



Simultaneous state-parameter estimation of rainfall-induced landslide displacement using data assimilation

Jing Wang¹, Guigen Nie^{1,2}, Shengjun Gao³, Changhu Xue¹

¹GNSS Research Center, Wuhan University, Wuhan, 430079, China

5 ²Collaborative Innovation Center for Geospatial Information Technology, Wuhan, 430079, China

³Chinese Antarctic Center of Surveying and Mapping, Wuhan, 430079, China

Corresponding to: Guigen Nie (ggnie@whu.edu.cn)

10 **Abstract.** Landslide displacement prediction has great practical engineering significance to landslide stability evaluation and early warning. The evolution of landslide is a complex dynamic process, applying classical prediction method will result in significant error. Data assimilation method offers a new way to merge multi-source data with the model. However, data assimilation is still deficient in the ability to meet the demand of dynamic landslide system. In this paper, simultaneous state-parameter estimation (SSPE) using particle filter-based data assimilation is applied to predict displacement of the landslide.

15 Landslide SSPE assimilation strategy can make use of time-series displacements and hydrological information for the joint estimation of landslide displacement and model parameters, which can improve the performance considerably. We select Xishan Village, Sichuan province, China as experiment site to test SSPE assimilation strategy. Based on the comparison of actual monitoring data with prediction values, results strongly suggest the effectiveness and feasibility of SSPE assimilation strategy in short-term landslide displacement estimation.

20

1 Introduction

Landslide is a common geological hazard which greatly endangers the security of property and lives of the people (Huang et al., 2017). The landslide in Sri Lanka in May 2017 resulted in more than 200 people died and 698,289 people injuries (Kumarasiri, 2018). In China, the landslide hazard accounts for about 72.6% of the total geological disasters from 2005 to

25 2014(Xue et al., 2016). Therefore, landslide research is a hot topic studied by people, and it is necessary to do some prevention study like the early warning and deformation prediction (Liu et al., 2014; Jiang et al., 2016; Michoud et al., 2016).

Landslide prediction and forecast method had been developed and improved continually (Crosta et al., 2013; Li et al., 2018.). Chaussard E(2014) used the time-series analysis method of ALOS data to resolve land displacement in the Mexico region. Dong L (2012) proposed a model coupled Gray method and General Regression Neural Network (GM-GRNN) and

30 applied it to the prediction of sliding deformation of Dahu landslide. Li X Z (2014) carried out a genetic algorithm and support vector machine (GA-SVM) method to establish a mathematical function prediction model. However, most of the current model-based prediction cannot use the newest observation data effectively and deviate from the actual value. Data assimilation



method is a new technology that can help to deal with such problems. By combining surface observational data with the process model, data assimilation provides an optimal “true value” that is continuously distributed over time and space (Xue C et al. 2018). Data assimilation has been widely tested and used in geoscience fields like hydrologic and atmospheric and field(Reichle R H et al. 2002; Abbaszadeh P et al. 2017; Wikle C K et al. 2002). However, there are few explorations in the
5 landslide field.

Data assimilation can be divided into two types: sequential-based method and continuous-based method (Qin J et al. 2009). A sequential-based way is an online approach that updates the prediction in each time (Nakano S. 2007), so it is more suitable for landslide system than continuous-based method. Particle Filter (PF) is a typical sequential data assimilation algorithm which was initially put forward by Gordon (Gordon N J et al. 2002). Because the PF is nonlinear filtering based on
10 Bayesian estimation, it can deal with non-linear and non-Gaussian problems (Moradkhani H et al. 2011). Refer to the geosciences field. The numerical model shows large nonlinearity (Leeuwen P J V. 2010). So we choose PF as the algorithm to integrate multi-source data with the model.

The evolution of landslide is a time-varying process, so the model parameters are required to be adjusted over time. However, the primal sequential data assimilation only updates state vector, and the model parameters are generally given by
15 known information, which will result in discrepancies between state and model parameters under a particular model relationship (Nearing G S et al., 2012). To meet the requirements of updating state values and model parameters simultaneously, we apply the simultaneous states and parameters estimation (SSPE) here. The SSPE method can continuously renew the output by sequentially merging new measurements. Moradkhani (2005) optimized it into the hydrological field. Vrugt (2006) combined the simultaneous optimization with data assimilation. Joint estimation of state-
20 parameter has proven to be a useful strategy to improve prediction performance (Qin J et al. 2009; Lü H et al. 2011).

In this paper, we applied the SSPE assimilation strategy to predict the landslide displacement. In landslide SSPE assimilation, the external factor hydrologic data has integrated into the dynamic model of landslide deformation data, which can adjust model parameters and state vector simultaneously according to the hydrologic information. During the process, internal factor of the landslide is combined with external observation factors. Thus reducing error and getting better predictive
25 effects.

First, the research method will be deduced including time-series decomposition, establishment of the model and landslide SSPE assimilation strategy with PF algorithm. Then Xishan Village landslide is taken as the study area to examine SSPE assimilation strategy. The prediction of deformation will be optimized by coupling GPS observation data and hydrological factor. Finally, the study results will be proposed.



2 Method

2.1 Time-series displacement decomposition

Landslide deformation is the interaction between internal geological conditions and the external environment (Desai et al., 1995), so the displacement can be divided into the trend term displacement generated by inter factor, the periodic term displacement caused by external factor (such as rainfall and reservoir water level, etc.) and the stochastic term displacement (human impacted, snowpack, etc.)(Zhou C et al., 2016). However, after noise filtering, the random term is too small and can be neglected. So the time-series displacement decomposition is as follows:

$$\mathbf{S}(t) = \boldsymbol{\varphi}(t) + \mathbf{x}(t) \quad (1)$$

where $\mathbf{S}(t)$ is the cumulative displacement of landslides, $\boldsymbol{\varphi}(t)$ denotes the trend term, $\mathbf{x}(t)$ denotes the periodic term.

The trend term of time series is extracted with moving average method because it can remove the disturbance effectively and leave long-term signals for research (Seng H. 2014).

$$\boldsymbol{\varphi}_i = \frac{S_{i-1} + S_{i-2} + \dots + S_{i-n}}{n} \quad (2)$$

where $\boldsymbol{\varphi}_i$ is the periodic term of step i, S_{i-1} is the cumulative displacement of step i-1, n is the moving average period.

So the periodic term displacement can be calculated using subtraction between the total displacement and the trend term.

15

2.2 Landslide periodic displacement modeling

For the rainfall-induced landslide, atmospheric rainfall is one of the most susceptible disaster-causing factors and directly affects the periodic displacement of the landslide (Lian C et al., 2015; Ren F et al., 2015). So the periodic term can be regarded as a function of time and rainfall. The numerical function method is adopted here for the establishment of periodic displacement model. The periodic displacement variation is tiny in a short time. Therefore, the model can be derived through expanding periodic displacement value using a Taylor-series expansion method:

20

$$x(t_{i+1}, r_{i+1}) = x(t_i, r_i) + \left(\frac{\partial x}{\partial t}\right)_{t_i}(t_{i+1} - t_i) + \frac{1}{2}\left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i}(t_{i+1} - t_i)^2 + \left(\frac{\partial x}{\partial r}\right)_{r_i}(r_{i+1} - r_i) + \frac{1}{2}\left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i}(r_{i+1} - r_i)^2 + g_i \quad (3)$$

where x denotes displacement of the landslide, r_{i+1} is the rainfall of time i+1, $\frac{\partial x}{\partial t}$ and $\frac{\partial x}{\partial r}$ are the first order partial derivative of displacement, $\frac{\partial^2 x}{\partial t^2}$ and $\frac{\partial^2 x}{\partial r^2}$ are the second order partial derivative, g_i is the remainder of Taylor's expansion.

25

2.3 Landslide SSPE assimilation strategy using PF

2.3.1 State estimation

The general state-space model for a nonlinear dynamic system is defined to be:

$$\text{State model: } x_{i+1} = f(x_i, u_i) + v_{i+1} \quad (4)$$



$$\text{Observation model: } y_{i+1} = g(x_{i+1}) + w_{i+1} \quad (5)$$

where x is the state vector and y is the observation vector, i is time step, f and g is nonlinear functions forecasting the state and observation, u represents the model parameters, v is model error and w is observation noise.

5 2.3.2 Landslide SSPE method

In sequential data assimilation, SSPE algorithm can be applied through the state augmentation method (Chen T, 2005).

Consider the model in Eq. (4), the original state vector x_i is now augmented with the parameters $u(t)$ to be

$$\mathbf{X}_i = \begin{bmatrix} x_i \\ u_i \end{bmatrix} \quad (6)$$

Apply simultaneous state-parameter estimation method into practical landslide state model in Eq. (3), the extended state vector can be expressed as:

$$\mathbf{X}_i = \left[x(t_i, r_i) \quad \left(\frac{\partial x}{\partial t}\right)_{t_i} \quad \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i} \quad \left(\frac{\partial x}{\partial r}\right)_{r_i} \quad \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i} \right]^T \quad (7)$$

And we set:

$$\left(\frac{\partial x}{\partial t}\right)_{t_{i+1}} = \left(\frac{\partial x}{\partial t}\right)_{t_i} + \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i}(t_{i+1} - t_i) + m_i \quad (8)$$

$$\left(\frac{\partial^2 x}{\partial t^2}\right)_{t_{i+1}} = \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i} + n_i \quad (9)$$

$$15 \quad \left(\frac{\partial x}{\partial r}\right)_{r_{i+1}} = \left(\frac{\partial x}{\partial r}\right)_{r_i} + \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i}(r_{i+1} - r_i) + u_i \quad (10)$$

$$\left(\frac{\partial^2 x}{\partial r^2}\right)_{r_{i+1}} = \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i} + v_i \quad (11)$$

Where m_i , n_i , u_i , v_i are noise.

So the next moment \mathbf{X}_{i+1} is :

$$20 \quad \mathbf{X}_{i+1} = \begin{bmatrix} x(t_{i+1}, r_{i+1}) \\ \left(\frac{\partial x}{\partial t}\right)_{t_{i+1}} \\ \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_{i+1}} \\ \left(\frac{\partial x}{\partial r}\right)_{r_{i+1}} \\ \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_{i+1}} \end{bmatrix} = \begin{bmatrix} x(t_i, r_i) + \left(\frac{\partial x}{\partial t}\right)_{t_i}(t_{i+1} - t_i) + \frac{1}{2} \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i}(t_{i+1} - t_i)^2 + \left(\frac{\partial x}{\partial r}\right)_{r_i}(r_{i+1} - r_i) + \frac{1}{2} \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i}(r_{i+1} - r_i)^2 + g_i \\ \left(\frac{\partial x}{\partial t}\right)_{t_i} + \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i}(t_{i+1} - t_i) + m_i \\ \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i} + n_i \\ \left(\frac{\partial x}{\partial r}\right)_{r_i} + \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i}(r_{i+1} - r_i) + u_i \\ \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i} + v_i \end{bmatrix} =$$



$$\begin{bmatrix} 1 & t_{i+1} - t_i & \frac{1}{2}(t_{i+1} - t_i)^2 & r_{i+1} - r_i & \frac{1}{2}(r_{i+1} - r_i)^2 \\ 0 & 1 & t_{i+1} - t_i & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & r_{i+1} - r_i \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x(t_i, r_i) \\ \left(\frac{\partial x}{\partial t}\right)_{t_i} \\ \left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i} \\ \left(\frac{\partial x}{\partial r}\right)_{r_i} \\ \left(\frac{\partial^2 x}{\partial r^2}\right)_{r_i} \end{bmatrix} + \begin{bmatrix} g_i \\ m_i \\ n_i \\ u_i \\ v_i \end{bmatrix} = \\
 \begin{bmatrix} 1 & t_{i+1} - t_i & \frac{1}{2}(t_{i+1} - t_i)^2 & r_{i+1} - r_i & \frac{1}{2}(r_{i+1} - r_i)^2 \\ 0 & 1 & t_{i+1} - t_i & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & r_{i+1} - r_i \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \cdot \mathbf{X}_i + \begin{bmatrix} g_i \\ m_i \\ n_i \\ u_i \\ v_i \end{bmatrix} \quad (12)$$

In Eq. (16) we make $\begin{bmatrix} 1 & t_{i+1} - t_i & \frac{1}{2}(t_{i+1} - t_i)^2 & r_{i+1} - r_i & \frac{1}{2}(r_{i+1} - r_i)^2 \\ 0 & 1 & t_{i+1} - t_i & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & r_{i+1} - r_i \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} = \boldsymbol{\omega}_{i+1}$, $\begin{bmatrix} g_i \\ m_i \\ n_i \\ u_i \\ v_i \end{bmatrix} = \boldsymbol{\varepsilon}_{i+1}$, so Eq.(12) can be

expressed as :

$$5 \quad \mathbf{X}_{i+1} = \boldsymbol{\omega}_{i+1} * \mathbf{X}_i + \boldsymbol{\varepsilon}_{i+1} \quad (13)$$

Refer to observation of landslide deformation:

$$y_{i+1} = \mathbf{x}_i + w_{i+1} \quad (14)$$

Combined the two expressions Eq. (13) and Eq. (14), we can build landslide SSPE state-space model to joint estimate the landslide periodic displacement and model parameters.

10

2.3.3 PF algorithm

However, some parameters in the landslide state space model Eq. (13) and Eq. (14) are difficult to obtain (e.g. $\left(\frac{\partial x}{\partial t}\right)_{t_i}$, $\left(\frac{\partial^2 x}{\partial t^2}\right)_{t_i}$). Based on Monte Carlo methods, PF can be adopted to solve this problem. Instead of calculating partial derivative directly, PF generates a large number of samples (particles) to approximate the posterior probability of the states, thus obtaining an optimal result (Maskell and Gordon, 2002).

15

From Bayesian theorem, the posterior probability of the states can be inferred through

(1) forecast:

$$p(\mathbf{x}_i | \mathbf{y}_{1:i-1}) = \int p(\mathbf{x}_i | \mathbf{x}_{i-1}) p(\mathbf{x}_{i-1} | \mathbf{y}_{1:i-1}) d\mathbf{x}_{i-1} \quad (15)$$

(2) update:

$$20 \quad p(\mathbf{x}_i | \mathbf{y}_{1:i}) = \frac{p(\mathbf{y}_i | \mathbf{x}_i) p(\mathbf{x}_i | \mathbf{y}_{1:i-1})}{p(\mathbf{y}_i | \mathbf{y}_{1:i-1})} \quad (16)$$

where i is time, \mathbf{x}_i is state vector, \mathbf{y}_i is observation vector, $\mathbf{y}_{1:i} = \{y_1, y_2, \dots, y_i\}$, $p(\mathbf{x}_{i-1} | \mathbf{y}_{1:i-1})$ is the posterior distribution function (PDF) for time step $i-1$, $p(\mathbf{x}_i | \mathbf{y}_{1:i-1})$ is the prior distribution for time step i , $p(\mathbf{x}_i | \mathbf{x}_{i-1})$ can be derived from the



model.

In PF, the posterior probability of the states are approximated by discrete random measures defined by particles and a set of weights associated with particles:

$$\hat{p}(x_i|y_{1:i}) \approx \sum_{k=1}^N w_i^k \delta(x_{0:i} - x_{0:i}^k) \quad (17)$$

5 where $\hat{p}(x_k|y_{1:k})$ is the approximate value of $p(x_k|y_{1:k})$, $x_{0:i}^k$ and w_k^i are particles and associated weight and $\sum_{i=1}^N w_k^i = 1$, δ denotes Dirac delta function.

The direct sampling of target $p(x_k|y_{1:k})$ is difficult. The sequential importance sampling (SIS) is considered here to solve this problem. The SIS gathers particles from a known density function and updates the importance weights by using the iterative method (Doucet A. et al. 2000). Meanwhile, the sampling importance resampling (SIR) is used to avoid the particles
10 deviate away from the truth value (Gordon N J et al. 2002). The SIR algorithm accumulate particles in high importance weight. So the estimates of the state vector come into

$$\hat{x}_i = \sum_{k=1}^N x_i^k w_i^k \quad (18)$$

So, the procedure of landslide SSPE assimilation strategy is shown in Fig. 1.

15 3 Study area and data

3.1 Study area

The study area is located in Xishan Village, Li County, Sichuan Province, China (Fig. 2), and it is in the upper part of the left bank slope of the Zagunao River. This landslide is a massive accumulative landslide, which is composed of three slopes. The slope of this landslide is about $25^\circ \sim 45^\circ$. The length is about 4200m, and the width is around 1700m. The altitude of the
20 leading edge is 1500m, and the trailing edge is 3400m. Thus the altitude difference is 1900m. The landform undulation leads to apparent local variations. Xishan Village landslide has a 52m thick sliding which can lead to about 85 million m^3 . Before 2008, many cracks appeared in the front and middle of this landslide, causing a direct economic loss of 0.5 million yuan and affecting 189 people. The creep deformation intensified after May 2008 Wenchuan earthquake which threatening the security of residents' lives and properties. According to estimates, the potential economic loss is 50 million yuan. In the purpose of
25 reducing the damage and giving the early warning, the study is taken to forecast the deformation of this landslide.

3.2 Data introduction

3.2.1 GPS derived time-series displacement

The Xishan Village landslide has been set up 5 GPS continuous observation stations for obtaining the deformation value.



The GPS receivers were connected to the network. So the observation data could be transferred in real time. At the same time, a GPS reference station was set in the stability area as the reference for calculation. Fig.3 shows the distribution of all stations. After the GPS baseline calculation, we get the deformation of every observation station from August 2015 to June 2017. Fig.4 shows the final results. Due to the transmission problem, there are several gaps in the data. The interpolation method is considered to be taken here to fill the missing data (Velicer and Colby, 2005; Lenda G et al., 2016).

3.2.2 Rainfall data

There are two rain gauges be settled in the landslide range of Xishan Village, which can transmit rainfall data in real time. The daily rainfall data is illustrated in Fig.5. Since the rain gauges are located near the GPS station, the mean values of the two gauges are taken as the rainfall of Xishan landslide.

4 Results and analysis

In this experiment, the SSPE assimilation method and model method without SSPE or data assimilation are used to predict landslide displacement. All the experimental data was obtained at Xishan Village landslide between August 2015 and June 2017. We only illustrate with two stations GPS03 and GPS04 because the deformation is more evident than others. The time step is set to five days with the purpose of saving computational time and increasing numerical accuracy correspondingly. The prediction work can be divided into the prediction of trend term, period term and cumulative term. Then the error analysis is taken to validate the efficiency of our method.

4.1 Prediction of trend term displacement

The trend term displacement is time monotone function so that it can be fitted by a polynomial, and the best results of trend term prediction and fitting formula are as shown in Fig. 6.

4.2 Prediction of period term displacement

The periodic term displacement can be calculated using the difference between the total displacement and the trend term. Fig. 7 shows the periodic displacement in station GPS03 and GPS04 and the rainfall data. It can be seen clearly that the period term is a complex nonlinear sequence series. Besides, fluctuation of the period term in two stations has the relatively same changing tendency, which is lagged behind that of rainfall. So we applied the SSPE assimilation method to predict it. The prediction results are as shown in Fig. 8. It can be seen that SSPE assimilation method get more close to the measured value



than the model method without assimilation.

4.3 Prediction of cumulative displacement

Finally, the predicted values of cumulative displacement can be obtained by summing up the predicted values of trend
5 and periodic displacement. The prediction results in each station are shown in Fig. 9. Additionally, some detailed prediction
data are enumerated (Table. 1 and Table.2). Then we calculate the difference between prediction and measured value and error
rate. Experimental results verify the feasibility of SSPE assimilation method.

4.4 Relative error analysis

10 In this section, more quantitative analysis is carried out to assess the performance of each method. Three criterions: Mean
Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Square Error (RMSE) were used to evaluate the prediction
effect. They can measure the deviation between the predicted value and the measured value, which calculated as

$$\text{MAE} = \frac{1}{N} * \sum_{i=1}^N |x_i - \hat{x}_i| \quad (19)$$

$$\text{MSE} = \frac{1}{N} * \sum_{i=1}^N (x_i - \hat{x}_i)^2 \quad (20)$$

$$15 \text{ RMSE} = \sqrt{\frac{1}{N} * \sum_{i=1}^N (x_i - \hat{x}_i)^2} \quad (21)$$

Where x_i is the measured value and \hat{x}_i is the prediction value.

The results are as shown in Table. 3. According to the prediction evaluation indexes, SSPE assimilation method offers
better forecast effect than the model method. The MAE, MSE and RMSE value of SSPE assimilation method were 46.27%,
70.99% and 46.25% lower than those of Model method in GPS03 station, and 39.48%,61.75% and 38.15% lower in GPS04
20 station. The result suggests that the SSPE assimilation method has achieved great performance in landslide displacement
prediction.

5 Conclusion

Aims at coupling landslide deformation with external factor meanwhile increasing the accuracy of landslide prediction,
25 this paper presents a practical strategy on landslide displacement prediction. During the research, one of data assimilation
algorithm, the PF improved with SSPE method had been presented and applied with the reality. In real data experiment,
landslide deformation from GPS measuring was decomposed into trend term and period term firstly. The period term was
predicted with the hydrological factor in simultaneous estimation data assimilation, while the trend term was computed by



polynomial fitting.

Our results show that SSPE assimilation strategy has an excellent ability for landslide displacement prediction and can provide assistance in early risk assessment and landslide forecasting. However, further analysis and modification are needed in the future, such as more influence factor and complete model.

5

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements: This study was financially supported by the National Program on Key Basic Research Project of China (grant numbers: 2013CB733205).

10

Reference:

Abbaszadeh P, Moradkhani H, Yan H.: Enhancing Hydrologic Data Assimilation by Evolutionary Particle Filter and Markov Chain Monte Carlo, *Adv Water Resour*, 111, 192-204, <https://doi.org/10.1016/j.advwatres.2017.11.011>, 2017.

15 Crosta G B, Frattini P, Agliardi F.: Deep seated gravitational slope deformations in the European Alps, *Tectonophysics*, 605, 13-33, <https://doi.org/10.1016/j.tecto.2013.04.028>, 2013.

Chaussard E, Wdowinski S, Cabral-Cano E, et al.: Land subsidence in central Mexico detected by ALOS InSAR time-series, *Remote Sens Environ*, 140, 94-106, <https://doi.org/10.1016/j.rse.2013.08.038>, 2014.

Chen T, Morris J, Martin E.: Particle filters for state and parameter estimation in batch processes, *J Process Contr*, 15(6), 665-673, doi:10.1016/j.jprocont.2005.01.001, 2005.

20 Desai C S, Samtani N C, Vulliet L.: Constitutive Modeling and Analysis of Creeping Slopes, *Journal of Geotechnical Engineering*, 122(6), doi:10.1061/(ASCE)0733-9410(1995)121:1(43), 1995.

Dong L, Li X.: An Application of Grey-General Regression Neural Network for Predicting Landslide Deformation of Dahu Mine in China, *J Comput Theor Nanos*, 6(1), 577-581, doi: 10.1166/asl.2012.2253, 2012.

25 Doucet, A., Godsill, S., & Andrieu, C.: On sequential monte carlo sampling methods for bayesian filtering. *Statist and Comput*, 10(3), 197-208, <https://doi.org/10.1023/A:1008935410038>, 2000.

Gordon N J, Salmond D J, Smith A F M.: Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEE Proceedings F-Radar and Signal Processing*, 140, 107-113, doi: 10.1049/ip-f-2.1993.0015, 2002.

Huang F, Huang J, Jiang S et al.: Landslide displacement prediction based on multivariate chaotic model and extreme learning machine, *Eng Geol*, 218, 173-186, <https://doi.org/10.1016/j.enggeo.2017.01.016>, 2017.

30 Jiang Y N, Liao M S, Zhou Z W et al.: Landslide Deformation Analysis by Coupling Deformation Time Series from SAR Data with Hydrological Factors through Data Assimilation, *Remote Sens*, 8, 179, <https://doi.org/10.3390/rs8030179>, 2016.



- Kumarasiri W.K.: Damage and loss assessment of Landslide Disasters in Sri Lanka - A case study based on Landslide Disasters in May 2017, in: Proceedings of the 8th Annual NBRO Symposium, At Colombo, Sri Lanka, January 2018, 2018.
- Leeuwen P J V.: Nonlinear data assimilation in geosciences: an extremely efficient particle filter, *Q J Roy Meteor Soc*, 136(653), 1991-1999, doi: 10.1002/qj.699, 2010.
- 5 Lenda G, Ligas M, Lewińska P, et al.: The use of surface interpolation methods for landslides monitoring, *Ksce J Civ Eng*, 20, 188-196, <https://doi.org/10.1007/s12205-015-0038-4>, 2016.
- Li H, Xu Q, He Y, et al.: Prediction of landslide displacement with an ensemble-based extreme learning machine and copula models, *Landslides*, 15, 2047–2059, <https://doi.org/10.1007/s10346-018-1020-2>, 2018.
- Li X Z, Kong J M.: Application of GA-SVM method with parameter optimization for landslide development prediction, *Nat*
- 10 *Hazard Earth Sys Sci*, 14, 5295-5322, <https://doi.org/10.5194/nhess-14-525-2014>, 2014.
- Lian C, Zeng Z, Yao W et al.: Multiple neural networks switched prediction for landslide displacement, *Eng Geol*, 186, 91-99, <https://doi.org/10.1016/j.enggeo.2014.11.014>, 2015.
- Lü H, Yu Z, Zhu Y, et al.: Dual state-parameter estimation of root zone soil moisture by optimal parameter estimation and extended Kalman filter data assimilation, *Adv Water Resour*, 34, 395-406, <https://doi.org/10.1016/j.advwatres.2010.12.005>,
- 15 2011.
- Liu Z, Shao J, Xu W, et al.: Comparison on landslide nonlinear displacement analysis and prediction with computational intelligence approaches. *Landslides*, 11, 889-896, <https://doi.org/10.1007/s10346-013-0443-z>, 2014.
- Maskell S. and Gordon N.: A tutorial on particle filters for on-line non-linear/non-gaussian Bayesian tracking, *IEEE T Signal Proces*, 50, 174–188, doi:10.1049/ic:20010246, 2002.
- 20 Michoud C, Baumann V, Lauknes T R, et al.: Large slope deformations detection and monitoring along shores of the Potrerillos dam reservoir, Argentina, based on a small-baseline InSAR approach, *Landslides*, 13, 451-465, <https://doi.org/10.1007/s10346-015-0583-4>, 2016.
- Moradkhani H, Sorooshian S, Gupta H V, et al.: Dual state–parameter estimation of hydrological models using ensemble Kalman filter, *Adv Water Resour*, 28, 135-147, <https://doi.org/10.1016/j.advwatres.2004.09.002>, 2005.
- 25 Moradkhani H, Weiermüller L.: Hydraulic parameter estimation by remotely—sensed top soil moisture observations with the particle filter, *J Hydrol*, 399, 410-421, <https://doi.org/10.1016/j.jhydrol.2011.01.020>, 2011.
- Nakano, S., Ueno, G., and Higuchi, T.: Merging particle filter for sequential data assimilation, *Nonlin. Processes Geophys.*, 14, 395-408, <https://doi.org/10.5194/npg-14-395-2007>, 2007.
- Nearing G S, Crow W T, Thorp K R, et al.: Assimilating remote sensing observations of leaf area index and soil moisture for



- wheat yield estimates: An observing system simulation experiment, *Water Resour Res*, 48, 213-223, <https://doi.org/10.1029/2011WR011420>, 2012.
- Qin J, Liang S, Yang K, et al.: Simultaneous estimation of both soil moisture and model parameters using particle filtering method through the assimilation of microwave signal, *J Geophys Res*, 114(D15), <https://doi.org/10.1029/2008JD011358>,
5 2009.
- Reichle R H, Mclaughlin D B, Entekhabi D.: Hydrologic Data Assimilation with the Ensemble Kalman Filter. *Monthly Weather Review*, 130,103-114, [https://doi.org/10.1175/1520-0493\(2002\)130<0103:HDAWTE>2.0.CO;2](https://doi.org/10.1175/1520-0493(2002)130<0103:HDAWTE>2.0.CO;2), 2002
- Ren F, Wu X, Zhang K et al.: Application of wavelet analysis and a particle swarm-optimized support vector machine to predict the displacement of the Shuping landslide in the Three Gorges, China, *Environ Earth Sci*, 73, 4791-4804,
10 <https://doi.org/10.1007/s12665-014-3764-x>, 2015.
- Seng H.: A new approach of moving average method in time series analysis. *New Media Studies*, 2014.
- Velicer W.F. and Colby, S. M.: A Comparison of Missing-Data Procedures for Arima Time-Series Analysis, *Educational & Psychological Measurement*, 65, 596-615, <https://doi.org/10.1177/0013164404272502>, 2005.
- Vrugt J A, Gupta H V, Nualláin B Ó et al.: Real-Time Data Assimilation for Operational Ensemble Streamflow Forecasting. *J Hydrometeorol*, 7, 548, <https://doi.org/10.1175/JHM504.1>, 2006.
15
- Wikle C K.: Atmospheric Modeling, Data Assimilation, and Predictability, *Technometrics*, 47, 521-521, <https://doi.org/10.1198/tech.2005.s326>, 2002.
- Xue, C., Nie, G., Li, H., and Wang, J.: Data assimilation with an improved particle filter and its application in the TRIGRS landslide model, *Nat. Hazards Earth Syst. Sci.*, 18, 2801-2807, <https://doi.org/10.5194/nhess-18-2801-2018>, 2018.
20
- Xue K, Yanxiang H U, Zou Y, et al.: Temporal-spatial distribution discipline of geological disaster in China in recent ten years. *Chinese Journal of Geological Hazard & Control*, 27, 90-97, doi:10.16031/j.cnki.issn.1003-8035.2016.03.14, 2016.
- Zhou C, Yin K, Cao Y, et al.: Application of Time Series Analysis and PSO-SVM Model in Predicting the Bazimen Landslide in the Three Gorges Reservoir, China, *Eng Geol*, 204, 108-120, <https://doi.org/10.1016/j.enggeo.2016.02.009>, 2016
25

30



Figures

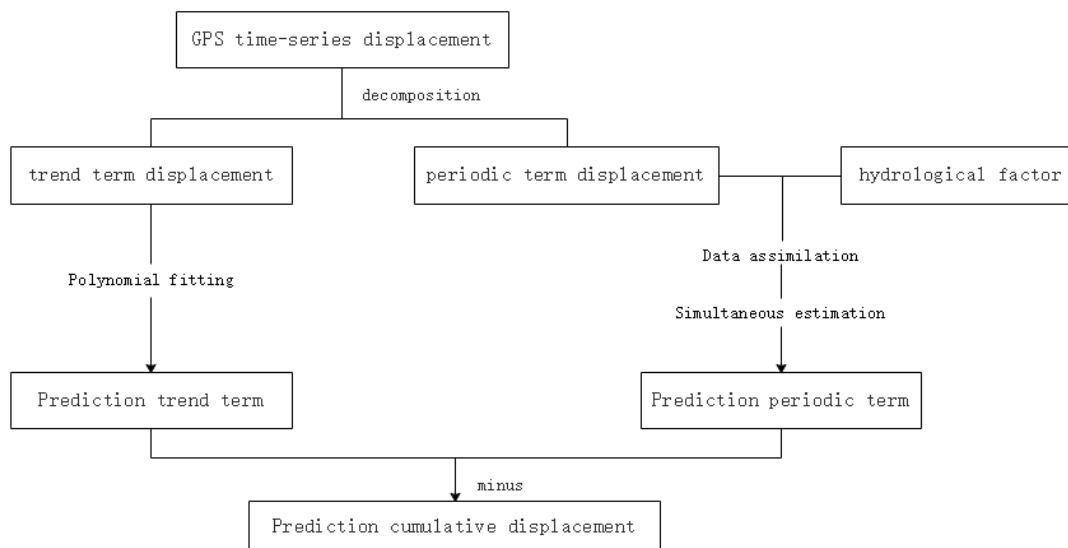


Figure 1. The flow chart of landslide SSPE assimilation strategy

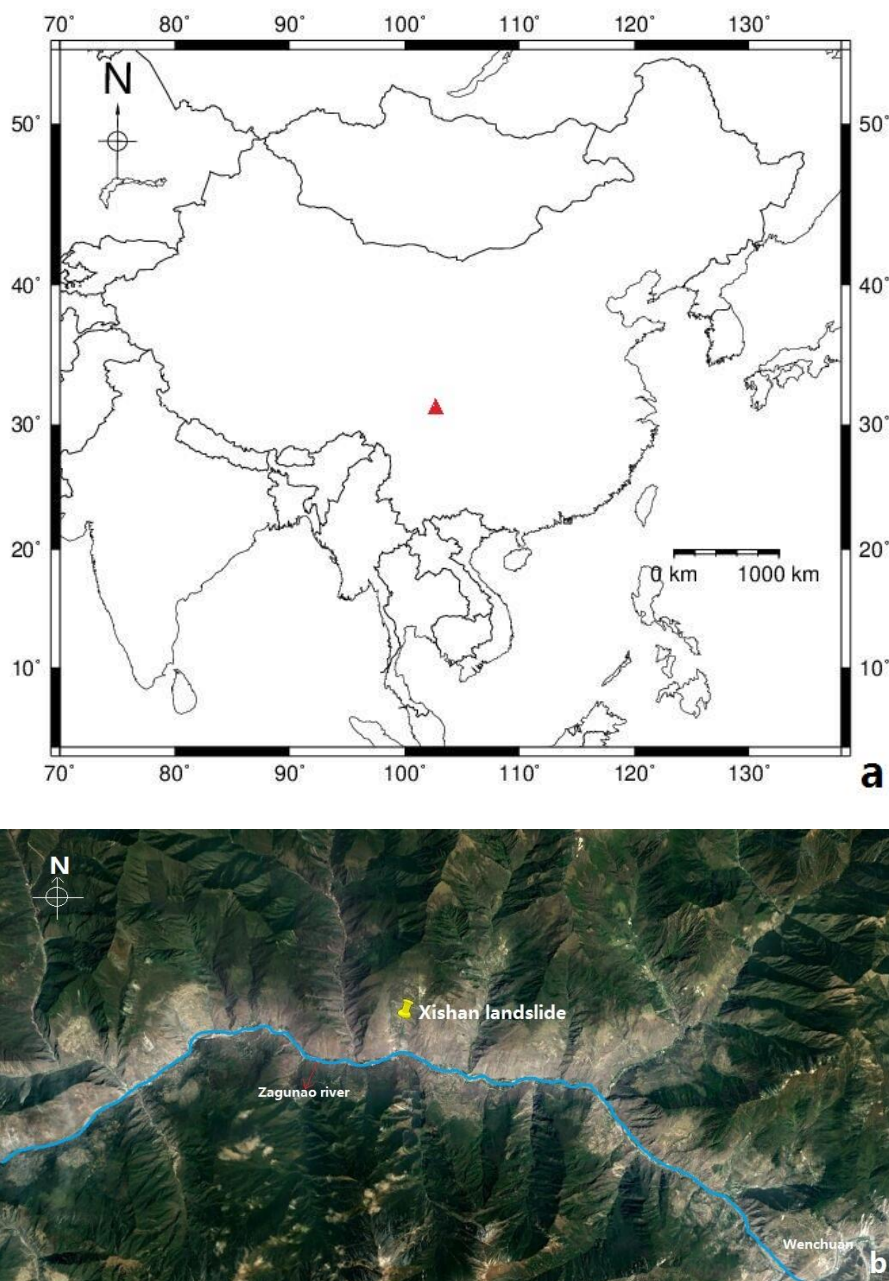


Figure 2. Location of the Xishan landslide in China (a); The Xishan landslides in the west of Wenchuan County associated with landform (b).

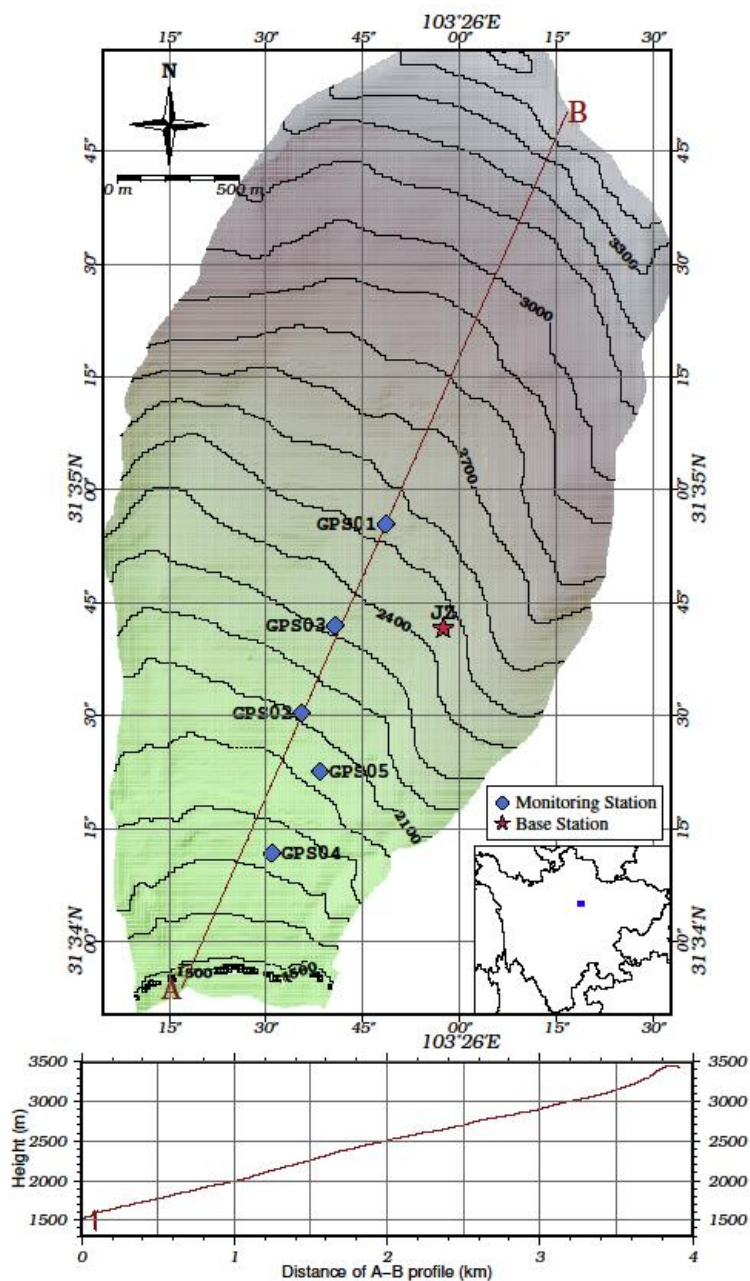


Figure 3. The distribution of GPS stations at Xishan landslide

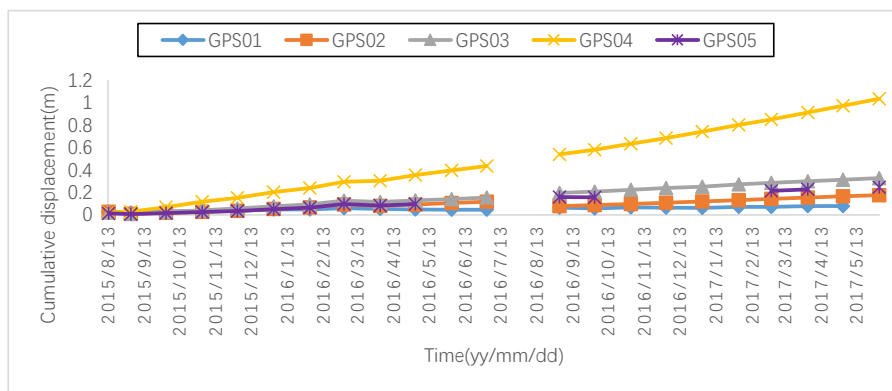


Figure 4. The GPS derived time-series displacement of Xishan landslide

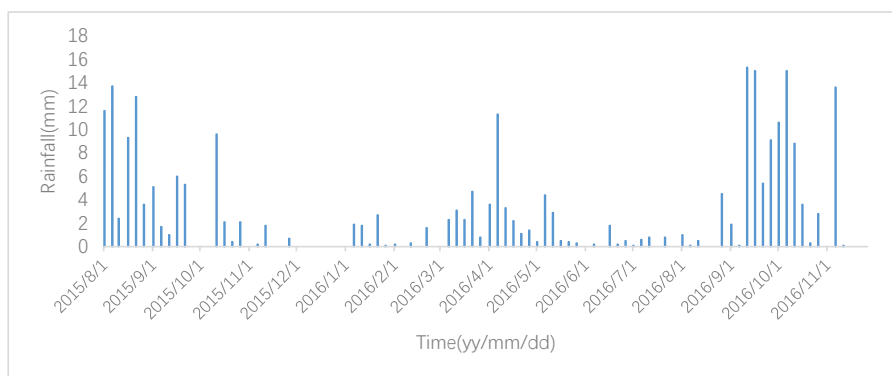


Figure 5. The rainfall of Xishan landslide

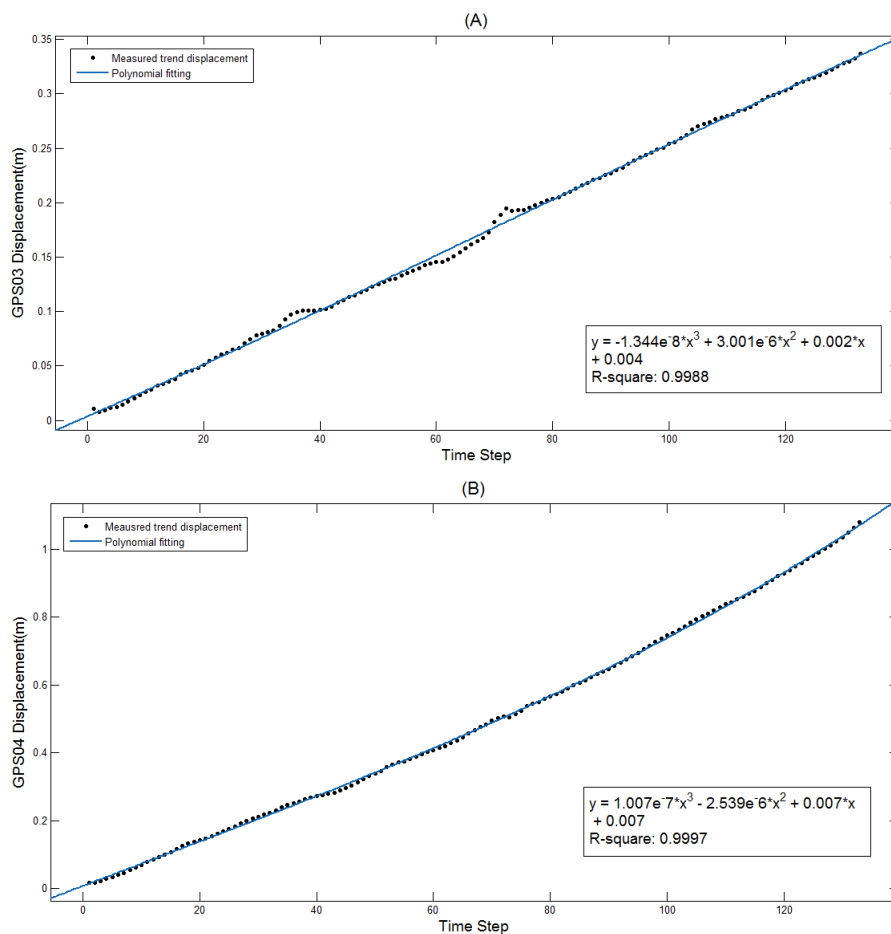


Figure 6. The trend term displacement prediction of (A)station GPS03, (B)station GPS04

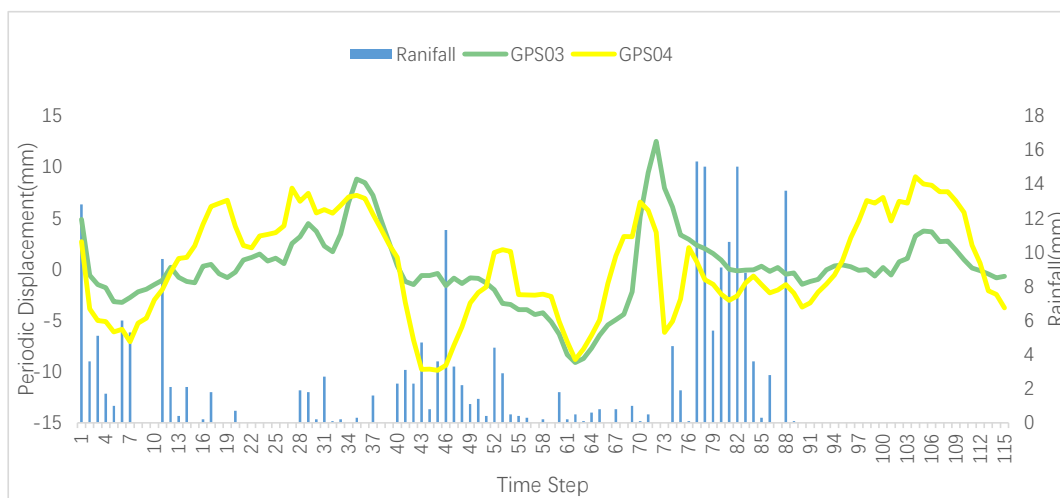


Figure 7. The periodic term displacement prediction combine with rainfall data in GPS03 and GPS04

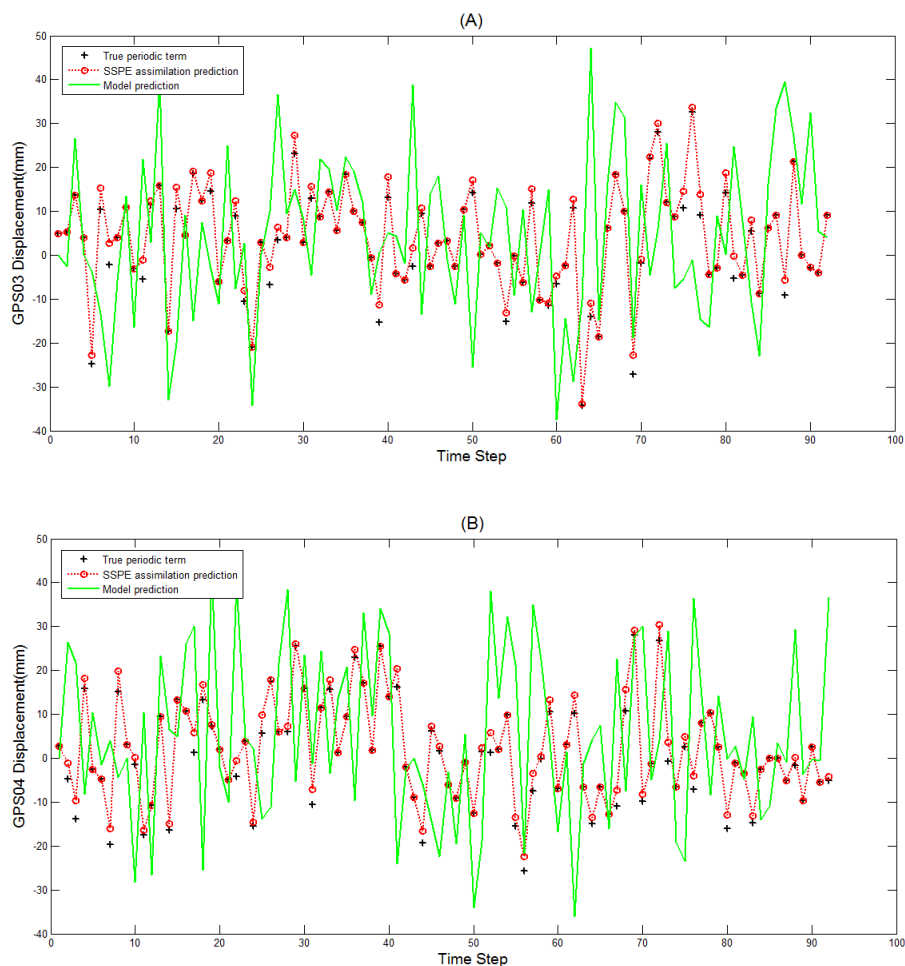


Figure 8. The periodic term displacement prediction of (A)station GPS03, (B)station GPS04

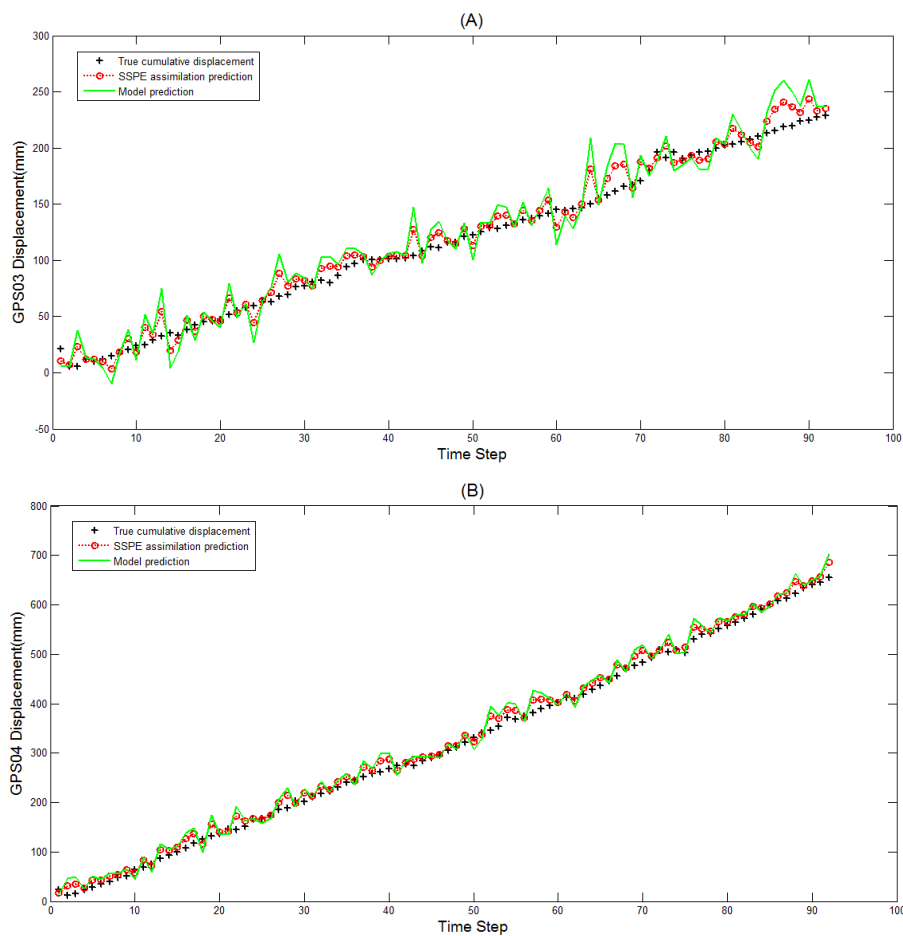


Figure 9. The cumulative displacement prediction of (A) station GPS03, (B) station GPS04



Tables

Table 1 Comparison between the predicted values of cumulative displacement and measured displacement using different methods in station GPS03

Time	Measured value (mm)	Model			SSPE assimilation		
		Prediction value (mm)	Difference (mm)	Error rate (%)	Prediction value (mm)	Difference (mm)	Error rate (%)
2015/11/26	47.0829	40.3051	6.7778	14.40	45.7590	1.3239	2.81
2015/12/6	55.0449	48.7331	6.3118	11.47	53.1385	1.9064	3.46
2016/1/21	80.4837	74.0365	6.4472	8.01	77.4370	3.0467	3.79
2016/3/25	108.0314	97.6699	10.3615	9.59	104.0814	3.9501	3.66
2016/4/21	116.0395	110.1579	5.8816	5.07	114.9779	1.0616	0.91
2016/6/1	137.1018	131.1846	5.9173	4.32	135.4042	1.6976	1.24
2016/8/1	166.8250	155.9336	10.8915	6.53	164.1888	2.6363	1.58

Table 2 Comparison between the predicted values of cumulative displacement and measured displacement using different methods in station GPS04

Time	Measured value (mm)	Model			SSPE assimilation		
		Prediction value (mm)	Difference (mm)	Error rate (%)	Prediction value (mm)	Difference (mm)	Error rate (%)
2015/10/21	75.7527	59.2630	16.4898	21.77	72.4569	3.2958	4.35
2015/12/1	146.0268	135.0044	11.0224	7.55	141.1449	4.8818	3.34
2016/1/11	203.0020	192.7036	10.2984	5.07	199.0452	3.9568	1.95
2016/3/11	274.8091	254.9907	19.8184	7.21	265.4005	9.4085	3.42
2016/4/26	331.1450	307.5421	23.6029	7.13	323.4631	7.6820	2.32
2016/5/26	374.9109	362.8496	12.0613	3.22	372.4185	2.4924	0.66
2016/8/21	504.4282	540.8718	-36.4436	-7.22	523.3166	-18.8885	-3.74

Table 3. Comparison of MAE, MSE, RMSE performance using different methods in two stations

Method	MAE(mm)		MSE(mm)		RMSE(mm)	
	GPS03	GPS04	GPS03	GPS04	GPS03	GPS04
SSPE assimilation	8.206	10.9272	110.9938	187.99	10.5137	13.7111
Model	15.2718	18.0565	382.5577	491.46	19.5591	22.1689