.fo type was highly correlated with estimated NPP (R^2=0.69). Furthermore, under different rangeland conditions, As-Da (R^2=0.64 in fair rangelands and R^2=0.49 in poor rangelands) and As-Br (R^2=0.74 in fair rangelands and R^2=0.58 in poor rangelands) showed different correlations between observed and estimated NPP values (Fig. 5).

Greater heterogeneity of plant and bare soil (patch and interpatch) was observed in bushlands than in lands with annual herbs and shrub-grass, affecting sampled data and decreasing homogeneity and plant vitality in degraded areas (Li et al., 2011). Therefore, low correlation between observed and estimated NPP values in degraded vegetation types could have been caused by reduced correlation between field and remotely sensed data in degraded areas and sampling error due to plant distribution patterns in shrublands compared to annual plant types. Previous research has confirmed the role of plant distribution pattern and regional heterogeneity in sampling accuracy and the effects of plant characteristics on correlation between field and remotely sensed data (Goldsmith, 1991). While CASA uses NDVI, values of this index can vary or decrease due to unique properties of each vegetation type, determined by plant species, soil, and physiography. Such differences or reductions can be another reason for decreased accuracy of CASA model in NPP estimation, seemingly having greater effects in degraded areas with low vegetation canopies (Jafari et al., 2007).

The level of correlations between observed and estimated NPP values at sampling sites could be influenced by different error sources. For example, field production data were collected over several days, while remotely sensed imagery captured landscape conditions at a particular point in time. Consequently, temporal variations in rangeland production resulting from continuous grazing and weather condition changes must be considered contributors to field data variability. Additionally, slight mismatch between exact area sampled in the field and pixels extracted from imagery could potentially reduce relationship strength between the two datasets. Finally, field data were measured by several field workers, adding another source of potential variation. It has been shown that there may be up to 20% difference in measurements obtained by experienced field workers using objective methods similar to the double sampling approach (Friedel and Shaw, 1987; Wilson et al., 1987).

NPP varied from one vegetation type to another, with the lowest (10.00 g C/($m^2 \cdot a$)) and highest (46.00 g C/($m^2 \cdot a$)) values belonging to An.gr-An.fo and As-Ag types, respectively. The role of plant physiology (e.g., vegetation form and leaf area index) in water use efficiency and production could be responsible for this finding. Additionally, regional plant composition can affect water penetration (Caylor and Shugart, 2004). Although trees and shrubs have deeper roots than bushes, grasses and annual plants have the highest sensitivity to drought and low soil nutrient contents, considerably affecting plant production and efficiency (Throop et al., 2012). Da-As (shrub-bush lands) had higher NPP values than species in bushlands, probably due to the latter' s high ability to use deep soil moisture.

Rangelands in very poor condition had lower NPP values, possibly due to degraded soil structure, reduced soil organic and inorganic matter contents, and decreased soil moisture. Soil had more desirable properties (e.g., absorbable moisture and nutrients) in rangelands with better conditions such as As-Ag rangelands (Zika and Erb, 2009). Plant species, vegetation forms, soil types and conditions (Schlesinger and Andrews, 2000), plant distribution patterns (Stephenson, 1990), and exploitation history (Zhang et al., 2007) are generally considered factors affecting efficiency and NPP of vegetation types.

LUE assessments in different rangeland types showed that LUE depended on vegetation types and rangeland conditions. In this study, the highest and lowest LUE values were found in As-Ag (0.117 g C/MJ) and An.gr-An.fo (0.010 g C/MJ), respectively (Fig. 5). Therefore, interaction between climatic and physiological factors in plant species seems responsible for LUE changes. In semiarid areas, shrubs and bushes have higher drought resistance due to woody stems, deep roots, and low evapotranspiration, giving them higher photosynthetic efficiency and greater annual biomass production compared to annual plants (Whitehead and Gower, 2001). Since rangeland condition changes can alter photosynthetic efficiency in a vegetation type, rangeland degradation decreased both LUE and NPP values in similar vegetation types (e.g., As-Da).

During the growing season, plants can have different production rates depending on temperature and humidity changes, germinating at the beginning of the growing season (when base temperature is reached) and increasing growth rate with temperature and precipitation increases. The growing season in the study area began on 21 March, peaked around 24 May, and started decreasing on 9 June. Observations have shown that when required moisture is accessible, plant production maximizes at optimal temperature, with growth rate decreasing and stopping as temperature rises (Clark et al., 2003). Increased leaf area index in the middle of the growing season has been identified as another reason for improving plant productivity (Roupsard et al., 2009). CASA considers optimum conditions and soil moisture content, calculating NPP values based on temperature changes (Potter, 2012a). According to our results, this model can be used to calculate seasonal NPP values in different vegetation types at regional levels, aligning with seasonal weather changes and previous findings (Potter et al., 2012b). Thus, NPP estimation for various applications is possible based on daily growth rates and climatic parameters at various phases of plant phenology (Cuadra et al., 2012).

Annual evaluations highlighted major effects of precipitation on NPP. Although drought conditions (2013–2016) reduced NPP levels in all vegetation types throughout the study area, NPP increased during the wet period (2004–2007) (Fig. 7). The results indicated a strong correlation between SPI and NPP changes in all vegetation types (Table 3). Studies in semi-arid regions have reported that precipitation affects NPP through its effects on soil moisture (Chen et al., 2013), potentially caused by drought effects on leaf area index as a determinant of NPP changes. Long-term and repeated drought periods could reduce carbohydrate storage and impair physiological balance, making plants unable to increase production even in wet periods (Holechek et al., 1989). Additionally, due to ecosystem fragility in semi-arid areas compared to humid areas, drought periods have more destructive effects on plants, intensified in degraded areas (Lei et al., 2015). Therefore, drought is considered the most important climatic factor controlling plant production and carbon cycle in semi-arid regions, with large annual fluctuations observed in these areas (Wessels et al., 2007; Peng et al., 2015).

An.gr-An.fo plants exhibit better responses to short-term and repeated precipitation due to their root structures. Shrub-bush plants (e.g., As-Da) have different root structures and woody stems, making them less sensitive to long periods without precipitation and giving them higher drought tolerance than grasses. Consequently, SPI had larger correlations with NPP in As-Ag and As-Br plants than in bushland species. NPP was less sensitive to climate in shrub-bush type (Da-As) than in bush type. Previous studies have reported similar findings (O' connor and Roux, 1995; Xu et al., 2013). According to previous research, due to destroyed soil structure, decreased soil permeability, and reduced vegetation canopy, the effect of precipitation on NPP decreases and runoff increases in poor and very poor rangelands (Gao et al., 2013).

High seasonal fluctuations in precipitation were observed in the study area, with precipitation mainly occurring during cold seasons and amounting to zero (in some parts) as temperature rose at the beginning of warm seasons. Consequently, plant growth declined and phenological stages gradually stopped in warm seasons. Moreover, since plants could not grow with temperature fall during cold seasons (until late March), their growth period was limited to the interval between 21 March and the first week of June (Fig. 6). These factors decreased NPP in semi-arid regions (Fridley et al., 2016). Low temperatures and delayed plant phenological stages at highlands reduced NPP values in the early growing season (Fig. 6). Therefore, exploitation of these areas in the early growing season disturbs plant physiological balance and leads to soil erosion (Wang et al., 2017).

CASA uses monthly precipitation data to measure soil moisture; however, shrubs and bushes can use deep soil moisture for extended periods due to their root structure, making the model more accurate in estimating NPP in annual plant types. Although soil moisture is the most important determinant of NPP in semi-arid areas, it only ranges between 0 and 1 in the CASA model, suggesting that parameters in the CASA model need revision for semi-arid areas.

5 Conclusions

The CASA model applied in this research could estimate NPP in semi-arid rangelands of Iran with high accuracy at the regional scale. The results suggested that vegetation types (vegetation forms and plant species), rangeland conditions, and regional topography affected LUE values and thus CASA model accuracy. Correlations between NPP changes and SPI indicated that within a particular region, NPP values differed depending on plant species, vegetation forms, and rangeland conditions. Annual plants and shrubs respectively showed the highest and lowest sensitivity to drought variations. Moreover, effects of seasonal precipitation distribution patterns on NPP varied among plant species. The effects of drought and wet periods on NPP were determined by rangeland conditions and local characteristics, with degraded areas and areas near villages mostly damaged by drought and less likely to be restored during wet periods. Furthermore, NPP values decreased in the study area where the growing season was limited to a few months due to low temperatures in cold seasons and lack of precipitation in warm seasons.

The results confirmed the applicability of the CASA model for NPP estimation in rangeland vegetation types at different spatial and temporal scales. CASA modeling can facilitate assessment of rangeland readiness based on NPP values and determination of rangeland capacity for various utilizations such as grazing and wildlife use. Additionally, rangeland degradation processes in various vegetation types can be studied through NPP evaluations. Therefore, this study recommends application of the CASA model for evaluation and monitoring of extensive rangelands in Iran (covering over 52% of the country). Model outputs provide up-to-date and valuable information on plant production that can be used for reporting rangeland conditions.

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