Predicting vegetation phenology in response to climate change using bioclimatic indices in Iraq

Afrah Daham, Dawei Han, W. Matt Jolly, Miguel Rico-Ramirez and Anke Marsh

ABSTRACT

Although most phenology models can predict vegetation response to climatic variations, these models often perform poorly in precipitation-limited regions. In this study, we modified a phenology model, called the Growing Season Index (GSI), to better quantify relationships between weather and vegetation canopy dynamics across various semi-arid regions of Iraq. A modified GSI was created by adding a cumulative precipitation control to the existing GSI framework. Both unmodified and modified GSI values were calculated daily from 2001 to 2010 for three locations in Eastern Iraq: Sulaymaniyah (north), Wasit (central) and Basrah (south) and a countrywide mean and compared to the Normalized Difference Vegetation Index (NDVI) from MODerate-resolution Imaging Spectroradiometer (MODIS) for the same time period. Countrywide median inter-annual correlations between GSI and NDVI more than doubled with the addition of the precipitation control and within-site correlations also show substantial improvements. The modified model has huge potential to be used to predict future phenological responses to changing climatic conditions, as well as to reconstruct historical vegetation conditions. This study improves our understanding of potential vegetation responses to climatic changes across Iraq, but it should improve phenological predictions across other semi-arid worldwide, particularly in the face of rapid climate change and environmental deterioration.

Key words | climate change, GSI phenological model, minimum temperature, photoperiod, precipitation, vapour pressure deficit

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INTRODUCTION

Mitigating against the effects of climate change is high on the agenda for many countries. As such, it is becoming increasingly vital to develop and use models that can not only measure recent climate and environmental change, but that can also be used to predict future change, especially in marginal, fragile environments such as those found in semi-arid and arid regions, with large populations. A number of different models and methods (such as those based on remote sensing) have been applied to measure and predict present and future temperature changes (Hansen *et al.* 2010; Amanollahi *et al.* 2012) (data from IPCC 2014; GISTEMP 2017), precipitation changes (Hawkins & Sutton 2011; Wu *et al.* 2011; IPCC 2014) and CO_2 variation (Meehl *et al.* 2007; IPCC 2014). All of these variables, of course, are interrelated and interdependent, in that changes in one or more variable will cause changes in the others. Further, these variables combine to limit plant physiological processes, particularly phenological processes that are dominated by climatic variations and that heavily influence the coupling between vegetation and the atmosphere.

Phenology is simply the study of plant and animal lifecycles. Vegetative lifecycles vary due to biotic and abiotic forcings, and it is important to understand these forcings (Lieth 1974, 1975, 2013; Jolly *et al.* 2005). Plant foliage,

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'greenness', is directly related to the carbon and water cycles, thus impacting and being impacted by surface-atmosphere dynamics, and in recent decades there have been many changes in the timings and duration of the greenness cycle (Myneni *et al.* 1995; Menzel & Fabian 1999; Schwartz & Reiter 2000; Matsumoto *et al.* 2003), impacting soil capacity, microclimates, and on a larger scale, the global carbon cycle (Jolly *et al.* 2005; Keeling *et al.* 2005; IPPC 2014). Modelling plant phenology depends on a solid understanding of the dominant climatic controls to govern phenological processes and these models are often developed and calibrated for a single region and they lack a solid, theoretical foundation.

Jolly *et al.* (2005) argued that extant phenology models, based mainly on satellite canopy coverage imagery, sparse phenological ground observations and various mathematical models, needed to be combined with surface weather data in order to create a more dynamic representation of the vegetation over large areas. They sought to 'develop a simple, generalized phenology model to test the hypothesis that there is such a set of common climatic conditions that interact to limit foliar phenology globally' (Jolly *et al.* 2005, p. 620). They proposed a simple approach that combined daily minimum temperature, vapour pressure deficit (VPD) and photoperiod into a simple index of plant canopy development called the growing season index (GSI). GSI showed a good agreement with satellite-derived foliage variations at sites across the world. Further, they also found that the model was not only able to simulate current differences in foliage in different regions across the globe, but that it could also be used to predict climate-mediated canopy variations in future because the model used common meteorological variables that could be derived from general circulation model outputs. Stöckli *et al.* (2011) used satellite data to calibrate GSI for better predicting vegetation phenology globally across plant functional types. Förster *et al.* (2012) applied the GSI approach to meso- and macro-scale water balance simulations. These studies were the direct application of the existing GSI method and improvement to the method itself has not been carried out.

Although most phenology models are designed to analyse and/or to predict future trends in response to climate change, a holistic bioclimatic index that includes precipitation as a dominant control has not been adequately considered in the existing phenology models. One simplification that the original GSI made was to use VPD as a surrogate for seasonal changes in water availability and daily precipitation measurements were not considered. In semi-arid regions, precipitation directly controls seasonal canopy variations (Jolly & Running 2004) and the use of VPD as a surrogate may not be sufficiently general to capture the range of potential plant responses during extended dry periods. A more generalized version of GSI should therefore include a direct precipitation control to improve predictions in semi-arid regions. In this paper, we seek to expand the GSI model to include a direct precipitation control and we evaluate the model across three semi-arid regions of Iraq with differing climate and vegetation. We then test the predictive quality of the model by comparing the unmodified and modified GSI models against satellite-derived estimates of the Normalized Difference Vegetation Index (NDVI) for a ten-year period (2001–2010).

Because of the political instability and continuous state of conflict in Iraq since the 1980s with the Iran–Iraq War, and continuing today with the presence of ISIS in Iraq, there has been very little in the way of environmental research in the region, and even less funding dedicated to environmental and agricultural research (Jaradat 2002). Some work was carried out in the 1970s, which was followed by sporadic research through the next few decades, until the early 2000s (Beaumont 1998; Jaradat 2002; Qader *et al.* 2015; Agha & Şarlak 2016; Najmaddin *et al.* 2017). Currently, there is more research being carried out, however, most of this concerns the effects of the conflicts on groundwater, agriculture, and so on (FAO 2013, 2016). Despite the new research being carried out, the region covered is patchy as there are still areas of conflict that are inaccessible to researchers. This is the first study to not only evaluate current canopy cover in various areas of Iraq using an enhanced phenological model, but also to use a model that has the potential to predict future vegetation change in the region. This is particularly important as desertification (and thus loss of greenness in the region) continues unabated, which will, in turn, create further water and food shortages in the future if mitigation strategies are not put in place. The paper will first describe the study areas, and then there will be a brief discussion on the model and the variables used. The results follow, with an in-depth discussion and concluding comments.

The study area

Iraq is situated in the Middle East, between longitudes 38–48°E and latitudes 29–37°N, with an area of 437,072 km^2. It is surrounded by Iran to the east, Turkey to the north, Syria, Jordan and Saudi Arabia to the west, and the Arabian/Persian Gulf to the south (Figure 1). The major environmental features consist of an expansive alluvial plain and associated marshlands, which have been created by the two historically significant rivers, the Tigris and the Euphrates; the desert in the south and southeast; and the mountainous region in the north, where Iraqi Kurdistan is bounded by the Zagros mountains and foothills.

Generally, Iraq is described as having a continental subtropical climate, with areas to the north experiencing a Mediterranean climate (Jaradat 2002; FAO 2008). The summers are extremely hot (average maximum temperature in July–August around 43 °C, in the shade) with no rainfall, and the winters are short and cool (FAO 2008, 2011). The majority of the precipitation occurs in winter, as a mix of snow and rain in the north between November and April

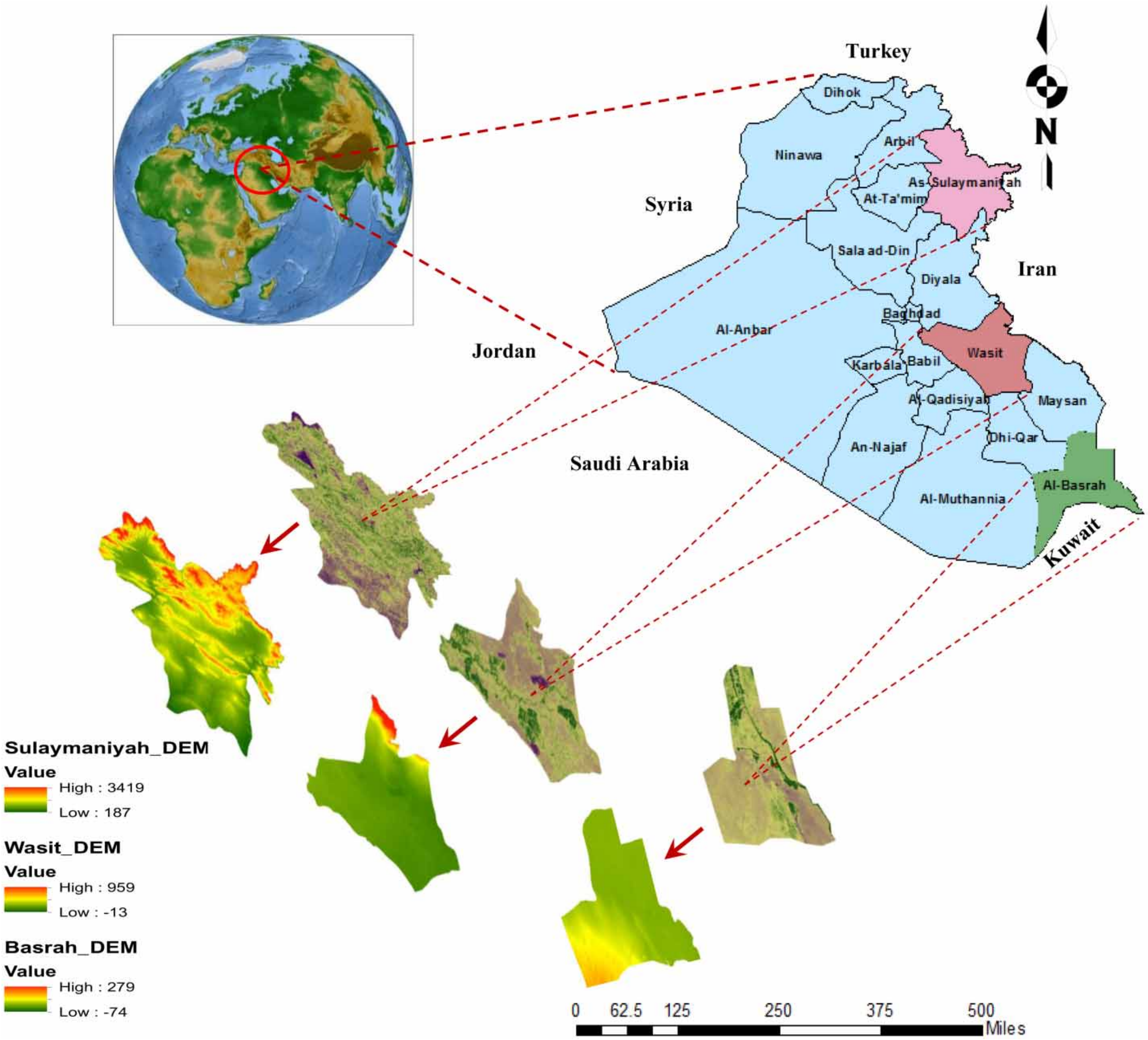

Figure 1 | Location of the study area and test sites with NDVI and Digital Elevation Model (DEM) images.

and as rain in the rest of Iraq from December to February (FAO 2008). The FAO (2008) divides Iraq into four 'agro-ecological zones', which are: the arid to semi-arid Mediterranean zone, where average rainfall is over 400 mm/year and which covers most of the northern parts of Iraq; the steppic zone, which receives about 200–400 mm of rain per year (mainly the Salelhadin area); the alluvial or irrigated zone between the two rivers and the desert zone (both of which have less than 200 mm per year). The study areas chosen for this research fall into either the irrigated zone or the Mediterranean zone, which are both more agriculturally productive (FAO 2003).

Three areas in Iraq were chosen to test the modified GSI model: Sulaymaniyah in the north (Iraqi Kurdistan), Wasit in the middle, and Basrah to the south (Figure 1). The three study areas have different climates and thus provide a way to test the model against gradients of temperature and precipitation and to explore their combined impact on vegetation greenness.

Sulaymaniyah is located in Iraqi Kurdistan in northern Iraq. It is one of the main population centres in the country. It is surrounded by the Zagros mountains in the east (bordering with Iran), and the Binzird, Baranan and Qara Dagh hills to the west and south. In the middle is the wide Shahrizor plain, which is used for agriculture (cereals and fruit) and grazing, and is dissected by the Tanjero River (Altaweel *et al.* 2012). Sulaymaniyah's climate is Mediterranean, and is characterized by its cooler summer temperatures and its rainier winters. Average temperatures range from 0 °C to 39 °C (although temperatures in the 40s have been recorded) and precipitation rates can reach over 1,000 mm/year. There is some snowfall during the winter, especially at higher elevations.

Wasit is located in central Iraq. It is bounded by the Zagros mountains and the Iranian border to the east, with Bagdad to the north. It is located in the alluvial plain created by the Tigris. The FAO (2011) indicates that there are two types of agro-ecological zones in Wasit: the Mandali and the Bagdad zones. The Mandali zone is one of low agricultural potential: there is low rainfall, the land is swampy, there are issues with salinity and irrigation is difficult (FAO 2011). The Bagdad zone, in the west, has a higher agricultural potential, especially when irrigation is used (FAO 2011). However, there is still an issue with salinization of soils. Rainfall in the region is generally less than 200 mm/year.

Basrah is located in the south of Iraq. It is characterized by having an arid climate, with temperatures in the summer exceeding 50 °C. However, because of its proximity to the Persian Gulf coast, there is also high humidity. The FAO (2011) report indicates that there are two agro-ecological zones in the Basrah region: the Basrah (mainly marshy) and Rutbah (desert) zones. Neither is agriculturally productive and there is very little rainfall in the region (usually less than 150 mm/year).

METHODS

Model development

The modified GSI uses three variables that can affect vegetation growth and development within a region. In addition to the minimum temperature, VPD, and photoperiod used by the original model, we add daily total precipitation.

For each variable, a daily index is calculated for each weather variable based on a set of limits that define the upper and lower bounds of those variables on phenological processes: the lower boundary (minimum) indicates no phenological activity (index = 0) whereas exceeding the upper boundary limit (maximum) indicates unconstrained growth (index = 1) and varies linearly between these two limits. Further discussion on how threshold limits were determined can be found in the supplementary materials, with accompanying data and graphs. The product of the three indices for the original model and four indices for the modified model creates a combined index (iGSI) that is smoothed using a 21-day running average to limit the influence of short-term weather fluctuations on modelled phenological states (Jolly *et al.* 2005). The first three variables are discussed briefly, and more detail can be found in Jolly *et al.* (2005), followed by a more lengthy discussion on how precipitation is integrated into the GSI framework. We then discuss the meteorological and vegetation datasets used, assess their quality and compare the unmodified and modified GSI with these satellite-derived datasets.

Minimum temperature

The Intergovernmental Panel on Climate Change IPCC (2014) regards minimum temperature as a more important indicator of climate change than maximum temperature or average temperature. However, minimum temperature here applies not so much to ambient temperatures, which undoubtedly have an impact on plant growth but rather, on the impact the temperatures have on soil and water uptake by the vegetation. As temperatures decrease, water uptake by plant roots slows down, thus inhibiting growth of vegetation, and in some cases, low temperatures can be lethal to vegetation.

In this study, given the broad temperature range and environments in the region, we have chosen a range of a lower threshold of minimum temperature 0 °C (T_{MMin}) and an upper threshold of 20 °C (T_{MMax}). A minimum temperature index (iT_{Min}) (Figure 2(a)), taken from Jolly *et al.* (2005) is:

$$iT_{Min} = \begin{cases} 0, & if\, T_{Min} \leq T_{MMin}, \\ \dfrac{T_{Min} - T_{MMin}}{T_{MMax} - T_{MMin}}, & if\, T_{MMax} > T_{Min} > T_{MMin}, \\ 1, & if\, T_{Min} \geq T_{MMax}, \end{cases} \quad (1)$$

where iT_{Min} is the daily indicator for minimum temperature and is bounded between 0 and 1 and T_{Min} is the observed daily minimum temperature in degrees Celsius. For all tests, $T_{MMin} = 0\,°C$ and $T_{MMax} = 20\,°C$. These thresholds are quite different from those used in Jolly *et al.* (2005), Stöckli *et al.* (2008, 2011) and Förster *et al.* (2012) (see also Supplementary materials, for a discussion and data on the

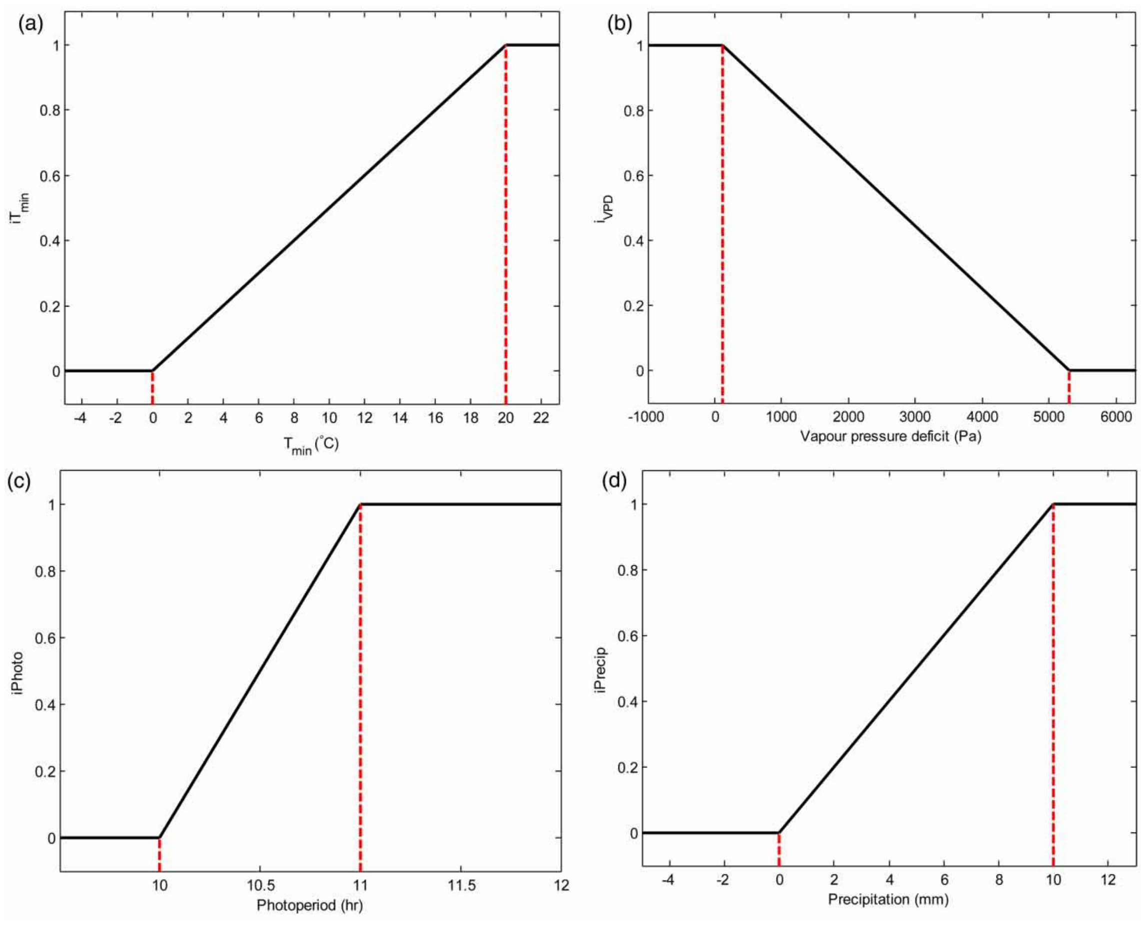

Figure 2 | Graphic representation of: (a) minimum temperature (iTMin), (b) vapour pressure deficit (iVPD), (c) photoperiod (iPhoto), and (d) precipitation (iPrecip) indicator functions used to predict foliar phenology. For each variable, threshold limits are defined, between which the relative constraint on phenology is assumed to vary linearly from inactive (0) to unconstrained (1).

thresholds), as our study operates at a regional scale rather than a global scale. In this case, differences are to be expected (White et al. 2000).

Vapour pressure deficit

VPD was selected as a variable in Jolly et al. (2005) as a surrogate for precipitation. Water stress is known to impact vegetation in terms of stomatal closure, leaf shed and cell division (Mott & Parkhurst 1991; Monteith 1995; Jolly et al. 2005). VPD, which is the measurement of the difference between the amount of water vapour in the air and the amount air can hold before it becomes saturated (i.e., humidity), impacts the evapotranspiration process of vegetation and thus has an impact on plant growth.

Jolly et al. (2005) discuss that VPD values of less than 900 Pa have little effect on stomata closure but at values greater than 4,100 Pa, stomata closure is generally complete, even if soils still contain moisture (Osonubi & Davies 1980; Tenhunen et al. 1982). However, these limits have been shown to vary by location and species (White et al. 2000), and so here we calculate a new set of parameters for our study area. The selecting parameters optimize the predictive power of the model for this region and its vegetation. The VPD index (iVPD), shown graphically in Figure 2(b), was, therefore, derived as follows:

$$iVPD = \begin{cases} 0, & if\, VPD \geq VPD_{Max}, \\ 1 - \dfrac{VPD - VPD_{Min}}{VPD_{Max} - VPD_{Min}}, & if\, VPD_{Max} > VPD > VPD_{Min}, \\ 1, & if\, VPD \leq VPD_{Min}, \end{cases} \quad (2)$$

where $iVPD$ is the daily indicator for VPD and is bounded between 0 and 1 (Jolly et al. 2005; Stöckli et al. 2008, 2011; Förster et al. 2012) and VPD is the observed daily VPD in pascals. For all study areas, $VPD_{Min} = 125$ Pa and $VPD_{Max} =$ 5,100 Pa. Also, these thresholds are different from those used by other researchers and further information on how we derived these thresholds can be found in the supplementary materials.

Photoperiod (daylength)

Photoperiod does not vary significantly from year to year at the different locations in Iraq. Photoperiod provides vegetation with reliable annual climatic cues and also provides the framework within which other climatic controls impact foliar development (Jolly et al. 2005). Studies have demonstrated that photoperiod is an important factor to both leaf flush and leaf senescence throughout the world (Njoku 1958; Rosenthal & Camm 1997; White et al. 1997; Häkkinen et al. 1998; Partanen et al. 1998; Borchert & Rivera 2001).

Due to the interaction between photoperiod and temperature in foliar phenology, temperature changes may not influence growth without a corresponding change in photoperiod (Roberts & Struckmeyer 1939; Partanen et al. 1998; Balasubramanian et al. 2006). Based on the literature research, we selected photoperiods of 10 h or less for completely limited canopy development and 11 h to allow unconstrained canopy development. The photoperiod index (*iPhoto*), shown graphically in Figure 2(c), was, therefore, derived as follows:

$$iPhoto = \begin{cases} 0, & if\, Photo \leq Photo_{Min}, \\ \dfrac{Photo - Photo_{Min}}{Photo_{Max} - Photo_{Min}}, & if\, Photo_{Max} > Photo > Photo_{Min}, \\ 1, & if\, Photo \geq Photo_{Max}, \end{cases} \quad (3)$$

where *iPhoto* is the daily photoperiod indicator and Photo is the daily photoperiod in seconds. For the study area, $Photo_{Min} = 10$ h (36,000 s) and $Photo_{Max} = 11$ h (39,600 s).

It would be possible to use the Stöckli et al. (2011) modified method to calculate photoperiod to account for cloud coverage, however, Jolly et al. (2005) is adequate here because Iraq is not particularly cloudy.

Precipitation

Precipitation is a key variable in vegetation phenology. Plants draw up moisture from the soil, which comes mainly through precipitation, in order to transpire and grow. Precipitation varies from year to year at a given location, and varies from location to location. Local vegetation communities have adapted themselves to these variations and changes over time. However, vegetation does not respond directly to variation in precipitation, but rather to the variations in soil moisture, which is a cumulative result of past precipitation events. Nevertheless, we found in an earlier study (Daham *et al.* 2018) that precipitation was a key variable in vegetation growth across Iraq. Jolly & Running (2004) investigated the relationship between soil water and precipitation and their impact on vegetation phenology and demonstrated that although precipitation is a 'direct driver of the water balance of a system' (p. 308), it does so in conjunction with VPD. Therefore, our model uses both precipitation and VPD, to more accurately account for leaf flush and variations in soil moisture content. It should be noted, however, that even with the inclusion of both VPD and precipitation, the model is still unable to account for all variations in the water budget: soil moisture has a number of sources including humidity, precipitation, surface run off and groundwater. Although potable water supplies (i.e., groundwater) are being investigated in Iraq (FAO 2008, 2011), figures are not robust enough to be included in this model as a 'potential water supply variable'.

Zhang *et al.* (2013) find a correlation between annual precipitation and the duration of the growing season and Zhou & Jia (2016) find that water availability is a hard limit on plant growth in arid and semi-arid ecosystems. As a result of these studies, we expect precipitation to be a primary driver for vegetation phenology, and particularly important in a semi-arid region such as Iraq. Furthermore, we expect that the combination of precipitation and VPD will make this model much more robust in its predictive power.

For the index, we used the same function for minimum temperature and chose a range encompassed by a lower minimum precipitation threshold of 0 mm ($Precip_{Min}$) and an upper threshold of 10 mm ($Precip_{Max}$). A precipitation index (*iPrecip*), is presented graphically in Figure 2(d), and is created as follows:

$$iPrecip = \begin{cases} 0, & ifPrecip \leq Precip_{Min,} \\ \dfrac{Precip - Precip_{Min}}{Precip_{Max} - Precip_{Min}}, & if\, Precip_{Max} > Precip > Precip_{Min}, \\ 1, & ifPrecip \geq Precip_{Max,} \end{cases} \tag{4}$$

where *iPrecip* is the daily indicator for precipitation and is bounded between 0 and 1 and $Precip_{Min}$ is the running total of precipitation in millimetres. For the study area, $Precip_{Min} =$ 0 mm and $Precip_{Max} = 10$ mm (the selection of the precipitation thresholds is presented in the supplementary materials).

The modified GSI model

Jolly *et al.* (2005) combined three variables, minimum temperature, VPD and photoperiod, to form a single metric, the GSI, which is continuous but bounded between 0 (inactive) and 1 (unconstrained) (Jolly *et al.* 2005). We have taken this model and added a new variable, precipitation, to better gauge the role of soil moisture in canopy development (as discussed above). This, we speculate, will enhance the predictive power of the GSI model. This modified GSI is calculated as follows:

$$iGSI = iTmin \times iVPD \times iPhoto \times iPrecip \tag{5}$$

where iGSI is the daily modified GSI, iT_{min} is the minimum temperature indicator, *iVPD* is the VPD indicator, *iPhoto* is the photoperiod indicator and *iPrecip* is the precipitation indicator.

The day to day variability of the included variables results in distinct fluctuations in iGSI. Therefore, Jolly *et al.* (2005) propose a 21-day moving average of the GSI to be calculated in order to obtain a smooth curve for further evaluation in order to find the beginning and the end of the growing season. We apply the modified model at different test sites, Sulaymaniyah, Wasit and Basrah, within the study area. Three locations were selected to represent a range of phenologically different biomes, as shown in Figure 2, and discussed above. The selection of these test sites further tests the modified GSI model, using more geographically constrained areas, rather than more global range as in Jolly *et al.* (2005).

Meteorological data

Meteorological datasets were obtained from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies. The dataset used was the AgMERRA Climate Forcing Dataset for Agricultural Modeling, which includes precipitation (mm/day), mean, minimum and maximum temperatures (°C), solar radiation (MJ/m^2/day), relative humidity at time of maximum temperature (%) and wind speed (m/s). The datasets are stored at $0.25° \times 0.25°$ horizontal resolution (~25 km), with global coverage and daily values from the period (1980–2010) in order to form a 'current period' climatology and described in detail in Bosilovich et al. (2006), Rienecker et al. (2011), Rosenzweig et al. (2013) and Ruane et al. (2015).

Because NDVI Moderate Resolution Imaging Spectroradiometer (MODIS) data (see below) are available only from 2001 until 2015 and AgMERRA data are only available until 2010, we selected the study period of 2001–2010 in order to cover the commonly available data for both climate and satellite. From the climate dataset, only average temperature, minimum temperature and maximum temperature were required. Daily VPD is estimated for both the whole study area and each site. It is assumed to be the difference between saturation vapour pressure and actual vapour pressure and these are estimated using the minimum and maximum temperatures, with a standard relationship between temperature and vapour pressure (Allen et al. 1998b, 1998c; Campbell & Norman 1998; Jolly et al. 2005). The daily photoperiod was estimated using site latitude and year day (Mott & Parkhurst 1991; Evapotranspiration 1998; Jolly et al. 2005). The dataset is available online at http://data.giss.nasa.gov/impacts/agmipcf/agmerra/.

Calculation of indices (VPD and photoperiod)

Intra-annual variability was best expressed over the yearly calendar because peak vegetation activity in Iraq is in April and May. Only average temperature, minimum temperature and maximum temperature were required. Daily VPDs were estimated for the whole study area and each test location as the difference between saturation vapour pressure (es) and actual vapour pressure (ea) estimated using minimum and maximum temperature, respectively, with a standard relationship between temperature and vapour pressure (Allen et al. 1998b, 1998c; Campbell & Norman 1998), as shown in Equations (6)–(11). The daily photoperiod was estimated using site latitude and year day (Mott & Parkhurst 1991; Evapotranspiration 1998), as shown in Equations (12)–(14). The details of the equations used to calculate VPD and photoperiod are shown as follows:

Saturation vapour pressure (es):

$$e^0(T_{Max}) = 0.6108 \exp\left(\frac{17.27 - T_{Max}}{T_{Min} + 237.3}\right) \tag{6}$$

$$e^0(T_{Min}) = 0.6108 \exp\left(\frac{17.27 - T_{Min}}{T_{Max} + 237.3}\right) \tag{7}$$

$$es = \left(\frac{e^0(T_{Max}) + e^0(T_{Min})}{2}\right) \tag{8}$$

Actual vapour pressure (ea):

$$ea = e^0(T_{Max})\left(\frac{RH_{Min}}{100}\right) \tag{9}$$

$$ea = e^0(T_{Min})\left(\frac{RH_{Max}}{100}\right) \tag{10}$$

Vapour pressure deficit (VPD):

$$\begin{aligned} &\textit{Vapour Pressure Deficit } (VPD) \\ &\quad = \textit{Saturation Vapour Pressure } (es) \\ &\qquad - \textit{Actual Vapour Pressure } (ea) \end{aligned} \tag{11}$$

where T_{Max} is the daily maximum temperature, T_{Min} is the daily minimum temperature, *ea* is the daily actual vapour pressure, *es* is the daily saturation vapour pressure derived from relative humidity data, RH_{Max} is the daily maximum relative humidity (%), RH_{Min} is the daily minimum relative humidity (%), $e^0(T_{Max})$ is the saturation vapour pressure at daily maximum temperature (kPa), and $e^0(T_{Min})$ is the saturation vapour pressure at daily minimum temperature (kPa) (Allen et al. 1998a).

Photoperiod (daylength):

$$N = \left(\frac{24}{\pi} W_s\right) \tag{12}$$

$$W_s = \arccos\ [-\tan(\varphi)\tan(\delta)] \tag{13}$$

$$\delta = 0.409\ sin\left(\frac{2\pi}{365} J - 1.39\right) \tag{14}$$

where N is the daylight hours, W_s is the sunset hour angle in radians given by Equations (12) and (14), φ is latitude in radians, δ is solar declination in radians and J is the number of the day in the year between 1 (1 January) and 365 or 366 (31 December) (Allen *et al.* 1998a).

MODIS NDVI satellite observation data

The monthly mean NDVI dataset was collected from the MODIS and was downloaded from NASA's Land Processes Distributed Active Archive Center (LP DAAC) (https://lpdaac.usgs.gov/data-access). MODIS is part of the NASA Earth Observing System (EOS) with 250 m spatial resolution. MODIS data cover the period from February 2000 (composite 045) until 2016. Each original MODIS (.hdf) file from the Distributed Active Archive Center (DAAC) contains the best NDVI value of a certain period, and so is called a composite. In this study, the MODIS Terra MOD13Q1 product from 2001 to 2015 was used, containing 16-day composites of red, near-infrared (NIR), mid-infrared (MIR) and NDVI. A 15-year span of MODIS vegetation indices was chosen due to the fact that Iraq's vegetation is highly dynamic, changing from one year to another due to the natural and human factors discussed above.

Quality assessment of NDVI

The monthly NDVI from 2001 to 2015 was extracted for all regions in the study area. MODIS is an optical/IR satellite, it is unable to retrieve information during cloudy conditions, resulting in some missing values in the dataset, which require spatial and temporal interpolation. The Time-Series Generator (TiSeG) software (Colditz *et al.* 2008) was used. This allows for quality assessment of the MODIS product, corrects any invalid data and uses linear interpolation to fill gaps (Zoungrana *et al.* 2014), and removes any false readings in NDVI due to atmospheric contamination. Similarly to Zoungrana *et al.* (2014), we found that the setting UI5-CS (perfect-intermediate, no cloud, and no shadow) gave results comparable to the undisturbed situation. The implications of this are that the data are of good quality and suitable for our analysis, due to the minimal cloud cover across Iraq. In order to reduce any impact from atmospheric contamination, the NDVI values were resampled to 0.25° using a spatial average (Jolly *et al.* 2005) and we extracted an NDVI that corresponded to the meteorological dataset.

RESULTS

Ten-year average, daily index values for minimum temperature, VPD, daylength and precipitation, for the whole study area and each selected test site are shown in Figure 4. These averages were used to summarize the individual yearly results (see supplementary materials) in order to reduce the number of graphs needed to present the data. The results indicate the influences of the different variables on the whole study area and at individual sites. Similar to the results from Jolly *et al.* (2005), we see here that there is no singular variable that acts as a limiting factor for foliar phenology, rather they act together, both temporally (as observed over time) and spatially (inter-site comparison). Modified GSI indexes show the relative influence of each variable on photosynthetic activity. As VPD increases, plant activity decreases. Multiplying VPD, daylength, Tmin and precipitation creates a composite seasonal curve (iGSI) that shows a photosynthetic reduction in the middle of the growing season due to the high summertime VPD. Also, we found the same interpretation for Sulaymaniyah, Wasit and Basrah. Following Jolly *et al.* (2005), we created a time-series plot of model-predicted foliar phenology (GSI) and NDVI values for the whole study area and each selected site (Figure 5) for the ten-year average. The ten-year averages were used to encapsulate the individual yearly results (see supplementary materials).

Modified GSI model comparisons with NDVI

GSI values are calculated daily for the whole study area and individual study sites using the modified GSI model parameters in Equations (1)–(5). The NDVI is derived from satellite images taken every 16 days, resulting in 23 data points per year. We compared the 16-day mean of both the unmodified and modified GSI with each respective NDVI point.

To compare with the satellite data, we then calculated the mean modified GSI for the corresponding 16-day

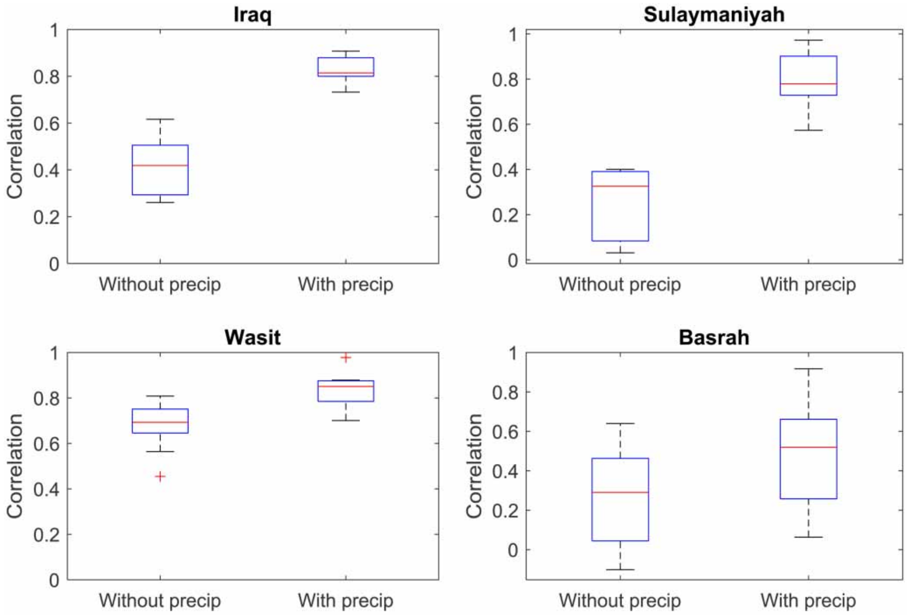

Figure 3 | Correlations between composite period NDVI values and modified modelled GSI values over ten years (2001-2010) for whole study area (Iraq) and for test sites (Sulaymaniyah, Wait, and Basrah). All correlations were significant (*P* value < 0.001).

satellite data composite period and compared these means with satellite-derived NDVI with a correlation coefficient. We computed the correlation coefficient between GSI values and NDVI values for each year for the model before and after modification (adding precipitation as an index after modification) and compared them as shown in Figure 3 (all correlations were significant (P value $<$ 0.001)). Further details can be found in the supplementary materials. In all cases, as can be seen in Figure 5(b)–5(d), the GSI-predicted canopy dynamics correspond well with satellite-derived NDVI changes.

Performance comparison of the modified GSI model of the whole study area (Iraq) and three different locations (Sulaymaniyah, Wasit and Basrah)

We then applied the unmodified and modified GSI models countrywide for the whole study area of Iraq and for the three different locations within Iraq and estimated modified GSI values and compared these simulations. Equations (1)–(5) were used for this analysis. Although it is better to compare the modified GSI model simulations with phenological field observations, this was not feasible for this study area because there are no existing ground vegetation phenology data and the difficulties with access to the country due to security risks mean that remote sensing is the only viable method to estimate and predict the vegetation extent. Following Jolly *et al.* (2005), model simulations were performed daily from 2001 to 2010. We then computed the correlation between the modified GSI model predicted values with NDVI values.

We computed the correlation between model-predicted unmodified and modified GSI values and NDVI as shown in Figure 3. We found that we could predict the intra-annual vegetation dynamics across the whole study area (Iraq) and at the selected test sites (Sulaymaniyah, Wasit and Basrah), regardless of the prevailing or co-prevailing climatic controls at the site, which suggests that both VPD and precipitation adequately depict the intra-annual canopy dynamics in the study area as a whole and at the selected sites, and we found that all the annual correlations over the period and over the whole study area and test locations are improved after including the precipitation index in the model. As expected, these results demonstrate that precipitation strongly influences vegetation dynamics in the semi-arid environment of Iraq and likely across much of the Middle East. The results show that there is a similarity between temporal patterns of NDVI and precipitation.

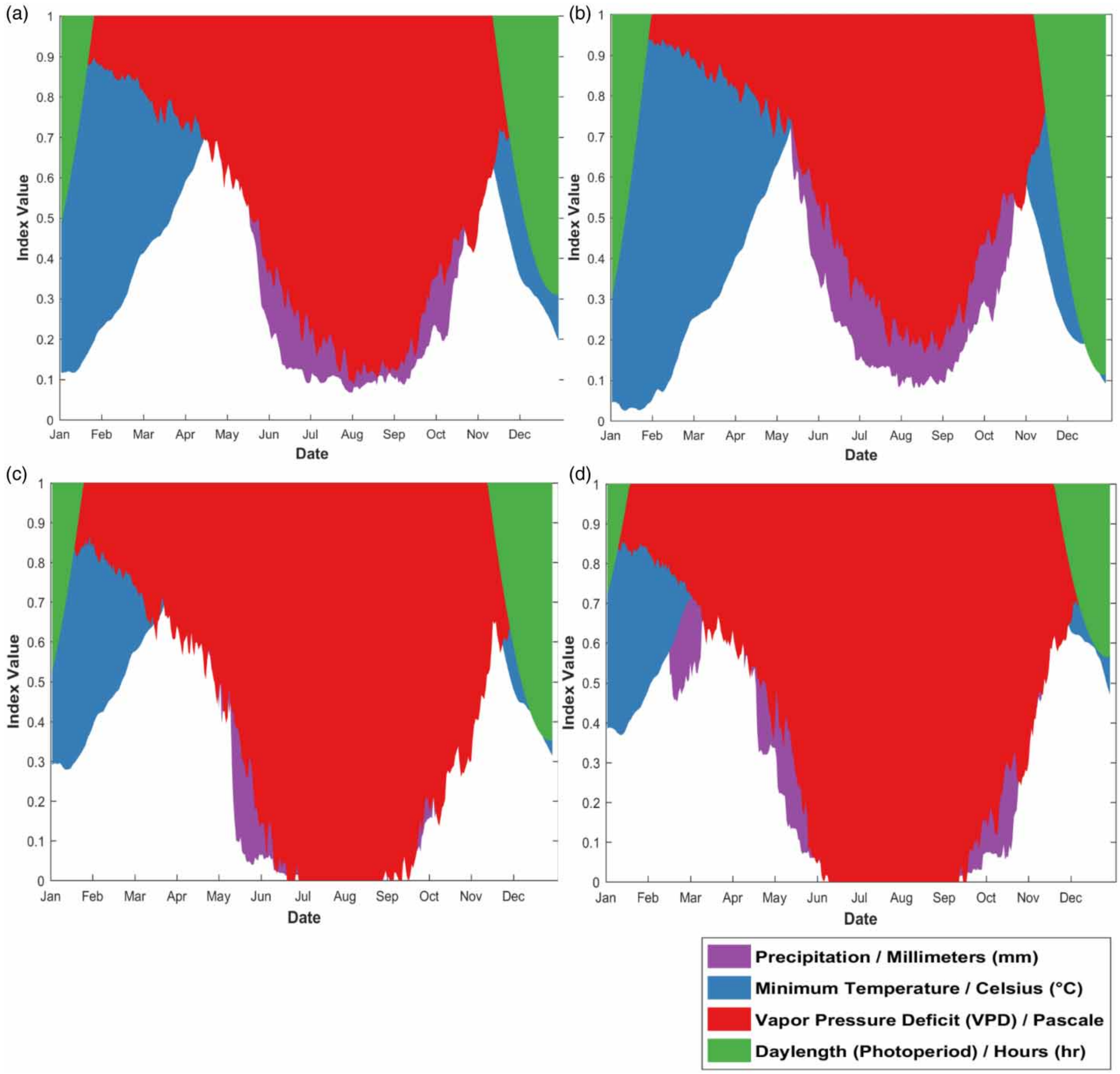

Figure 4 | The seasonal index values for minimum temperature, vapour pressure deficit, precipitation and photoperiod for whole study area for Iraq: (a), Sulaymaniyah (b), Wasit (c), and Basrah (d), showing the seasonal limits of each variable for ten-year average. Indices are presented as a 21-day running average to better depict seasonal trends.

This similarity is stronger than that of NDVI and air temperature, so it can be concluded that NDVI is a sensitive indicator of the inter-annual variability of precipitation and that precipitation constitutes the primary factor in germination while the air temperatures only assist with a lesser effect.

The highest correlations between GSI and NDVI were found at the whole study area scale (Iraq), and Sulaymaniyah in the north of Iraq, presumably because the north of Iraq experiences much higher precipitation levels, followed by the site of Wasit (central Iraq), then Basrah (south), which experiences the least rain. However, correlations at Basrah were still high and the addition of precipitation consistently improved the model predictions, reinforcing that the VPD and precipitation controls are adequate in depicting the intra-annual canopy dynamics in Iraq,

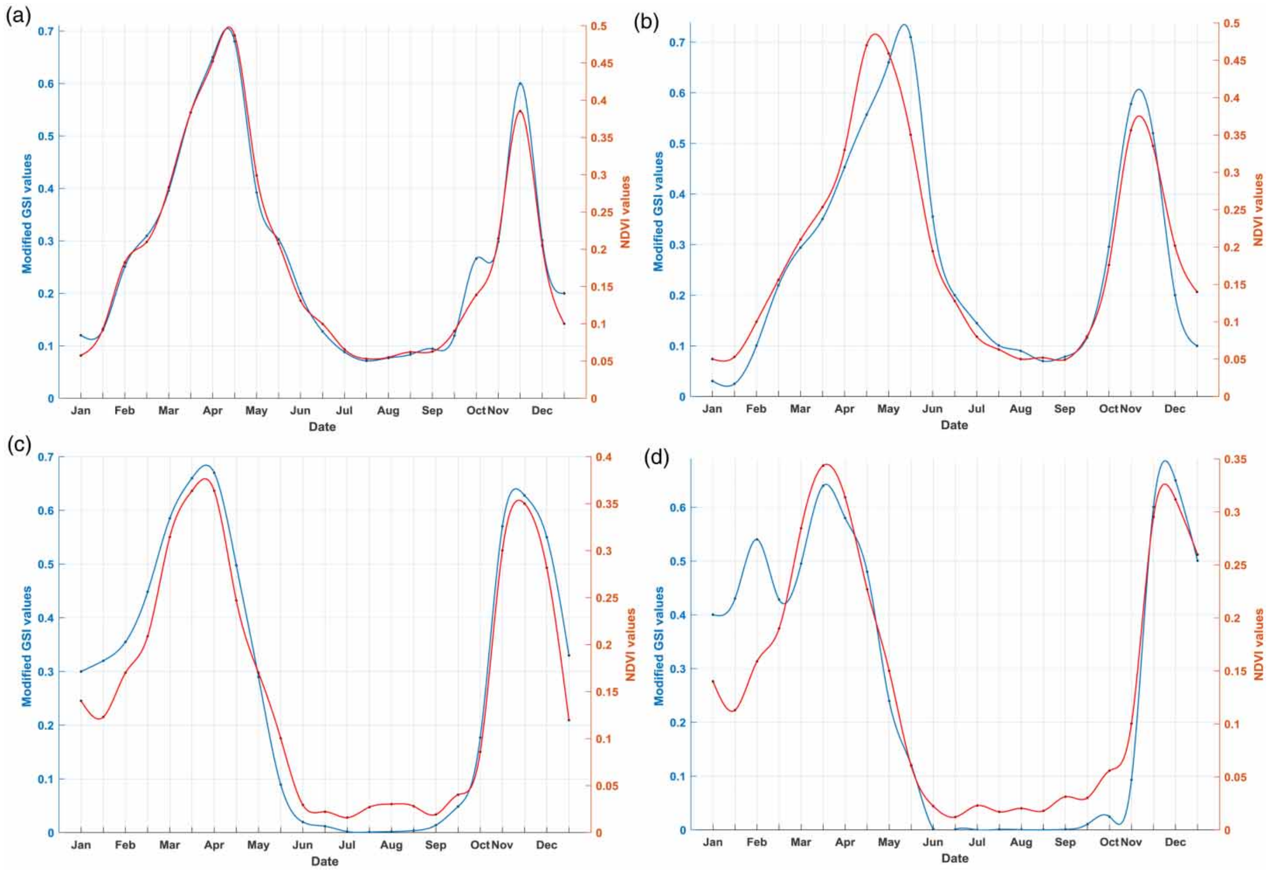

Figure 5 | A comparison of seasonal variation in the modified modelled Growing Season Index (GSI) with the Normalized Difference Vegetation Index (NDVI) obtained from satellite coverage at 16-day intervals at whole study area Iraq (a), Sulaymaniyah (b), Wasit (c), and Basrah (d) for ten-year average, (see correlation coefficients in Figure 3).

both at a countrywide level and at regional levels. The underperformance of prediction in Basrah noted in some years may, in part, be due to lower rainfall data accuracy, rather than indicating that the performance of modified GSI model in this area is inadequate.

In Figure 5(a), we observe a peak in the modified GSI and NDVI in March, April and May (it is picking up the dominant vegetation signal), which makes sense given that this is the peak flowering season, following the rainy winter months of December to February in Iraq. We also note that there are fluctuations in the predictive power of the modified GSI model throughout the year. Predictive power is high from March to May and in November and December because during these periods, vegetation growth is primarily driven by persistent precipitation. In the summer and autumn months, vegetation is responding to more erratic or sudden rainfall events, which the modified GSI model is less able to capture. These patterns are consistent for all years across the entire study period, although with some differences resulting from the natural variability of precipitation and temperature (temporally and spatially).

In Figure 5(b), which shows the Sulaymaniyah region for the ten-year average, we see an approximately similar profile of predictable NDVI in March through until May. We can observe a drop in prediction at the beginning of June until the beginning of September, which is then followed by a sharp increase in the middle of September to October, the predictive power slowly decreases again, with a subsequent rise at the end of October to November. These fluctuations are the result of the fact that plant growth is driven by persistent precipitation (as mentioned above) and, in this case, Sulaymaniyah has a high level of precipitation (over 1,000 mm/year), with rain falling even during the summer months. The modified GSI model and

NDVI for Sulaymaniyah is generally consistent for all years across the entire study period, albeit with some slight differences resulting from the natural variability of rainfall and temperature from year to year.

In Figure 5(c), depicting the Wasit region for the ten-year average, we observe a similar profile of predictable NDVI for Iraq and Sulaymaniyah, with one difference: the predictability from the beginning of June until the beginning of September is very weak. This is the result of the lack of rainfall during these months in central Iraq. We see a similar trend for Basrah (Figure 5(d)). However, as with Sulaymaniyah, there is better predictability from March until May and from October until November, because, as mentioned earlier, vegetation growth is primarily driven by persistent precipitation, while in the summer and autumn months, especially in the middle and south of Iraq, there is lesser response, which the modified GSI model is not able to capture.

In all cases, however, the modified GSI-predicted canopy dynamic appears to correspond well with satellite-derived NDVI. For example, across Iraq and at individual test sites, the start-of-season is determined from temperature limits, but the growing season has high VPD. This is shown clearly in Figure 4(a)–4(d), where the smaller areas in summer indicate water stress and the larger areas indicate the lack of precipitation during the months of summer. During the period of the predicted canopy activity drop, the rate of increase of NDVI is less than the early season, suggesting that VPD and precipitation may influence the rate of canopy growth. Similarly to the model tested in Jolly *et al.* (2005), the modified GSI also overpredicts changes in the timing of satellite-derived NDVI increases in canopy leaf area, but also similarly, the changes in canopy greenness seen in the modelled changes still correspond well with those of the satellite-derived NDVI at all sites.

DISCUSSION

In this paper, we presented a modified GSI model by expanding on that of Jolly *et al.* (2005), in order to examine vegetation phenological dynamics in Iraq. This model incorporates the three original variables used by Jolly *et al.* (2005), minimum temperature, VPD and daylength, with an additional precipitation variable. It was found that the modified GSI model reproduces similar results in terms of intra-annual vegetation dynamics to the satellite-derived vegetation indices across the study area (Iraq) as a whole, and at the individual sites of Sulaymaniyah, Wasit and Basrah, which represent different climatic regions.

In all cases, the modified GSI phenology model predicts the suitable conditions when observed changes in canopy were evident. We notice that across the whole study area (Iraq), VPD was low early in the growing season and high in summer, photoperiods were long during the summer, precipitation was very low during summer, and canopy changes were observed; these trends occur over the entire study period (2001–2010). When summer temperatures were high, VPD was also high, and vegetation changes were observed clearly. Similar observations were made over the individual sites (Sulaymaniyah, Wasit and Basrah). This indicates that the selected model variables or parameters are adequate for these locations.

Figure 4(a) and 4(b) represent the seasonal index for the four variables for a ten-year average for Iraq and Sulaymaniyah. We observe that the distribution of the rainfall index is even (low amplitude fluctuations), and very high in the winter months and very low in the summer months. However, when looking at the indices for individual years, we find anomalous cases, such as sudden drops in the amount of rainfall during the winter months or a sudden rise of precipitation in the summer months (these cases can be found in the Supplementary materials). For instance, there was a drop in the precipitation index in the months of March, April, May, November and December in different years within the study period (2001–2010). This decline is not expected during these months, especially in the Sulaymaniyah region, which is an area of heavy precipitation. Additionally, there was a decline noted in the precipitation index for Wasit (central Iraq) during December. However, these anomalies can be explained by natural variability of weather and precipitation from one year to another.

We also observe an unexpected rise in the precipitation index during the months of March, April and May (Figure 4(d)). This rise in precipitation is unexpected in the Basrah area (southern Iraq), because these months are marked by increased temperatures and very low to no rainfall. This anomaly may be due to missing data, or it may be due, again, to natural climate variation.

Despite these anomalies, it can be seen that the precipitation data for Iraq, Sulaymaniyah and Wasit were generally very good and there are no real issues in using precipitation as an index (whether over the ten-year average or individual years). The resulting graphs were very clear, smooth, and logical.

Figure 4 also shows the low temperature index during the winter months and the high temperature index during the summer months, which leads to the evaporation index increasing significantly during the summer months and decreasing during the winter months (December and January). As for the daylight/photoperiod index, we see a decrease during the winter months and a significant rise from the end of January until the middle of November. We observe the rise of the temperature index, especially in the middle and south of Iraq (Wasit and Basrah), which, in turn, leads to a high VPD index clearly indicated during the summer months.

At sub-regional areas, the model showed a good agreement between the predicted and observed (satellite) NDVI. For this test, we followed Jolly *et al.* (2005), by defining a threshold value, in this case, 0.6, above which a plant canopy is assumed and which represents a proportion of days within the smoothing window, wherein plant canopy conditions are suitable. Predicted vegetation values at Basrah, Wasit and Sulaymaniyah were consistently highly correlated with satellite observations. This convergence in values might suggest that the threshold is suitable for Iraq as the study area. It should be noted that this threshold value could vary from region to region (Jolly *et al.* 2005).

The most important finding of this research was that the addition of precipitation significantly added to the robustness of the original model, and made the modified model more applicable to smaller scale studies, such as this one in Iraq. The original model used VPD as a surrogate for precipitation, and the advantages and disadvantages of this have been discussed in more detail elsewhere (Jolly *et al.* 2005). Previously, it was thought that VPD was a better variable to utilize because it is continuous, whereas precipitation data may be missing (i.e., a single event leading to leaf flush), which could potentially bias the model (Childes 1988; Jolly *et al.* 2005). The main disadvantage of using VPD as a substitute for precipitation is that previous models (Jolly *et al.* 2005; Stöckli *et al.* 2011; Förster *et al.* 2012) assume that changes in VPD result directly from seasonal changes in precipitation. However, the vegetation itself may influence VPD through evapotranspiration. Therefore, we are left with a predicament of cause and effect: does VPD influence phenology or does phenology influence VPD? Or both? This interdependent relationship is not yet well understood.

To overcome this problem, we combine VPD and precipitation together in the modified model, where precipitation datasets are available. Precipitation is highly correlated with vegetation growth; it is the primary driver in seed germination. However, it is important to note that vegetation does not respond directly to precipitation, but rather to increased soil moisture, resulting from the cumulative effects of the precipitation in December to February, with commensurate vegetation growth occurring in April and May. Hence, as noted above, phenology itself may influence VPD through evapotranspiration, and vegetation is affected by precipitation. Therefore, there is a close, interdependent relationship between VPD, vegetation and precipitation, and precipitation should be added to increase the robustness of the model.

It is worth mentioning that we can use the modified model to estimate leaf onset and leaf offset and compare them with the observations of Jolly *et al.* (2005). This suggests that the model is robust to inter-annual variability and that, while continuous changes in canopy activity are predicted, it can also predict start and end dates of the foliage period. The model prediction could provide surrogate phenological data in areas with a virtual nonexistence of ground vegetation phenology data and difficulties with access to the country due to security problems. As such, this modified model could also be used in other geographical regions facing similar security problems and logistical issues. Additionally, this modified model can be used to produce a regional (i.e., across the Middle East, for instance) climatic map depicting constraints to foliar phenology, similar to Jolly *et al.*'s (2005) global map, which could address phonological issues at a more regional level.

Additionally, the model parameters used in the original model reproduced large-scale variation (Jolly *et al.* 2005). For this study, we fine-tuned the model to include precipitation data in order to reproduce observed variations in phenology at regional (i.e., Iraq) and sub-regional scales (i.e., Sulaymaniyah, Wasit and Basrah). We were able to improve the correlations between modified GSI model predictions and NDVI at both the regional and sub-regional scales after adding the precipitation as indicator in the GSI model. As an example, correlations between the modified GSI model and NDVI for 2001 for Iraq improved from 0.4846 to 0.8615 (more information on the values can be found in supplementary materials).

The addition of precipitation, combined with VPD, strengthens the existing GSI model, enhancing its predictive power and significantly improving the correlation of the model to NDVI, as presented in Figure 3. This, in turn, makes the modified model an invaluable tool for those working to better understand current and future phenological dynamics at regional levels, in order to help policymakers create better strategies to mitigate against climate change.

Finally, this modified model can still be driven by simple, easily obtainable weather data derived from either point-source weather stations or gridded analyses and forecasts. Therefore, the model can be used to explore historical or future changes in vegetation phenology at nearly any spatial scale, making the model useful for a variety of future works exploring the complex interactions between vegetation dynamics and atmospheric carbon and water cycle feedbacks.

CONCLUDING COMMENTS

As with Jolly *et al.*'s (2005) somewhat simpler model, the modified model does not require a priori knowledge of vegetation or climate in the region (data which could be difficult to attain due to security risks) and uses the same type of data. As such, there is no need to use different models when looking at different spatial or temporal parameters. Because there is the possibility of switching from one dominant variable to another, there is no need to apply a different phenology model, which, in turn, makes this model (modified or not) well suited to a variety of climate change studies (Jolly *et al.* 2005). The GSI model can also be used in conjunction with ecosystem process models through the use of monthly instead of daily running averages, as well as generating dynamic estimate leaf area indices (LAIs) for sites, especially after introducing precipitation into the model due to its impact on the probability of a plant canopy. Although there are tested ways to define optimal LAIs (Stöckli *et al.* 2011), this modified phenology model, like the original GSI model, could be used to calculate daily estimates for LAI through a chosen growing season in order to scale potential maximum LAI values (Jolly *et al.* 2005).

Most importantly, however, is that the lack of assumption of a priori knowledge of vegetation and climate, combined with the flexibility in switching variables is especially useful in places such as Iraq, which not only are difficult to access but also which are characterized as having marginal, fragile environments. Canopy greenness dynamics are especially important to model in such environments, particularly when the economy and populace are so dependent on agriculture and related sectors and where the security situation is so precarious due to continued conflict. With accurate modelling, sensitive areas can be identified, and mitigation strategies can be put into place when possible to provide for the well-being of the population.

'Iraq faces serious problems of environmental degradation that must be addressed immediately because failure to act now will greatly compound the cost and complexity of later remedial efforts, and because environmental degradation is beginning to pose a major threat to human well-being, especially among the poor' (Jaradat 2002). This modified GSI model fine-tunes and makes the predictions more robust, and thus provides a valuable tool for researchers, NGOs and governments to not only more accurately assess climate change in a particular region, but also to better predict future changes in the environment. This will enable them to formulate more suitable mitigation strategies to better counter the effects of desertification and other climate changes, in order to take care of populations living in increasingly marginal and fragile environments.

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SUPPLEMENTARY DATA

The Supplementary Data for this paper is available online at http://dx.doi.org/10.2166/wcc.2018.142.

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