# Spatiotemporal Evolution of Fractional Vegetation Cover in China and Its Response to Climate Change and Urbanization (Postprint)

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## Abstract

Changes in vegetation cover are intimately associated with climate factors and also influenced by human activities. Currently, research on the spatiotemporal variation characteristics of vegetation in China at the provincial scale, as well as quantitative analysis of the combined impacts of climate factors and human activities on vegetation cover, remains limited. Utilizing the Google Earth Engine (GEE) platform, 2000-2020 Landsat data, and concurrent climate and nighttime light data, this study analyzed the spatiotemporal evolution of vegetation coverage in China and its response to climate change and urbanization using methods including the dimidiate pixel model, linear regression analysis, coefficient of variation, partial correlation analysis, and contribution model. The results indicate: (1) From 2000 to 2020, vegetation coverage in China increased at a rate of 0.32% · a-1. Vegetated areas were predominantly characterized by high coverage, accounting for 38% of the study area, and exhibited an overall decreasing trend from southeast to northwest. (2) The Loess Plateau, Yunnan Province, Tibet Autonomous Region, and western Xinjiang Uygur Autonomous Region showed increasing trends in vegetation coverage. Interannual variation in vegetation was more stable in the south than in the north, and in the east than in the west. Heilongjiang Province had the highest vegetation coverage at 91.7%; Xinjiang Uygur Autonomous Region had the lowest at 14.4%; Ningxia Hui Autonomous Region' s vegetation coverage increased at a rate of 0.98% · a-1, indicating significant vegetation improvement. (3) The impacts of climate factors and urbanization on vegetation coverage exhibited significant spatial heterogeneity. Temperature and precipitation showed negative and positive correlations, respectively, with vegetation coverage in northern China, while urbanization primarily affected economically developed provinces. Temperature was the main contributing factor in Ningxia Hui Autonomous Region, with an average contribution of 84.3%; precipitation was the main contributing factor

in Taiwan Province, with an average contribution of 71.7%; Shanghai had the highest urbanization contribution at 26.5%.

## Full Text

## Spatiotemporal Evolution of Fractional Vegetation Cover in China and Its Response to Climate Change and Urbanization

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**Abstract:** Variation in fractional vegetation cover (FVC) is not only closely related to climatic factors but also influenced by human activities. Currently, few studies have examined the spatiotemporal characteristics of vegetation change across China at the provincial scale or quantitatively analyzed the combined effects of climatic factors and human activities on FVC. Based on Google Earth Engine platform and Landsat data from 2000 to 2020, together with contemporaneous climate and nighttime light data, this study analyzed the spatiotemporal evolution of FVC in China and its response to climate change and urbanization using the dimidiate pixel method, linear regression analysis, coefficient of variation, partial correlation analysis, and contribution modeling. The results show that: (1) From 2000 to 2020, FVC in China increased at a rate of $0.32\% \cdot a^{-1}$. Vegetation-covered areas were dominated by high coverage levels, accounting for 91.7% of the study area, with an overall decreasing trend from southeast to northwest. (2) The Loess Plateau, Yunnan Province, Tibet Autonomous Region, and western Xinjiang Uygur Autonomous Region showed increasing trends in FVC. Interannual fluctuations were more stable in the south than in the north, and in the east than in the west. Heilongjiang Province had the highest vegetation coverage at 91.7%, while Xinjiang had the lowest at 14.4%. The FVC in Ningxia Hui Autonomous Region increased at $0.98\% \cdot a^{-1}$, indicating significant improvement. (3) The impacts of climatic factors and urbanization on FVC showed significant spatial heterogeneity. Temperature and precipitation had negative and positive correlations with FVC in northern China, respectively, while urbanization mainly affected economically developed provinces. Temperature was the primary contributing factor in Ningxia, with an average contribution of 84.3%; precipitation was the main contributor in Taiwan Province, with an average contribution of 71.7%; and urbanization contributed most in Shanghai, with an average contribution of 26.5%.

**Keywords:** fractional vegetation cover; Google Earth Engine; climate change; urbanization; Landsat

## 1 Introduction

As a crucial component of terrestrial ecosystems, vegetation serves as a natural "link" connecting soil, atmosphere, and water, playing a vital role in global material cycling and energy flow. Fractional vegetation cover (FVC), defined as the percentage of vertical projection area of vegetation (including leaves, stems, and branches) on the ground relative to the total statistical area, is an important indicator reflecting vegetation community growth status and fundamental data for describing ecosystems. Since 1999, China has implemented various ecological restoration projects such as the Grain for Green Program. In 2005, Xi Jinping, then Secretary of the Zhejiang Provincial Committee, proposed the scientific concept that "lucid waters and lush mountains are invaluable assets." Over recent decades, China has restored natural ecological environments through afforestation and green agriculture initiatives to achieve harmonious coexistence between humans and nature. Therefore, understanding the interannual variation patterns of terrestrial vegetation and exploring the driving effects of climatic factors and human activities are essential for evaluating environmental quality of China' s terrestrial ecosystems.

Remote sensing technology offers advantages of wide coverage, strong spatiotemporal continuity, high data reliability, and low cost. Detecting broad-scale vegetation spatiotemporal changes and estimating vegetation productivity based on remote sensing has become a major trend in vegetation cover research. The Normalized Difference Vegetation Index (NDVI) can largely eliminate instrument and topographic interference and shows a significant positive correlation with FVC, making it a practical method for FVC retrieval. Li Yuebin et al. used the dimidiate pixel method with Landsat TM/ETM+ data to retrieve FVC in Kunming, finding that high coverage dominated overall. Wang Jin et al. used MODIS NDVI data to analyze vegetation cover in Inner Mongolia, revealing generally low coverage but a slow increasing trend as environmental protection gained attention. Guo Yongqiang et al. studied the Loess Plateau vegetation using Google Earth Engine, showing low coverage areas accounted for 31.32% of the study area, but FVC increased at $0.59\% \cdot a^{-1}$ since the Grain for Green Program. Liu Yaoyi et al. analyzed vegetation cover changes in the Yangtze River Delta integration demonstration zone, finding overall degradation strongly related to human activities. These studies demonstrate that FVC varies significantly across regions due to climate, geography, and human activities.

Vegetation growth changes result from combined natural factors and human activities. Temperature and precipitation directly affect photosynthesis, respiration, and soil moisture. In densely urbanized areas, human activities often exert greater influence on FVC than natural factors. Previous research has analyzed driving effects of natural factors or human activities separately, but studies at national and provincial scales examining both spatiotemporal characteristics of FVC and quantitative impacts of climate factors combined with human activities remain insufficient. This study uses the Google Earth Engine platform with Landsat data from 2000 to 2020, combined with precipitation, temperature, and nighttime light data, to analyze spatiotemporal patterns of terrestrial FVC across China and its provinces using the dimidiate pixel method, linear regression, and coefficient of variation. Through partial correlation analysis and contribution modeling at the provincial scale, we quantitatively assess the impacts and contributions of climate change and urbanization on FVC variations, providing scientific basis for national ecological environment quality assessment.

## 2 Data and Methods

### 2.1 Data Sources

**2.1.1 Landsat Data** The Landsat satellite provides Earth observation data with a spatial resolution of 30 m and a temporal resolution of 16 days. Currently, Landsat has a data record spanning over 40 years. This study performed fusion, clipping, and cloud removal operations on the Google Earth Engine platform to obtain surface reflectance data. The final selected images and temporal distribution are shown in . Due to missing Landsat imagery for western Tibet and Xinjiang in 2000, 2005, 2010, 2015, and 2020, this study compensated for unphotographed areas by clipping, fusing, and mosaicking remote sensing images from adjacent years.

**2.1.2 Precipitation and Temperature Data** Precipitation data were obtained from the CHIRPS dataset (2000–2020) with monthly temporal resolution and 5.5 km spatial resolution, covering 50°S–50°N. Temperature data were obtained from the MODIS land surface temperature dataset (2000–2020) with monthly temporal resolution and 1.0 km spatial resolution. Using China’ s vector map, we performed clipping and mosaicking operations to generate annual mean temperature and total precipitation datasets for July each year.

**2.1.3 Nighttime Light Data** Nighttime light data can map human activity density and urbanization processes, thereby revealing urbanization impacts on vegetation cover changes. The main nighttime light remote sensing datasets include DMSP/OLS (2000–2012) with 927 m spatial resolution, providing pixel digital number (DN) values representing average nighttime light intensity, and NPP/VIIRS (2013–2020) with 500 m spatial resolution, providing day-night band (DNB) radiance values accurately recording nighttime radiation intensity. Since these datasets have different satellite sensor constants and resolutions, they cannot be directly fused. This study performed cross-sensor calibration using the extended time series dataset constructed by Chen et al. (2021) through new calibration methods, which shows good spatial pattern and temporal consistency and is freely accessible at https://doi.org/10.7910/DVN/YGIVCD.

## 2.2 Methods

**2.2.1 Normalized Difference Vegetation Index (NDVI)** NDVI is an important parameter reflecting vegetation growth status, primarily used for monitoring vegetation growth and coverage. Its calculation formula is:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where $NIR$ is the reflectance of the near-infrared band and $RED$ is the reflectance of the red band. Higher NDVI values indicate better vegetation conditions.

**2.2.2 Maximum Value Composite** The maximum value composite method synthesizes annual maximum NDVI imagery, which better reflects the best stage of vegetation growth. The calculation formula is:

$$NDVI_i = \max(NDVI_{ij})$$

where $NDVI_i$ is the annual maximum NDVI for a pixel in year $i$, and $NDVI_{ij}$ is the NDVI value of the $j$-th image passing through that pixel in year $i$.

**2.2.3 Fractional Vegetation Cover (FVC)** FVC refers to the percentage of vertical projection area of vegetation on the ground relative to the total statistical area. Based on the dimidiate pixel model, the calculation formula is:

$$FVC = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}}$$

where $NDVI_{soil}$ and $NDVI_{veg}$ are the NDVI values for pure soil and pure vegetation pixels, respectively (i.e., the lower and upper thresholds). Higher FVC indicates better vegetation cover. According to the Soil Erosion Classification and Grading Standard issued by the Ministry of Water Resources in 2008, FVC can be divided into five levels: low coverage [0, 30%), medium-low coverage [30%, 45%), medium coverage [45%, 60%), medium-high coverage [60%, 75%), and high coverage [75%, 100%].

**2.2.4 Trend Analysis** A unary linear regression method was used to analyze trends in FVC for each pixel, with slope (*slope*) representing the change trend:

$$slope = \frac{n \times \sum_{i=1}^{n} i \times FVC_i - (\sum_{i=1}^{n} i)(\sum_{i=1}^{n} FVC_i)}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where $n$ is the number of monitoring years (21 in this study), $i$ is the observation year, and $FVC_i$ is the FVC in year $i$. When $slope > 0$, FVC shows an increasing trend; when $slope < 0$, FVC shows a decreasing trend. To assess significance, F-tests were performed on the trends. Based on linear regression and significance test results, the study area was classified into: significantly improved ($slope > 0$, $P < 0.01$), improved ($slope > 0$, $0.01 < P < 0.05$), basically stable ($P > 0.05$), degraded ($slope < 0$, $0.01 < P < 0.05$), and significantly degraded ($slope < 0$, $P < 0.01$).

To analyze spatial fluctuation characteristics, the coefficient of variation ($C_\nu$) was calculated:

$$C_\nu = \frac{\sigma}{\mu}$$

where $\sigma$ is the standard deviation and $\mu$ is the mean value of FVC over $n$ years. A lower $C_\nu$ indicates more stable data with less fluctuation. Based on $C_\nu$ results, the study area was divided into: low fluctuation ($C_\nu < 0.05$), relatively low fluctuation ($0.05 \leq C_\nu < 0.10$), moderate fluctuation ($0.10 \leq C_\nu < 0.15$), relatively high fluctuation ($0.15 \leq C_\nu < 0.20$), and high fluctuation ($C_\nu \geq 0.20$).

**2.2.5 Partial Correlation Analysis** Partial correlation analysis was used to calculate the correlation between climatic factors, anthropogenic factors, and FVC:

$$r_{wx.yz} = \frac{r_{wx.z} - r_{wy.z} \times r_{xy.z}}{\sqrt{(1 - r^2_{wy.z})(1 - r^2_{xy.z})}}$$

where $w$ represents FVC; $x$, $y$, and $z$ represent precipitation, temperature, and anthropogenic factors, respectively; $r_{wx.yz}$ is the partial correlation coefficient between $w$ and $x$ when $y$ and $z$ are fixed; $r_{wx.z}$ is the partial correlation between $w$ and $x$ when $z$ is fixed; $r_{wy.z}$ is the partial correlation between $w$ and $y$ when $z$ is fixed; and $r_{xy.z}$ is the partial correlation between $x$ and $y$ when $z$ is fixed. Compared with simple linear correlation, partial correlation analysis more accurately reveals relationships between two variables by controlling for other variables. Higher partial correlation indicates greater influence on FVC.

**2.2.6 Contribution Analysis** Climate factors and human activities are the main drivers of FVC interannual variation. The contribution of each factor to FVC change for each pixel can be expressed as:

$$\Delta FVC = C(PRE) + C(LST) + C(URB)$$

where $\Delta FVC$ is the interannual change in FVC, and $C(PRE)$, $C(LST)$, and $C(URB)$ represent the contributions of precipitation, temperature, and urbanization to FVC interannual variation, respectively. The contribution of precipitation to FVC change is calculated as:

$$C(PRE) = \frac{\partial FVC}{\partial PRE} \times \Delta PRE$$

where $\Delta PRE$ is the interannual change in precipitation, and $\frac{\partial FVC}{\partial PRE}$ represents the sensitivity of FVC to precipitation. Sensitivity values indicate correlation strength—larger values mean stronger correlation between FVC and precipitation. Other factors are calculated similarly. Since contribution magnitudes vary across regions, absolute values were used to calculate relative contribution ratios:

$$P(PRE) = \frac{|C(PRE)|}{|C(PRE)| + |C(LST)| + |C(URB)|} \times 100\%$$

where $P(PRE)$ is the relative contribution of precipitation to FVC change. Other factors are calculated analogously.

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## 3 Results

### 3.1 Interannual Spatiotemporal Distribution Characteristics of FVC

From 2000 to 2020, China' s FVC increased at a rate of $0.32\% \cdot a^{-1}$, showing a favorable trend [Figure 1: see original paper]. The maximum FVC occurred in 2018 at 56.8%, while the minimum occurred in 2000 at 50.0%. The mean FVC over the 21-year study period was 52.4%. According to the FVC level distribution [Figure 2: see original paper], high and medium-high coverage accounted for 91.7% of the study area, mainly located in eastern China; medium-low and low coverage accounted for 8.3%, primarily distributed in northwestern desert regions.

Based on China' s FVC distribution from 2000 to 2020 [Figure 3: see original paper], using the Hohhot-Lhasa line (Hula Line) as a boundary, FVC showed a northwest-low, southeast-high pattern, decreasing from southeast to northwest. High coverage areas were mainly the Northeast Plain and regions south of the Qinling Mountains, while low coverage areas were primarily northwestern deserts and highly developed economic zones. Over the 21-year period, vegetation cover in northwestern Xinjiang and the Loess Plateau showed significant improvement.

### 3.2 Provincial Spatial Variation and Trend Analysis of FVC

Provincial FVC spatial variation characteristics showed that 75.0% of the study area exhibited increasing trends ($slope > 0$), widely distributed in Shaanxi, Shanxi, Ningxia, Yunnan, Tibet, and western Xinjiang. Only 25.0% showed decreasing trends ($slope < 0$), concentrated along the Yangtze River, the Pearl River Delta economic belt, and in Sichuan and eastern Xinjiang [Figure 4: see original paper]. The area of significant degradation was small, with significantly degraded and degraded regions accounting for 4.5% and 3.5% of the study area, respectively, mainly distributed in Tianjin, Hong Kong, Macao, Taiwan, along the Yangtze River, and around urban agglomerations.

Basically stable areas accounted for 67.0% of the study area, the largest proportion, mainly distributed in border regions between Sichuan, Tibet, and Qinghai, as well as in Guizhou, Hubei, northern Inner Mongolia, and the three northeastern provinces. Significantly improved and improved areas accounted for 18.0% and 10.5%, respectively, mainly in the Loess Plateau, Northeast Plain, and western regions. To further analyze FVC stability, the spatial distribution of coefficient of variation showed that low and relatively low fluctuation areas accounted for 31.0%, mainly in the three northeastern provinces, provinces south of the Qinling Mountains, and northwestern desert provinces. High and relatively high fluctuation areas accounted for 53.0%, mainly in the Loess Plateau, North China Plain, Inner Mongolia, Xinjiang, Tibet, and urban economic belts.

Provincial mean FVC values [Figure 5: see original paper] revealed that Heilongjiang had the highest coverage at 91.7%, followed by Jilin (84.7%), Guangxi (84.4%), Chongqing (84.1%), and Hubei (83.9%). Xinjiang had the lowest at 14.4%, with Tibet (24.2%), Gansu (38.9%), Qinghai (32.7%), Ningxia (34.6%), Macao (32.2%), and Hong Kong (38.9%) also showing low values. Linear fitting showed that Ningxia, Shanxi, Shaanxi, and Beijing had the highest annual increase rates at $0.98\% \cdot a^{-1}$, $0.95\% \cdot a^{-1}$, $0.94\% \cdot a^{-1}$, and $0.60\% \cdot a^{-1}$, respectively. These provinces are mainly located in the Loess Plateau, where vegetation restoration is closely related to the Grain for Green Program. Vegetation degradation occurred in Jiangsu, Tianjin, and Zhejiang with annual slopes of $-0.14\% \cdot a^{-1}$, $-0.08\% \cdot a^{-1}$, and $-0.07\% \cdot a^{-1}$, likely due to urbanization and industrialization.

### 3.3 Impacts of Climate Change and Urbanization on FVC Variation

The average partial correlation coefficient between FVC and temperature was -0.12, showing an overall non-significant negative correlation, indicating that temperature has some inhibitory effect on vegetation growth [Figure 6: see original paper]. Areas with positive correlations accounted for 58.8% of the study area, while negative correlations accounted for 41.2%. Significantly positive ($P < 0.05$) and significantly negative ($P < 0.05$) correlations accounted for only 10.0% and 32.2% of the study area, respectively. Northwestern regions showed mostly negative correlations, with some areas showing strong negative correlations, transitioning from negative to positive from inland to coastal areas. Provincially, Ningxia, Shaanxi, Beijing, and Shanxi showed negative correlations, while Tibet, Sichuan, and Shandong showed positive correlations.

The average partial correlation coefficient between FVC and precipitation was 0.15, showing an overall non-significant positive correlation, indicating that precipitation promotes vegetation growth to some extent [Figure 6: see original paper]. Positive correlations accounted for 58.9% of the study area, with significantly positive areas ($P < 0.05$) accounting for 19.6%. Negative correlations accounted for 41.1%, with significantly negative areas ($P < 0.05$) accounting for 38.9%. Areas negatively correlated with temperature were mostly positively correlated with precipitation. Provincially, Beijing, Inner Mongolia, Ningxia, and Shanxi showed positive correlations with precipitation, while Jiangsu, Taiwan, and Hong Kong showed negative correlations.

The average partial correlation coefficient between FVC and urbanization was 0.08, showing a non-significant positive correlation [Figure 6: see original paper]. Positive correlations accounted for 58.7% of the study area, while negative correlations accounted for 41.3%. Significantly positive ($P < 0.05$) and significantly negative ($P < 0.05$) correlations accounted for only 4.5% and 3.5% of the study area, respectively. Hong Kong, Taiwan, Shaanxi, and Guangdong showed positive correlations with urbanization, while Jiangsu and Anhui showed weak negative correlations.

Spatial distributions and provincial average contributions of temperature, precipitation, and nighttime light to FVC [Figure 7: see original paper] revealed that temperature was the main contributing factor for vegetation change in the Loess Plateau and northwestern regions. Temperature contributed most to Ningxia' s FVC with an average contribution of 84.3%, followed by Gansu (83.2%), Xinjiang (74.5%), Shaanxi (74.0%), and Inner Mongolia (69.1%). Temperature had low average contributions to Hong Kong, Macao, and Shanghai, likely due to their highly developed economies. Precipitation was the main contributing factor in regions south of the Qinling-Huaihe River and Tibet, with Taiwan (71.7%), Hainan (68.8%), and Hong Kong and Macao (68.2% and 67.3%) most affected. Urbanization was the main contributing factor in city centers, with Shanghai showing the highest average contribution at 26.5%. Multiple factors jointly influenced FVC in some regions: Tianjin was co-modulated by temperature (37.6%), precipitation (41.6%), and urbanization (20.8%), while Fujian and Chongqing were mainly affected by temperature and precipitation.

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## 4 Discussion

From a temporal perspective, China' s FVC showed an overall increasing trend at $0.32\% \cdot a^{-1}$ from 2000 to 2020, indicating improving ecological conditions. Influenced by monsoon climate, eastern China has abundant rainfall and heat, creating favorable conditions for vegetation growth, while western regions are far from the ocean, dry and rain-scarce, with harsh ecological conditions. Spatially, FVC decreases from southeast to northwest, with the Hula Line essentially matching China' s 400 mm isohyet. High and medium-high coverage account for 91.7% of the study area, mainly east of the Hula Line, dominated by forests and mountains; medium-low and low coverage account for 8.3%, mainly west of the Hula Line, dominated by deserts and meadows.

Spatially, China' s FVC is generally stable, with significant improvement in Ningxia, Shanxi, Shaanxi, and western Xinjiang, related to national ecological restoration projects. FVC fluctuates more in the west than east and more in the north than south, primarily because FVC is lower in northwestern China where harsh ecological conditions make vegetation growth susceptible to climatic factors. Provincially, Heilongjiang has the highest FVC (91.7%), possibly due to increased grain production, intensive cultivation, and urban greening; Xinjiang has the lowest (14.4%), related to its desert and grassland geography; Jiangsu shows significant degradation trends, related to its pollution-intensive industrial structure of smelting and chemicals.

Climatic factors and urbanization show distinct spatial heterogeneity in their impacts on FVC. Temperature has an inhibitory effect on vegetation growth, while precipitation and urbanization promote it to some extent. Temperature inhibits vegetation in Loess Plateau provinces due to drought, while promoting growth in Tibet and Sichuan. Precipitation generally has positive effects on FVC, but strong human activities in eastern economic development zones can trigger urban microclimates, showing negative correlations. Urbanization-vegetation partial correlations reveal city network distributions: city centers show negative correlations due to construction demands, indicating urbanization inhibits vegetation cover, while suburbs show positive correlations, demonstrating that environmental protection in urban construction promotes vegetation growth.

This study only examined temperature, precipitation, and nighttime light effects on FVC, without considering topography, soil, and sunshine duration. The driving mechanisms of FVC are complex; future research should incorporate more detailed data and field measurements over longer time scales for more reliable analysis.

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## 5 Conclusions

This study investigated interannual variation patterns and spatial distribution characteristics of FVC across China and its provinces from 2000 to 2020, and quantitatively analyzed the impacts and contributions of climate change and urbanization. The main conclusions are:

(1) From 2000 to 2020, China' s mean FVC was 52.4%, showing a fluctuating growth trend at $0.32\% \cdot a^{-1}$. Vegetation-covered areas were dominated by high coverage (91.7%), mainly distributed in eastern China. FVC showed a northwest-low, southeast-high pattern bounded by the Hula Line.

(2) Significantly improved and improved areas were mainly distributed in the Loess Plateau, Northeast Plain, and western regions; significantly degraded and degraded areas were mainly in Tianjin, Hong Kong, Macao, Taiwan, along the Yangtze River, and around urban agglomerations. In-

terannual fluctuations were more stable in the south than north and east than west. Heilongjiang had the highest FVC (91.7%) and Xinjiang the lowest (14.4%). Ningxia showed the highest growth rate at $0.98\% \cdot a^{-1}$, indicating significant improvement.

(3) Climate factors and urbanization showed significant spatial heterogeneity in their effects on FVC. Temperature was the main contributor in Ningxia (84.3%), precipitation in Taiwan (71.7%), and urbanization in Shanghai (26.5%).

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