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Analysis of the Relationship between Vegetation and Radar Interferometric Coherence

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Abstract: To effectively reduce the impact of vegetation cover on surface settlement monitoring, the relationship between normalized difference vegetation index (NDVI) and coherence coefficient was established. It provides a way to estimate coherence coefficient by NDVI. In the research, a new method is tried to make the time range coincident between NDVI results and coherence coefficient results. Using the coherence coefficient results and the NDVI results of each interference image pair in the study area, the mathematical relationship between NDVI and the coherent coefficient was established based on statistical analysis of the fitting results of the exponential model, logarithmic model, and linear model. Four indicators were selected to evaluate the fitting results, including root mean square error, determinant coefficient, prediction interval coverage probability, and prediction interval normalized average width. The fitting effect of the exponential model was better than that of the logarithmic model and linear model. The mean of error was -0.041 in study area ROI1 and -0.126 in study area ROI2. The standard deviation of error was 0.165 in study area ROI1 and 0.140 in study area ROI2. The fitting results are consistent with the coherence coefficient results. The research method used the NDVI results to estimate the InSAR coherence coefficient. This provides an easy and efficient way to indirectly evaluate the interferometric coherence and a basis in InSAR data processing. The results can provide pre-estimation of coherence information in Ningxia by optical images.

Keywords: interferometry; correlation; curve fitting; NDVI



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1. Introduction

Interferometric synthetic aperture radar (InSAR) is a useful technique in generating a digital elevation model and monitoring surface deformation [1–4]. It is based on the phase difference of the echoes received by a satellite or aircraft. It has the advantage of acquiring data over a site during day or night time under all weather conditions and not impeded by cloud cover.

Interferometric coherence is one of the most important parameters for measuring the quality of interferograms in data processing of InSAR. It is predominantly evaluated using the coherence coefficient. The main factors affecting the interferometric coherence are Doppler decorrelation, thermal noise decorrelation, spatial decorrelation, and temporal decorrelation. Doppler decorrelation refers to a decorrelation phenomenon due to the inconsistency of the Doppler center frequency for twice imaging, which can be suppressed by azimuth filtering and can be further reduced by estimating the Doppler function [5]. The thermal noise decorrelation generates in the radar system when transmitting, receiving electromagnetic wave signals, and recording ground echo information [2]. Radar systems mainly rely on hardware settings to reduce the impact of system thermal noise. Spatial decorrelation refers to a decorrelation phenomenon caused by the spatial baseline of two radar images being too long and the side looking angles observed on the same targets for two images being different, resulting in considerable changes in phase [6]. The critical

baseline can be used to evaluate the spatial decorrelation. With the baseline increasing, the correlation decreases. When the baseline increases to critical baseline, the coherence coefficient is 0. To reduce the effect of spatial decorrelation, it is necessary to set a short spatial baseline. Temporal decorrelation refers to a decorrelation phenomenon caused by large changes in the scattering characteristics of the ground objects when imaging twice [2]. To reduce the effect of temporal decorrelation, it is necessary to set a short temporal baseline. Additionally, long wavelength has a good effect on temporal correlation [7].

The growth of surface vegetation is one of the main factors causing the decorrelation of radar images. It is difficult to reduce its impact through post-processing. The normalized difference vegetation index (NDVI) can be obtained through calculations based on optical imagery and it is often used to monitor vegetation cover and growth. The relationship between NDVI and the coherence coefficient of radar images can effectively reflect the influence of vegetation cover on the interferometric coherence. There has been research conducted on it [8–15]. Bai et al. (2020) built a liner relationship between interferometric coherence and NDVI and found that the months with low NDVI are suitable for deformation monitoring [10]. Chen et al. (2021) used Landsat and ALOS-1 data to establish the relationship between NDVI and coherence coefficient in Meitanba in Hunan Province [14]. Liu et al. (2021) studied the relationship between the coherence coefficient and NDVI in southern China using linear and power function models and determined that it has a negative correlation relationship, considering the accuracy of the power function model is higher than that of the linear function model [15]. The relationship can be used in simple estimating of coherence coefficient.

The function between NDVI and coherence coefficient can be effectively used to extract the decoherent area covered by vegetation in the radar image with accessible optical images. It may provide an easy way to get the decoherent area in SAR images and provide a basis in InSAR data processing. In this study, we got the Sentinel-1 and Sentinel-2 images acquired in Ningxia Hui Autonomous Region, China. We established three models to establish the relationship between NDVI and the coherent coefficient and selected four indicators to evaluate the fitting results. The results can provide pre-estimation of coherence information in Ningxia by optical images.

This paper is organized as follows. In the next section, the study area and the data information of Sentinel-1 and Sentinel-2 are described in detail. The critical method for establishing the model is introduced in Section 3. A new method is tried to make the time range of NDVI results and coherence coefficient results coincident. Section 4 is dedicated to the presentation of the obtained results. Finally, conclusions are addressed.

2. Overview of the Study Area and Data

2.1. Overview of the Study Area

Located in the eastern part of Ningxia, the study area is in Yanchi County and is represented by red rectangles in Figure 1. ROI1 is used for model building and model accuracy validation. ROI2 is used for model feasibility analysis. The study area has a mid-temperate semi-arid continental monsoon climate. The climate is dry and hot, and the winter is severely cold and the summer is extremely hot with changeable conditions [16]. There are high diurnal fluctuations in temperature and the average annual temperature is approximately 9 °C, with the average annual precipitation being 205.2 mm [16]. The terrain of the study area is high in the south and low in the north, with a gentle terrain in the north.

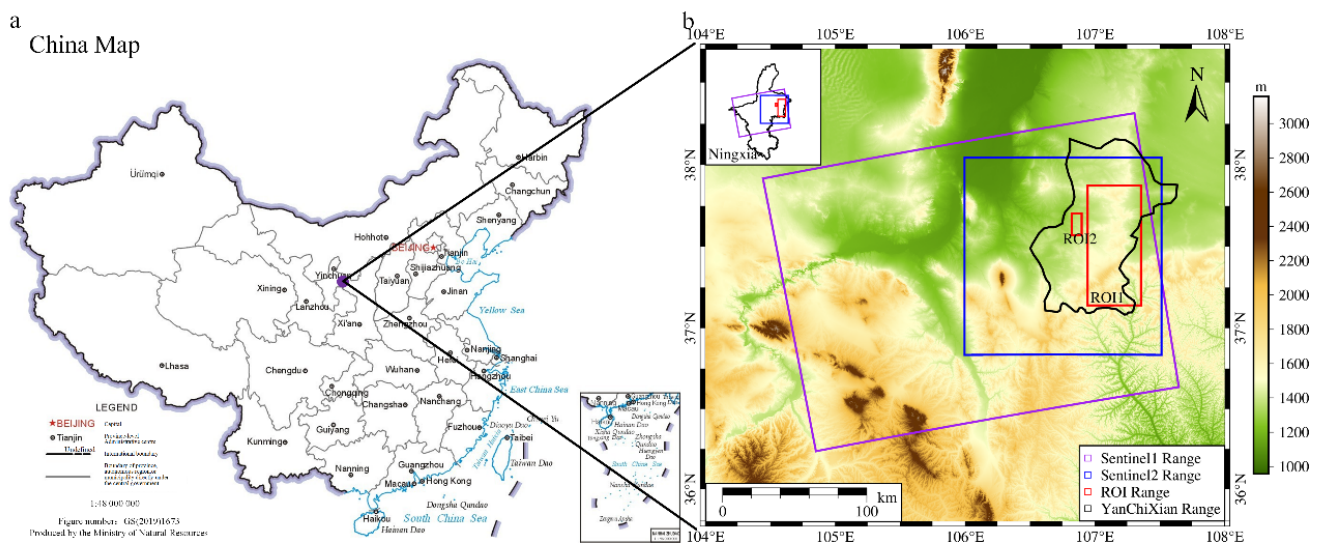


Figure 1. (a) is China map and (b) is the location of the study area and remote sensing image coverage. Two red angles represent the study areas. A purple rectangle represents Sentinel-1 image coverage. A blue rectangle represents Sentinel-2 image coverage. And basemap bases on SRTM 30 m digital elevation model (DEM) data. Note: Figure (a) is based on the standard map with the review number GS(2019) 1673 downloaded from the standard map service website of the National Administration of Surveying, Mapping and Geographic Information, and the basemap has not been modified.

2.2. Data

2.2.1. Radar Data

Sentinel-1 is a C-band radar satellite with a wavelength of approximately 5.6 cm, which has advantages of all-weather and day-and-night observation, a stable revisit time, and convenient access. Sentinel-1 has a 12-day revisit cycle and can be downloaded from the Earth Data website (<https://asf.alaska.edu/> (accessed on 6 December 2021)). The time range of SAR images is from September 2017 to August 2018. The information of acquisition date is shown in Table A1. During the time range, study area ROI1 was stable without obvious deformation. It can reduce the impact of deformation on the model. Single look complex images were used in the research. The data scan mode is IW mode, with an ascending track mode. The Sentinel-1 image coverage is represented by a purple rectangle in Figure 1.

2.2.2. Optical Image Data

Sentinel-2 is a high-resolution multispectral imaging satellite, which consists of two satellites, Sentinel-2A and Sentinel-2B. Under cloudless conditions, the single-satellite revisit cycle is 10 days and the double-satellite revisit cycle can reach 5 days. Sentinel-2 has 12 bands and three resolutions, with detailed information shown in Table 1. The red band and the near-infrared band are used for NDVI calculation, and the resolution is 10 m. The Sentinel-2 image coverage is represented by a blue rectangle in Figure 1. The Sentinel-2 data includes two product levels: the L1C product and the L2A product. The L2A product can be obtained using the L1C product and atmospheric correction processing. The L2A product was used in the research and the cloud coverage was less than 10%. The information of optical image data used in the research is shown in Table A2.

Table 1. Band information of Sentinel-2.

Sensor	Band Number	Band Name	Sentinel-2A		Sentinel-2B		Resolution (meters)
			Central Wavelength (nm)	Bandwidth (nm)	Central Wavelength (nm)	Bandwidth (nm)	
MSI	4	Red	664.5	30	665	30	10
MSI	8	NIR	835.1	115	833	115	10

3. Modeling Processing

3.1. Preprocessing

Critical steps in preprocessing include obtaining the coherence coefficient of the radar images and the NDVI from optical images of the study area, resampling the NDVI results, selecting images, and using the maximum value composite (MVC) algorithm to calculate the NDVI.

3.1.1. Coherence Coefficient Calculation

Interferometric coherence is one of the key parameters for measuring the quality of interferograms in the data processing of InSAR and is mainly evaluated using the coherence coefficient. The coherence coefficient value is between $[0, 1]$. The higher the value, the better the interferometric coherence. The coherence coefficient calculation equation is shown in (1) [17,18].

$$\gamma = \frac{E[v_1 v_2^*]}{\sqrt{E[v_1 v_1^*]} \sqrt{E[v_2 v_2^*]}} \quad (1)$$

where v_1 and v_2 represents the reference and secondary images, $*$ represents the conjugate complex number. The tool to calculate coherence coefficient is GMTSAR, an open source InSAR processing system [5,19], and the spatial resolution of the coherence coefficient results is 25 m. The DEM data is SRTM 30 m digital elevation model (DEM) data.

The information about interferometric pairs is shown in Table A3, and the coherence coefficient results are shown in Figure A1. The temporal baseline threshold for the interferometric images was 24 days, and the vertical baseline threshold was 100 m. A short perpendicular baseline means the high baseline correlation, which represents the high spatial correlation [20]. The equation for calculating baseline correlation is shown in (2) [21].

$$\gamma_{baseline} = 1 - \frac{B_{\perp}}{B_{\perp,crit}} \quad (2)$$

where $B_{\perp}$ represents perpendicular baseline and $B_{\perp,crit}$ represents critical perpendicular baseline. The equation for calculating critical baseline is shown in (3) [21].

$$B_{\perp,crit} = \frac{\lambda R \tan(\theta - \alpha)}{2d_R} \quad (3)$$

where λ is the wavelength, R is the slant range, θ is the incident angle, α is the slope, d_R is the range resolution. Set Sentinel-1 as an example. R is 90 km, θ is 44 degrees. We can get the critical perpendicular baseline is about 5 km by using (3) in the flat range. When the perpendicular baseline is 100 m, baseline correlation is about 0.98.

3.1.2. NDVI Calculation

The NDVI value is between $[-1, 1]$ and a negative value indicates that the surface is covered with water, ice, or snow. Zero indicates bare soil, rock, or buildings. Positive values indicate the presence of vegetation, and the NDVI value increases as vegetation

cover increases. The NDVI calculation equation is shown in (4) and the NDVI results are shown in Figure A2.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (4)$$

where ρ_{NIR} is the reflectance value of the near-infrared band and ρ_{RED} is the reflectivity value of the red band. The tool to calculate NDVI is SNAP, an open-source data processing software provided by the European Space Agency (ESA).

3.1.3. Resampling, Selecting Images, and Calculating the NDVI Using the MVC Algorithm

The resolution of the coherent coefficient images is equal to interferometric images. Because it is lower than the resolution of the NDVI images, the resolution of the NDVI images are resampled to the resolution of the coherent coefficient images so that there are same numbers of grids in the coherent coefficient and NDVI images.

In ideal conditions, the SAR data have a 12-day revisit cycle, and optical data have a 5-day revisit cycle. The imaging time being inconsistent between the NDVI, and the interferometric pairs is the main problem. Chen et al. (2021) solved this problem by establishing the relationship between the time baselines and the coherence coefficient, and introducing the time variable t into the function of the NDVI and the coherence coefficient [14]. Liu et al. (2021) solved the inconsistency imaging problem between the NDVI and the interferometric pair based on the monthly NDVI dataset from 2016–2017 and by using the average coherence coefficient of the interferometric pairs for the months [15]. In this research, the MVC algorithm was used to calculate the NDVI images in the time range between the imaging time of the main and auxiliary images, so that the interferometric pair can correspond with the NDVI image. MVC refers to obtaining the maximum value of each grid in the NDVI images over a certain period, which is relatively easy to achieve. It can effectively reduce the influence of cloud, atmosphere, solar altitude angle, and other factors on remote sensing images and is widely used in the production of NDVI. The MVC results are shown in Figure A3.

3.2. Data Sampling

The images are sampled according to main parameter: the sample window size is 40×40 pixels. Although the NDVI images were processed using the MVC method, there is a considerable number of grids containing information from the cloud, with water also having a considerable influence on the experiment. Because compared with the images of coherence coefficient and the NDVI in water, some values of the coherence coefficient and the NDVI are smaller than 0.2, so the grid need be masked. The mean value and the correlation coefficients R are calculated for sampling and selecting. If the correlation coefficient was greater than 0.6, the mean value of the coherence coefficient and the NDVI are fitted. The correlation coefficient calculation formula is shown in (5).

$$R = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 - \sum_{i=1}^N (y_i - \bar{y})^2}} \quad (5)$$

where x_i and y_i represent the value of each raster element, and $\bar{x}$ and $\bar{y}$ represent the mean value of the raster element being sampled.

3.3. Data Fitting Results Evaluation

The fitting functions are evaluated using the root mean square error (RMSE) and determined coefficient (R^2). Under the condition of a 99% confidence level, the prediction intervals coverage probability (PICP) and the prediction intervals normalized averaged width (PINAW) are used to evaluate the fitting functions.

RMSE is the deviation between the true value and the predicted value, which is calculated as shown in (6). The smaller the *RMSE* value, the smaller the gap between the true and predicted values.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_{real}^{(i)} - \hat{y}_{predict}^{(i)})^2} \quad (6)$$

where $y_{real}^{(i)}$ is the true value and $\hat{y}_{predict}^{(i)}$ is the predictive value calculated by fitting function.

R^2 is used to determine the fitting degree of the regression equation, which is calculated as shown in (7). The value field is [0,1]. The larger the R^2 value, the better the degree of the model fitting.

$$R^2 = \frac{\sum_{i=1}^N (\hat{y}_{predict}^{(i)} - \bar{y}_{real})^2}{\sum_{i=1}^N (y_{real}^{(i)} - \bar{y}_{real})^2} = 1 - \frac{\sum_{i=1}^N (y_{real}^{(i)} - \hat{y}_{predict}^{(i)})^2}{\sum_{i=1}^N (y_{real}^{(i)} - \bar{y}_{real})^2} \quad (7)$$

where $\hat{y}_{predict}^{(i)}$ is the predictive value calculated by fitting function, $y_{real}^{(i)}$ is the true value, and $\bar{y}_{real}$ is the average value.

$$TSS = \sum_{i=1}^N (\hat{y}_{predict}^{(i)} - \bar{y}_{real})^2 \quad (8)$$

$$RSS = \sum_{i=1}^N (y_{real}^{(i)} - \hat{y}_{predict}^{(i)})^2 \quad (9)$$

$$ESS = \sum_{i=1}^N (y_{real}^{(i)} - \bar{y}_{real})^2 \quad (10)$$

The relationship among the three is:

$$TSS = RSS + ESS \quad (11)$$

where *TSS* is the total square sum, *RSS* is the residual square sum, and *ESS* is the explained square sum.

PICP represents the actual frequency that observations fall within the prediction interval and is used to evaluate the reliability of the prediction interval, which is calculated as shown in (12) [22]. The higher the *PICP* value, the better the prediction result and the more reliable the model.

$$PICP = \frac{1}{N} \sum_{i=1}^N \varepsilon_i, \varepsilon_i = \begin{cases} 1, y_i \in [L_i, U_i] \\ 0, y_i \notin [L_i, U_i] \end{cases} \quad (12)$$

where N is the sample size, ε_i is a Boolean variable that represents the relationship between the prediction interval and the observed value, y_i is the sample truth value, and L_i and U_i are the smallest and biggest bounds of the prediction interval, respectively.

The formula for calculating the *PINAW* is shown in (13). A smaller *PINAW* value means a more sensitive prediction interval and more reliable model [22].

$$PINAW = \frac{1}{NR} \sum_{i=1}^N (U_i - L_i) \quad (13)$$

where N is the sample size, R is the range of the sample target variable, and L_i and U_i represent the smallest and biggest bounds of the prediction interval, respectively.

3.4. The Method of Model Accuracy Validation

Comparing the calculated coherence coefficient with the real coherence coefficient, the error can be obtained to evaluate the precision of the fitting function. The error calculation equation is shown in (14):

$$Error = \gamma_{true} - \gamma_{predict} \quad (14)$$

where γ_{true} represents the true coherence coefficient, and $\gamma_{predict}$ represents the predicted coherence coefficient calculated by γ_1 and the NDVI image.

4. Results and Discussion

4.1. Data Fitting Results

The results from sampling are shown in Figure 2a. The range of the NDVI is [0.084717, 0.709237] and the range of the coherence coefficient is [0.175292, 0.88656]. The NDVI and the coherence coefficient show a negative relationship. With the increase in NDVI, the interferometric coherence decreases. The exponential model, linear model, and logarithmic model are used to fit and the fitting results are shown in (15), (16), and (17), and four evaluation indicators in Section 3.3 are used to evaluate the fitting functions.

$$\gamma_1 = 0.9259e^{-3.982 \cdot NDVI} + 0.1753, 0.029 \leq NDVI \leq 1 \quad (15)$$

$$\gamma_2 = -1.226NDVI + 0.8673, 0 \leq NDVI \leq 0.7074 \quad (16)$$

$$\gamma_3 = -0.315 \ln(NDVI) + 0.08049, 0.054 < NDVI \leq 1 \quad (17)$$

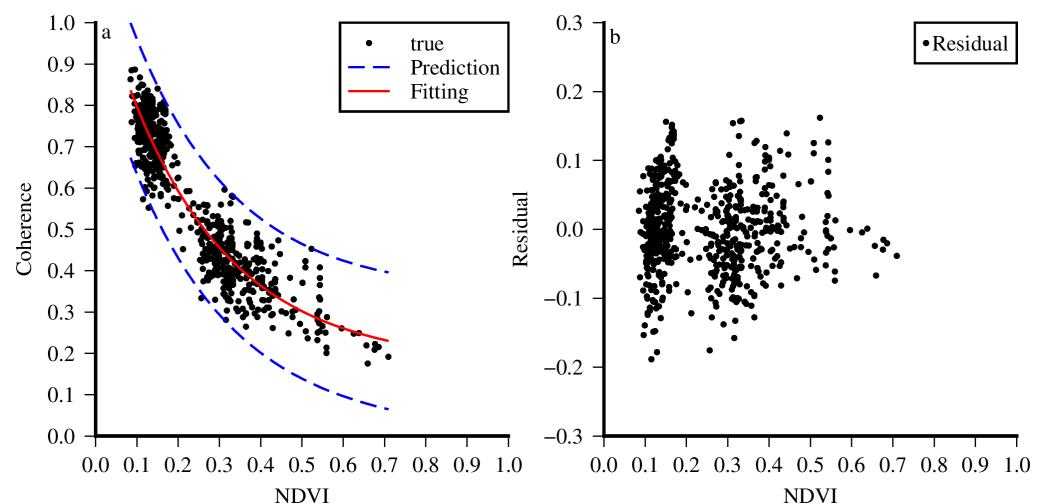


Figure 2. Fitting result of exponential model γ_1 (a) is the fitted curve graph, the red line is the fitted function curve, and the blue break line is the prediction interval curve. (b) is the residual graph.

As shown in Figure 2a, almost all the points are inside the prediction interval. Figure 2b is a residual distribution map, showing that the residuals are roughly distributed $[-0.2, 0.2]$ and the residual distribution is relatively uniform. According to the statistical results, $RMSE$ is 0.06272 and R^2 is 0.8767. Under the condition of a 99% confidence level, $PICP$ is 99.52% and $PINAW$ is 0.3249.

As shown in Figure 3a, almost all the points are inside the prediction interval. Figure 3b is a residual distribution plot, showing that the residuals are roughly distributed $[-0.3, 0.3]$ and there is an anomaly in the residuals, which becomes larger when the NDVI value is higher than 0.6. According to the statistical results, $RMSE$ is 0.07551 and R^2 is 0.8207. Under the condition of a 99% confidence level, $PICP$ is 99.36% and $PINAW$ is 0.3908.

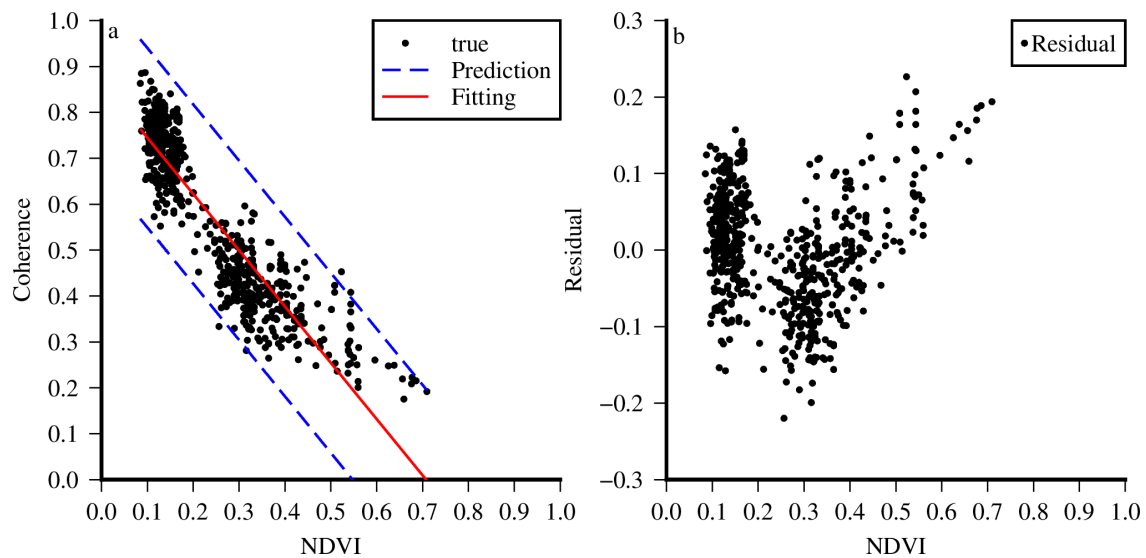


Figure 3. Fitting result of linear model γ_2 (a) is the fitted curve graph, the red line is the fitted function curve, and the blue break line is the prediction interval curve. (b) is the residual graph.

As shown in Figure 4a, almost all the points are inside the prediction interval. Figure 4b is a residual distribution plot, showing that the residuals are roughly distributed $[-0.2, 0.2]$ and the residual distribution is relatively uniform. According to the statistical results, $RMSE$ is 0.06407 and R^2 is 0.8711. Under the condition of a 99% confidence level, $PICP$ is 99.36% and $PINAW$ is 0.3316.

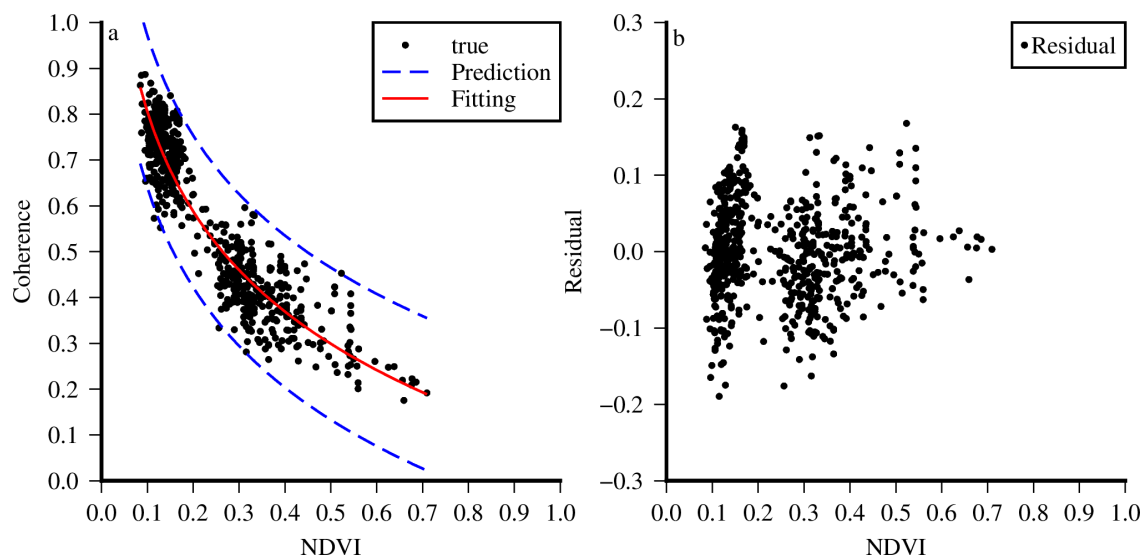


Figure 4. Fitting result of logarithmic model γ_3 (a) is the fitted curve graph, the red line is the fitted function curve, and the blue break line is the prediction interval curve. (b) is the residual graph.

The results of the evaluation are shown in Table 2. Comparing the $RMSE$, it can be considered that the gap between the true value and the predicted value of γ_1 is less than those of γ_2 and γ_3 . Comparing R^2 , it can be seen that the model fits of γ_1 is better than those of γ_2 and γ_3 . Under the condition of a 99% confidence level, comparing $PICP$ and $PINAW$, it can be seen that model reliability and prediction interval sensitivity of γ_1 is higher than those of the others. In summary, the γ_1 evaluation results are better than γ_2 and γ_3 . Therefore, it is more reliable to choose γ_1 as the fitting function.

Table 2. Evaluation results.

Fitting Curve	RMSE	R^2	PICP/%	PINAW
γ_1	0.06272	0.8767	99.52	0.3249
γ_2	0.07551	0.8207	99.36	0.3908
γ_3	0.06407	0.8711	99.36	0.3316

4.2. Model Accuracy Validation

One of interferometric pairs is selected to verify the precision of the fitting function in ROI1. The reference imaging time is 15 August 2019, and the secondary imaging time is 27 August 2019. The results are shown in Figure 5. Figure 5a shows the ROI1 NDVI result in the study area. Figure 5b shows the ROI1 coherence coefficient result in the study area. Figure 5c shows the error between the true values and the prediction values of the coherence coefficient. The overall fitting effect of the study area is good, and the larger error values are concentrated in the south of the study area. Figure 5d represents the error distribution, and the error is approximately followed by a normal distribution. The mean of error is -0.041 , and the standard deviation of error is 0.165 , with the error mainly being concentrated $[-0.3, 0.3]$. Figure 5e is the slope distribution in ROI1.

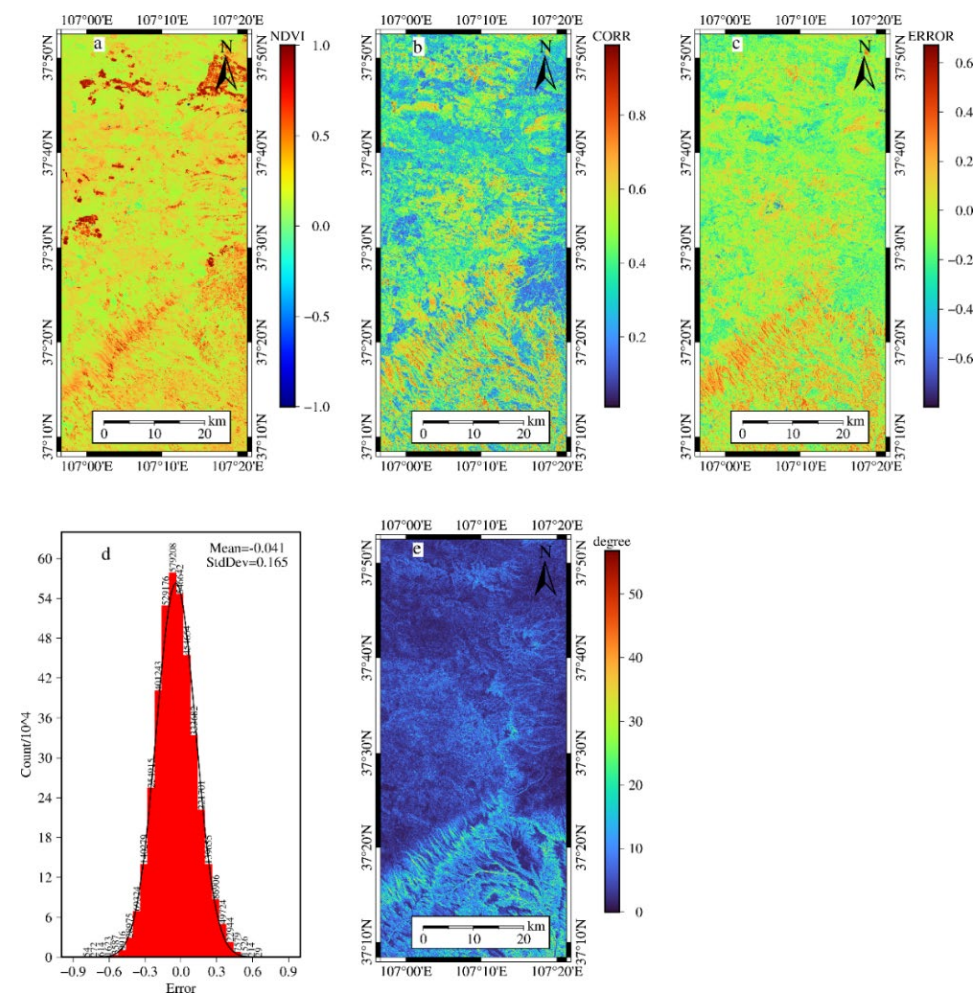


Figure 5. Fit function accuracy verification plot of interferometric pair 20190815–20190827 in ROI1, (a) is the NDVI result; (b) is the coherence coefficient map; (c) is the error result; (d) is the error distribution; (e) is the slope of ROI1.

It can be seen from Figure 5c that the error in the northern part of the study area is $[-0.2, 0.2]$. However, the estimated values in some areas are higher than the true values. In

the southern part of the study area, there are larger error values. The estimated values for this area are predominantly lower than the true values. From Figure 5c,e, the large error values and high slope degrees have roughly the same spatial distribution. The high relief maybe the main reason for larger error values [14].

Then, another interferometric pair is selected, which has a temporal baseline of 24 days. The reference imaging time is 3 August 2019, and the secondary imaging time is 27 August 2019. The results are shown in Figure 6. Figure 6a shows the ROI1 NDVI result in the study area. Figure 6b shows the ROI1 coherence coefficient result in the study area. Figure 6c shows the error between the true values and the prediction values of the coherence coefficient. The overall fitting effect of the study area is good, and the larger error values are concentrated in the south of the study area. Figure 6d represents the error distribution and the error is approximately followed by a normal distribution. The mean of error is -0.069 , and the standard deviation of error is 0.170 , with the error mainly being concentrated $[-0.3, 0.3]$. Figure 6e is the slope distribution in ROI1. The results shown in Figure 6 are consistent with the results shown in Figure 5. The mean and standard deviation of error show a small increase, and the large error values and high slope degrees show the same spatial distribution as Figure 5.

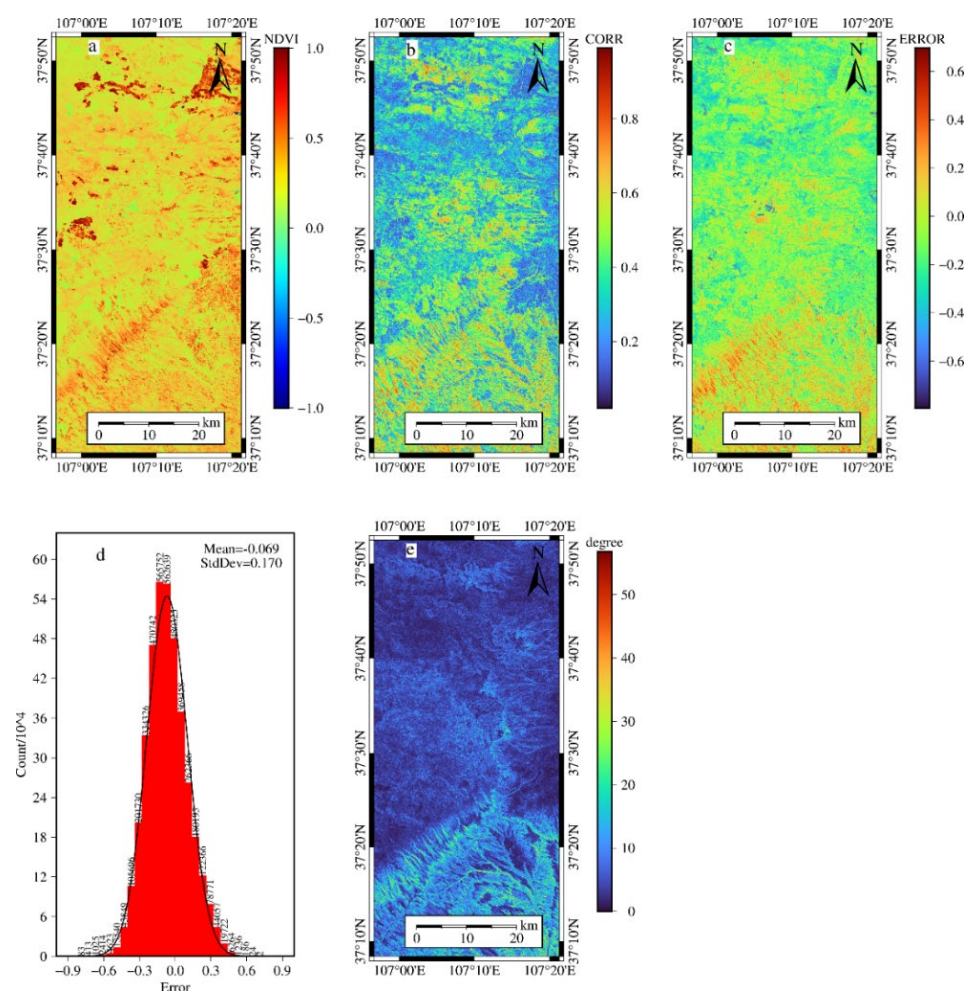


Figure 6. Fit function accuracy verification plot of interferometric pair 20190803–20190827 in ROI1, (a) is the NDVI result; (b) is the coherence coefficient map; (c) is the error result; (d) is the error distribution; (e) is the slope of ROI1.

The other study area, ROI2, is used to verify model feasibility. The results are shown in Figure 7. Figure 7a shows the NDVI result of ROI2 and Figure 7b shows the prediction result of coherence coefficient in ROI2 by Figure 7a and fitting model. Figure 7c shows

the true value of coherence coefficient in ROI2. Figure 7d shows the error between the true values and the prediction values of the coherence coefficient, and the overall fitting effect of the study area is good. Figure 7e shows the error distribution, and the error is approximately followed by the normal distribution. The mean of error is -0.126 , and the standard deviation of error is 0.140 , with the error being mainly concentrated $[-0.4, 0.2]$. Figure 7f is the map of DEM, and Figure 7g is the map of slope. Figure 7h is the map of land use type distribution in 2018.

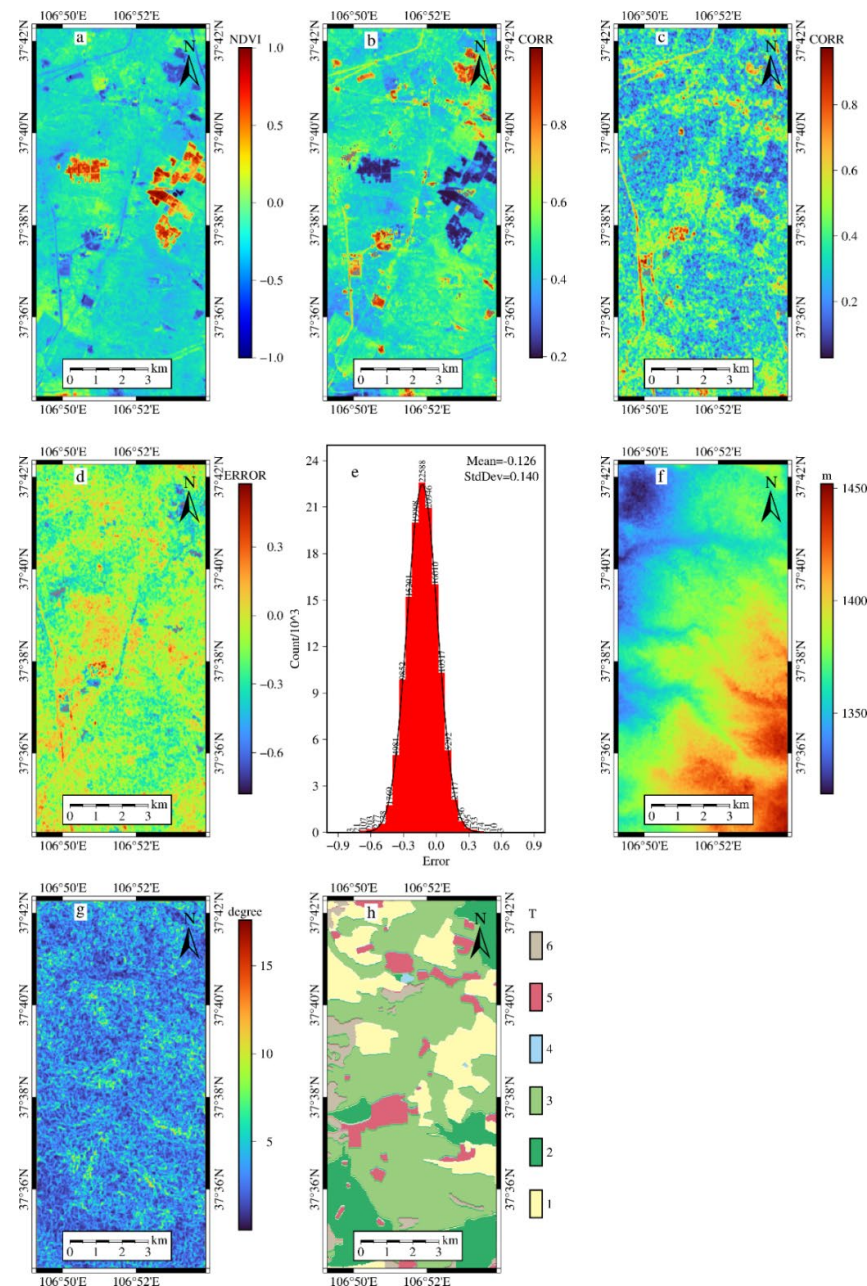


Figure 7. Fit function accuracy verification plot of interferometric pair 20190803–20190827 in ROI2, (a) is the NDVI result; (b) is the prediction result of coherence coefficient; (c) is the coherence coefficient map; (d) is the error result; (e) is the error distribution; (f) is the map of DEM; (g) is the map of slope; (h) is the map of land use type distribution in 2018 [23], and T represents the land use type. Among them, 1 represents cultivated land, 2 represents woodland, 3 represents grassland, 4 represents waters, 5 represents urban and rural, industrial and mining, and residential land, construction land, and 6 represents unused land. Note: (f) is provided by Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (<http://www.resdc.cn> (accessed on 20 July 2021)).

Compared with Figure 7c, the prediction result of coherence coefficient in Figure 7b is consistent. The high NDVI value region in Figure 7a is the region with low coherence coefficient in Figure 7b,c. It can be seen from Figure 7d that the error is $[-0.3, 0.3]$, which is similar to the result showed in Figure 7e. Compared with the same interferometric pair result in ROI1, the absolute value of the mean error became larger and the standard deviation became smaller, with both following the normal distribution. Figure 7f,g shows ROI2 is flat area, and it is inconsistent between error distribution and slope degree. Figure 7d,h show that the larger error area distribution is generally in areas of urban and rural, industrial and mining and residential land, construction land, which are mostly misestimated. However, the results from ROI2 show that γ_1 fits well for most of the area. Therefore, the model is effective.

In this paper, an empirical model for NDVI and the coherence coefficient is obtained for study area ROI1 and the model accuracy is verified in study areas ROI1 and ROI2. Research shows that the model is reliable. The research result is useful in DInSAR data processing of deformation monitoring:

(1) The NDVI value can be used as a standard for evaluating the usability in DInSAR. It would be good with lower NDVI and bad in higher NDVI area. It is not useful in area when NDVI higher than 0.4. In this condition, longer band SAR data or technology is better.

(2) It can be used to reduce the impact of vegetation in deformation monitor. The deformation got in DInSAR technology should be masked in higher NDVI to improve the deformation result reliable.

(3) It also can be used as a basis to evaluate the precision of InSAR monitoring results. The DInSAR deformation results and precision with different NDVI area should be discussed separately. It is an important basis to calculate the error of DInSAR deformation results.

In the future, the different types of land cover in the correlation between NDVI and interferometric coherence should be considered [24]. Also, introducing a time parameter to the model maybe a good idea [14]. In addition, the model connected among multi-band, multi-polarization, and multi-vegetation indexes can be built [9].

5. Conclusions

The relationship between NDVI and interferometric coherence in Ningxia was studied using optical images and C-band SAR images and an empirical model between the NDVI and the coherence coefficient was constructed through fitting analysis. The main conclusions were as follows:

(1) In the research, a new way is used to make the time range of NDVI results and coherence coefficient results coincident. The good fitting results show that it may be a good way to study the relationship between NDVI and interferometric coherence.

(2) Three statistical models between the coherence coefficient and the NDVI were constructed using the exponential model, logarithmic model, and linear model. The RMSE, determinant coefficient, PICP, and PINAW, under the condition of a 99% confidence level, are calculated, respectively. Results show that the fitting effect of the exponential model is better than the other models. Based on the exponential function, the calculation accuracy was analyzed in study areas ROI1 and ROI2. Results showed that the error of the calculation conformed to the normal distribution. The mean of error was -0.041 in ROI1 and -0.126 in ROI2. The standard deviation of error was 0.165 in ROI1 and 0.140 in ROI2, which showed good fitting results using the exponential function.

(3) The result shows that it is possible to evaluate the coherence coefficient values using optical remote sensing data. It can be the complementary content to the study of the relationship between NDVI and coherence and can guide the selection of incoherent areas in radar images due to excessive vegetation coverage, which can provide the basis for DInSAR data processing of deformation monitoring. The results can provide pre-estimation of coherence information in Ningxia by optical images.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Sentinel-1 acquisition date information.

Num	Imaging Time	Num	Imaging Time	Num	Imaging Time
1	20180901	12	20190111	22	20190511
2	20180913	13	20190123	23	20190523
3	20180925	14	20190204	24	20190604
4	20181007	15	20190216	25	20190616
5	20181019	16	20190228	26	20190628
6	20181031	17	20190312	27	20190710
7	20181112	18	20190324	28	20190722
8	20181124	19	20190405	29	20190803
9	20181206	20	20190417	30	20190815
10	20181218	21	20190429	31	20190827
11	20181230				

Table A2. Sentinel-2 acquisition date information.

Num	Imaging Time	Num	Imaging Time	Num	Imaging Time
1	20181218	7	20190318	13	20190522
2	20190102	8	20190323	14	20190601
3	20190107	9	20190328	15	20190606
4	20190117	10	20190417	16	20190706
5	20190122	11	20190512	17	20190731
6	20190211	12	20190517	18	20190815

Table A3. Interferometric information.

Num	Reference Image	Secondary Image	Temporal Baseline /m	Perpendicular Baseline /m	Resolution /m
1	20180901	20180913	12	87.0489	25
2	20180913	20180925	12	36.5774	25
3	20180913	20181007	24	27.866	25
4	20180925	20181007	12	8.71134	25
5	20181007	20181019	12	96.421	25
6	20181019	20181031	12	4.10631	25
7	20181019	20181112	24	54.6995	25
8	20181031	20181112	12	58.8058	25

Table A3. Cont.

Num	Reference Image	Secondary Image	Temporal Baseline /m	Perpendicular Baseline /m	Resolution /m
9	20181112	20181124	12	78.5131	25
10	20181112	20181206	24	20.324	25
11	20181124	20181206	12	58.1891	25
12	20181124	20181218	24	9.97468	25
13	20181206	20181218	12	48.2144	25
14	20181206	20181230	24	39.6463	25
15	20181218	20181230	12	87.8607	25
16	20181218	20190111	24	66.7602	25
17	20181230	20190111	12	21.1005	25
18	20181230	20190123	24	10.6224	25
19	20190111	20190123	12	10.4781	25
20	20190123	20190216	24	40.7835	25
21	20190204	20190216	12	96.5544	25
22	20190216	20190228	12	74.7184	25
23	20190216	20190312	24	75.875	25
24	20190228	20190312	12	1.15659	25
25	20190228	20190324	24	8.94817	25
26	20190312	20190324	12	7.79159	25
27	20190312	20190405	24	36.0626	25
28	20190324	20190405	12	43.8542	25
29	20190324	20190417	24	44.4763	25
30	20190405	20190417	12	0.622107	25
31	20190405	20190429	24	96.1843	25
32	20190417	20190429	12	96.8064	25
33	20190417	20190511	24	23.9404	25
34	20190429	20190511	12	72.866	25
35	20190429	20190523	24	96.0215	25
36	20190511	20190523	12	23.1555	25
37	20190511	20190604	24	38.3302	25
38	20190523	20190604	12	15.1747	25
39	20190523	20190616	24	59.171	25
40	20190604	20190616	12	43.9963	25
41	20190604	20190628	24	30.9379	25
42	20190616	20190628	12	74.9343	25
43	20190616	20190710	24	56.8686	25
44	20190628	20190710	12	18.0656	25
45	20190628	20190722	24	32.9689	25
46	20190710	20190722	12	51.0345	25
47	20190710	20190803	24	32.2786	25
48	20190722	20190803	12	83.3131	25
49	20190722	20190815	24	56.3615	25
50	20190803	20190815	12	26.9516	25
51	20190803	20190827	24	68.1896	25
52	20190815	20190827	12	41.2379	25

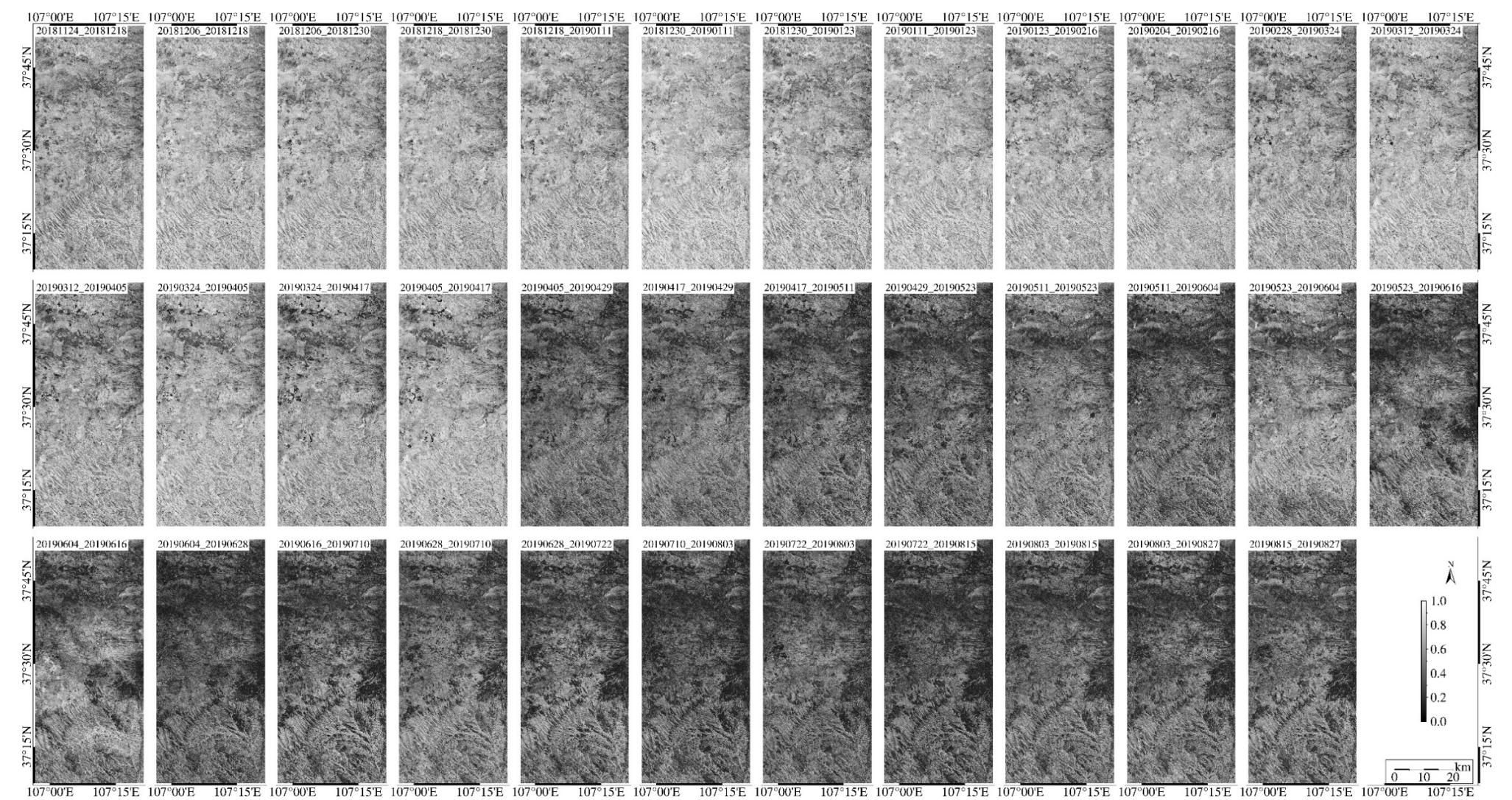


Figure A1. Result of γ .

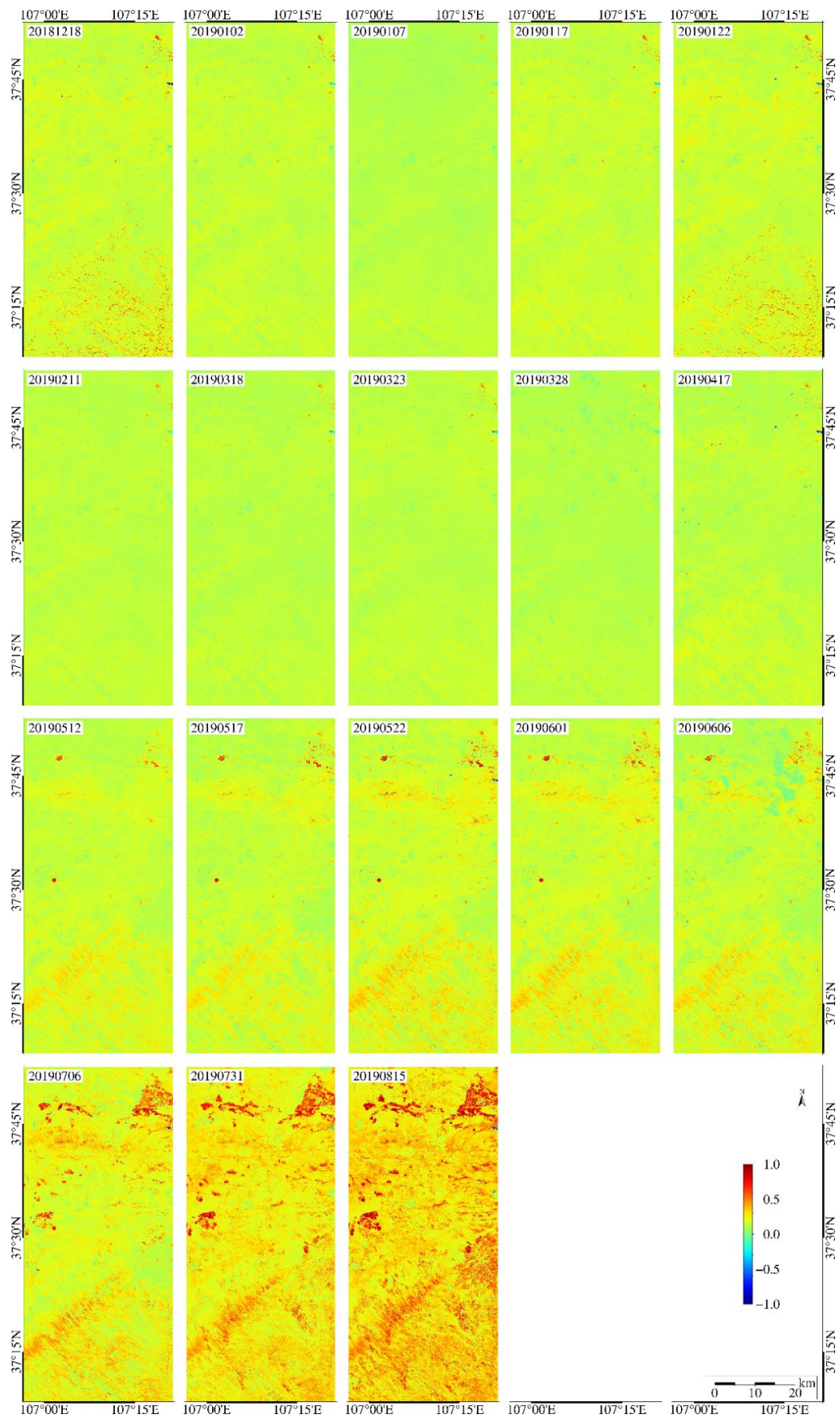


Figure A2. The result of NDVI.

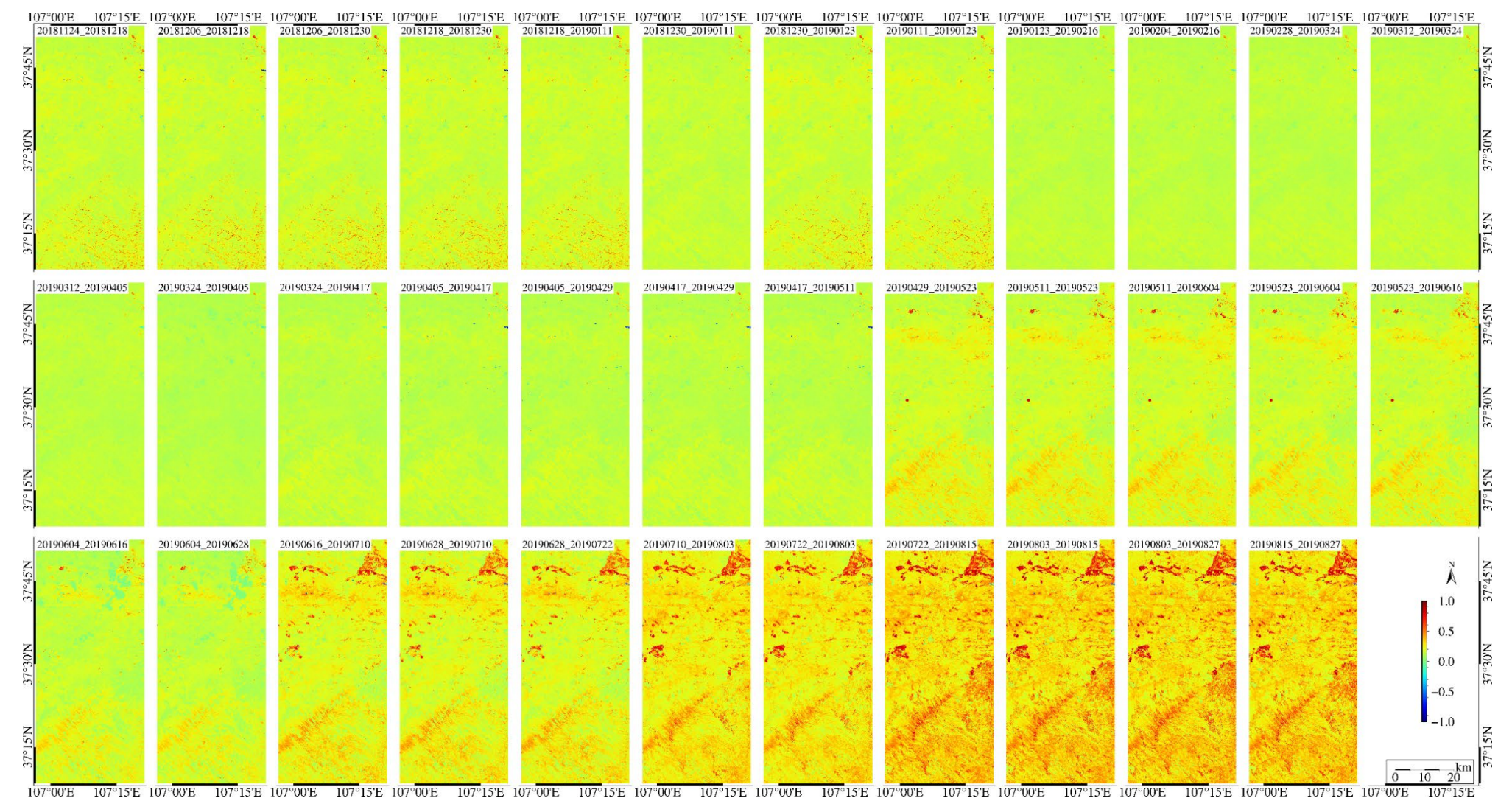


Figure A3. Result of MVC.

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