Land Use Change and Its Driving Factors in Ecological Function Areas: A Case Study of the Hedong Region in Gansu Province, China Postprint

Authors: WEI Zhudeng

Date: 2024-01-12T00:00:00+00:00

Abstract

Land use and cover change (LUCC) is important for the provision of ecosystem services. An increasing number of recent studies link LUCC processes to ecosystem services and human well-being at different scales recently. However, the dynamic of land use and its drivers receive insufficient attention within ecological function areas, particularly in quantifying the dynamic roles of climate change and human activities on land use based on a long time series. This study utilizes geospatial analysis and geographical detectors to examine the temporal dynamics of land use patterns and their underlying drivers in the Hedong Region of the Gansu Province from 1990 to 2020. Results indicated that grassland, cropland, and forestland collectively accounted for approximately 99% of the total land area. Cropland initially increased and then decreased after 2000, while grassland decreased with fluctuations. In contrast, forestland and construction land were continuously expanded, with net growth areas of 6235.2 and 455.9 km2, respectively. From 1990 to 2020, cropland was converted to grassland, and both of them were converted to forestland as a whole. The expansion of construction land primarily originated from cropland. From 2000 to 2005, land use experienced intensified temporal dynamics and a shift of relatively active zones from the central to the southeastern region. Grain yield, economic factors, and precipitation were the major factors accounting for most land use changes. Climatic impacts on land use changes were stronger before 1995, succeeded by the impact of animal husbandry during 1995-2000, followed by the impacts of grain production and gross domestic product (GDP) after 2000. Moreover, agricultural and pastoral activities, coupled with climate change, exhibited stronger enhancement effects after 2000 through their interaction with population and economic factors. These patterns closely correlated with ecological restoration projects in China since 1999. This study implies the importance of synergy between human activity and climate change for optimizing land use via ecological patterns in the ecological function area.

Full Text

Preamble

Land use change and its driving factors in the ecological function area: A case study in the Hedong Region of Gansu Province, China

WEI Zhudeng*, DU Na, YU Wenzheng
School of Geographical Science, Nanjing University of Information Science & Technology, Nanjing 210044, China

Abstract: Land use and cover change (LUCC) is critical for ecosystem service provision. Recent studies increasingly link LUCC processes to ecosystem services and human well-being across scales, yet the dynamics of land use and its drivers receive insufficient attention within ecological function areas, particularly regarding quantification of climate change and human activity impacts based on long time series. This study employs geospatial analysis and geographical detectors to examine temporal dynamics of land use patterns and their underlying drivers in the Hedong Region of Gansu Province from 1990 to 2020. Results indicate that grassland, cropland, and forestland collectively accounted for approximately 99% of the total land area. Cropland initially increased then decreased after 2000, while grassland decreased with fluctuations. In contrast, forestland and construction land expanded continuously, with net growth of 6235.2 km^2 and 455.9 km^2, respectively. From 1990 to 2020, cropland converted to grassland, and both converted to forestland overall. Construction land expansion primarily originated from cropland. From 2000 to 2005, land use experienced intensified temporal dynamics, with relatively active zones shifting from central to southeastern regions. Grain yield, economic factors, and precipitation were the major drivers accounting for most land use changes. Climatic impacts on land use changes were stronger before 1995, succeeded by animal husbandry impacts during 1995-2000, followed by grain production and gross domestic product (GDP) impacts after 2000. Moreover, agricultural and pastoral activities, coupled with climate change, exhibited stronger enhancement effects after 2000 through their interaction with population and economic factors. These patterns closely correlate with ecological restoration projects in China since 1999. This study highlights the importance of synergy between human activity and climate change for optimizing land use via ecological patterns in ecological function areas.

Keywords: land use; land type; geographic detector; driving mechanism; Hedong Region

Citation: WEI Zhudeng, DU Na, YU Wenzheng. 2024. Land use change and its driving factors in the ecological function area: A case study in the Hedong Region of Gansu Province, China. *Journal of Arid Land*, 16(1): 71-90. https://doi.org/10.1007/s40333-024-0001-7

1 Introduction

Land use and cover change (LUCC) alters Earth' s energy balance and biogeochemical cycles, influencing land surface properties and ecosystem services [?, ?, ?, ?, ?]. An estimated three-quarters of Earth' s land surface has undergone human-induced alterations in the last millennium [?, ?]. Within just six decades (1960–2019), nearly one-third of global land area experienced land use change, indicating significant and accelerating transformation of land systems [?, ?]. These substantial changes have led to regional and global environmental challenges by influencing Earth system processes, including impacts on carbon sources and sinks [?, ?], land degradation [?, ?], ecological productivity [?, ?, ?], climate change [?, ?], habitat and species diversity loss [?, ?], ecosystem services decline [?, ?], and threats to food security [?, ?]. Consequently, LUCC has become fundamental to prominent international scientific research programs such as the International Geosphere-Biosphere Programme (IGBP), International Human Dimensions Programme (IHDP) on Global Environmental Change, and Future Earth [?, ?, ?, ?].

Understanding LUCC driving mechanisms and spatiotemporal patterns is crucial for assessing land use change direction and extent. This knowledge is essential for sustainable land use, enhancing ecosystem services, and mitigating global environmental challenges associated with LUCC [?, ?]. Particularly, as global population consumption rates grow, heightened demand for natural resources and food will intensify ecosystem stress, posing increasingly severe sustainability challenges. In recent decades, numerous studies have focused on LUCC across spatiotemporal scales, encompassing detection of spatiotemporal LUCC processes, analysis of driving factors and mechanisms, construction of quantitative indicators, and simulation of LUCC processes [?, ?, ?, ?]. These studies aim to evaluate ecological and social effects of LUCC at different scales. Under the Future Earth project influence, recent LUCC research has progressively shifted toward global sustainability, focusing on coupling relationships among LUCC processes at different scales, ecosystem services, and human well-being [?, ?, ?, ?, ?].

Despite LUCC being a core issue, land use change driving mechanisms remain unclear. Although significant progress has been made in quantifying land use change dynamics [?, ?, ?], debates persist in monitoring land use dynamics. Song et al. (2018) reported a 7.1% increase in tree cover, challenging the prevailing view that global forest area has declined. Quantifying relative contributions of various driving factors is particularly challenging. While anthropogenic activities are widely acknowledged as direct and dominant LUCC drivers at various spatial scales [?, ?, ?, ?], other studies indicate natural factors outweigh human factors [?, ?, ?], especially in ecologically fragile areas. Batllori et al. (2020) revealed that warming and drying climate led to 10% conversion of forest land into shrubland and grassland. Climate change is considered the main reason for grassland degradation in Central Asia [?, ?]. This complexity arises from multiple factor interactions influencing LUCC processes. Land use intensity varies within single land types, and transformations among different land types are intricate [?, ?, ?]. Accordingly, strong geographically diverging characteristics of land use change processes play significant roles [?, ?].

The Hedong Region in Gansu Province serves as a typical area for investigating regional land use change processes and underlying driving mechanisms, focusing on ecological function maintenance and space optimization. Surrounded by the Qinghai-Tibet Plateau Eco-zone, the Sichuan-Yunnan and Loess Plateau Ecological Barrier, and the North Sand Prevention Belt [?, ?, ?], the region is a crucial part of national ecological function areas in China [?, ?]. The Hedong Region' s distinctive geographical characteristics raise important questions: What are the characteristics of local land use pattern changes over the past 30 years? How can we quantify the relative contribution of climate and human activities to land use dynamics? What differences exist in driving mechanisms of various factors on land use patterns over time or under different stages of ecological restoration projects? This study utilizes an annual high-resolution LUCC dataset from 1990 to 2020 to analyze spatiotemporal dynamics of land use in the Hedong Region. The primary objective is to optimize ecological patterns, enhance land resource allocation, and promote sustainable development within designated ecological function areas.

2.1 Study area

The Hedong Region (32°52 -37°30 N, 100°73 -108°73 E) is located east of the Yellow River in Gansu Province, China. It is bordered by the Qinghai-Tibet Plateau to the west, the Qinling Mountains to the south, the Tengger Desert to the north, and the Loess Plateau to the east. Terrain slopes from west to east, showing significant elevation variation ranging from 600 to 4830 m. The Gannan Plateau is characterized by a high-altitude cold and humid climate, while other regions are influenced by the tailing edge of summer monsoon, resulting in a semi-arid and semi-humid climate. Consequently, the local ecosystem exhibits distinctive characteristics, serving as ecotones between forest, steppe, and agricultural land. In terms of land use, it represents a typical agro-pastoral transitional zone. Corresponding to complex and diverse landforms, ecological functions in the Hedong Region span from water conservation in the southwest to soil-water conservation in the northeast, sand fixation in the north, biodiversity protection in the south, and agricultural product provision in the central part. Administrative divisions include 9 prefecture-level cities (Lanzhou, Baiyin, Tianshui, Pingliang, Dingxi, Qingyang, Longnan, Linxia Hui Autonomous Prefecture, and Gannan Tibetan Autonomous Prefecture) and 67 counties, comprising a total area of 178\$×10^{3}\$ km^{2}.

2.2 Data sources and processing

Annual LUCC data from 1990 to 2020 were obtained from the Chinese Land Cover Yearly Data (CLCD) published by Yang and Huang (2021). The data have a high resolution of 30 m, with overall accuracy averaging 79.31% for nine land types. This dataset is widely used in recent LUCC studies [?, ?, ?]. In this study, forest and shrub land were classified as "forest," while snow/ice, water, and wetland were classified as "water." Six major land use types were used: cropland, forest land, grassland, water body, bare land, and construction land.

Annual precipitation and annual average temperature data were derived from meteorological observations at 62 stations within the study area, sourced from the National Meteorological Science Data Center of China (https://data.cma.cn/). County-level climatic data were obtained by averaging values from meteorological stations within each county or through spatial interpolation. Socioeconomic statistical data at the county level were compiled from the Gansu Provincial Bureau of Statistics (https://tjj.gansu.gov.cn/), Gansu Economic Information Network (https://www.gsei.com.cn/), and statistical yearbooks of various cities (prefectures) from 1990 to 2020. Seven indicators were selected, considering land use characteristics and the advanced state of agriculture and animal husbandry in the Hedong Region .

2.3.1 Land use transition matrix

The land use transition matrix is a widely used method to quantify area transformation among different land use types between two periods. It helps understand the destination of each land type at the initial period and the sources and composition of land use types at the final period [?, ?]. The equation is as follows:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix}$$

where S_{ij} is the land area transitioning from land use type i to j (km^2), and n is the number of land use types ($n = 6$). This study computes a land use transition matrix every five years to facilitate comprehensive examination of land use dynamic characteristics and explore changes corresponding to different stages of ecological restoration projects. Furthermore, a transition matrix from 1990 to 2020 provides an overview of land use changes during the past 30 years.

2.3.2 Land use dynamic degree

The land use dynamic degree index reveals quantitative characteristics of certain land use changes and represents the LUCC change rate [?, ?]. Dynamic degree for single land use type is calculated using Equation 2:

$$D = \frac{S_j - S_i}{S_i} \times \frac{1}{T} \times 100\%$$

where D is the dynamic degree; S_i and S_j are the areas of land use type i in the initial and final years, respectively (km^2); and T is the time span between the initial and final years (years). Dynamic degree of all land types, also known as comprehensive dynamic degree (total changed area divided by total area for all land types and time), is calculated to reflect overall land use change speed in the study area and examine regional differences in land use dynamics.

2.3.3 Geographical detector

Geographical detector is a spatial statistical method that detects spatial heterogeneity and quantifies relative significance of driving forces on dependent variables [**?**, **?**, **?**]. The core idea is that if an explanatory variable impacts a response variable, it will exhibit similar spatial distribution characteristics. Compared with other methods such as logistic regression, this method has the advantage of immunity to multicollinearity among multiple explanatory variables [**?**, **?**]. Geographical detector includes factor detectors, risk detectors, ecological detectors, and interactive detectors.

Specifically, factor detectors can determine whether explanatory variable X is an influencing factor of response variable Y (change rate of land use area) and explain the spatial differentiation mechanism of the response variable. It is represented by the q value as:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where L is the stratification of response variable Y or explanatory factor X. In this study, it represents different-level rates of land area change at the county scale within the study area. N_h and N are the number of units in stratum h and the whole area, respectively; σ_h^2 and σ^2 are variances of response variable Y values in stratum h and the whole area, respectively. Significance level is denoted by P value. A smaller P value and a q-statistic closer to 1 indicate stronger explanatory power of the driving factor for land use change.

Interactive detectors can evaluate whether driving factors X_1 and X_2 have interactive influence on response variable Y. Interaction relationships are determined by comparing the combined contribution (q value) of two individual factors and their independent contributions. In this study, nine explanatory variables (X_1-X_9; Table 1) and the response variable (Y; Table 1) at the county scale (67 counties total) are defined as temporal change rates over the study period. The rate of change is determined through simple linear regression. Additionally, data discretization can significantly impact detection results. This study employs the method provided by Cao et al. (2013) to determine the optimal number of intervals and discretization method, with results listed in Table S1.

3.1 Spatiotemporal pattern of LUCC

The spatial pattern of LUCC in the Hedong Region over the past 30 years is shown in Figure 1 [Figure 1: see original paper]. Grassland, forest land, and cropland are the dominant land use types, constituting 99.00% of the total area. From southeast to northwest, a discernible distribution pattern emerges, transitioning from forest land to cropland and grassland. This phenomenon can be attributed to diminishing hydrothermal conditions from southeast to northwest, influenced by regional terrain and summer monsoon circulation patterns.

Grassland is the largest land use type, mainly distributed in the Gannan Plateau and northern parts of Lanzhou, Baiyin, and Qingyang cities. In 2020, grassland area was 96,768.41 km^2, accounting for 54.42% of the total area. Cropland and forest land areas in 2020 were approximately equal, with proportions of 23.02% and 21.38%, respectively. Cropland was predominantly concentrated in the central and eastern parts, mostly situated in the Loess Plateau in eastern Gansu and valley plains of the river system in the Longnan Mountains. In contrast, forest land is mainly distributed in the southern part, specifically within the Longnan Mountains (Fig. 1).

Water body, construction land, and bare land had very small areas. In 2020, their proportions were 0.26%, 0.44%, and 0.48%, respectively. Construction land exhibited a distinct strip-shaped distribution, with major cities situated on both banks of rivers, reflecting the constraining impact of water resources on human activities. Notably, Lanzhou City is located along the Yellow River, Tianshui City along the Weihe River, and Pingliang City along the Jinghe River. The primary urban area of Lanzhou City made the largest contribution to construction land. Water bodies mainly include rivers, reservoirs, wetlands, and snow/ice, such as the Liujiaxia Reservoir and Yellow River in Gansu Province. Wetlands and snow/ice were mainly distributed in Maqu and Luqu counties in Gannan Tibetan Autonomous Prefecture. Bare land was primarily limited to the northern part.

Visual comparison of land use spatial distribution across different time periods revealed a discernible expansion trend for forest land and construction land. The most notable construction land expansion occurred around Lanzhou, Pingliang, and Tianshui cities. In the southeastern part (Fig. 1), forest land presented a visibly greener and more continuous pattern. Water body distribution remained relatively stable. Table 2 provides land use area statistics for different years. Grassland area decreased and fluctuated from 1990 to 2020, with the most significant change occurring from 1990 to 2000 (net decrease of 4434.60 km^2). Cropland area showed an initial increase followed by decrease. From 1990 to 2000, there was a net increase of 3114.11 km^2, while from 2000 to 2020, there was a net decrease of 5311.22 km^2. Forest land area exhibited steady increase, with net growth of 6235.24 km^2. Water body area had a small base, showing decreasing trend followed by gradual recovery after 2010 to the initial 1990 level. Bare land area decreased sharply by half from 1990 to 2000 and gradually increased since 2000, showing significant fluctuations. Construction land expansion was evident, with 2020 area exceeding twice that of 1990.

3.2.1 Characteristics of land use conversion

Over the past 30 years, the study area exhibited significant spatial variations in land use conversion (Fig. 2 [Figure 2: see original paper]). Between 1990 and 2020, converted land area totaled 31,430.90 km^2, with primary conversions observed in grassland and cropland. Among other land use types, 12,251.06 km^2 converted to grassland, of which 11,019.61 km^2 came from cropland, accounting for 90.00% of total conversion area (Table 3). Additionally, 10,942.02 km^2 of other lands converted to cropland, with 96.00% coming from grassland. Forest land and barren land conversion followed, with inflow areas of 556.09 km^2 and 592.11 km^2, respectively. However, both grassland and cropland areas decreased from 1990 to 2020 (Table 1). In contrast, forest land area experienced net increase of 6235.24 km^2, indicating conversion of cropland to grassland and transition of both cropland and grassland to forest land overall from 1990 to 2020.

Grassland played a prominent role in the spatial distribution of land use conversions, covering most areas of the Hedong Region (Fig. 2). Cropland expansion predominantly occurred in the Loess Plateau in eastern Gansu Province and the Longnan Mountains. Conversion of other lands to forest land occurred mainly in the Longnan Mountains, resulting primarily from grassland reduction. Therefore, mutual conversions among cropland, forestland, and grassland mainly occurred at connecting belts of the three land types, especially noticeable in Longnan City, Tianshui City, and Qingyang City. Construction land expansion concentrated mainly in large cities at the expense of cropland. Conversion of other land use types to barren land occurred mainly in northern parts of Lanzhou and Baiyin cities. Water body increase was mainly attributed to wetland and snow/ice area changes in Gannan Tibetan Autonomous Prefecture, totaling 155.29 km^2 converted to water body. Additionally, construction of the Yingwu Reservoir in Jingtai County in 2010, designed to support agricultural production and domestic water use in northern Baiyin City, substantially contributed to water body expansion in the northern part.

3.2.2 Dynamics of land use conversion

The dynamic degree index reveals variations in both rate and direction of area change for each land use type across periods (Fig. 4 [Figure 4: see original paper]). Construction land consistently exhibited high positive values in all six periods, indicating continuous expansion trend in the Hedong Region over the past 30 years, particularly reaching 4.07% from 2005 to 2010. Bare land exhibited the most significant fluctuations among all land use types, decreasing significantly from 1990 to 1995 with the largest dynamic degree of -8.87% among all land use types during all periods. In contrast, it showed dramatic rebound from 2000 to 2005 and from 2015 to 2020, with expansion exceeding that of construction land. Water body dynamic change experienced significant reduction from 1995 to 2000 and significant expansion from 2015 to 2020. Cropland, forest land, and grassland underwent relatively narrow fluctuations of decrease or expansion throughout all periods.

Dynamic degree of land use can reflect overall land use change influenced by various factors. Results show a dynamic degree of 0.25% from 1990 to 2020. The average dynamic degree across all periods for the study area during the same time scale is 0.56%, more than twice the initial value, suggesting significant temporal differentiation in impacts of natural and human activities on land use. Exploring land use change characteristics in different periods provides more detailed insights into driving factor impacts. From Figure 4, the most active dynamic changes occurred from 1990 to 1995 and from 2015 to 2020, with rates of 0.90% and 0.80%, respectively. The period from 2010 to 2015 ranked second, with a rate of 0.60%. Since 2000, the comprehensive dynamic degree of land use in the entire region increased on average by 0.15% on the basis of 0.23% during 1995-2000 in each five-year period, reaching 0.80% during 2015-2020, indicating steadily rising impact of driving forces on land use.

Moreover, significant spatial variations occurred in county-level land use dynamics across periods. As shown in Figure 5 [Figure 5: see original paper], dynamic changes primarily occurred in central and eastern parts. The most significant change occurred from 1990 to 1995, with Jingning County in Pingliang City experiencing the highest comprehensive dynamic degree (6.96%). From 2005 to 2010, overall change was relatively moderate, with Chongxin County in Pingliang City having the highest comprehensive dynamic degree (3.69%). Counties with strong dynamic changes varied through time, but clustering areas with higher dynamic rates showed overall shifting trend from central to east and southeast (Fig. 5). Dynamic changes in northern counties gradually shifted from active to inactive, with comprehensive dynamic changes in northern parts (mainly Lanzhou and Baiyin cities) stabilizing after 2005. In contrast, southeastern counties became more active after 2005. Spatiotemporal fluctuations of land use in Longnan City were very obvious. Some counties exhibited stable changes, such as Maqu County in Gannan Tibetan Autonomous Prefecture, which maintained the lowest dynamic change level, possibly due to its plateau environment and low population density.

3.3.1 Driving factors of LUCC

Each factor showed low explanatory power for change rates of six land use types over the past 30 years (Table 4). Factors affecting cropland changes ranked as grain yield (0.42) > GDP (0.36) > secondary industry (0.35) = precipitation (0.35) > primary industry (0.23). The Hedong Region still relies on agricultural production as its basic economic source. However, local population decreased in past decades. The region faces multiple challenges, including strain on agricultural economic inputs, adverse natural conditions, and food security, resulting in cropland area fluctuations. The main driving factor for forest land is GDP, with a q value of 0.45, followed by secondary industry, indicating that forest land changes are mainly influenced by human economic intervention. Factors affecting grassland ranked as grain yield (0.58) > precipitation (0.46) > GDP (0.40) > tertiary industry (0.25) > primary industry (0.20). Both grain yield and GDP have close relationships with ecological project effectiveness, such as returning farmland to forest land and grassland, while precipitation directly affects grass growth.

Primary driving factors for water body are GDP (0.49) and precipitation (0.48), followed by livestock inventory (0.32). Precipitation is vital for water supply in the Hedong Region, where water resources heavily rely on precipitation. In semi-arid areas, livestock requires substantial water resources. The main factor influencing construction land is socio-economic development level, with dominant factors being added values of three industries and GDP.

Interactive detection further reflects coupling effects of two factors on land use change (Fig. 6 [Figure 6: see original paper]), with bifactor analysis discernible for specific factors, particularly cropland, forest land, grassland, and construction land. For cropland, interactive effects followed a hierarchy of GDP population (0.74) = GDP secondary industry > GDP tertiary industry > secondary industry temperature, suggesting interactive effects involving GDP or secondary industry and other factors exhibited heightened explanatory power. Even considering grain yield, interactive effects for GDP grain yield and secondary industry grain yield demonstrated enhanced bifactor effects. Changes in GDP or secondary industry, coupled with alterations in annual precipitation and temperature, also augmented explanatory power. Similarly, interaction effects of nine factors on forest land displayed more pronounced nonlinear enhanced effects, particularly for GDP, population, grain yield, precipitation, and temperature, which exhibited enhanced effects in interaction with other factors. The most interactive effects followed a hierarchy of GDP secondary industry (0.80) > secondary industry temperature (0.65) > GDP grain yield (0.63). For grassland, stronger interactive effects were observed in the order of GDP secondary industry (0.64) > GDP grain yield (0.63) > GDP large livestock inventory (0.62).

For construction land, the most notable interactive effects were found between grain yield, tertiary industry, secondary industry, and other factors. For water body, only the interaction effect for grain yield GDP showed higher explanatory power of 0.68. For bare land, interactions between temperature or precipitation and other factors showed stronger nonlinear effects, with highest explanatory power reaching 0.59. In summary, primary driver factors for land use types were grain yield, GDP, and precipitation. For coupling effects, dominant interactive factors are economic factors (GDP and secondary industry) and others, followed by interaction between grain yield and other factors. For cropland, temperature impact was more pronounced than precipitation. Conversely, temperature and precipitation equally enhanced forest land and grassland changes when interacting with other factors. Moreover, large livestock inventory influence on grassland experienced significant enhancement through interaction with GDP. Construction land showed sensitivity to various factor interactions, particularly those involving grain yield and industries.

3.3.2 Dynamics

Dominant drivers for the six land types varied across periods, and dominant factors also differed for the same land type in different periods. As shown in Figure 7 [Figure 7: see original paper], grain yield had the strongest explanatory power during 2000-2005 (q value reached 0.59), 2005-2010, and 2010-2015 for cropland. Additionally, precipitation and temperature impacts on cropland and grassland fluctuated over time, with periods 2005-2010, 2010-2015, and 1990-1995 having better explanatory power. The difference was that livestock inventory had higher explanatory power during 1995-2000 and 2015-2020 for grassland. For forest land, GDP became particularly pronounced after 2000. Livestock inventory also had relatively better contribution to forest land during 2005-2020 compared to other periods, with strongest explanatory power during 2015-2020. Precipitation had strongest explanatory power during 1990-1995, 2005-2010, and 2010-2015 (Fig. 7).

In summary, primary drivers for cropland successively shifted from temperature to livestock inventory and grain yield. Similarly, for grassland, dominant drivers successively changed from temperature to livestock inventory, grain yield, and precipitation. For forest land, dominant drivers successively transitioned from precipitation to population, GDP, precipitation, and livestock inventory. Results indicated significant climate change impacts before 1995 shifted to animal husbandry impacts during 1995-2000, followed by grain production and GDP impacts after 2000 (2000-2015). Predominant driving factors in water body varied across periods, changing from population to livestock inventory, GDP, grain yield, precipitation, and grain yield. Grain yield emerged as the primary driving factor for bare land during 1990-2000 and 2010-2015, followed by precipitation or grain yield during 2000-2005, and primary industry during 2005-2010. This signifies that grain production and precipitation played pivotal roles in driving bare land changes across periods. For construction land, dominant factors shifted from three industries combined with GDP to climate changes, suggesting potential constraints imposed by climate change on construction land expansion.

Interaction detection analysis shows that combined effects of different factors on land use changes also varied across periods (Fig. 8 [Figure 8: see original paper]). Interaction effects on cropland were strong after 2000, significant between population and secondary industry/temperature/grain yield/precipitation during 2000-2010, and between grain yield and precipitation/large livestock inventory/temperature during 2010-2020. Climatic impact became notably more pronounced due to interactions with other factors after 2000. For forest land, factor interactive effects exhibited upward trend after 2005, especially during 2005-2010 and 2015-2020. Overall, stronger interactions were identified between large livestock inventory and grain yield/secondary industry/population/temperature, between grain yield and population/secondary industry, and between population and precipitation (Fig. 8). For grassland, interactive enhancement effects were relatively lower during 2000-2005 and peaked during 2015-2020, especially interaction between grain yield and climate change, suggesting grain yield and climate change could exert stronger influence on grassland.

For water body, nonlinear enhancement significantly occurred during 2000-2005. Enhancement effect on bare land changes was generally more significant during 1990-1995 and 2005-2010. Interaction between grain production or climate change and other factors could more significantly impact bare land. For construction land, interaction effects culminated during 2000-2005. In summary, interactive effects among various factors on different land uses displayed considerable complexity over time. Broadly, agricultural activities (reflected in grain yield), pastoral endeavors (represented by livestock inventory), and climate change exhibited heightened enhancement after 2000 through interactions with population and economic factors.

4.1 Driving mechanism of LUCC

Previous studies have identified LUCC and associated factors in different regions, such as Northwest China [**?**, **?**], the Taperoá River basin in northeastern Brazil [**?**, **?**], the north-western coastal desert of Egypt [**?**, **?**], Jimma Geneti District in western Ethiopia [**?**, **?**], and the Middle Suluh Valley in northern Ethiopia [**?**, **?**]. Many studies revealed LUCC patterns characterized by agricultural land expansion at the expense of woodland, grassland, and wetland over past decades. For instance, Hailu et al. (2020) reported wetlands declined by 19.2% from 1973 to 2019 in Jimma Geneti District, while dominant cultivated land increased by 13.0% at 7.4 km^2/year. This pattern appears similar to land use dynamics in the Hedong Region before 2000 but is not applicable after 2000.

This study suggests dividing land use and cover in the Hedong Region into two primary stages during 2000-2005, with significantly different land use dynamics between stages. In the first stage (1990-2000), land use transition structure was not conducive to enhancing ecological function, environmental sustainability, and socioeconomic well-being. Construction land encroached on cultivated land, and in quest for more food, grasslands, bare land, and water body were reclaimed as cultivated land, resulting in ecological problems such as desertification and sandstorms [**?**, **?**]. Although local forests increased during this stage, it was largely a result of the Three-North Forest Shelterbelts Program launched in 1979 in China [**?**, **?**]. However, some studies indicated this forest land increase was mainly achieved by destroying grassland and farmland, as only small areas of unused lands were converted in Gansu Province [**?**, **?**].

In the second stage (2000-2020), land use structure in the Hedong Region tended to become more rational, extending beyond the Hedong Region to encompass the broader Yellow River basin in China, particularly after 2005 [?, ?, ?]. This positive shift was primarily attributed to major ecological restoration programs, such as the Natural Forest Protection Program launched in 1998 [?, ?] and the Grain for Green Project initiated in 1999 [?, ?, ?]. These ecological projects directly impacted local land use, recognized as key LUCC driving factors [?, ?, ?]. Consequently, cropland and grassland gradually transformed into forest land, contributing to overall increase in land use dynamic degree in the Hedong Region since 2000. Furthermore, dominant factors influencing land use changes increasingly leaned toward grain production, GDP, and added value of secondary industry, as interactive enhancement effects intensified after 2000, especially for the three major land use types: grassland, forest land, and cropland.

The spatial shift in land use activity center from central to southeastern parts around 2005 was also linked to ecological restoration programs. The Longnan Mountains were included in the Yangtze River Shelter-Forest Project Phase II (2001-2010) and III (2011-2020). Moreover, the second phase of the Grain for Green Project starting in 2014 focused more on sloping land conversion and gully reclamation [?, ?], aligning with broader goals of building a moderately prosperous society, poverty alleviation, and ecological security construction [?, ?]. These efforts stimulated land use activities, particularly in the southeastern mountainous area, as evidenced by forest land changes (Fig. 2). This contrasts sharply with deforestation impacts on land degradation in other regions, such as North Africa [?, ?].

However, land uses in the Hedong Region over the past 30 years retained strong regional characteristics, diverging from LUCC situation in Gansu Province as a whole, where forest land, grassland, cropland, and water body significantly increased from 2005 to 2018 [?, ?]. Urban expansion in Gansu Province mainly occupied unused lands rather than lands with more ecological benefits, such as forest land and grassland, after 2005 [?, ?]. In the Hedong Region from 2000 to 2020, construction land expansion primarily occurred at the expense of cropland. Cropland had positive contribution to grassland, and both cropland and grassland positively contributed to forest land overall. However, underlying driving mechanisms likely differed from those before 2000. This study identifies grain yield, GDP, and secondary industry as major factors influencing most land use changes after 2000, with driving mechanisms closely related to ecological restoration programs.

Taking grain yield as an example, grain yield in the study area showed upward trend, mainly driven by counties with developed agriculture, contradicting declining cropland trend after 2000. Thus, increasing grain production might not be the direct driving force for land use transition; instead, the driving mechanism conveyed by grain yield was related to ecological restoration programs, though further verification is warranted. The significant forest land increase, coupled with controlled grassland reduction, could mitigate environmental impacts of construction land expansion after 2000. Extensive construction land expansion might be associated with increasing population, primarily due to migration from rural areas to major cities [?, ?], leading to increased abandoned arable land [?, ?].

Compared with precipitation and temperature, grain yield and economic factors demonstrated superior explanatory power for land use changes in the Hedong Region. Nevertheless, climatic impacts, especially on grasslands [?, ?], should not be underestimated. Numerous studies emphasize the importance of climate change in driving grassland dynamics [?, ?]. Some scholars suggest that Loess Plateau climate tended toward warm and humid conditions, conducive to sloping land conversion program implementation from 2000 to 2018 [?, ?]. However, since the 1990s, noticeable temperature increase and decreasing precipitation trend occurred in the Hedong Region [?, ?]. Li et al. (2020) highlighted that natural factors were the primary force influencing LUCC changes in Gansu Province from 1980 to 2018. Climatic impact could be amplified through interactions with socioeconomic factors such as overgrazing [?, ?].

Our findings align with studies emphasizing the role of environmental protection policies in contributing to vegetation recovery in Northwest China and Northern Africa [?, ?]. The conclusion on driving factors is consistent with studies in Gannan Tibetan Autonomous Prefecture [?, ?], but differs from the notion that natural factors were generally the main force influencing LUCC changes in Gansu Province, possibly due to larger arid and semi-arid areas in the province. Moreover, compared with previous studies, this study provides more detailed driving mechanisms for evolution of land use spatial patterns in ecological function areas. Climatic impacts on land use changes were stronger before 1995, succeeded by animal husbandry impacts during 1995-2000, followed by grain production and GDP impacts after 2000. Given its unique position within ecological function areas in the Hedong Region of Gansu Province, land use changes are shaped by coupling effects of climate change, ecological construction, and socioeconomic development.

4.2 Limitations

This study primarily employed geographical detectors to analyze LUCC driving factors. While geographical detectors have the advantage of determining dominant factors influencing LUCC spatial patterns, they fall short in identifying direct and indirect factors and driving pathways. Consequently, this study may not fully elucidate intricate driving mechanisms of interactive factors. Other applicable methods, such as random forest algorithm [?, ?], correlation network analysis [?, ?], and structural equation modeling [?, ?], could be employed for comparison or to quantify interactions among land use change drivers in future research. Moreover, due to data acquisition limitations, this study only considered indices of representative driving factors. For instance, ecological restoration projects significantly impact local LUCC, but the study did not use direct policy indicators to quantify ecological program influence, relying solely on economic indicators to measure construction land expansion factors. This might affect analysis results regarding policy influence on land use dynamics. Therefore, selection of multidimensional indicators requires further consideration.

5 Conclusions

This study examined temporal dynamics of land use patterns and their underlying drivers in the Hedong Region of Gansu Province from 1990 to 2020. We found that grassland, cropland, and forest land accounted for approximately 99% of total land area. From 1990 to 2020, land use transition indicated shift from cropland to grassland, and both cropland and grassland converted to forest land, contributing to forest land expansion. Continuous construction land expansion primarily originated from cropland. During 2000-2005, land use experienced intensified temporal dynamics, with relatively active zones shifting from central to southeastern parts. Generally, grain yield and economic factors demonstrated superior explanatory power for land use changes, followed by precipitation. However, climate change impacts were relatively stronger before 1995, succeeded by animal husbandry impacts during 1995-2000, followed by grain yield and GDP impacts after 2000. Agricultural and pastoral activities, coupled with climate change, exhibited heightened nonlinear or bifactor enhanced effects after 2000 through intricate interaction with population and economic factors. These patterns closely correlate with ecological restoration projects in China since 1999.

This study highlights the importance of considering interrelated effects of climate change, socioeconomic development, and ecological construction. Particularly, the study underscores pronounced synergistic effects between human activities and climate change on land use since 2000 due to China’ s Grain for Green Project. Therefore, a balanced approach is recommended to ensure sustainability of land use and ecological systems in these areas.

Conflict of interest: The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Acknowledgements: This study was funded by the National Natural Science Foundation of China (U20A2098, 41701219) and the National Key Research and Development Program of China (2019YFC0507801). The authors appreciate anonymous reviewers for constructive comments and suggestions.

Author contributions: Conceptualization: WEI Zhudeng; Methodology: WEI Zhudeng, DU Na; Formal analysis: WEI Zhudeng, DU Na; Writing—original draft preparation: DU Na; Writing—review and editing: WEI Zhudeng, YU Wenzheng; Funding acquisition: WEI Zhudeng, YU Wenzheng; Resources: WEI Zhudeng, DU Na; Supervision: WEI Zhudeng. All authors approved the manuscript.

References

Alkama R, Cescatti A. 2016. Biophysical climate impacts of recent changes in global forest cover. *Science*, 351(6273): 600-604.

Batllori E, Lloret F, Aakala T, et al. 2020. Forest and woodland replacement patterns following drought-related mortality. *Proceedings of the National Academy of Sciences of the United States of America*, 117(47): 29720-29729.

Bennett M T. 2008. China' s sloping land conversion program: Institutional innovation or business as usual? *Ecological Economics*, 65(4): 699-711.

Cao F, Ge Y, Wang J. 2013. Optimal discretization for geographical detectors-based risk assessment. *GIScience & Remote Sensing*, 50(1): 78-92.

Damtea W G, Kim D, Im S. 2020. Spatiotemporal analysis of land cover changes in the Chemoga Basin, Ethiopia, using Landsat and Google Earth images. *Sustainability*, 12(9): 3607, doi: 10.3390/su12093607.

De Hertog S J, Havermann F, Vanderkelen I, et al. 2023. The biogeophysical effects of idealized land cover and land management changes in Earth system models. *Earth System Dynamics*, 14(3): 629-667.

Deng Y, Jia L, Guo Y, et al. 2022. Evaluation of the ecological effects of ecological restoration programs: A case study of the sloping land conversion program on the Loess Plateau, China. *International Journal of Environmental Research and Public Health*, 19: 7841, doi: 10.3390/ijerph19137841.

Dong L, Wang W, Ma M, et al. 2009. The change of land cover and land use and its impact factors in upriver key regions of the Yellow River. *International Journal of Remote Sensing*, 30(5): 1251-1265.

Erb K H, Haberl H, Jepsen M R, et al. 2013. A conceptual framework for analysing and measuring land-use intensity. *Current Opinion in Environmental Sustainability*, 5(5): 464-470.

Fan J. 2015. Draft of major function oriented zoning of China. *Acta Geographica Sinica*, 70(2): 186-201. (in Chinese)

Fang Z, Ding T, Chen J, et al. 2022. Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. *Science of the Total Environment*, 831: 154967, doi: 10.1016/j.scitotenv.2022.154967.

Feng Y, Zhu J, Zeng L, et al. 2021. Profit and loss prediction of ecosystem service value under county land use change: A case study of Banan District, Chongqing. *Acta Ecologica Sinica*, 41(9): 3381-3393. (in Chinese)

Foley J A, DeFries R, Asner G P, et al. 2005. Global consequences of land use. *Science*, 309(5734): 570-574.

Future Earth. 2013. *Future Earth Initial Design: Report of the Transition Team.* Paris: International Council for Science (ICSU).

Geng X, Hu S, Wang X, et al. 2023. Adaptive change of land use to nature and society in China' s agro-pastoral ecotone. *Land Use Policy*, 126: 106554, doi: 10.1016/j.landusepol.2023.106554.

Grace J B, Keeley J E. 2006. A structural equation model analysis of post fire plant diversity in California shrublands. *Ecological Applications*, 16(2): 503-514.

Hailu A, Mammo S, Kidane M. 2020. Dynamics of land use, land cover change trend and its drivers in Jimma Geneti District, Western Ethiopia. *Journal of Land Use Policy*, 99: 105011, doi: 10.1016/j.landusepol.2020.105011.

Halmy M W A, Gessler P E, Hicke J A, et al. 2015. Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography*, 63: 101-112.

He C, Zhang J, Liu Z, et al. 2022. Characteristics and progress of land use/cover change research during 1990-2018. *Journal of Geographical Sciences*, 32(3): 537-559. (in Chinese)

Hishe S, Bewket W, Nyssen J, et al. 2020. Analysing past land use land cover change and CA-Markov-based future modelling in the middle Suluh Valley, Northern Ethiopia. *Geocarto International*, 35(3): 225-255.

Hu Y, Hu S, Yao J. 2014. Factors affecting farmland abandonment behavior of farmers in semi-arid regions of Gansu Province. *Guizhou Agricultural Sciences*, 42(9): 227-231. (in Chinese)

Jin S, Li B, Yang Y, et al. 2016. Basic characteristics and pattern of land use change in Gansu Province. *Journal of Lanzhou University: Natural Science*, 52(3): 334-341. (in Chinese)

Kleyer M, Trinogga J, Cebrián-Piqueras M A, et al. 2019. Trait correlation network analysis identifies biomass allocation traits and stem specific length as hub traits in herbaceous perennial plants. *Journal of Ecology*, 107(2): 829-842.

Lambin E F, Baulies X, Bockstael N, et al. 1995. Land-use and land-cover change (LUCC): Implementation strategy. A core project of the International Geosphere-Biosphere Programme and the International Human Dimensions Programme on Global Environmental Change. In: *IGBP Report 48. IHDP Report 10.* IGBP, Stockholm, Sweden.

Lambin E F, Meyfroidt P. 2011. Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences of the United States of America*, 108(9): 3465-3472.

Le Quéré C, Andrew R M, Canadell J G, et al. 2016. Global carbon budget 2016. *Earth System Science Data*, 8(2): 605-649.

Leroux L, Begue A, Lo Seen D, et al. 2017. Driving forces of recent vegetation changes in the Sahel: Lessons learned from regional and local level analyses. *Remote Sensing of Environment*, 191: 38-54.

Li G, Sun S B, Han J C, et al. 2019. Impacts of Chinese Grain for Green program and climate change on vegetation in the Loess Plateau during 1982-2015. *Science of the Total Environment*, 660: 177-187.

Li K, Feng M, Biswas A, et al. 2020. Driving factors and future prediction of land use and cover change based on satellite remote sensing data by the LCM model: A case study from Gansu Province, China. *Sensors*, 20(10): 2757, doi: 10.3390/s20102757.

Li X Y, Wang L X, Zhang Y S. 2004. Analysis of roles of human activities in land desertification in arid area of Northwest China. *Scientia Geographica Sinica*, 24(1): 68-75. (in Chinese)

Liu J, Kuang W, Zhang Z, et al. 2014. Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. *Journal of Geographical Sciences*, 24: 195-210.

Long Y, Jiang F, Deng M, et al. 2023. Spatial-temporal changes and driving factors of eco-environmental quality in the Three-North region of China. *Journal of Arid Land*, 15(3): 231-252.

Lunyolo L D, Khalifa M, Ribbe L. 2021. Assessing the interaction of land cover/land use dynamics, climate extremes and food systems in Uganda. *Science of the Total Environment*, 753: 142549, doi: 10.1016/j.scitotenv.2020.142549.

Luyssaert S, Jammet M, Stoy P C, et al. 2014. Land management and land-cover change have impacts of similar magnitude on surface temperature. *Nature Climate Change*, 4: 389-393.

Lyu J, Jiang W, Wang W, et al. 2018. Wetland landscape pattern change and its driving forces in Beijing-Tianjin-Hebei region in recent 30 years. *Acta Ecologica Sinica*, 38(12): 4492-4503. (in Chinese)

Parihar C M, Yadav M R, Jat S L, et al. 2018. Long-term conservation agriculture and intensified cropping systems: Effects on growth, yield, water, and energy-use efficiency of maize in northwestern India. *Pedosphere*, 28(6): 952-963.

Powers R P, Jetz W. 2019. Global habitat loss and extinction risk of terrestrial vertebrates under future land-use-change scenarios. *Nature Climate Change*, 9: 323-329.

Qacami M, Khattabi A, Lahssini S, et al. 2023. Land-cover/land-use change dynamics modeling based on land change modeler. *Annals of Regional Science*, 70(1): 237-258.

Refati D C, da Silva J L B, Macedo R S, et al. 2023. Influence of drought and anthropogenic pressures on land use and land cover change in the Brazilian semi-arid region. *Journal of South American Earth Sciences*, 126: 104362, doi: 10.1016/j.jsames.2023.104362.

Shao W Y, Zhang Z P, Guan Q Y, et al. 2024. Comprehensive assessment of land degradation in the arid and semiarid area based on the optimal land degradation index model. *Catena*, 234: 107563, doi: 10.1016/j.catena.2023.107563.

Silva L, Xavier A, Silva R, et al. 2020. Modeling land cover change based on an artificial neural network for a semiarid river basin in northeastern Brazil. *Global Ecology and Conservation*, 21: 00811, doi: 10.1016/j.gecco.2019.e00811.

Song W, Feng Y, Wang Z. 2022. Ecological restoration programs dominate vegetation greening in China. *Science of the Total Environment*, 848: 157729, doi: 10.1016/j.scitotenv.2022.157729.

Song X P, Hansen M C, Stehman S V, et al. 2018. Global land change from 1982 to 2016. *Nature*, 560: 639–643.

Song Z F. 2010. Jingtai water supply project: Yingwu reservoir commences construction. *Gansu Daily*, [2010-10-19(02)]. (in Chinese)

Sy S, Quesada B. 2020. Anthropogenic land cover change impact on climate extremes during the 21st century. *Environmental Research Letter*, 15(3): 034002, doi: 10.1088/1748-9326/ab702c.

Turner B L, Skole D, Sanderson S, et al. 1995. *Land Cover Change Science/Research Plan*. Stockholm and Geneva: The International Geosphere Biosphere Program (IGBP) of the International Council for Science (ICSU) and Human Dimensions Programme (HDP) of the International Social Science Council (ISSC).

Turner B L, Lambin E F, Reenberg A. 2007. The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, 104: 20666–20671.

Wang J F, Xu C D. 2017. Geodetector: Principle and prospective. *Acta Geographica Sinica*, 72(1): 116–134. (in Chinese)

Wang K, Li X, Lyu X, et al. 2022. Optimizing the land use and land cover pattern to increase its contribution to carbon neutrality. *Remote Sensing*, 14(19): 3607, doi: 10.3390/su12093607.

Wang X, LESI M, Zhang M. 2019. Ecosystem pattern change and its influencing factors of "Two Barriers and Three Belts" . *Chinese Journal of Ecology*, 38(7): 2138–2148.

Winkler K, Fuchs R, Rounsevell M, et al. 2021. Global land use changes are four times greater than previously estimated. *Nature Communications*, 12: 2501, doi: 10.1038/s41467-021-22702-2.

Yan J J, Zhang G P, Deng X Y, et al. 2019a. Does climate change or human activity lead to the degradation in the grassland ecosystem in a mountain-basin system in an arid region of China? *Sustainability*, 11(9): 2618–2632.

Yan X, Li L. 2023. Spatiotemporal characteristics and influencing factors of ecosystem services in Central Asia. *Journal of Arid Land*, 15(1): 1-19.

Yan X Y, Zhang Q, Yan X M, et al. 2019b. An overview of distribution characteristics and formation mechanisms in global arid areas. *Advances in Earth Science*, 34(8): 826-841. (in Chinese)

Yang J, Huang X. 2021. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth System Science Data*, 13(8): 3907-3925.

Yuan X L, Li L H, Chen X, et al. 2015. Effects of precipitation intensity and temperature on NDVI-based grass change over Northern China during the period from 1982 to 2011. *Remote Sensing*, 7(8): 10164-10183.

Zerouali B, Celso A G S, do Nascimento T V M, et al. 2023. A cloud-integrated GIS for forest cover loss and land use change monitoring using statistical methods and geospatial technology over Northern Algeria. *Journal of Environmental Management*, 341: 118029, doi: 10.1016/j.jenvman.2023.118029.

Zhang G L, Biradar C M, Xiao X M, et al. 2018. Exacerbated grassland degradation and desertification in Central Asia during 2000-2014. *Ecological Applications*, 28(2): 442-456.

Zhao Y F, Zhang B, Wang B L, et al. 2012. Spatiotemporal climate change in Hedong Region in Gansu Province in recent 54 years. *Arid Zone Research*, 29(6): 956-964. (in Chinese)

Appendix

Table S1 Optimal number of intervals and discretization method for driving factors

Land type	Factor	Optimal intervals	Discretization method
Cropland	X1	6	QU
	X2	6	QU
	X3	6	QU
	X4	6	QU
	X5	6	QU
	X6	6	QU
	X7	6	QU
	X8	6	QU
	X9	6	QU
Forest land	X1	6	QU
	X2	6	QU
	X3	6	QU
	X4	6	QU
	X5	6	QU
	X6	6	QU

Land type	Factor	Optimal intervals	Discretization method
	X7	6	QU
	X8	6	QU
	X9	6	QU
Grassland	X1	6	QU
	X2	6	QU
	X3	6	QU
	X4	6	QU
	X5	6	QU
	X6	6	QU
	X7	6	QU
	X8	6	QU
	X9	6	QU
Water body	X1	6	QU
	X2	6	QU
	X3	6	QU
	X4	6	QU
	X5	6	QU
	X6	6	QU
	X7	6	QU
	X8	6	QU
	X9	6	QU
Bare land	X1	6	QU
	X2	6	QU
	X3	6	QU
	X4	6	QU
	X5	6	QU
	X6	6	QU
	X7	6	QU
	X8	6	QU
	X9	6	QU
Construction land	X1	6	QU
	X2	6	QU
	X3	6	QU
	X4	6	QU
	X5	6	QU
	X6	6	QU
	X7	6	QU
	X8	6	QU
	X9	6	QU

Note: X1-X9 represent nine explanatory variables listed in Table 1. Initial number of intervals were set as 3-8. QU, quantile method; GI, geometrical interval; SD, standard deviation; NB, natural breaks method; EI, equal-interval method.

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

Source: ChinaXiv —Machine translation. Verify with original.