Assessment of drought hazard, vulnerability and risk in Iran using GIS techniques Postprint

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Date: 2021-01-15T00:00:00+00:00

Abstract

The drought has enormous adverse effects on agriculture, water resources and environment, and causes damages around the world. Drought risk assessment and prioritization of drought management can help decision makers and planners to manage the adverse effects of drought. This paper aims to determine the risk of drought in Iran. At the first stage, standardized precipitation index (SPI) was calculated for the period 1981-2016. Then the probability map of different drought classes or drought hazard probability map were prepared. After that the indicator-based vulnerability assessment method was used to determine the drought vulnerability index. Five indices including climate, topography, waterway density, land use and groundwater resources were chosen as the most critical factors of drought in Iran and followed by the analytical hierarchy process questionnaire, the weights of each index were obtained based on expert opinions. Fuzzy membership maps of each index and sub-index were prepared using ArcGIS software. The drought vulnerability map of Iran was plotted using these weights and maps of each indicator. Finally, the drought risk map of Iran was provided by multiplying drought hazard and vulnerability maps. According to the 43-completed questionnaires by experts, climate index has the highest vulnerability to drought. Climate does not have an important role in drought hazard index, but it is the most crucial factor to classified drought vulnerability index. The results showed that central, northeast, southeast and west parts of Iran are at high risks of drought. There are regions with different risks in Iran due to unusual weather and climatic conditions. We realized that the climate and the groundwater situation is almost the same in the central, east and south parts of Iran, because the land use plays a crucial role in the drought vulnerability and risk in these areas. The drought risk decreases from the center of Iran to the southwest and northwest.

Full Text

Abstract

Drought exerts enormous adverse effects on agriculture, water resources, and the environment, causing damages worldwide. Drought risk assessment and prioritization of management strategies can help decision-makers and planners mitigate these adverse effects. This paper aims to determine drought risk in Iran. First, the Standardized Precipitation Index (SPI) was calculated for the period 1981-2016 to prepare probability maps of different drought classes (drought hazard probability maps). Subsequently, the indicator-based vulnerability assessment (IBVA) method was used to determine the drought vulnerability index. Five indices—climate, topography, waterway density, land use, and groundwater resources—were identified as the most critical factors influencing drought in Iran. Using an Analytical Hierarchy Process (AHP) questionnaire, the weights of each index were obtained based on expert opinions. Fuzzy membership maps for each index and sub-index were prepared using ArcGIS software, and the drought vulnerability map of Iran was generated by combining these weighted maps. Finally, the drought risk map was produced by multiplying the drought hazard and vulnerability maps. Analysis of 43 completed expert questionnaires revealed that the climate index has the highest weight in vulnerability assessment. While climate does not play a significant role in the drought hazard index, it is the most crucial factor in determining drought vulnerability. The results indicate that central, northeastern, southeastern, and western Iran are at high drought risk. The study found that although climate and groundwater conditions are similar across central, eastern, and southern Iran, land use plays a decisive role in determining drought vulnerability and risk in these regions. Drought risk decreases from central Iran toward the southwest and northwest.

Keywords: climate map; standardized precipitation index; analytical hierarchy process; fuzzy membership; weight

1 Introduction

Drought is one of the most destructive natural phenomena, with devastating impacts on agriculture, water resources, and the environment [?, ?, ?]. This phenomenon develops slowly but can persist for long periods and cover extensive areas compared to other natural hazards [?, ?, ?]. With the projected increase in severe weather incidents, drought is expected to occur more frequently and with greater intensity in the future [?].

Drought definitions are classified into meteorological drought, hydrologic drought, agronomic drought, and socioeconomic drought [?, ?, ?]. Meteorological drought is the most important type [?] and serves as the driving force behind other drought categories, resulting from reductions in long-term average precipitation. As meteorological drought develops, its adverse effects emerge and other drought types gradually manifest, with combined impacts causing destructive consequences in affected areas.

Economically, drought is the most dangerous natural phenomenon in history [?] and has consistently endangered global food security [?, ?]. Owing to increased water resource consumption in recent decades, new aspects of drought have emerged, affecting enormous human populations worldwide for extended periods [?, ?]. Consequently, drought management represents one of the essential challenges worldwide [?].

In recent years, a risk-oriented approach has been adopted for disaster risk management [?, ?]. In this context, governments have attempted to develop drought management policies emphasizing risk management rather than traditional crisis response approaches [?, ?]. Drought risk evaluation is a function of two components: drought hazard and vulnerability [?, ?, ?].

Drought hazard assessment is a vital aspect of drought risk [?], involving investigation of drought intensity probability and frequency [?]. Repetition of high-intensity drought can have hazardous effects [?]. Drought hazard describes the physical aspects of drought and plays an essential role in connecting drought risk and vulnerability [?]. Therefore, drought hazard is the most important component of drought risk [?], defined as the probability of drought occurrence. The drought hazard index is calculated through statistical analysis of drought indices such as the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index [?, ?].

Vulnerability is a broad concept with various definitions [?, ?, ?], referring to the potential sensitivity of human and natural systems when drought occurs. In other words, differences in natural properties and socioeconomic features create varying sensitivities to drought [?]. Multiple methods exist to measure drought vulnerability, with index-based vulnerability assessment (IBVA) being among the most common. IBVA quantifies vulnerability by combining several potential indices with related vulnerability levels, and has been widely applied at local and global scales [?, ?, ?, ?]. Two options exist for calculating vulnerability using IBVA: assigning equal importance and weights to all factors [?], or assigning different weights based on varying emphases. Techniques such as the Analytical Hierarchy Process (AHP) can be used to determine factor weights.

Numerous studies have investigated drought hazard, vulnerability, and risk. For example, Shahid and Behrawan (2008) used physical factors (soil water capacity, production amount, irrigated area percentage) and socioeconomic factors (population density, gender ratio, agricultural employment rate) to map drought vulnerability in western Bangladesh. Han et al. (2016) calculated a comprehensive drought risk index for southwestern China using climatic, geographic, soil, and remote sensing data with AHP, finding that prevention capacity, drought hazard, sensitivity, and environmental vulnerability contributed to the risk index. Nasrollahi et al. (2018) studied drought risk in Semnan Province, Iran, using SPI for hazard calculation and indices such as agricultural land and water use for vulnerability assessment, revealing that 62.46% of the area had medium risk and 53.12% had very intense risk. Chen et al. (2019) evaluated agricultural drought risk in China using SPI, showing risk decreasing from northeast to southwest and suggesting results could mitigate future drought effects. Ahmadalipour et al. (2019) studied future drought risk in Africa using SPEI for hazard index and layers such as land use and water resources for vulnerability, predicting unprecedented drought hazard without climate change risk management.

Drought is one of the most costly natural disasters [?, ?], with adverse environmental, social, and economic impacts in Iran. Climate change research indicates that drought frequency and duration will increase in the Middle East [?]. Government activities in Iran have focused on drought crisis management (response and recovery), while risk management through preparedness and capacity building has been neglected [?]. Therefore, assessing drought risk and prioritizing management strategies to cope with this phenomenon is necessary. This paper aims to demonstrate the probability of drought across Iran to identify vulnerable areas for management when severe drought occurs.

2.1 Study Area

Iran (1.65$\times10^{6}$ km^2; 25°03 -39°47 N, 44°14 -63°20 E) exhibits diverse weather conditions due to its broad ecological diversity and varied terrain [?, ?]. Figure 1 [Figure 1: see original paper] shows Iran' s climatic diversity, prepared by combining different climate classes developed by the Forests, Range, and Watershed Management Organization (http://www.frw.org.ir/00/En/default.aspx).

2.2 Data

Data from 46 meteorological stations, including mean annual precipitation, temperature, and evaporation, were obtained from the Iran Meteorological Organization (http://www.irimo.ir). Meteorological data were interpolated using the Inverse Distance Weighting (IDW) method in ArcGIS 10.3 (Esri, USA). Station locations and interpolated results are shown in Figure 1. Groundwater resource data from piezometer wells were provided by the Iran Water Resources Management Company (https://www.wrm.ir/). Waterway and land use layers were prepared by the Forests, Range, and Watershed Management Organization of Iran (http://www.frw.org.ir/02/En/). For topographic analysis, a 90 m Digital Elevation Model (DEM) of Iran (https://cgiarcsi.community/data/srtm-90m-digital-elevation-database-v4-1/) was used to derive slope, aspect, and elevation layers.

3.1 Drought Hazard

Monthly precipitation data from 46 synoptic stations with reliable long-term records (1981-2016) were selected to calculate drought hazard (Fig. 1). Missing data were estimated from nearest neighbor stations using linear regression. The

Standardized Precipitation Index (SPI) was then used to determine drought hazard [?].

To calculate SPI, precipitation data for each station' s statistical period were fitted to the gamma probability distribution function, g(x), as shown in Equation 1:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}, \quad x > 0 \tag{1}$$

where α is the shape parameter estimated using maximum likelihood, β is the scale parameter, x is precipitation (mm), and $\Gamma(\alpha)$ is the gamma function.

The parameters were calculated using the following equations:

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \tag{2}$$

$$\beta = \frac{\bar{x}}{\alpha} \tag{3}$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{4}$$

where A is a dimensionless component used to calculate α and β, n is the number of precipitation observations, and $\bar{x}$ is the average precipitation (mm) for a given month during the statistical period. These parameters allow precipitation distribution to be represented by the cumulative probability function G(x) in Equation 5:

$$G(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} dx \tag{5}$$

Since the gamma function is undefined at x=0, the precipitation distribution includes zero values. The cumulative probability function H(x) for x=0 is given by Equation 6, where q is the probability of zero precipitation:

$$H(x) = q + (1-q)G(x) \tag{6}$$

H(x) is then converted to the standard normal distribution to calculate SPI values [?].

To simplify operations and improve calculation accuracy, DIP (Drought Index Package) software version 2 was used to calculate SPI at a 12-month timescale [?]. Drought severity classification followed standard categories (Table 1).

Table 1. SPI (Standardized Precipitation Index) classification [?]

Drought category	SPI value
Too severe drought	≤ -2.00
Severe drought	-1.99 < SPI < -1.50
Medium drought	-1.49 < SPI < -1.00
Normal	-0.99 < SPI < 0.99
Medium wet	1.00 < SPI < 1.49
Severe wet	1.50 < SPI < 2.00
Too severe wet	≥ 2.00

Drought hazard was evaluated using drought occurrence probability. First, the frequency of different drought classes (moderate, severe, and very severe) was determined for each synoptic station. The probability percentage for each category was then calculated by dividing its occurrence frequency by all possible states. Point data interpolation was performed using geostatistical analysis tools via the IDW method in ArcGIS 10.3.

Since various drought intensities have different impacts, weights were assigned to each drought class (Table 2). Ratings of 1 to 4 were assigned to moderate, severe, and very severe drought groups. Each intensity class map was subdivided into four subclasses based on probability percentage using the natural breaks method, which minimizes within-class differences while maximizing between-class distinctions. ArcGIS 10.3 was used to determine natural break points, with values of 1 and 4 assigned to subclasses with lowest and highest drought probabilities, respectively.

Table 2. Weight and rating assigned to drought classes at 12-month timescale

Drought class	Weight	Rating	Occurrence probability* (%)	Area (%)
Moderate drought	1	1–4	$ $6.96	$ $10.56
Severe drought	2	1–4	$ $3.76	$ $6.84
Very severe drought	3	1–4	$ $1.59	$ $3.03

*Occurrence probability for each rating was calculated using the natural breaks method in ArcGIS 10.3.

Finally, the Drought Hazard Index (DHI) was calculated using Equation 7 in ArcGIS 10.3:

$$\mathrm{DHI} = (\mathrm{MD}_r \times \mathrm{MD}_w) + (\mathrm{SD}_r \times \mathrm{SD}_w) + (\mathrm{VSD}_r \times \mathrm{VSD}_w) \tag{7}$$

where MD, SD, and VSD represent moderate, severe, and very severe drought, respectively; subscripts r and w denote rating and weight. DHI values range from 6 to 24 and were classified into four categories: low, moderate, severe, and very severe.

3.2 Drought Vulnerability

The IBVA method was employed to calculate drought vulnerability. First, effective vulnerability indices were identified based on study objectives, area characteristics [?, ?], and their variability [?]. Drawing from previous studies and consultation with Iranian drought experts, five indices were selected: climate, topography, waterway density, land use, and groundwater resources, each with associated sub-indices (Fig. 2 [Figure 2: see original paper]).

The AHP method using pairwise comparison matrices was applied to weight each index and sub-index [?]. After matrix formation, weights were calculated if the consistency ratio was acceptable [?, ?]. Forty-three completed questionnaires from drought experts were used to estimate weights, with Expert Choice software (Expert Choice Inc., USA) employed for matrix formation, consistency ratio calculation, and weight determination.

Figure 2. Analytic Hierarchy Process (AHP) for drought vulnerability determination

Index and sub-index maps were prepared in ArcGIS 10.3 as follows:

- **Groundwater resources index**: Groundwater significantly affects drought vulnerability [?]. This index comprised two sub-indices: average water depth and annual groundwater decline. Based on 17 years of data (2000–2016), each sub-watershed was assigned values for these parameters. Maximum weights were assigned to watersheds with highest decline and depth (most drought-sensitive), and vice versa.
- **Waterway density index**: High waterway density indicates greater runoff, increasing drought sensitivity [?].
- **Climate index**: Climate is crucial for determining drought vulnerability, with three sub-indices: precipitation, evaporation, and temperature. Mean annual precipitation, evaporation, and temperature data from 46 synoptic stations (1981–2016) were used. Zoning was performed using ordinary Kriging in ArcGIS 10.3. Higher precipitation decreases drought severity, so regions with more precipitation received lower weights. Increased temperature raises drought susceptibility, so maximum weights were assigned to hottest areas and minimum weights to coolest areas. The evaporation-precipitation difference was also considered, with larger differences receiving higher weights.

- **Land use index**: Land use significantly affects vulnerability [?, ?]. The index layer was prepared in ArcGIS 10.3, with maximum and minimum weights assigned to irrigated cultivation areas and rangeland/bare lands, respectively.
- **Topography index**: Topography substantially affects water availability and thus drought vulnerability. This index comprises three sub-indices: slope, aspect, and elevation. Higher elevation reduces drought sensitivity, so maximum elevations received lower weights and vice versa. Increased slope causes rapid water runoff, making it unavailable to plants, so steeper slopes received higher weights. For aspect, weights were assigned in descending order: south, west, east, and north-facing slopes.

Fuzzy logic was used to combine and overlay index layers. In fuzzy logic, element membership in a set is defined by values between 0 and 1 [?, ?], where 0 indicates minimal impact and 1 indicates maximum impact on drought vulnerability.

The fuzzy gamma operation combines algebraic product and sum operators (Eq. 8):

$$\mu(x) = (\text{Fuzzy Algebraic Sum})^{\gamma} \times (\text{Fuzzy Algebraic Product})^{1-\gamma} \tag{8}$$

where (x) is the fuzzy gamma operation and γ ranges from 0 to 1. Appropriate γ selection creates output values showing flexible adaptation between multiplication' s downward tendencies and summation' s upward trends [?]. This study used $\gamma = 0.9$, following [?] who achieved acceptable results assessing drought risk in southeastern Australia. The drought vulnerability index map was obtained by overlaying all index and sub-index maps.

3.3 Drought Risk

Using the Drought Hazard Index (DHI) and Drought Vulnerability Index (DVI), the Drought Risk Index (DRI) was calculated (Eq. 9) [?, ?, ?, ?]:

$$\text{DRI} = \text{DHI} \times \text{DVI} \tag{9}$$

Drought risk increases with DRI. All maps (hazard, vulnerability, and risk) were classified into five categories—very low, low, moderate, high, and very high —using natural breaks in ArcGIS 10.3.

4.1 Drought Hazard

The 12-month severe drought probability map (Fig. 3 [Figure 3: see original paper]) shows high drought probability in northeastern, central, southwestern, and parts of northwestern Iran. Coastal areas near the Strait of Hormuz, southern coasts, northern coasts, and regions around Lake Urmia have very low probability of 12-month severe drought. Generally, eastern and southeastern Iran exhibit the highest severe drought potential, while northwestern areas, the northeastern Persian Gulf coast, and central Iran show minimum probability. Dispersed parts from northwest to southeast have the highest probability, whereas western, eastern, and northeastern Iran have the lowest drought probability.

4.2 Drought Vulnerability

The spatial distribution of 12-month DHI in Iran for 1981-2016 (Fig. 4 [Figure 4: see original paper]) shows high drought probability in Iran' s central belt from east to west and in the southwest. The Strait of Hormuz coast to central Fars Province and the northwest region have the lowest drought hazard. Nearly half of Iran (48.2%) falls in the very high class, while the smallest area (9.9%) is in the low class. Over 65% of the country is in high and very high classes.

Index and sub-index weights were calculated using AHP to determine drought vulnerability. Table 3 shows that the climate index has the highest susceptibility to drought, playing the major role (>50%) in identifying vulnerable areas. Among sub-indices, precipitation, slope, and depletion have the most significant impacts on climate, topography, and groundwater resources, respectively.

Table 3. Index and sub-index weights determined by the Analytic Hierarchy Process

Index	Weight
Climate	0.52
Waterway density	0.11
Topography	0.09
Land use	0.15
Groundwater resources	0.13

Sub-index	Weight
Precipitation	0.38
Evaporation	0.08
Temperature	0.06
Slope	0.04
Aspect	0.03
Height	0.02
Depletion	0.08
Depth	0.05

The fuzzy membership map of waterway density (Fig. 5 [Figure 5: see original paper]) shows lower vulnerability in north-central and eastern Iran, while southwestern and western Iran are more susceptible due to high waterway density.

Fuzzy membership maps of land use (Fig. 6 [Figure 6: see original paper]) indicate that areas with greater vegetation cover play a more significant role in determining drought vulnerability. Central Iran, particularly the Dasht-e Kavir and Kavir-e Lut deserts, has minimal influence on land use-related vulnerability. The groundwater resources fuzzy membership map (Fig. 7 [Figure 7: see original paper]) shows watershed-specific requirements based on groundwater management. The topographic fuzzy membership map shows no specific trend, with each pixel weighted according to slope, aspect, and elevation (Fig. 8 [Figure 8: see original paper]). The climate index fuzzy membership map reveals that central Iran is more sensitive and vulnerable compared to western, northwestern, and northern regions (Fig. 9 [Figure 9: see original paper]).

After determining fuzzy memberships, Iran' s drought vulnerability map was generated using fuzzy overlay in ArcGIS 10.3 and classified into five classes (Fig. 10 [Figure 10: see original paper]). Central, northeastern, and southeastern Iran fall in the very high class, while southeastern, eastern, and north-central parts are in the very low class. The Zagros and Alborz highlands are in the high class, while most northwestern and western Iran plus the northern coast are in moderate and low classes.

4.3 Drought Risk

The drought risk map of Iran was prepared by multiplying hazard and vulnerability maps, classified into five classes (Fig. 11 [Figure 11: see original paper]). Results show that central, northeastern, southeastern, and western Iran are in high and very high risk classes, while northern and northwestern Iran are in low and very low risk classes.

5 Discussion

Drought is a complex phenomenon requiring comprehensive risk management to reduce negative effects. This study evaluated Iran' s DRI using DHI and DVI. DHI was estimated from occurrence probability analysis of different drought intensities calculated via SPI. Drought occurrence probability significantly affects DHI [?, ?, ?]. Results show that drought occurrence probability decreases as intensity increases, consistent with [?]. Drought probability maps (Fig. 3) indicate that occurrence across different intensities is not a function of regional climate, making DHI climate-independent. This occurs because drought manifests across various climate types [?, ?, ?] without direct climate-intensity relationships. Iran' s DHI shows that very high-risk areas may have lower very-severe drought probability than low-risk areas. For example, eastern Iran has low 12-month very-severe drought probability but falls in the very high-risk class, demonstrating that DHI combines multiple intensities for drought planning purposes.

Drought risk assessment requires vulnerability determination [?, ?, ?]. This study used IBVA with five indices and sub-indices as effective vulnerability factors. While many methods exist for weight determination, precise weighting is challenging [?, ?, ?]. We used AHP, with results showing climate index has the most significant weight and greatest effect on drought vulnerability (>50%). Figure 9 confirms that drier climates increase vulnerability.

Groundwater resources and land use are also important DVI indices directly related to human activities, reflecting Iran' s socioeconomic conditions. Groundwater is Iran' s main water supply source [?] and plays a vital role in drought vulnerability due to high agricultural dependency. Uncontrolled consumption has created groundwater crises [?, ?], making groundwater risk management crucial for vulnerability reduction. Land use' s significant influence demonstrates that drought timing, duration, and intensity affect different land uses differently [?].

The vulnerability map (Fig. 10) shows that regions near Lake Urmia in moderate and high vulnerability classes require risk management attention, as drought and human activities (especially agriculture and groundwater use) have reduced lake levels [?]. The Caspian Sea' s western coasts have lower vulnerability than eastern shores due to more humid climate. Based on selected indices, the Alborz and Zagros Mountains are in high vulnerability classes.

Drought risk evaluation shows spatial variation due to different climatic conditions. Most semi-arid to humid areas (Fig. 10) are classified as high to very high risk, where most of Iran' s population resides, making risk management in these areas particularly important.

In hyper-arid and arid regions with similar groundwater conditions, land use plays a decisive role in drought vulnerability and risk in central, eastern, and southern Iran. For instance, arid areas like Lut and central deserts with high drought probability are in low risk classes. Drought risk gradually decreases from central to southwestern Iran, while the very high-risk class increases from northwest to central Iran. Land use represents human-nature interactions [?], so excessive resource exploitation and human activities play decisive roles in drought risk management in dry regions.

6 Conclusions

This research produced Iran' s drought hazard, vulnerability, and risk maps to identify vulnerable areas during severe drought events. Monthly precipitation from 46 synoptic stations (35-year record) was used to calculate 12-month SPI. The drought hazard map was derived from drought occurrence probability maps. Using IBVA, five indices—groundwater resources, waterway density, climate, land use, and topography—were selected as most drought-sensitive for vulnerability mapping. Multiplying hazard and vulnerability maps created Iran' s drought risk map.

The 12-month drought hazard map showed >60% of Iran has high to very high drought probability, with eastern and southeastern Iran having the highest severe drought potential and northwestern areas plus the northeastern Persian Gulf coast to central Iran having the lowest. The vulnerability map indicated that central, northeastern, and southeastern Iran in the very high class are most sensitive to drought, influenced by topography and waterway density. Among topographic sub-indices, slope weight exceeded height and aspect. In arid and hyper-arid regions, slope changes are much less than in semi-arid and humid areas, reducing topography' s weight. Waterway density is also lower in arid regions, decreasing its weight relative to semi-arid and humid areas.

Results demonstrate that climate, groundwater resources, and land use significantly impact drought vulnerability in Iran. Groundwater and land use as human activity indices reveal human influence on vulnerability and risk. Due to population density and resource pressure, land use and groundwater weights were greater in semi-arid and humid than in arid and hyper-arid areas.

Based on hazard and vulnerability maps, climate index is not essential for DHI but is crucial for determining vulnerability. The risk map showed central, northeastern, southeastern, and western Iran in high-risk classes. Recommended risk reduction activities include establishing drought monitoring and forecasting systems, developing water-independent livelihoods, and societal training to improve water consumption efficiency across sectors.

The drought risk map revealed land use's unique role in dry areas, showing close land use-drought risk relationships where land use changes can affect risk and vice versa. Hyper-arid and arid regions with high drought probability are in low-risk classes, warranting lower management priority. Natural risk management is most important where human interests are at stake. Arid and hyper-arid regions have lower population density, less resource pressure, and more stable land use, resulting in lower drought risk than humid and semi-arid regions.

Future research should assess drought risk separately for each land use under different topographic and climatic conditions to improve risk management in arid regions and reduce population center bias in vulnerability identification. Additionally, vegetation changes from satellite imagery should be incorporated as a new vulnerability index.

Acknowledgements

We are grateful to the Faculty of Natural Resources, University of Tehran.

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