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Key Points:

- A theoretical model of inconsistent desert-oasis interactions is presented
- The model is verified through a study of Minqin County in northwestern China
- Impacts of climate change and human interference on desertification are revealed

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Nonstationary desertification dynamics of desert oasis under climate change and human interference

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Abstract Desertification is becoming a major ecological concern in arid and semiarid regions, especially under climate change. Globally, it is burning up lands for human habitats with a rapidly spreading tendency. Many scientists have been struggling to explore the related mechanisms. Challenges remain in revealing the fundamental principle in terms of desert-oasis interactions that are associated with nonstationary variations. Here we present a theory of desertification dynamics through examining nonstationary effects of climate change and human interference. We hypothesize that such dynamics can be described as the fate and transport of dry air mass continuously generated from desert. We simulate a region in northwestern China and reveal that dynamics of the nonstationary desertification process is subject to interactive impacts from a variety of factors. Our study moves forward the field of desertification studies through initiation of the dynamics and nonstationarity concepts which allow the fundamental mechanism to be disclosed.

1. Introduction

Globally, desertification is becoming a major natural disaster in arid and semiarid regions. Desertification is a manifestation of climate, and its spatial and temporal patterns are shaped by geology and biology. As a result of climate change and human interference, nonstationary variations of environmental conditions, which implies that the conditions no longer fluctuated within an unchanging envelope of variability, are becoming more conspicuous [Danfeng et al., 2006; Jordan et al., 2014; Milly et al., 2008; Song et al., 2014; Weng et al., 2011; Wang et al., 2014]. Consequently, the unfolding of desertification dynamics at spatial and temporal scales is not physically or statistically indistinguishable from the past, which leads to the nonstationarity of desertification process. Such nonstationarity presents a major challenge to understanding the desertification mechanism and the simulation of the related processes, which are of similar importance to hydrodynamics for water systems or aerodynamics for atmospheric ones [Kuehl et al., 1995; Madanian et al., 2014; Sun, 2015; U.S. National Research Council (USNRC), 2012].

Many scientists claim that desertification is primarily due to human interference [Mulitza et al., 2010; Schlesinger et al., 1990], vegetation pattern variations [D'Odorico et al., 2005; Kéfi et al., 2007; Klausmeier, 1999; Maestre et al., 2012], and land (soil) degradations [Mueller et al., 2007; Ni et al., 2014; Reynolds et al., 2007; Wang et al., 2005]. More recent studies have shown that desertification is likely to be controlled by climate change and the related geomorphological processes [Guo et al., 2002; Munson et al., 2011; Seely et al., 2008; Sun et al., 2006; Tietjen and Jeltsch, 2007; Wang et al., 2009; Xue et al., 2015]. In the past decades, tremendous efforts were made in studying desertification dynamics [Ding et al., 2009; Sun, 2015; USNRC, 2012]. Hahn et al. [2005] developed a model to describe long-term climate, livestock, and vegetation interactions on rangelands in the semiarid region of South Africa. Kéfi et al. [2007] used a modeling approach to analyze how vegetation patchiness changes when desertification is imminent. Ding et al. [2009] used remote sensing data to analyze the relationships between desertification and its driving factors, including vegetation cover, soil texture, climate factor, terrain factor, hydrology factor, and human activities. Sun and Wang [2011] used coupled biosphere-atmosphere models to study the dynamics of land surface processes. Xu et al. [2012] proposed a method to assess the driving processes of desertification in North China. However, these studies were limited in descriptive analyses for system behaviors or statistical inferences for individual processes. No systematic study on nonstationary desertification dynamics was reported. This gap leads to our lack of insight into the desertification process that is related to not only climate but also a variety of related climatic, hydrological,

biological, geophysical, ecological, and human factors [Collado et al., 2002; Ehrlich et al., 1994; Garbulsky and Paruelo, 2004; Niu et al., 2014; Reynolds et al., 2004; Sun et al., 2005; Tucker et al., 1991; Wang et al., 2008, 2004].

Therefore, the objective of this study is to reveal the desertification dynamics through examining the nonstationary effects of climate change and human interference. In detail, (1) a concept of dry air mass (DAM), which can directly relate to desertification level, will be initiated; (2) a DAM dispersion model will be constructed to simulate the transport of DAM in the atmosphere; (3) with some assumptions regarding DAM source intensity, dispersion velocity, convection, and residuals, the model will be solved analytically to describe the transport of DAM influenced by a single source at a fixed location; (4) a Markov process will be introduced to further extend the analytical solution and to represent variations of source locations; and (5) the model will be applied to describe the desertification process at the Minqin County in northwest China, one of the representative arid and semiarid regions.

2. Methodology

A concept of DAM, which is regarded as a complex atmospheric component without presence of water, was firstly initiated. DAM concentration then denotes a ratio of DAM to total air mass (TAM), where TAM = DAM + mass of moisture vapor. DAM was used because (a) its concentration is significantly related to desertification level [Qin et al., 2004], (b) variations of DAM concentrations correspond to those of desertification dynamics [Huang et al., 2009], and (c) such variations are driven by many impact factors that lead to nonstationary desertification dynamics, such as climate change and human interference [Huang et al., 2009]. The transport of DAM in the atmosphere due to continuous contributions (or “emissions”) of it from desert zone(s) was simulated. When viewing the DAM movement at a fixed location, a period of increasing concentrations would be experienced as the DAM plume approaches the location, and another with decreasing concentrations will be experienced when the plume meanders away; moreover, the expansion of the DAM plume with time would be observed due to molecular diffusion. It is thus implied that the movement (or “dispersion”) of DAM is dominated by air mass advection and molecular diffusion [Moncrieff et al., 1996; Moreira et al., 2006; Vilhena et al., 2008]. The advection leads to instantaneous spreading of DAM in the down-gradient directions; meanwhile, as a result of the diffusion, DAM disperses to various directions (defined as dispersion direction) and the DAM level fluctuates along the direction. These can be expressed as

$$\frac{\partial \omega}{\partial t} = -\frac{\partial u \omega}{\partial x} - \frac{\partial v \omega}{\partial y} - \frac{\partial w \omega}{\partial z} + D_x \frac{\partial^2 \omega}{\partial x^2} + D_y \frac{\partial^2 \omega}{\partial y^2} + D_z \frac{\partial^2 \omega}{\partial z^2} + \Phi \quad (1a)$$

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0 \quad (1b)$$

where ω is DAM concentration ($M \cdot L^{-3}$); D_x , D_y , and D_z are diffusivities in x , y , and z directions, respectively ($L^2 \cdot T^{-1}$); u , v , and w are DAM dispersion velocities in x , y , and z directions, respectively ($L \cdot T^{-1}$); and t is time (T).

When the horizontal meteorological conditions are homogeneous over each spatial unit, and the contribution rate of DAM is a constant within each temporal unit, the following assumptions can be established: (a) DAM source intensity is in a steady state, i.e., $\partial \omega / \partial t = 0$, (b) dispersion is negligible in x direction, (c) dispersion in y and z directions take the form of Gaussian distribution about the centerline, (d) convection is dominant in x direction, i.e., $\partial u \omega / \partial x \gg D_x \partial^2 \omega / \partial x^2$, and (e) residual (Φ) is zero.

Given these assumptions, analytical solutions of (1a) and (1b) were obtained $\omega(x, y, z) = A / (\pi u \xi \eta) \exp [-(y^2 \eta^2 + z^2 \xi^2) / (2 \xi^2 \eta^2)]$, where A is DAM source intensity, i.e., DAM emission rate, $M \cdot T^{-1}$; ξ and η are, respectively, reciprocals of D_y and D_z , representing diffusivities of DAM in lateral and vertical directions (L). For A , we have its detailed expression as $A = k_1 (SVP - VP)$ ($M \cdot T^{-1}$), where k_1 is intensity coefficient ($L \cdot T$), SVP is saturated vapor pressure ($M \cdot T^{-2} \cdot L^{-1}$), and VP is vapor pressure ($M \cdot T^{-2} \cdot L^{-1}$). These equations describe the transport of DAM as influenced by a single source at a fixed location. Such a location can vary with time, depending merely on its present state (but not on any past states). It can be estimated through a Markov process, $\Pr[L_{t+1} = l_{t+1} | L_t = l_t, L_{t-1} = l_{t-1}, \dots, L_0 = l_0] = \Pr[L_{t+1} = l_{t+1} | L_t = l_t]$, where L is a random process representing variations of the source location, which can be defined through random vector $\{X, Y, Z\}$; l is

the realization of L which can be represented as $\{x, y, z\}$. In fact, DAM transport is affected by multiple sources. Thus, the DAM concentration can be given as follows:

$$\omega(x, y, z) = \sum_{p=1}^M \sum_{j=1}^N \sum_{i=1}^I \frac{f_p f_j k_{1,ip} (SVP_{ip} - VP_{ip})}{\pi u_{ip} \zeta_i \eta_i} e^{-\frac{y^2 \eta_i^2 + z^2 \zeta_i^2}{2 \zeta_i^2 \eta_i^2}} \quad (2)$$

where $k_{1,ip}$ is the intensity coefficient for source i in DAM transport direction p ($L \cdot T$); SVP_{ip} is the saturated vapor pressure ($M \cdot T^{-2} \cdot L^{-1}$) for source i in DAM transport direction p ; VP_{ip} is the vapor pressure ($M \cdot T^{-2} \cdot L^{-1}$) for source i in DAM transport direction p ; $k_{1,ip} (SVP_{ip} - VP_{ip})$ represents DAM source intensity for source i in DAM transport direction p , i.e., $A_{ip} = k_{1,ip} (SVP_{ip} - VP_{ip})$ ($M \cdot T^{-1}$); f_p is the probability of movement from the existing source location to the p th source; f_j is the probability of movement from the existing source toward the j th direction; M is the number of locations (at time $t+1$) toward which source i (at time t) moves; N is the number of dispersion directions; I is the number of sources at time t ; subscripts i, p , and j denote source, source-moving direction, and DAM transport direction, respectively.

The source intensity is related to the difference between saturated and actual vapor pressures. A source intensity coefficient (k_1) is introduced to quantify its magnitude. It is intended to represent combined effects of DAM molecular properties as well as climatic and nonclimatic factors. Generally, the higher the k_1 value, the larger the source intensity. The dispersion velocity is proportional to the rate of vapor pressure variation with the DAM movement:

$$u = k_2 \frac{dVP}{dX} \quad (3)$$

where k_2 is dispersion velocity coefficient ($L^2 \cdot T \cdot M^{-1}$) which represents the mobility of DAM. It is potentially related to various climatic, topographical, and atmospheric conditions and determines the DAM dispersion velocity and thus affects the desertification process. The higher the k_2 value, the more rapid the desertification process.

The DAM dispersivity levels in lateral and vertical directions (ζ and η), varying with location and time, are related to meteorological, geographical, and topological conditions. They govern the transport of DAM relative to the surrounding air.

The initial temporal resolution for the DAM simulation is based on daily meteorological data, such as air temperature, dew point temperature, relative humidity, wind direction and speed, and cloud cover. Subsequently, monthly, seasonal, and yearly average values can be obtained through compound computation based on daily information of DAM sources, wind directions, wind speeds, and k_1 and k_2 variables. Estimation of the k_1 , k_2 , ζ , and η values are discussed in the following section.

3. Case Study

3.1. Study Area

The study County is besieged by two deserts (Badain Jaran Desert and Tengger Desert) from the north, west, and east (Figure 1). Its cultivable land accounts for merely 6% of the total area (15,900 km²) but supports a population of 313,100. The prevailing arid climate, coupled with excessive land reclamation and water consumption, leads to expansion of the deserts during the 1980s to 2000s; oasis is encroached by 8 to 10 m per year [Huang et al., 2009; Li et al., 2007; Sun et al., 2006, 2007; Wang et al., 2004]. The County is one of the locations currently subject to the worst desertification threat in China. Two sites within the County (Donghu and Huangjiang Villages), where considerable desertification has proceeded since the 1980s, were selected as study areas. The two sites represent cases with and without human interventions. The 6.8 km² Huangjiang site (#1) is located 120 km southeast of the Minqin Oasis, surrounded by deserts from the west, east, and north. Its land cover is dominated by heterogeneous vegetation patches and active dunes. The 0.5 km² Donghu site (#2) is at the edge of the Minqin Oasis. Its landscape is characterized by homogeneous vegetation patches and semifixed dunes, representing a situation where human intervention is significant.

The model was set up on a 30 × 30 m² grid system with a simulation period of 1987 to 2006. Climatic data are provided by the *China Meteorological Administration* [2010]. Data of land cover, soil, and topography are obtained from the national and global databases provided by the *Chinese Academy of Sciences* [2010] and the *United States Geological Survey* [2010a, 2010b].

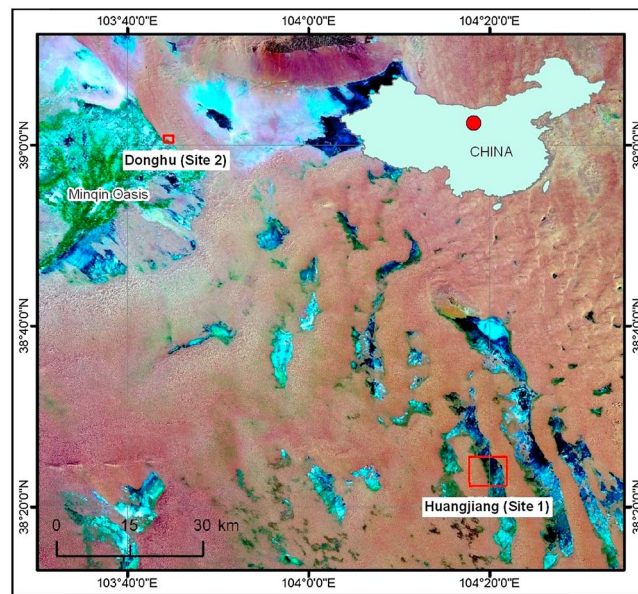


Figure 1. The study area.

3.2. Parameter Estimation

To calculate the DAM concentration using the proposed model, the k_1 and k_2 values were estimated based on statistical assumption, literature survey, and facts from various field investigations. This is the first attempt to use multiplicative equations to quantify the effects of various factors on model parameters. The validity of such equations may be affected by system nonlinearity and local geological/climate conditions, and the related factor values should be validated or updated through testing a greater number of real cases. The source intensity coefficient (k_1 , [L·T]) correlates vapor pressure deficit with DAM source intensity which is assumed based on two major factors in each source zone: desert type and near-

surface sand moisture level. They could be used for approximating conditions that could affect the magnitude of source intensity and thus facilitating long-term forecasting. Therefore, k_1 is assumed to be formulated as follows:

$$k_1 = DT \times SM \quad (4)$$

DT is a desert-type factor (assuming a scale ranging from 0.5 to 2.0), which is a measure of susceptibility of sandification to sand mobility, vegetation, and morphology. Sandification is defined as the process where the fine soil particles and organic content of sparsely vegetated lands decrease, and the soil texture becomes sandy. Deserts are subject to different forms and sizes based on their interaction with the wind. The morphology is referred to the shape, height, length, and slope of a desert. Based on such information, desert is divided into three general groups, including small isolated crescentic dune, large barchan chain, and complex sand dune. The complex sand dune (or star dune) is considered to be the most mature desert type, and small isolated crescentic dunes could present at the early stage in forming a larger sand dune. During its early to mature stages, the potential of a sand zone for significant sandification (i.e., generation of significant DAM) would increase. Sand mobility (i.e., the sands' ability to be moved freely and easily) also poses considerable effects on sandification. It is mainly related to vegetation density and sand type. A fully vegetated (and fixed) sand zone is considered nonmovable, and the corresponding DAM level will be low; conversely, a sand zone without vegetation will be significantly mobile with a high DAM level. The detailed DT levels under different desert conditions are shown in Table 1. SM is a near-surface sand moisture factor, which is a measure for

Table 1. DT Factor

Desert Morphology	Desert Type	DT
Small isolated crescentic dune, longitudinal dune, or linear ridge (maximum height < 50 m)	Free of vegetation and active	1.9517
	Partially vegetated and active	0.9535
	Partially vegetated and semifixed	0.3912
	Fully vegetated and fixed	0.0796
Large crescent dune or barchan chain (maximum height = 50 to 150 m)	Free of vegetation and active	3.9035
	Partially vegetated and active	1.9070
	Partially vegetated and semifixed	0.9198
	Fully vegetated and fixed	0.2407
Star dune or complex sand dune (maximum height > 150 m)	Free of vegetation and active	7.8069
	Partially vegetated and active	3.8140
	Partially vegetated and semifixed	1.6015
	Fully vegetated and fixed	0.5680

Table 2. SM^a Factor

Average Moisture Content in the Upper Soil Layer (20 to 60 cm Deep)	SM
Very dry (<0.1%)	0.85
Relatively dry (0.1 to 1%)	0.70
Medium dry (1 to 2%)	0.65
Medium (2 to 3%)	0.50
Medium wet (3 to 5%)	0.45
Relatively wet (5 to 8%)	0.30
Very wet (>8%)	0.15

^aSM = 0.7960 − 0.1380x + 0.0162x² − 0.0011x³, where x denotes average moisture content.

susceptibility of soil particles to desertification drivers (i.e., DAM). Many previous studies revealed that SM is related to a number of factors [Wiggs *et al.*, 1995]. First, considerable spatial and temporal variability in topsoil moisture exists over seasons. A twofold to threefold increase in moisture content during spring or fall was significantly correlated with increase in precipitation. Second, biomass density (or vegetation cover) is a factor that influences the stability of moisture levels on the sand surface. Third, near-surface moisture is denoted as moisture level at a given depth. Beneath a dry layer of 10 to 20 cm, there is a relatively stable wet sand layer. Other factors such as texture, structure, permeability, and organic matter content can also affect the SM level; however, they are considered insignificant compared with the above principal factors [Wischmeier and Smith, 1960, 1978; Lane and Shirley, 1988]. More details of the SM are given in Table 2.

The dispersion velocity ($L \cdot T^{-1}$) is assumed linearly related to the derivative of vapor pressure over two observation points (e.g., source and receptor points). Generally, the higher the derivative, the faster the DAM transformation (from source zone to down-gradient regions). The derivative reflects impacts of meteorological, climatic, and atmospheric factors. The dispersion velocity coefficient, k_2 [$L^2 \cdot T \cdot M^{-1}$], represents the slope of such a linear relation and is assumed related to a number of factors including topographical condition, hydrological effect, wind velocity, and human interference:

$$k_2 = TF \times HE \times WV \times HI \quad (5)$$

TF represents a topographic factor. It describes the effects of surface features in the area between the sand source and the desertification-stricken region, such as lakes, mountains, and canyons. TF decreases with increasing terrain roughness. The TF levels for different topographic features are listed in Table 3. For combinations of multiple features, a weighted mean can be calculated based on the significance level of each feature's contribution. Details of the HE and WV factors are shown in Tables 4 and 5, respectively. HE denotes a hydrologic factor. It is assumed that the presence of water bodies will slow down the dispersion velocity of DAM. This factor involves both artificial and natural water bodies. WV is a wind velocity factor. Wind power can significantly affect desert morphology, sand structure, and vegetation cover and thus the speed of sandification. The dispersion velocity of DAM is assumed positively proportional to wind velocity. HI denotes a human interference factor reflecting effects of artificial barriers (e.g., trees, grasslands, and shelter belts) on dispersion velocity of DAM. Such barriers may thus hinder the spread of desertification (see Table 6).

The DAM dispersivity levels in lateral and vertical directions (ζ and η), varying spatially and temporally, are related to climatic, geographical, and topological conditions. They govern the transport of DAM relative to the surrounding air. Estimations of ζ and η are acquired through statistical analysis and site investigations. The resulting functions for estimating five typical conditions in western China are provided in Table 7.

3.3. Results and Discussion

The DAM model can be used to analyze the desertification process at the Minqin County. The years of 1987, 1996, and 2006 were considered as representative points of time of the desertification process during the

Table 3. TF Factor

Topographic Features Between Two Observation Points	TF
Depressed basin (or valley)	0.95
Flat surface (or plateau)	0.80
Hillock (small hill) (maximum height < 10 m)	0.65
Hill terrain (10 m < maximum height < 100 m)	0.50
Mountain terrain (maximum height > 100 m)	0.25

1980s to 2000s. Therefore, results of the 3 years were examined in detail [Sun *et al.*, 2006; Xue *et al.*, 2015]. Seasonal average concentrations of DAM are produced and mapped as isolines (Figures 2a and 3a). Both sites see expansions of high-DAM zones during 1987 to 2006. Based on preliminary field observations, the desert

Table 4. HE Factor

Hydrologic Features Between Two Observation Points	HE
No water body	0.80
Sparse swamps, bogs, and/or marshes	0.70
Dense swamps	0.50
Sparse ponds (or small lakes) and/or lagoons	0.40
Dense ponds (or small lakes) and/or lagoons	0.20
Lakes, reservoirs, and/or rivers with large water surface area	0.10

source zone is defined as areas with DAM concentrations higher than 0.7 t/m^3 ; this threshold is derived based on the extent of desert at the study area [Huang *et al.*, 2009]. At the Donghu site, the source zone experienced an increase of 7.46% during 1987 to 1996, while it stayed stable with a slight decrease of

0.69% during 1997 to 2006. At the Huangjiang site, the annual rate of source zone expansion was relatively stable (i.e., 3.71% and 2.05% during the two successive decades, respectively). Such differences are also identified in spatial patterns of DAM distribution at the two sites. At Donghu, there is an increasing interlacement among areas with different concentrations while DAM is moving out of the source zone. Strong heterogeneity of soil and topographical features contributes to such a spatial fragmentation. At Huangjiang, DAM generally moves southward and exhibits a homogeneous distribution along the longitudinal direction. As this site is close to the oasis, human activities (such as land reclamation) contribute significantly to the reduced heterogeneity of surface and subsurface resistances against the DAM movement.

When DAM moves from deserts toward oases, it gradually depletes atmospheric moisture, prompts soil evaporation, and increases air and soil temperatures. These lead to degradation of ground vegetation (in terms of area and density) due mainly to moisture deficiency. Therefore, the DAM simulation results can be partially verified through comparing variations of DAM (or source zone expansion rate) with those of vegetation coverage, expressed through remotely sensed vegetation indicators such as the normalized difference vegetation index (NDVI). NDVI data were calculated from Landsat 5 TM images obtained on 14 September 1987, 26 September 1996, and 5 August 2006. Georegistration and radiometric calibration were conducted using ERDAS-Imagine 9.0 and RSI-ENVI 4.0. The comparison results demonstrate acceptable agreements between the DAM distributions and the NDVI images (Figures 2 and 3). Areas with low DAM levels correspond to high-density vegetation patches; degradation of ground vegetation is correlated to variations of DAM concentration. The results demonstrate that the oasis-desert transition zones were well reproduced in the DAM maps, and the desert source zone can well represent the desertification at a regional scale. From 1987 to 1996, the area without vegetation ($\text{NDVI} < 0.05$) increased by 59.45% at Donghu and 13.05% at Huangjiang, correspondingly, while the desert source zones expanded by 7.46% and 3.71%. Even though the percentage changes were different, the results of desert source zones and nonvegetated areas exhibited consistent increase trends. During the subsequent decade, the nonvegetated area increased by 21.14% at Donghu and 6.24% at Huangjiang, while the desert source zone stayed stable with a slight decrease of 0.69% at Donghu and expanded by 2.05% at Huangjiang. The vegetation at the Huangjiang site was mainly natural vegetation, and the patterns of desertification were well reproduced in the DAM maps. At the Donghu site, the DAM source zone area was relatively stable with only a slight annual decrease. The presence of DAM plume implies a nonstop process of desertification, which is consistent with the expansion of observed nonvegetated area. However, some local vegetation variations revealed by NDVI maps were not reflected in the simulation outputs. Particularly, at the southeastern corner of Donghu, there was an unexpected bloom against the simulated DAM presence. The increase of local vegetation density is mainly due to the growth of irrigated farmland and was not captured by the DAM model [Wang *et al.*, 2008]. This can be

explained by the existence of human habitats in this area that were associated with a variety of local human activities, which might have interfered with the modeling performance.

The source intensity coefficient (k_1) represents the combinative effects of nonmeteorological factors on the DAM source intensity. Based on the previous investigation of main factors affecting dune mobility and

Table 5. WV Factor

Wind Description	Speed (m/s)	WV
Calm	0	0.10
Light breeze	0 to 2	0.50
Moderate breeze	2 to 6	0.80
Strong breeze	6 to 13	1.0
High wind, moderate gale	13 to 19	1.3
Gale	19 to 25	1.6
Strong gale	25 to 32	1.8
Storm, whole gale	>32	2.0

Table 6. HI Factor

Artificial Barriers	HI
No artificial barrier	1.00
Grass or shrub zones	0.50
Shelter belt or sand-catching fences or walls	0.20
Grazing zones	0.65

the related erosion and deposition processes [Von Hardenberg *et al.*, 2001; Wiggs *et al.*, 1995], desert type (with different vegetation coverage and desert morphology) and near-surface moisture level were found to be the main parameters that affect k_1 . This is based on the following

assumptions: (i) morphology and viability of the desert's top layer have significant effects on DAM source intensity; (ii) vertical variations of desert surface stability are significantly affected by sand type, water content, plant coverage, and distribution of soil microbiotic crust. Relations between k_1 and its related factors (i.e., soil moisture and desert type) are shown in Figures 4a–4c. Figure 4a presents small isolated crescentic dune, longitudinal dune, or linear ridge (maximum height < 50 m); Figure 4b presents large crescent dune or barchan chain (maximum height 50 to 150 m); and Figure 4c presents star dune or complex sand dune (maximum height > 150 m). Coefficient k_2 represents the mobility of DAM out of the source zone. To estimate k_2 , it is assumed that a mobile sand belt, with frequent sand deposition and erosion, lies between source and receptor zones. Intensities of such deposition and erosion are controlled by wind regime and surface conditions (e.g., topographical, hydrological, and human interference) [Wiggs *et al.*, 1995]. The ability to resist sand erosion varies spatially, leading to relevant variations in the mobility of desertification. Relationships between k_2 and related factors, including topographic and hydrologic conditions, wind speed, and human interference, are provided in Figures 4d–4f. Figures 4d–4f present flat ground, hilly ground, and basin terrain, respectively. Low human interference signifies cultivation activities of grasses and/or shrubs; high interference refers to the establishment of shelter belts and/or sand-catching fences or walls. Overall, k_1 and k_2 are correlated to a variety of impact factors; many empirical models for long-term erosion assessment and conservation analysis also show similar correlations [Lane and Shirley, 1988; Wischmeier and Smith, 1960; Wischmeier and Smith, 1978]. The related data are referred to various investigations, surveys, and literature reviews [Huang, 1992; Saco *et al.*, 2007; Wang *et al.*, 2005].

Monte Carlo simulation is used to find out cumulative distribution functions (CDFs) of parameters k_1 and k_2 at Huangjiang and Donghu, respectively, considering uncertainties and spatial nonstationarities associated with the related factors. Figures 5a and 5b show the empirical cumulative distribution functions (CDFs) of k_1 and k_2 under multiple DAM sources in summer 1996 and 2006, respectively. Parameters k_1 and k_2 are normalized based on their maximum and minimum possible values. The results demonstrate that the geographical heterogeneity can lead to significant variations in k_1 and k_2 . Such heterogeneity is related to geographical conditions of DAM sources. For example, a desert in a tropical zone may be devoid of vegetation, while that along humid regions may be stabilized. The existence of water or artificial structure (e.g., cultivated grasses, shrubs, or shelter belts) between DAM sources and receptor zones can lead to increased resistibility toward DAM dispersion. Generally, the CDF curves of k_2 at Huangjiang and Donghu are relatively closer to each other, suggesting similar dispersive velocities. In comparison, the k_1 values at Donghu are significantly lower than those at Huangjiang (over 90% normalized k_1 values are lower than 0.2); this is mainly because Donghu is partly vegetated with moderate soil moisture, which mitigates DAM impacts. Donghu is more vulnerable where surface condition and wind speed play significant roles. Comparing parameters of 1996 and 2006, it is indicated that the decreasing trend of k_1 is not as significant as that of k_2 . This may be because the dispersion velocity has been affected by more factors that are more sensitive to human interference.

Table 7. Functions for Estimating ζ and η ^a

Meteorological Conditions	ζ (km)	η (km)
Most advantageous	$0.13x \exp(-0.0003x) + 0.012$	$0.08x^2 \exp(-0.006x) + 0.017$
Advantageous	$0.15x \exp(-0.0004x) + 0.026$	$0.12x^2 \exp(-0.012x) + 0.023$
Average	$0.23x \exp(-0.0013x) - 0.125$	$0.23x^2 \exp(-0.023x) + 0.310$
Disadvantageous	$0.32x \exp(-0.0051x) + 0.457$	$0.42x^2 \exp(-0.046x) - 0.121$
Most disadvantageous	$0.38x \exp(-0.0063x) + 0.537$	$0.62x^2 \exp(-0.052x) - 0.108$

^a ζ and η are dispersion capacities (km) in the lateral and vertical directions, respectively; x is longitudinal distance (km).

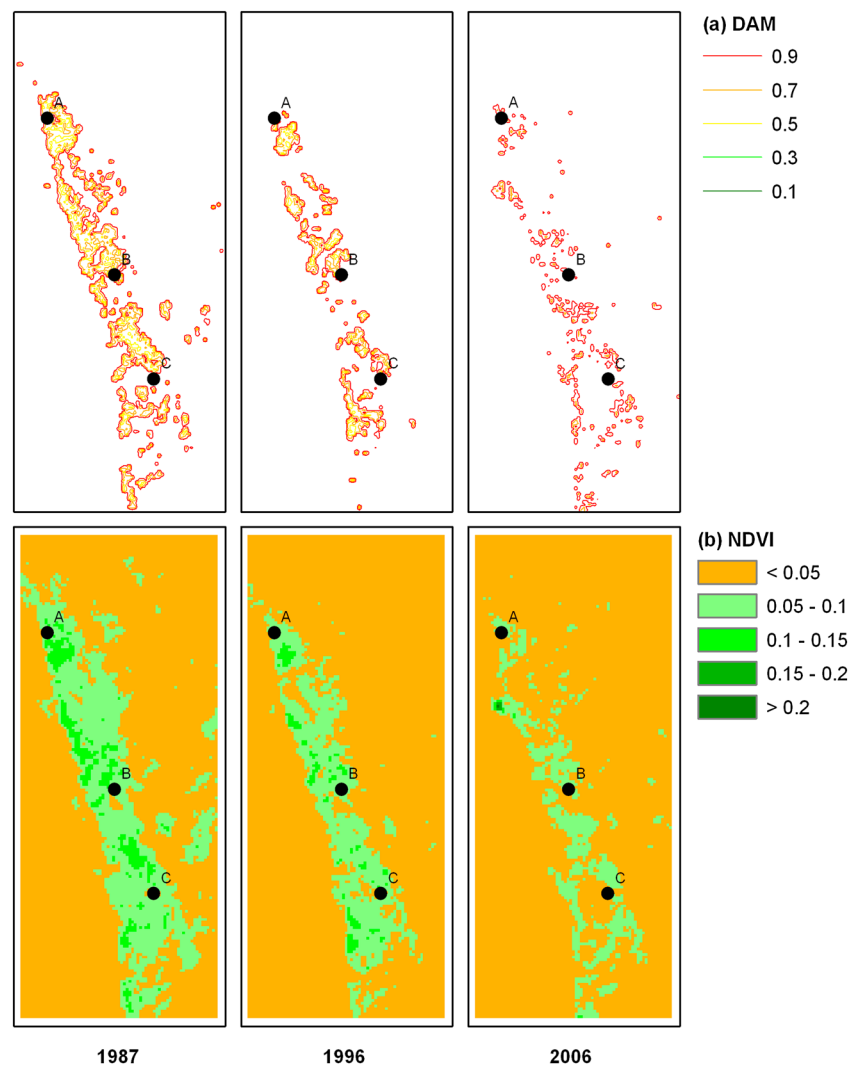


Figure 2. Distributions of (a) DAM and (b) NDVI at the Huangjiang site. Locations A ($104^{\circ}19'5''\text{E}$, $38^{\circ}25'2''\text{N}$), B ($104^{\circ}19'58''\text{E}$, $38^{\circ}24'6''\text{N}$), and C ($104^{\circ}20'16''\text{E}$, $38^{\circ}23'9''\text{N}$) were selected for further analyses.

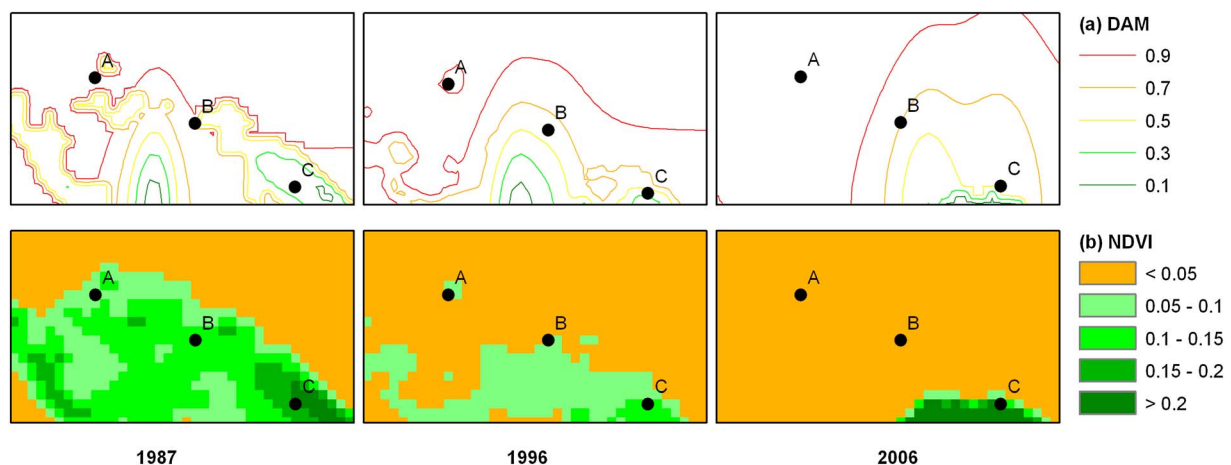


Figure 3. Distributions of (a) DAM and (b) NDVI at the Donghu site. Locations A ($103^{\circ}44'15''\text{E}$, $39^{\circ}0'34''\text{N}$), B ($103^{\circ}44'30''\text{E}$, $39^{\circ}0'27''\text{N}$), and C ($103^{\circ}44'38''\text{E}$, $39^{\circ}0'23''\text{N}$) were selected for further analyses.

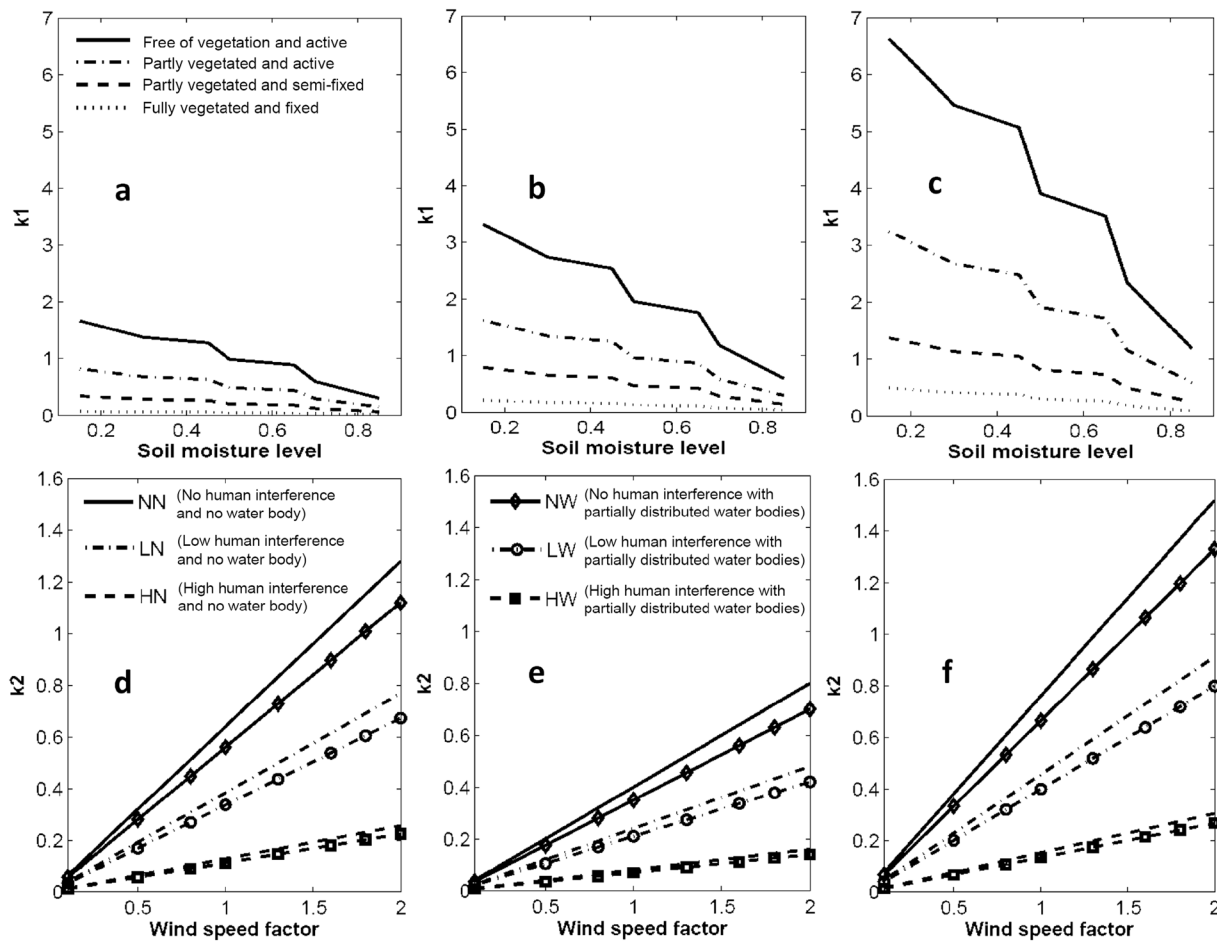


Figure 4. Relationships between parameters (a–c) k_1 and (d–f) k_2 and their impact factors.

It is shown that k_1 and k_2 are useful for analyzing effects of surface process and wind energy on DAM movement, where a multitude of uncertainties exist under various scenarios of climate change and human interference. The magnitudes of k_1 and k_2 variations are informative for quantifying influences of various desertification-driving factors. Furthermore, k_1 and k_2 may also reflect dynamics of impacts from vegetation

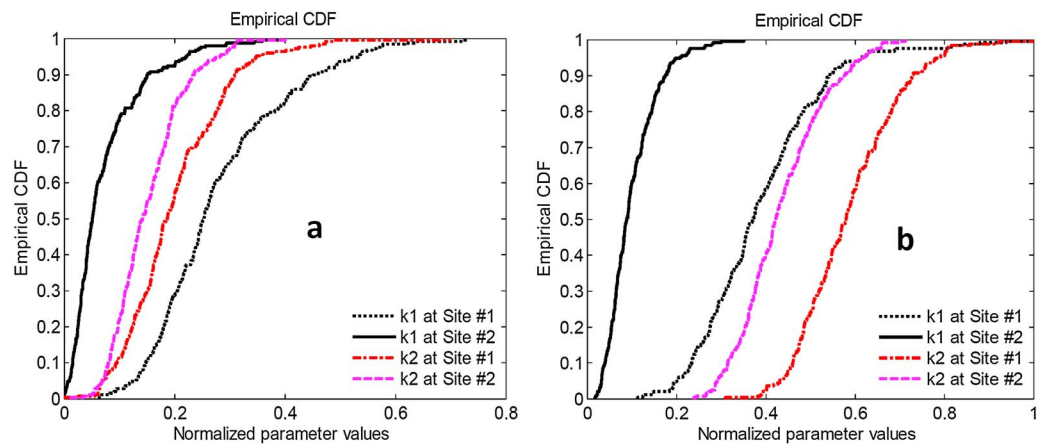


Figure 5. Stochastic characteristics of k_1 and k_2 in summer (a) 1996 and (b) 2006.

cover, desert activity, soil moisture, wind energy, hydrological effects, and human interference through reflection of their temporal variations. They are also applicable to other desertification-stricken areas where multiple geological, geographical, hydrological, and climatic conditions exist. Further sensitivity analyses also demonstrate significant effects of k_1 and k_2 on the desertification process. The spatial heterogeneity is related to distribution of DAM sources and geographical conditions of receptor zones. These results demonstrate that climatic conditions (e.g., temperature, vapor pressure, and wind speed) and human interference do have significant impacts on the desertification process.

4. Conclusions

Disentangling the underlying mechanisms of nonstationary desert-oasis interactions is of key importance for preventing and reversing desertification for vast tracts around the world under climate change. The work initiates a new concept of DAM and a DAM-based theoretical model to conceptualize and analyze desertification processes. The DAM concept was used to reveal nonstationary complexities of desertification process in the Minqin County under climate change and human interference. Various factors responsible for desertification, such as climate conditions, human activities, desert morphology, soil moisture, topographic conditions, and hydrologic features, were considered. Desertification level and its spatiotemporal dynamics were conceptualized through differential analyses. Although some physical and biological components are simplified, the results reveal a number of interesting phenomena and tendencies. The result suggests that climate change (e.g., variations in moisture content and wind) and human interference (e.g., artificial barriers such as trees, grasslands, and shelter belts) have significant impacts on the desertification of northwestern China over the past two decades. It is concluded that land degradation can be well simulated as the spreading of DAM. The proposed approach can be extended to other arid or semiarid regions for describing desert-oasis interactions, quantifying influences of various desertification-driving factors, and analyzing dynamics of nonstationary desertification processes. In future studies, the proposed method can also be improved through including more details of the land surface processes.

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References

- Chinese Academy of Sciences (2010), Thematic database for human-Earth system, *Rep.*
- China Meteorological Administration (2010), China Meteorological Data Sharing Service System, edited.
- Collado, A. D., E. Chuvieco, and A. Camarasa (2002), Satellite remote sensing analysis to monitor desertification processes in the crop-rangeland boundary of Argentina, *J. Arid Environ.*, 52(1), 121–133.
- Danfeng, S., R. Dawson, and L. Baoguo (2006), Agricultural causes of desertification risk in Minqin, China, *J. Environ. Manag.*, 79(4), 348–356.
- Ding, H. P., J. P. Chen, and G. W. Wang (2009), A model for desertification evolution employing GIS with cellular automata, paper presented at Computer Modeling and Simulation, 2009. ICCMS'09. International Conference on, IEEE.
- D'Odorico, P., F. Laio, and L. Ridolfi (2005), Noise-induced stability in dryland plant ecosystems, *Proc. Natl. Acad. Sci. U.S.A.*, 102(31), 10,819–10,822.
- Ehrlich, D., J. Estes, and A. Singh (1994), Applications of NOAA-AVHRR 1 km data for environmental monitoring, *Remote Sens.*, 15(1), 145–161.
- Garbulsky, M. F., and J. M. Paruelo (2004), Remote sensing of protected areas to derive baseline vegetation functioning characteristics, *J. Vegetation Sci.*, 15(5), 711–720.
- Guo, Z. T., W. F. Ruddiman, Q. Z. Hao, H. B. Wu, Y. S. Qiao, R. X. Zhu, S. Z. Peng, J. J. Wei, B. Y. Yuan, and T. S. Liu (2002), Onset of Asian desertification by 22 Myr ago inferred from loess deposits in China, *Nature*, 416(6877), 159–163.
- Hahn, B., F. Richardson, M. Hoffman, R. Roberts, S. Todd, and P. Carrick (2005), A simulation model of long-term climate, livestock and vegetation interactions on communal rangelands in the semi-arid Succulent Karoo, Namaqualand, South Africa, *Ecol. Modell.*, 183(2), 211–230.
- Huang, G. H. (1992), A stepwise cluster analysis method for predicting air quality in an urban environment, *Atmos. Environ. Part B Urban Atmos.*, 26(3), 349–357.
- Huang, G. H., X. S. Qin, and L. He (2009), An integrated modeling framework for supporting airshed environmental management in the Windsor-Detroit Pilot Area, *Rep.*, Environment Canada, Ottawa.
- Jordan, Y., A. Ghulam, and M. Chu (2014), Assessing the impacts of future urban development patterns and climate changes on total suspended sediment loading in surface waters using geoinformatics, *J. Environ. Inf.*, 24(2), 65–79.
- Kéfi, S., M. Rietkerk, C. L. Alados, Y. Pueyo, V. P. Papanastasis, A. ElAich, and P. C. De Ruiter (2007), Spatial vegetation patterns and imminent desertification in Mediterranean arid ecosystems, *Nature*, 449(7159), 213–217.
- Klausmeier, C. A. (1999), Regular and irregular patterns in semiarid vegetation, *Science*, 284(5421), 1826–1828.
- Kuehl, R. O., R. P. Breckenridge, and M. Panda (1995), Integrated response plot designs for indicators of desertification, *Environ. Monit. Assess.*, 37(1–3), 189–209.
- Lane, L. J., and E. D. Shirley (1988), Modelling erosion on hillslopes, in *Modelling Geomorphological Systems*, edited by M. G. Anderson, John Wiley, New York.
- Li, X., D. Xiao, X. He, W. Chen, and D. Song (2007), Evaluation of landscape changes and ecological degradation by GIS in arid regions: A case study of the terminal oasis of the Shiyang River, northwest China, *Environ. Geol.*, 52(5), 947–956.
- Madanian, M., A. Soffianian, and A. Hajian (2014), Change detection through four techniques using multi-temporal landsat thematic mapper data: A case study on Falavarjan area, Isfahan, Iran, *J. Environ. Inf.*, 23(2), 58–66.
- Maestre, F. T., J. L. Quero, N. J. Gotelli, A. Escudero, V. Ochoa, M. Delgado-Baquerizo, M. García-Gómez, M. A. Bowker, S. Soliveres, and C. Escolar (2012), Plant species richness and ecosystem multifunctionality in global drylands, *Science*, 335(6065), 214–218.

- Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer (2008), Climate change—Stationarity is dead: Whither water management?, *Science*, 319(5863), 573–574.
- Moncrieff, J., Y. Malhi, and R. Leuning (1996), The propagation of errors in long-term measurements of land-atmosphere fluxes of carbon and water, *Global Change Biol.*, 2(3), 231–240.
- Moreira, D. M., M. T. Vilhena, D. Buske, and T. Tirabassi (2006), The GILTT solution of the advection-diffusion equation for an inhomogeneous and nonstationary PBL, *Atmos. Environ.*, 40(17), 3186–3194.
- Mueller, E. N., J. Wainwright, and A. J. Parsons (2007), The stability of vegetation boundaries and the propagation of desertification in the American Southwest: A modelling approach, *Ecol. Modell.*, 208(2), 91–101.
- Mulitza, S., D. Heslop, D. Pittauerova, H. W. Fischer, I. Meyer, J.-B. Stuu, M. Zabel, G. Mollenhauer, J. A. Collins, and H. Kuhnert (2010), Increase in African dust flux at the onset of commercial agriculture in the Sahel region, *Nature*, 466(7303), 226–228.
- Munson, S. M., J. Belnap, and G. S. Okin (2011), Responses of wind erosion to climate-induced vegetation changes on the Colorado Plateau, *Proc. Natl. Acad. Sci. U.S.A.*, 108(10), 3854–3859.
- Ni, J., A. Wu, T. Li, Y. Yue, and A. Borthwick (2014), Efficient soil loss assessment for large basins using smart coded polygons, *J. Environ. Inf.*, 23(2), 47–57.
- Niu, X., J. Williams, D. Miller, K. Lehnert, B. Bills, and S. Brantley (2014), An ontology driven relational geochemical database for the Earth's critical zone: CZchemDB, *J. Environ. Inf.*, 23(2), 10–23.
- Qin, X. S., G. H. Huang, L. He, and R. F. Liao (2004), Air dispersion modeling of air pollutant emissions, *Rep.*, Environmental Affairs, TransGas and SaskEnergy.
- Reynolds, J. F., P. R. Kemp, K. Ogle, and R. J. Fernández (2004), Modifying the 'pulse-reserve' paradigm for deserts of North America: Precipitation pulses, soil water, and plant responses, *Oecologia*, 141(2), 194–210.
- Reynolds, J. F., D. M. S. Smith, E. F. Lambin, B. Turner, M. Mortimore, S. P. Batterbury, T. E. Downing, H. Dowlatabadi, R. J. Fernández, and J. E. Herrick (2007), Global desertification: Building a science for dryland development, *Science*, 316(5826), 847–851.
- Saco, P. M., G. R. Willgoose, and G. R. Hancock (2007), Eco-geomorphology of banded vegetation patterns in arid and semi-arid regions, *Hydrol. Earth Syst. Sci.*, 11(6), 1717–1730.
- Schlesinger, W. H., J. F. Reynolds, G. L. Cunningham, L. F. Huenneke, W. M. Jarrell, R. A. Virginia, and W. G. Whitford (1990), Biological feedbacks in global desertification, *Science*, 247(4946), 1043–1048.
- Seely, M., E. Dirks, C. Hager, P. Klintonberg, C. Roberts, and D. von Oertzen (2008), Advances in desertification and climate change research: Are they accessible for application to enhance adaptive capacity?, *Global Planet. Change*, 64(3), 236–243.
- Song, K., L. Li, L. Tedesco, H. Duan, L. Li, and J. Du (2014), Remote quantification of total suspended matter through empirical approaches for inland waters, *J. Environ. Inf.*, 23(1), 23–36.
- Sun, D. (2015), Detection of dryland degradation using Landsat spectral unmixing remote sensing with syndrome concept in Minqin County, China, *Int. J. Appl. Earth Observ. Geoinf.*, 41, 34–45.
- Sun, D., R. Dawson, H. Li, and B. Li (2005), Modeling desertification change in Minqin county, China, *Environ. Monit. Assess.*, 108(1–3), 169–188.
- Sun, D., D. Richard, and B. Li (2006), Agricultural causes of desertification risk in Minqin, China, *J. Environ. Manag.*, 79(4), 348–356.
- Sun, D., R. Dawson, H. Li, R. Wei, and B. Li (2007), A landscape connectivity index for assessing desertification: A case study of Minqin County, China, *Landsc. Ecol.*, 22(4), 531–543.
- Sun, S., and G. Wang (2011), Diagnosing the equilibrium state of a coupled global biosphere-atmosphere model, *J. Geophys. Res.*, (1984–2012), 116, doi:10.1029/2010JD015224.
- Tietjen, B., and F. Jeltsch (2007), Semi-arid grazing systems and climate change: A survey of present modelling potential and future needs, *J. Appl. Ecol.*, 44(2), 425–434.
- Tucker, C. J., H. E. Dregne, and W. W. Newcomb (1991), Expansion and contraction of the Sahara Desert from 1980 to 1990, *Science*, 253(5017), 299–301.
- United States Geological Survey (2010a), Provided by the China Meteorological Administration.
- United States Geological Survey (2010b), Global 30 Arc-Second Elevation Data Set.
- U.S. and National Research Council (USNRC) (2012), *Urban Meteorology: Forecasting, Monitoring, and Meeting Users' Needs*, National Academies Press, Washington, D. C.
- Vilhena, M. T., C. P. Costa, D. M. Moreira, and T. Tirabassi (2008), A semi-analytical solution for the three-dimensional advection-diffusion equation considering non-local turbulence closure, *Atmos. Res.*, 90(1), 63–69.
- Von Hardenberg, J., E. Meron, M. Shachak, and Y. Zarmi (2001), Diversity of vegetation patterns and desertification, *Phys. Rev. Lett.*, 87(19), 198101.
- Wang, L., Y. Huang, L. Wang, and G. Wang (2014), Pollutant flushing characterizations of stormwater runoff and their correlation with land use in a rapidly urbanizing watershed, *J. Environ. Inf.*, 23(1), 44–54.
- Wang, X., F. H. Chen, Z. Dong, and D. Xia (2005), Evolution of the southern Mu Us Desert in North China over the past 50 years: An analysis using proxies of human activity and climate parameters, *Land Degrad. Dev.*, 16(4), 351–366.
- Wang, X., Y. Yang, Z. Dong, and C. Zhang (2009), Responses of dune activity and desertification in China to global warming in the twenty-first century, *Global Planet. Change*, 67(3), 167–185.
- Wang, Z. Y., G. H. Huang, G. Q. Wang, and J. Gao (2004), Modeling of vegetation-erosion dynamics in watershed systems, *J. Environ. Eng.*, 130(7), 792–800.
- Wang, Z. Y., G. Q. Wang, and G. H. Huang (2008), Modeling of state of vegetation and soil erosion over large areas, *Int. J. Sediment. Res.*, 23(3), 181–196.
- Weng, Q. H., U. Rajasekar, and X. F. Hu (2011), Modeling urban heat islands and their relationship with impervious surface and vegetation abundance by using ASTER images, *IEEE Trans. Geosci. Remote Sens.*, 49(10), 4080–4089.
- Wiggs, G. F., D. S. Thomas, J. E. Bullard, and I. Livingstone (1995), Dune mobility and vegetation cover in the southwest Kalahari Desert, *Earth Surf. Processes Landforms*, 20(6), 515–529.
- Wischmeier, W. H., and D. D. Smith (1960), A universal soil-loss equation to guide conservation farm planning, *Trans. 7th int. Congr. Soil Sci.*, 1, 418–425.
- Wischmeier, W. H., and D. D. Smith (1978), Predicting rainfall erosion losses—A guide to conservation planning, *Predicting rainfall erosion losses-A guide to conservation planning*.
- Xu, D. M., X. Z. Xu, Y. Z. Xie, and K. Wang (2012), Dynamics of sandy desertification and detection of sandy land/steppe boundary: Vegetation and soil properties, *Pol. J. Ecol.*, 60(2), 251–263.
- Xue, X., J. Liao, Y. T. Hsing, C. H. Huang, and F. M. Liu (2015), Policies, land use, and water resource management in an arid oasis ecosystem, *Environ. Manag.*, 55(5), 1036–1051.