Drought analysis for the Seyhan Basin with NDVI and VCI vegetation indices

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Highlights

- The positive contribution of the increasing temperature values to the photosynthesis process may have consequences.
- Snow cover decreases in the Seyhan Basin due to climate change.
- Changes in land use may also cause differentiation in NDVI values.
- Migration from village to city can cause artificial tendencies in the results.
- With the decline of forestland and agricultural areas, the drought seen in the past years increases with each passing time.

Abstract

Various drought indices have been developed to monitor the drought, which is one of the results of climate change and mitigates its adverse effects on water resources, especially agriculture. Vegetation indices determined by remote sensing have been the subject of many studies in recent years and shed light on drought risk management. This study is examined in the Seyhan River Basin, a basin with Turkey's considerable population density counts and is situated south of the country. Normalized Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI) are the most widely used vegetation indices and are very useful because they give results only based on satellite images. This study examined the Seyhan Basin by using satellite data in which the vegetation transformation occurring due to the decline of agricultural and forest areas was also seen. An increase in drought frequency was detected in the Seyhan Basin using NDVI and VCI indices. It was determined that climate change and drought increased with a linear uptrend. It is recommended that decision-makers should take the necessary measures by considering the drought risk maps and that long-term drought management plans should be made and implemented.

Keywords: Drought; vegetation indices; NDVI; VCI

1 Introduction

The status of water resources adversely affected by climate change, hence drought, is a major concern in agriculture, water resources management, and human use. Drought is defined as a natural event that negatively affects land and water resources, and hydrological equilibrium is disrupted due to precipitations falling below normal levels (Benson et al., 1997). It is possible to classify drought as meteorological, agricultural, and hydrological drought. Meteorological drought is the decrease, which occurs according to the long-year averages, in precipitation. On the other hand, agricultural drought is based on the amount of water available in the root zone of the plant. In terms of agriculture, the periods in which the amount of water to meet the water needs of plants in the soil is not present are defined as arid. Precipitation, plant water consumption, and soil characteristics can be shown as the main factors for agricultural drought. Hydrological drought refers to the decrease in surface and groundwater resources due to the lack of long-term precipitation. Even long after the end of the meteorological drought, hydrological drought may exist (Dinç et al., 2016). Drought risk management constitutes a vital part of water-resource management policies and strategies. National drought policies have an essential role in managing drought risk (Meza et al., 2020; Vogt et al., 2018; Wilhite et al., 2014). It is necessary to prepare drought management plans to mitigate the effects of drought depending on the legislation of the country and by considering the specific drought characteristics and effects of the basin (EuropeanCommission, 2007). Elements of the drought management plan include knowing the characteristics of the river basin, investigation of historical drought events in the basin, evaluation of the possible risk(s), determination of indicators and threshold values for drought analysis, creation of a program of measures to reduce the effects of drought, and establishment of the early warning system and organizational structure (GWP, 2015; Pérez-Blanco & Gómez, 2014). Drought risk management includes the following stages: hazard, impact assessment, and affectability, early warning system, including drought monitoring and forecasting, and preparedness and harm reduction (Wilhite, 2000). Drought early warning systems typically aim to monitor, evaluate, and present information on climate, hydrological features, water supply conditions, and trends (Funk & Shukla, 2020). The goal here is to provide early information before or during the onset of drought within a drought risk management plan to mitigate the potential impacts. Since drought is a slow-starting and progressive hydrological event, monitoring and analyzing drought is of great importance. Monitoring and analysis of drought are done employing various indicators and indices. These indicators and indices help characterize drought by providing information on the severity, location, duration, and timing of drought to determine, classify, and monitor drought conditions. Some indicators and indices can also be used to validate indicators of drought data that have been modelled, remotely detected, or assimilated into the model. The geographic information systems have made it possible to overlap, map, and compare different indicators and indices thanks to the power of evolving computational and imaging techniques (Svoboda & Fuchs, 2017).

Indicators are variables or parameters used to describe drought conditions. In general, drought indicators include the variables summarized in Table 1.

Table 1. Variables used in drought detection (Svoboda & Fuchs, 2017).

The index values initiate or terminate the implementation stages of a drought management plan. Therefore, drought management plans should be formed based on index values (Svoboda & Fuchs, 2017). The indicators and indices in the "Handbook of Drought Indicators and Indices", published by the World Meteorological Organization (WMO) in partnership with the Global Water Partnership (GWP) in the context of the Integrated Drought Management Programme (IDMP), are classified into five main categories according to their characteristics. These are meteorology, soil moisture, hydrology, remote sensing, and compounded or modelled.

Two of the most practical and widely used indices are NDVI and VCI. Quiring and Ganesh (2009) were applied the VCI index to 254 Texas counties during 18 growing-seasons and found a good correlation between this index and many frequently used meteorological drought indices (Quiring & Ganesh, 2010). Interannual variations of NDVI were investigated and their relationships with temperature and precipitation variables and human activity in China between 1982 and 1999 (Piao et al., 2003). Variability of the NDVI over Botswana was worked by Nicholson and Farrar (1994) during 1982-1987 (Nicholson & Farrar, 1994). Shad et al. (2017)

were pointed out that NDVI and VCI indices concerning MODIS sensors can be a good alternative for estimating the drought concerning meteorological indices for Isfahan (Shad et al., 2017). Chodhary et al. (2015) used NDVI and VCI indices to investigate drought effects on corn cultivation (Choudhary et al., 2015). Indices are especially vital in examining regions with sporadic or insufficient measuring stations and estimating drought (Klisch & Atzberger, 2016; Nanzad et al., 2019; Rezaei Moghaddam et al., 2014).

Several studies mentioned that NDVI and VCI indices are useful methods to detect drought and make a prediction. The main aim of the study was to answer the following questions based on remote sensing technologies. Advances in space technologies and computer systems have brought along a broader and more efficient use of remote sensing technologies and geographic information systems (GIS). The ability to easily transfer various geospatial data to the GIS environment with images taken from space via satellites has increased the possibilities for analysis of issues such as natural resource management, land use and land cover, environmental and ecological analysis, disaster risk assessment, and meteorological, hydrological and agricultural applications. Remote sensing technologies, especially satellite products, are used effectively and extensively in various hydrological applications for various regions of the world (Kundu et al., 2020). Jafari et al. (2020) compared satellite products with field measurements for drought monitoring for Iran’s southern part (Jafari et al., 2020). Shojaei and Rahimzadegan (2020) improved a comprehensive drought index for the west of Iran (Shojaei & Rahimzadegan, 2020). Vegetation and soil moisture, which can be obtained by remote sensing, are data sources commonly used in drought studies (Drisya et al., 2018; Zhu et al., 2018). High-resolution vegetation change information provided both temporal and spatial by vegetation indices (e.g., NDVI), can contribute to drought-related research without requiring additional information on drought. Vegetation indices are preferred because they are easy to use, and they do not require any assumptions and/or additional information other than themselves (Bulut & Yilmaz, 2016). Vegetation indices can be determined by remote sensing methods and have a wide range of applications because the green vegetation gives high reflectivity values in the near-infrared region of the electromagnetic spectrum (Gökdemir, 2002). Most of the satellite sensors measure red and near-infrared light waves reflected from the land surface. Using mathematical formulas, raw satellite data related to these light waves are converted into vegetation indices. Vegetation indices describe the greenness (relative density and health status) of the plant for each cell in the satellite image. Not all vegetation indices perceive greenness in vegetation directly by measuring rays at visible and near-infrared wavelengths; some can indirectly perceive the change in vegetation. The water content in the plant allows the plant to perform less temperature swing in the day than the soil; thus, using the knowledge of temperature change throughout the day, those indices reach the knowledge of vegetation change (Hatfield & Prueger, 2015). Because such indices are sensitive to vegetation, they can provide important information about the drought experienced in the basin. Various indices are used for this purpose in different geographical regions of the world in the literature. Main indices were developed on remote sensing data that find wide usage areas in the literature, especially in determining drought e.g. Enhanced Vegetation Index (EVI) (Brede et al., 2015; Jiao et al., 2016; Khusfi et al., 2020), Evaporative Stress Index (ESI) (Anderson et al., 2016; Nguyen et al., 2019, 2020), Normalized Difference Vegetation Index (NDVI) (Solangi et al., 2019; Tsiros et al., 2004; Zaw et al., 2020), Temperature Condition Index (TCI) (Rahman, 2019; Tsiros et al., 2004), Vegetation Condition Index (VCI) (Abraham et al., 2018; Baniya et al., 2019; Gebrehiwot et al., 2016), Vegetation Drought Response Index (VegDRI) (Tadesse et al., 2017), Vegetation Health Index (VHI) (Bento et al., 2018; Masitoh & Rusydi, 2019), Water Requirement Satisfaction Index (WRSI) (Masupha & Moeletsi, 2020), Normalized Difference Water Index (NDWI) (Amalo et al., 2018), Land Surface Water Index (LSWI) (Chandrasekar et al., 2010, 2011).

The authors were motivated to get answers to the following questions during the work.

- Is it possible to apply NDVI and VCI indices to the Seyhan Basin?

- Are the results that NDVI and VCI indices will produce in the Seyhan Basin reasonable?

- Is there a drought problem in the Seyhan Basin, and how is it progressing?

- What is the frequency of the drought in the basin?

In this study, the remote sensing method was used, and drought analysis was performed for the Seyhan Basin with NDVI and VCI vegetation indices.

2 Research Site and Method

The Seyhan Basin River Basin is located in the Eastern Mediterranean, Turkey, within the range 34.25–37.0 °E and 36.5–39.25 °N., and its basin area constitutes 2.07% of the area of Turkey with 22,035 km^2. Mainstream in the basin is Seyhan River, and it forms after the confluence of the Zamanti and Göksu rivers and discharges into the East Levantian side of the Mediterranean Sea. The Mediterranean climate dominates the lower basin, and the middle and upper basins are influenced by the continental climate.

Annual precipitation in the coastal area is about 700 mm, and it increases to 1000 mm with the altitude. The part of the basin’s shore-side, Cukurova, is an important agricultural area for Turkey. Including the Seyhan Basin, the Coastal Mediterranean, and Eastern Mediterranean Agricultural Basins of Turkey are the important agricultural areas for Turkey and neighborhood agricultural importer countries. In light of this reason, many researchers have developed or applied different methods for monitoring and predicting the drought in the region (Altın et al., 2020; Dikici, 2018, 2020; Dikici et al., 2018; Gumus & Algin, 2017; Keskiner et al., 2020). The drought that occurred in 2021 once again demonstrated the importance of these studies (Patel, 2021).

2.1 Remote sensing and data sources

Within the scope of the drought analysis studies of the Seyhan Basin, vegetation indices, which provided information about the change in plant greenness, were preferred. Accordingly, the "Normalized Difference Vegetation Index (NDVI)" and the "Vegetable Condition Index (VCI)" were analyzed both temporal and spatial within the boundaries of the Seyhan Basin.

The study in which the vegetation index was associated with precipitation (Şahin et al., 2009) showed a correlation between the data obtained from the precipitation stations in different regions of Turkey and the NDVI data. Similar studies performed with data for rainfall monitoring stations in Turkey and compliance with the drought indices data were discussed (Dikici, 2013; Dikici & Aksel, 2021). NDVI is one of the vegetation indices that is quite widely used in forest classification and agricultural studies as well as in the detection of the change in land cover. On the other hand, high NDVI values indicate areas in which there is healthy plant development (Yıldız et al., 2012).

NDVI data obtained from National Oceanic and Atmospheric Administration (NOAA), Advanced Very High-Resolution Radiometer (AVHRR), and Moderate Resolution Imaging Spectroradiometer (MODIS) satellites are satellite images commonly used to monitor vegetation changes in large sites. AVHRR and MODIS satellites provide NDVI data as ready to use. Therefore, the atmospheric correction is not needed in these satellite data; thus, no additional data are required for the atmospheric correction. Data at the NIR and RED wavelengths obtained from the LANDSAT satellite need atmospheric correction before NDVI is calculated. Although the normalizing phase reduces these atmospheric components' effect on NDVI, NDVI data obtained from AVHRR and MODIS satellites that do not require atmospheric correction were used in this study. The time interval, resolution, and recurrence time of the NDVI values obtained from these two satellites are given in Table 2.

Table 2. Characteristics of AVHRR and MODIS satellite data

Several studies in the literature show that NDVI values calculated using AVHRR satellite data (Cracknel, 1997) differ from NDVI values obtained from other satellite data (Lee, 2014; Nagol et al., 2014; J Pinzon et al., 2005; JE Pinzon & Tucker, 2014; Tucker et al., 2005; Yin et al., 2012). As a result of the study conducted to partial correction of the AVHRR NDVI time series, the AVHRR NDVI3g product has been obtained. In the context of this conducted study and the AVHRR NDVI product, the time series of the AVHRR NDVI3g products was also used.

Modis's difference from the other sensors is that it has a high temporal and positional resolution and can collect data from 0.4 μm to 14 μm in 36 separate spectral bands (Hall & Riggs, 2007). MODIS sensor has 250 m spatial resolution between bands 1-2, 500 m spatial resolution between bands 3-7, and 1 km spatial resolution between bands 8-36 (Lillesand et al., 2015). Although MODIS images are shot twice a day, NDVI products are broadcasted as 8-day composites. MODIS NDVI images, consisting of 4800 rows and 4800 columns, provide the opportunity to analyze the change in vegetation activity in an extensive area (Çelik & Karabulut, 2013). Many studies have compared the NDVI data obtained from different satellites. While some studies have argued that MODIS NDVI values are better compared to AVHRR NDVI and AVHRR NDVI3g (Beck et al., 2011), some studies have indicated that long-time trends show high consistency with each other (Nayak et al., 2016). AVHRR NDVI, AVHRR NDVI3g, and MODIS NDVI values were used in this study. NDVI time series were compared among themselves (Figure 2). When calculating the data series, the period was selected as 2001-2015.

Figure 2. Satellite-based time-series for Seyhan Basin (a) NDVI index (b) NDVI Anomaly for the period 1982 - 2017 (c) long term NDVI index average per month

For this study, the VCI was calculated using the NDVI values obtained from MODIS and AVHRR satellite data to compare the drought determined by drought analyses conducted for the Seyhan basin. Accordingly, the VCI time series obtained using satellite data covering the years 2001-2016 for each 250 m satellite cell within the basin area boundaries are presented in Figure 3.

Figure 3. VCI index for the Seyhan Basin using (a) MODIS satellite data for the 2001-2016 period and (b) AVHRR satellite data for the 1982-2015 period

In the time series, the VCI values shown by red indicate drought in the plant state, while blue values can be interpreted so that the plant state is at the seasonal and climatic normal conditions. VCI can provide information about the onset, duration, and severity of drought by considering the impact of drought on vegetation. VCI compares the NDVI data of a given period with the highest (max) and lowest (min) data values of the NDVI values belonging to the analyzed entire period (Quiring & Ganesh, 2010). VCI is expressed as a percentage (%) and provides information on when the observed value’s highest and lowest values occurred in past years. Whereas low VCI values indicate poor vegetation status, high VCI values indicate that vegetation is good [59].

VCI can be considered as a normalized version of the NDVI. In addition to NDVI, VCI was also evaluated in this study since VCI is a more appropriate index in assessing the deviation of vegetation from the normal state. Therefore, VCI allows the comparison of simultaneously measured NDVI values for different ecosystems, i.e., for different vegetation in different geographies. VCI is a better indicator of soil moisture vulnerability than NDVI because it can distinguish short-term climate signals from long-term ecological signals. The importance of VCI relates to the vegetation index’s viability studied by the vegetation index (Jain et al., 2010). VCI data, like NDVI, have high resolution and reasonable areal extent. In the literature, several studies related to the use of VCI for drought analysis purposes (Domenikiotis et al., 2004; Quiring & Ganesh, 2010).

3 Results

The scope of drought index studies aimed to analyze climatic change responses of irregularly irrigated or non-irrigated agricultural areas and forest-vegetation areas within the Seyhan Basin. Coordination of Information on the Environment (CORINE) layers used in these analyzes was selected, and temporal NDVI changes in these layers were calculated. The distribution of these CORINE layers over the basin is given in Figure 4. In contrast, the layer list is given in Table 3 (In the CORINE classification, while the layers beginning with the number two represent agricultural areas, the layers beginning with the number 3 represent the classes of forest and semi-natural areas).

Table 3. Layers of the Seyhan Basin examined for CORINE NDVI comparison

The fact that the AVHRR-3G and MODIS NDVI data used in the analysis were at different resolutions led to the differentiation of the classified areas. The eight km-resolution pixels in AVHRR-3G data corresponds to 1024 pixels at 250 m resolution in MODIS data. Therefore, some pixels sometimes consist of a mosaic of classes with very different properties alongside the class designated as the dominant class. Another issue to be considered when making the assessment is that land usage may change over time.

Figure 4. CORINE layers (a) AVHRR-3g (b) MODIS and (c)original used in NDVI comparison of the Seyhan Basin

The NDVI temporal change series for agricultural areas starting with Code 2 in the CORINE 2012 land use data is given annually in Figure 5. While the dashed lines represent the AVHRR-3G data, the continuous lines represent the MODIS data. December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON) refer to the winter, spring, summer, and autumn months, respectively.

Figure 5. Temporal change of calculated NDVI value for natural vegetation coded CORINE 243 in the Seyhan Basin

When the time series of the examined layers were evaluated in the general framework, it was observed that NDVI values decreased between 2002 and 2004 and rose significantly between 2007 and 2013. Except for short-term fluctuations, it has been calculated that NDVI values are generally higher in spring and decrease in autumn. Since olive grove, pasture, and non-irrigated mixed agriculture classes covered areas too small to be represented in AVHRR-3G resolution, they were not included in the related charts. In olive groves, which are resistant to cold and known as the evergreen undead tree, values above the average have been observed in winter, unlike other classes. The natural vegetation class is a vital suppressor in the results as it covers large areas in the Seyhan Basin. For this reason, the value calculated from different satellite data has always been close. This layer in which the human influence is limited is one of the classes where the effects of drought on plants can be better observed, and it has shown significant declines in 1982, 1989, 2004, 2007, 2012, 2014.

On the other hand, 2011 and 2015 are the years in which the highest values were observed. The NDVI annual temporal change series for forest and semi-natural areas starting with the Code 3 of CORINE classification is given in Figure 6. In the studied forest layers, annual changes seen in agricultural areas were observed similarly. In their NDVI calculations, the lowest values were determined during winter, and the highest values were determined in summer and spring.

Figure 6. Temporal change of calculated NDVI value for plant change areas coded CORINE 324 in the Seyhan Basin

Coniferous trees, which are cold-resistant and evergreen species, received the highest MODIS data values during the winter months. They received the lowest values in the AVHRR-3G data. In this case, it was evaluated that the coniferous forests class was confused with other classes as a result of the failure of a good class differentiation at 8 km resolution and that because deciduous trees are located within the same pixel as conifers, they received much lower values in winter than expected.

4 Conclusions

The years in which two indices jointly indicated drought for the Seyhan Basin were determined as 1973-1974, 1989, 2001, 2007-2008, 2014, and 2016. The drought return period for the Seyhan Basin is decreasing over the years. On the other hand, overall NDVI mean values have been increasing since the 2000s for all seasons. This increase may result from the fact that the snow cover, which decreases the NDVI values due to climate change, has reduced in terms of process and area. It is thought that contribution of the increasing temperature values positive effects on the photosynthesis process. Changes in land use may also cause differentiation in NDVI values. Especially considering the long-period (e.g., 1982 - 2016), this change is inevitable. It should be taken into account that with the population growth, forestlands can transform into agricultural areas and agricultural areas can transform into artificial pavement areas, or sometimes the opposite situations can occur due to reasons such as migration from village to city, and this can cause artificial tendencies in the results. Based on the plant indices, it is understood that there is a drought trend in the press. It is clear that with the decline of forestland and agricultural areas, the drought seen in the past years will increase with each passing time for the Seyhan Basin. In the case of drought estimation at intervals covering long periods, the changes in the land-use patterns and demography of the region should also be considered.

It is possible to make plans covering different purposes with drought indices, which have a wide application area, include practical application methodology and can make a higher resolution and precise solutions thanks to remote sensing technologies. However, these indices should be used to associate field data and other GIS layers such as land-use, population growth, etc.

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Conflict of Interest

The authors confirm that there are no known conflicts of interest associated with this publication, and there has been no significant financial support for this work that could have influenced its outcome.

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1

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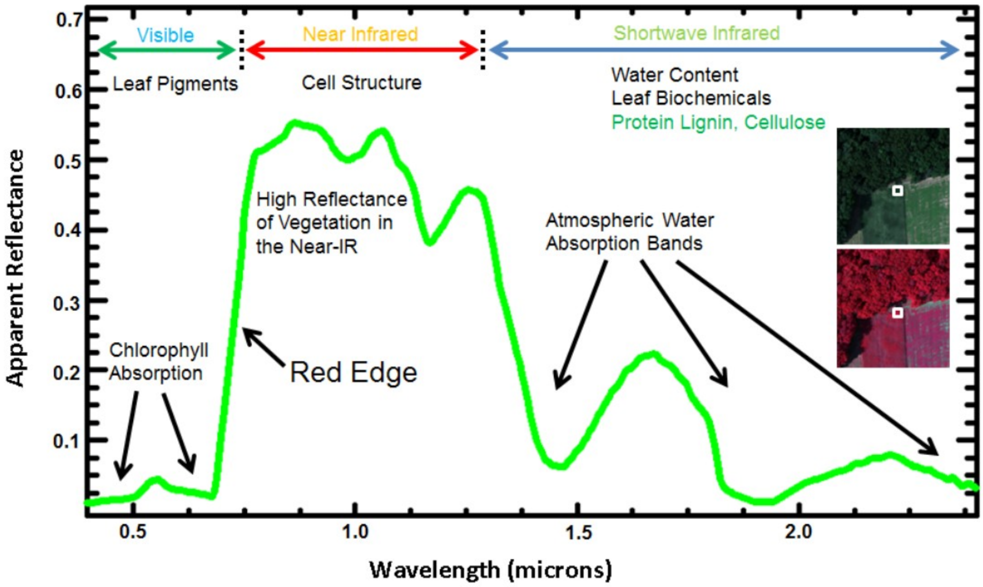

Figure 1. Vegetation spectrum [48]

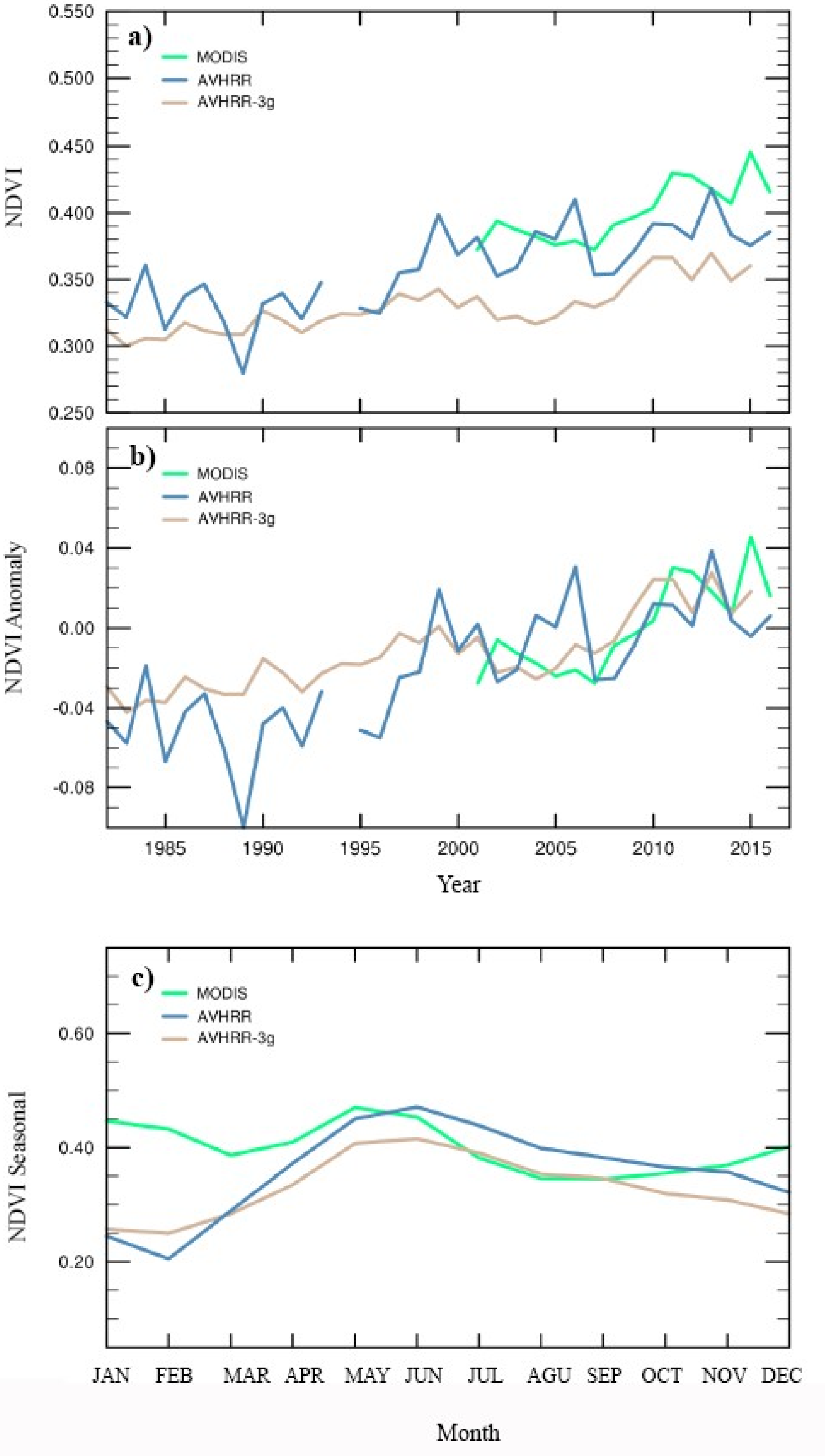

Figure 2. Satellite-based time-series for Seyhan Basin (a) NDVI index (b) NDVI Anomaly for the period 1982 - 2017 (c) long term NDVI index average per month

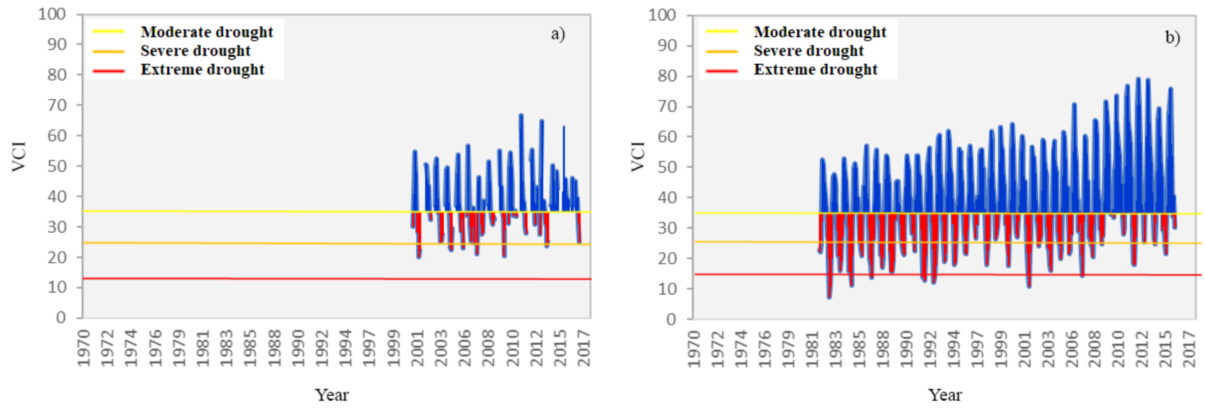

Figure 3. VCI index for the Seyhan Basin using (a) MODIS satellite data for the 2001-2016 period and (b) AVHRR satellite data for the 1982-2015 period

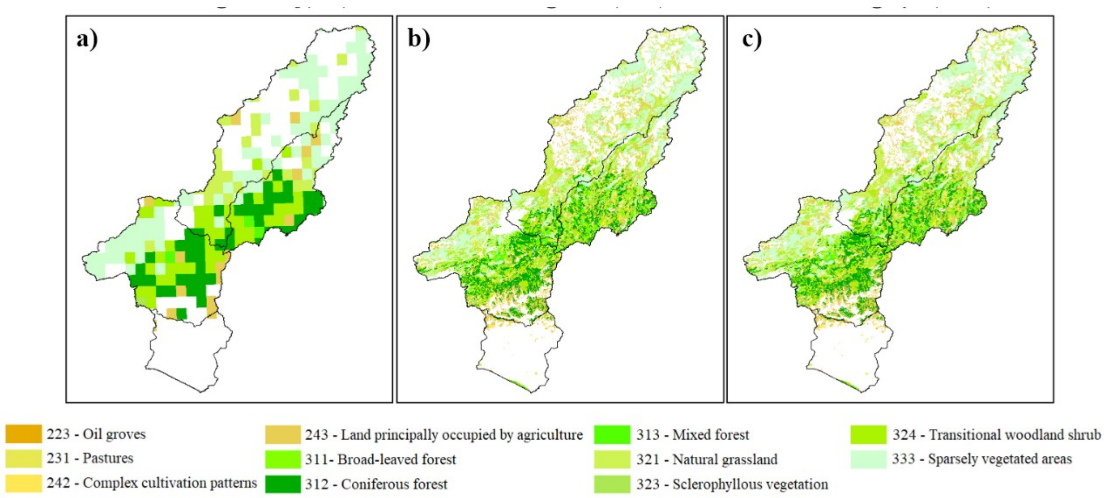

Figure 4. CORINE layers (a) AVHRR-3g (b) MODIS and (c)original used in NDVI comparison of the Seyhan Basin

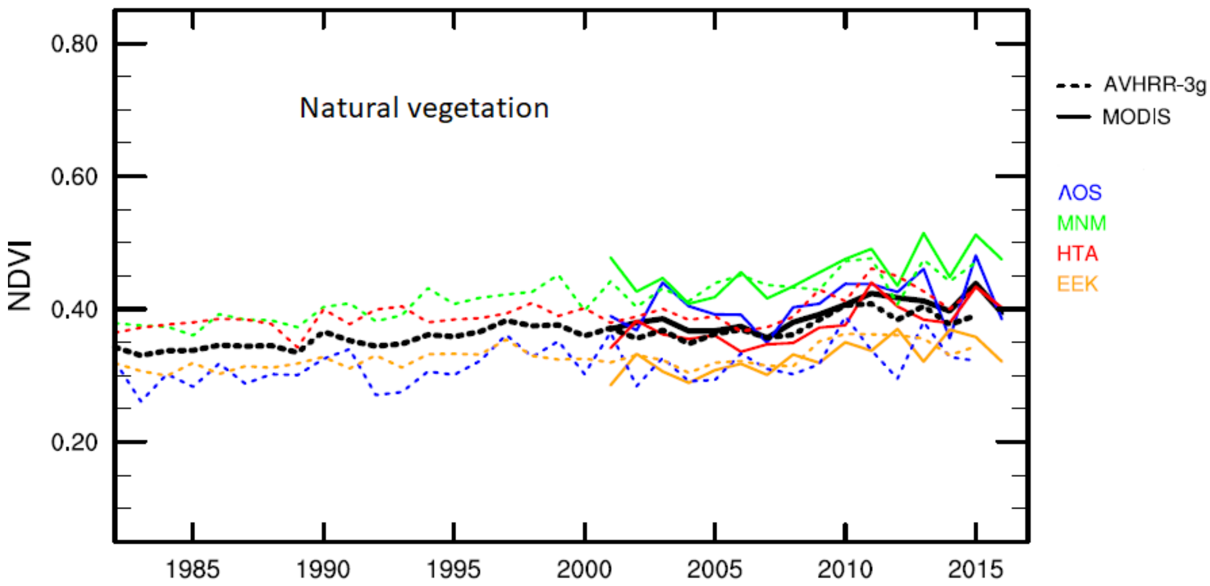
Natural vegetation
NDVI
0.80
0.60
0.40
0.20
1985
1990
1995
2000
2005
2010
2015
AVHRR-3g
MODIS
ΛOS
MNM
HTA
EEK

Figure 5. Temporal change of calculated NDVI value for natural vegetation coded CORINE 243 in the Seyhan Basin

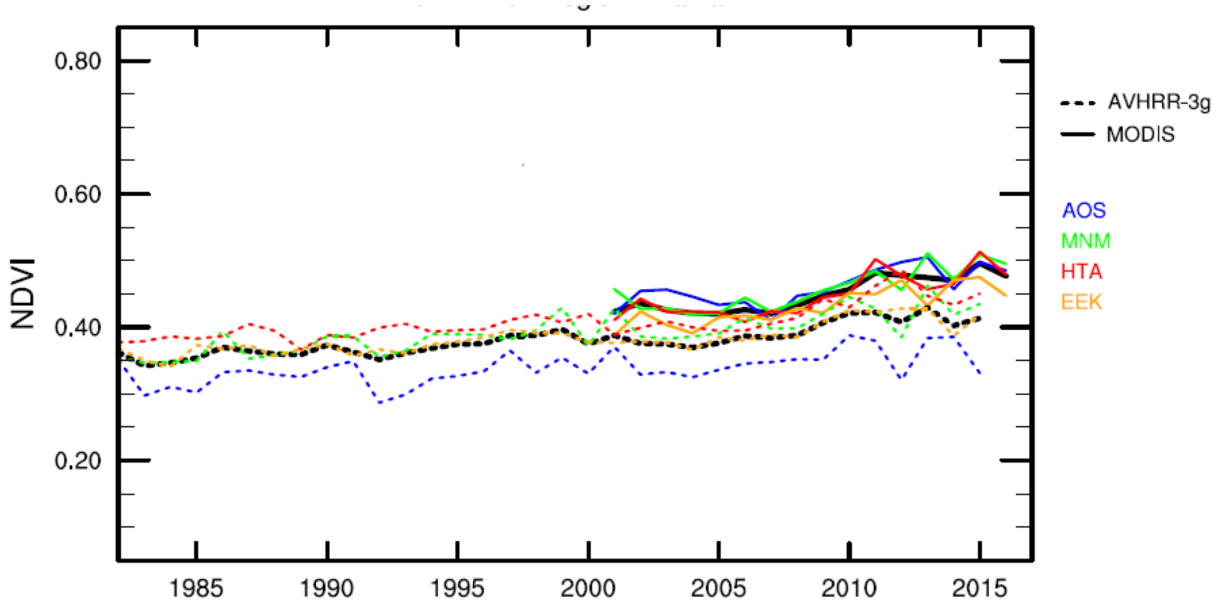

Figure 6. Temporal change of calculated NDVI value for plant change areas coded CORINE 324 in the Seyhan Basin

Table 1. Variables used in drought detection [11].

Scope of variable	Variables
Climatical	Temperature, relative humidity, evaporation, evapotranspiration, solar radiation, wind, etc.), snow cover and thickness, precipitation
Hydrological/hydrogeological	Groundwater level, reserve exchange, reservoir, lake and dam level values, precipitation, streamflow
Geotechnical	Soil properties and soil (field capacity, the water-holding capacity of the soil or beneficial soil water content, etc.)
Agricultural	Vegetation types and characteristics
Other	Remote sensing (satellite products etc.), seasonal and long-term model predictions

Table 2. Characteristics of AVHRR and MODIS satellite data.

Satellite	Data Name	Time	Resolution	Recurrence
AVHRR	AVHRR NDVI	1981 –2016	3.6 km	16 days
AVHRR	AVHRR NDVI3gc	1981 –2015	8.0 km	16 days
MODIS	MODIS MOD13Q1 NDVI	2000 –2016	250 m	16 days

Table 3. Layers of the Seyhan Basin examined for CORINE NDVI comparison.

Main Cod	Sub Cod	Explanation	Main Cod	Sub Cod	Explanation
2- Agricultural Areas	223	Olive Groves	3 - Forest and semi-natural areas	311	Broadleaf Forests
	231	Pastures		312	Coniferous Forests
	243	Natural Vegetation Found Agricultural Area		313	Mixed Forests
	2421	Non-Irrigated Mixed Agricultural Area		321	Natural Meadows
				323	Sclerophyll Vegetation
				324	Plant Change Areas
				333	Sparse Plant Areas