



Technical Note Detection of Particulate Matter Changes Caused by 2020 California Wildfires Based on GNSS and Radiosonde Station

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Abstract: From August to October 2020, a serious wildfire occurred in California, USA, which produced a large number of particulate matter and harmful gases, resulting in huge economic losses and environmental pollution. Particulate matter delays the GNSS signal, which affects the like precipitable water vapor (LPWV) derived by the GNSS non-hydrostatic delay. Most of the information of GNSS-derived LPWV is caused by water vapor, and a small part of the information is caused by particulate matter. A new method based on the difference (ΔPWV) between the PWV of virtual radiosonde stations network and GNSS-derived LPWV is proposed to detect the changes of particulate matter in the atmosphere during the 2020 California wildfires. There are few radiosonde stations in the experimental area and they are far away from the GNSS station. In order to solve this problem, we propose to use the multilayer perceptron (MLP) neural network method to establish the virtual radiosonde network in the experimental area. The PWV derived by the fifth-generation European center for medium-range weather forecasts reanalysis model (PWV_{ERA5}) is used as the input data of machine learning. The PWV derived by radiosonde data (PWV_{RAD}) is used as the training target data of machine learning. The ΔPWV is obtained based on PWV derived by the virtual radiosonde station network and GNSS in the experimental area. In order to further reduce the influence of noise and other factors on ΔPWV , this paper attempts to decompose ΔPWV time series by using the singular spectrum analysis method, and obtain its principal components, subsequently, analyzing the relationship between the principal components of ΔPWV with particulate matter. The results indicate that the accuracy of PWV predicted by the virtual radiosonde network is significantly better than the fifth-generation European center for the medium-range weather forecast reanalysis model, and the change trend of ΔPWV is basically consistent with the change law of particulate matter in which the value of ΔPWV in the case of fire is significantly higher than that before and after the fire. The mean of correlation coefficients between Δ PWV and PM10 at each GNSS station before, during and after wildfires are 0.068, 0.397 and 0.065, respectively, which show the evident enhancement of the correlation between ΔPWV and particulate matter during wildfires. It is concluded that because of the high sensitiveness of Δ PWV to the change of particulate matter, the GNSS technique can be used as an effective new approach to detect the change of particulate matter and, then, to detect wildfires effectively.

Keywords: global navigation satellite system; 2020 California wildfires; virtual radiosonde stations network; multilayer perceptron neural network; PM10/PM2.5

1. Introduction

In 2020, huge wildfires that raged through California killed 91 people, and fiercer wildfires occur in the western United States more frequently [1], impinging on the ecosystem. Additionally, wildfires cannot only cause great economic damage, but also produce incalculable impacts on the environment. Therefore, the research on wildfires detection methods



Citation: Guo, J.; Hou, R.; Zhou, M.; Jin, X.; Li, G. Detection of Particulate Matter Changes Caused by 2020 California Wildfires Based on GNSS and Radiosonde Station. *Remote Sens.* 2021, *13*, 4557. https://doi.org/ 10.3390/rs13224557

Academic Editor: Stefania Bonafoni

Received: 26 October 2021 Accepted: 10 November 2021 Published: 12 November 2021

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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). grows in popularity. Wildfires produce a large number of smoke particles [2], of which PM10 (particles from 0 microns to 10 microns) and PM2.5 (particles from 2.5 microns or less) are considered as two important indicators, affecting human health. Long-term exposure to particles seriously damages human bodies. Anjali et al. studied the Australian wildfires in 2019, concluding through experimenters that long-term exposure to wildfires smoke has a serious impact on the respiratory tract [3]. Angeliki et al. collected statistics on particulate matter from 1980 to 2020. Moreover, it was concluded that PM10 and PM2.5 concentrations are associated with mortality, and that the risk of cardiovascular death and the incidence rate of the respiratory system will mount with the increase in PM2.5 concentration in smoke [4]. The occurrence of wildfires is often triggered by natural causes such as heatwaves and droughts in summer and lightning, as well as smoking, picnics, and other human activities [5,6]. Wildfires are unpredictable and harmful. The earlier detection of wildfires can significantly alleviate the impact on people and the loss [7,8]. Antonio et al. developed a layered wireless sensor network, which is combined with originated wildfires in dangerous areas and integrated with a fire command center, geographic information system, and fire detector so as to detect wildfires [9]. Hu et al. applied Sentinel-2 remote sensing data to classify wildfire areas and non-fire areas, and established a fully automatic algorithm based on adaptive thresholds which can be applied to onboard processing [10]. Taking the 2020 California wildfires as the research object, Alan et al. modeled 54 million wildfires and 25 million building locations in the study area, conducting a risk assessment and experiments for wildfire prediction [11]. Currently, the research methods of wildfire detection mainly use unmanned aerial vehicles, remote sensing, various smoke sensors, etc., but these methods have the disadvantages of a huge cost and poor real-time performance.

The Global Navigation Satellite System (GNSS) has been widely used in the field of meteorology by virtue of its advantages of wide distribution of stations, all-weather observation, low cost, and high temporal and spatial resolution [12–15]. The content of precipitable water vapor (PWV) in the atmosphere changes sharply with time and space [16–18], so the PWV is widely used in meteorology research [19–21]. The GNSS-derived PWV (PWV_{GNSS}) has been verified, and its accuracy is the same as that of traditional technologies such as a radiosonde station, airborne radiometer, water vapor radiometer, and lidar [22,23]. Moreover, Abbasy et al. conducted experiments on GNSS stations in the province of Zanjan, Iran, and compared PWV_{GNSS} with the radiosonde-derived PWV (PWV_{RAD}) value and PWV value in the global reanalysis datasets [24]. It has been concluded that GNSS inversion PWV has a better inversion accuracy. Yahaya et al. studied the correlation between GNSS inversion PWV and particulate matter in Nigeria, and determined statistics on the correlation between GNSS inversion PWV and particulate matter PM10 [25]. It has been concluded that GNSS inversion PWV and PM10 are highly correlated. Guo et al. studied the correlation between the inversion of the zenith total delay (ZTD) and PM2.5 by GNSS, and predicted the particulate matter PM2.5 in short-term, proving the influence of the GNSS-based inversion on ZTD, including particulate matter [26]. Wen et al. verified the relationship between the zenith wet delay and PM2.5 based on GNSS and meteorological factors, and predicted the PM2.5 value in short-term [27]. The feasibility of particle detection based on GNSS has been proved by relevant research.

The GNSS signal is delayed due to the influence of the troposphere. The hydrostatic delay can be obtained by the tropospheric model with millimeter accuracy, mainly considering the influence of the standard atmosphere without particles such as PM10/PM2.5. Therefore, the influence of particulate matter is included in the non-hydrostatic delay [26] and GNSS-derived like PWV(LPWV). Most of the information of GNSS-derived LPWV is caused by water vapor, and a small part of the information is caused by particulate matter. The PWV observed by the radiosonde station is mainly caused by water vapor, without being affected by particles. Therefore, the difference (Δ PWV) between GNSS-derived LPWV and PWV_{RAD} is mainly caused by particles in theory [28]. Because of a few available ground sounding stations without colocation, this paper proposes a method to detect

the change of atmospheric particles during the 2020 California wildfires by obtaining the Δ PWV based on the PWV of virtual sounding stations and GNSS stations.

This paper aims to use the GNSS technique to detect particulate matter changes caused by the 2020 California wildfires. A new method based on the Δ PWV between the PWV of the virtual radiosonde stations network and GNSS-derived LPWV is proposed. The relationship between particulate matter and Δ PWV is studied. Section 2 introduces study areas, data collection and research methods. Processing results and analyses are presented in Section 3. Finally, the conclusion is given in Section 4.

2. Data and Research Methods

2.1. Study Area

California is a wildfire hot spot in the western United States [29]. In order to deal with the occurrence of wildfires, California's fire prevention budget has mounted year by year, but still cannot solve the problem of wildfires. The most destructive wildfires recorded broke out in the 21st century [30]. Since August 2020, another wildfire consumed swathes of California with a burned area of more than 2.09 million acres (about 8457 square kilometers), reaching an all-time high. The 2020 California wildfires have led to huge economic losses and environmental pollution.

As California is located in the west of the Rocky Mountains and positioned in the Mediterranean climate zones, it is affected by anticyclones caused by Pacific high pressure in summer with dry air and little rainfall, which is very prone to triggering wildfires. In winter, affected by the Pacific moderation, it belongs to the wet season (from December to April), and the precipitation on the windward slope (west slope) is abundant [31]. Heatwaves and dryness in summer can induce wildfires easily, so California has become a hot spot of wildfires in the world.

2.2. Research Data

2.2.1. Wildfire Data

The wildfires map provided by National Aeronautics and Space Administration (NASA) is shown in Figure 1b (https://firms.modaps.eosdis.nasa.gov/map Access date: 6 September 2021). The wildfires mainly occur in northern California with a large area and long duration. Additionally, the wildfires mainly happen in August, September, and October, of which the area of wildfires in September is regarded as the largest. According to the area of the wildfires, the area with longitude from 113°W to 124°W and latitude from 33°N to 41°, mainly in California, was chosen for the current study. The distribution of GNSS stations, air quality monitoring stations, and ground radiosonde sounding stations is shown in Figure 1.

2.2.2. GNSS Data

Based on wildfire information, 10 GNSS stations in California were selected as the research data which were taken from the Système d'Observation du Niveau des Eaux Littorales (SONEL) website (https://www.sonel.org/ Access date: 6 September 2021). The GNSS data only included GPS data with a 30s data sampling interval and a data length from day 001 of year 2020 to day 366 of year 2020. The distribution of selected GNSS stations is shown in Figure 1b.

The Global Positioning System(GPS) data processing strategy is shown in Table 1.

The GPS data were processed based on the data processing strategy in Table 1. The solution average accuracy of GNSS-derived ZWD and GNSS-derived LPWV at each site is shown in Table 2. According to Table 2, the average accuracy of ZWD and LPWV at ten GNSS stations in the experimental area from 001 days to 366 days in 2020 was between 3.09 mm~4.53 mm and 0.52 mm~0.75 mm, respectively. The solution accuracy met the requirements.

Parameters	Value
Cut-off height angle	10°
Tropospheric model	Saastamoinen
Mapping function	GMF
Tropospheric parameter estimation interval	1 h
Ocean tide model	Fes2004
Epoch interval	30 s
Solar pressure model	BERNE

Table 1. The Global Positioning System (GPS) data processing strategy.



Figure 1. Global Navigation Satellite System (GNSS) stations, radiosonde sounding stations, and air quality monitoring stations.

Table 2. The average accuracy of GNSS-derived zenith wet delay (ZWD) and GNSS-derived like precipitable water vapor (LPWV)(mm).

Site	GNSS-Derived ZWD	GNSS-Derived LPWV
QUIN	4.03	0.67
GOLD	4.02	0.66
GOL2	4.07	0.68
FVPK	3.98	0.66

Site	GNSS-Derived ZWD	GNSS-Derived LPWV	
SLAC	3.09	0.52	
TIBB	4.18	0.70	
UCSF	4.53	0.75	
STFU	4.49	0.74	
CSST	4.37	0.73	
EOCG	4.28	0.73	

Table 2. Cont.

2.2.3. Air Quality Data

The PM10/PM2.5 data were selected to indicate the wildfire situation, which were taken from the global air quality data platform (https://aqicn.org/data-platform/register/Access date: 6 September 2021) with the data period from day 001 of year 2020 to day 366 of year 2020. The global air quality data platform provides an average of PM data every day. The distribution of selected air quality stations is shown in Figure 1b.

2.2.4. PWV Data

The PWV_{RAD} data were derived from the measured data of radiosonde stations (http://weather.uwyo.edu/upperair/sounding.htm Access date: 6 September 2021). This paper adopted four radiosonde stations in which the observation data at 0:00 am every day was taken as the experimental data with the data period from day 001 of year 2016 to day 366 of year 2020, with its geographical distribution shown in Figure 1a,b.

The PWV derived by the fifth-generation European center for medium-range weather forecasts reanalysis model (ERA5) dataset (https://cds.climate.copernicus.eu/cdsapp# !/dataset/reanalysis-era5-single-levels?tab=form Access date: 6 September 2021) was also used in this study. The ERA5 uses physical laws to combine the model data with the observation results throughout the world to form a global complete dataset [32–34]. The ERA5 can provide PWV data extending from the earth's surface to the top of the atmosphere. Thereinto, data grid size was 0.25° and the time resolution was 24 h. Moreover, the data at 0:00 (UTC) in a day was taken as the experimental data in this study with the data period from day 001 of year 2016 to day 366 of year 2020.

Due to the systematic error between ERA5-derived PWV (PWV_{ERA5}) and PWV_{RAD} , in order to establish the PWV network model of virtual radiosonde station, the PWV data of radiosonde sounding stations in the Rockies were used as the neural network learning data to train PWV_{ERA5} , so as to construct the PWV model of virtual radiosonde station in the Rockies of California and eliminate the systematic error. The PWV data in radiosonde station were derived from the Department of Atmospheric Science at the University of Wyoming (http://weather.uwyo.edu/upperair/sounding.html Access date: 6 September 2021). The data were measured twice at 0:00 am (UTC) and 12:00 am every day, and the research period was selected from day 001 of year 2016 to day 366 of year 2020, a total of five years. The distribution of selected radiosonde stations is shown in Figure 1a, where ZXS, BOI and EPZ were self-inspection data.

2.3. Research Methods

2.3.1. Acquirement of ΔPWV

GAMIT 10.74 was used to process GPS data for obtaining GNSS-derived LPWV. The principle was that the total tropospheric delay (ZTD) was taken as an unknown parameter and solved by the GNSS carrier phase observation equation. GNSS phase observation equation was [35]:

$$L_{i,f}^{j} = \rho_{i}^{j} + c\left(dt_{i} - dt^{j}\right) + M \cdot ZTD - I_{i,f}^{j} + \lambda_{f}N_{i,f}^{j} + \varepsilon_{i,f}^{j}$$
(1)

where *I*, *j*, and *f* denote the satellite, receiver, and signal frequency, respectively. ρ_i^j denotes the geometry distance from receiver to satellite. c represents the speed of light in vacuum. dt_i and dt^j are the receiver clock offset and the satellite clock offset, respectively. *M* is the mapping function of troposphere. The ZTD and $I_{i,f}^j$ denote the total tropospheric delay and the slant ionosphere delay. $N_{i,f}^j$ and λ_f are the phase ambiguity and the wavelength of phase observation. $\varepsilon_{i,f}^j$ denotes other unmodelled errors.

The ZTD can be expressed as:

$$\text{ZTD} = [L_{i,f}^j - \rho_i^j - c\left(dt_i - dt^j\right) + I_{i,f}^j - \lambda_f N_{i,f}^j - \varepsilon_{i,f}^j]/M$$
(2)

The ZTD is the zenith total delay, including the delay caused by standard dry atmosphere, water vapor, and particulate matter. The ZHD was calculated using the Saastamoinen model [36]. The equation was:

$$ZHD = \frac{0.0022768P}{1 - 0.00266COS(2L) - 0.00028H}$$
(3)

where *P* denotes atmospheric pressure. *L* denotes latitude. *H* denotes the GPS station geodetic height. The ZHD is a delay due to standard dry atmosphere. The standard dry atmosphere did not include PM10, PM2.5, and other particles. Finally, zenith non-hydrostatic delay (also known as zenith wet delay, ZWD) could be calculated by:

$$ZWD = ZTD - ZHD$$
(4)

Therefore, the delay caused by water vapor and particles was included in ZWD. The GNSS-derived LPWV could be calculated by [37]:

$$LPWV = ZWD \cdot \sigma \tag{5}$$

$$\sigma = \frac{10^6}{\rho_w g_s \left[k_2 + \left(\frac{k_3}{T_m}\right)\right]} \tag{6}$$

where σ , T_m and ρ_w are the conversion factor, the weighted average temperature of the troposphere, and the density of liquid water. $g_s = 461 \text{ J} \cdot \text{kg}^{-1} \text{ K}^{-1}$. $k_2 = 16.48 \text{ K/hPa}$, $k_3 = 105 \text{ K}^2 (3.776 \pm 0.014)/\text{hPa}$.

Since GNSS-derived LPWV was calculated according to ZWD, GNSS-derived LPWV would also be affected by particles.

The PWV_{RAD} threes directly calculated by meteorological parameters, so it threes only caused by water vapor and threes not affected by particles. In order to deduct the influence of water vapor in GNSS-derived LPWV, the PWV_{RAD} threes introduced.

The relative humidity (U) and the saturated water vapor pressure (E) of radiosonde data should have been used to calculate the precipitable water pressure (*e*) [38] to obtain PWV_{RAD} from radiosonde stations:

$$e = \frac{\mathsf{OE}}{100} \tag{7}$$

The specific humidity (*q*) was obtained according to water vapor pressure:

$$q = \frac{\varepsilon e}{p - e * (1 - \varepsilon)}$$
(8)

The PWV_{RAD} from radiosonde stations was obtained by integration [39]:

$$PWV_{RAD} = \frac{1}{g} \int_0^{p_0} q dp \tag{9}$$

where, $\varepsilon = 0.622 \text{ gkg}^{-1}$ as an empirical constant. *p* and *p*₀ represent pressure of different heights measured by the sounding balloon sensor. *g* is gravitational acceleration. The PWV_{RAD} was calculated from the measured meteorological data. Therefore, the influence of particulate matter was not included.

Therefore, the Δ PWV affected by particulate matter was expressed as:

$$\Delta PWV = LPWV - PWV_{RAD} \tag{10}$$

The Δ PWV was obtained through the calculation from Equations (1) to (10) above. Theoretically, Δ PWV was caused by particles. The occurrence of fire would produce a large number of smoke particle pollutants such as PM2.5 and PM10. Therefore, the correlation between Δ PWV and PM10/PM2.5 could be used to detect wildfires.

2.3.2. Establishment Methods of Virtual Radiosonde Station Networks

Since only 4 radiosonde stations were available in the area of the wildfires without colocation with GNSS stations, this situation affected the calculation of Δ PWV. In this study, establishing PWV network of virtual radiosonde stations based on multilayer perceptron (MLP) neural network was proposed. Thereinto, the PWV_{ERA5} data at the radiosonde stations provided by the European center for medium-range weather forecasts, the longitude, latitude and elevation of GNSS station, as well as the annual and the day of year (doy) of PWV data, were used as training input data. Moreover, the PWV_{RAD} value at radiosonde stations was used as the learning target data. As the experimental area was located in the west of the Rockies and close to the Pacific Ocean, the terrain fluctuated greatly. To validate the science of virtual radiosonde network, the PWV_{ERA5} and the PWV_{RAD} at 40 radiosonde stations were used as input data and learning target data for training. Radiosonde stations are distributed around North American Rockies (as shown in Figure 1). The period of PWV data was doy 001 of 2016 to doy 366 of 2020. The geographical distribution of radiosonde stations used for training and verification is shown in Figure 1a.

The MLP neural network is defined as a distributed algorithm mathematical model for information processing based on the interaction of a large number of neurons with the characteristics of self-adaptive, self-learning, and real-time learning. The MLP neural network is generally composed of input layer, hidden layer, and output layer, in which there are a large number of nodes connected by weight between each network layer [40]. When MLP neural network receives a group of input signals, it performs nonlinear weight calculation through activation function, and transmits the calculation results to the next neuron. Because the initial weight is randomly generated, the output value reaches the predetermined goal by continuously adjusting the weight between each neuron in the training process.

The MLP neural network model constructed in this study is shown in Figure 2, in which the input layer contained 6 parameters—year, doy, latitude, longitude, geodetic height, and 0:00 (UTC) PWV_{ERA5}; 2 hidden layers were included in the middle, and the output layer was the 0:00 PWV_{RAD} value of ground radiosonde station. In this study, Levenberg–Marquart (LM) algorithm was used for neural network training. The LM algorithm has proved to be an optimization algorithm with excellent performance, strong convergence, and high precision by combining the strengths of gradient method and Newton–Raphson method. In this study, it was used for neural network fitting training algorithm, eliminating the systematic error between PWV_{ERA5} and PWV_{RAD} to improve the accuracy of PWV_{ERA5}.

2.3.3. Singular Spectrum Analysis (SSA)

In theory, the Δ PWV was influenced by particulate matter. However, the LPWV could be affected by climate temperature and precipitation. Therefore, it was also affected by many other factors besides particles. Since the singular spectrum analysis (SSA) method could decompose the one-dimensional sequence into a series of time series with their characteristics, such as tendency, cycle, and noise, it was possible to extract the trend, identify the period of the original time series, and smooth the data [41–44]. Therefore, the SSA was used to decompose ΔPWV to obtain its principal component. The technical route is shown in Figure 3.



Figure 2. Structure chart of neural network.



Figure 3. The main steps of singular spectrum analysis (SSA) analysis.

As shown in Figure 3, first, input Δ PWV time series. Second, the construction of delay matrix. In general, oscillations with periods of M/5~M could be well recognized when the window length was M. Third, singular value decomposition, which could construct a new matrix by choosing its eigenvalues and eigenvectors. The fourth grouping divided the original time series into disjoint groups. Fifth, diagonal averaging, the purpose of which was to convert the decomposed primary matrix back into a new time series of the original length, called the reconstruction component (RC), and the sum of all the RC values equaled the original sequence. Sixth, the correlation analysis of all RCs was carried out, and the principal components were determined.

3. Result and Analysis

3.1. Accuracy Analysis of PWV of Virtual Radiosonde Station Network

In order to verify the accuracy of the virtual radiosonde station network PWV (PWV_{VR}), the fitting rate (R) of the neural network and performance of machine learning at different stages of learning were analyzed, and the results are shown in Table 3 and Figure 4. It can be seen from Figure 4 that the fitting rate of the regression analysis in the training stage, validation stage, test stage, and the whole process was 0.977, 0.987, 0.984, and 0.979, respectively. The mean squared error (MSE) in the training stage, validation stage, test stage, and the whole process was 3.12 mm, 1.17 mm, and 1.37 mm, respectively. The results show that the effect of machine learning was good.

Table 3. Performance of machine learning.

Progress	Samples	MSE (mm)	Fitting Rate
Training	52,428	3.12	97.75%
Validation	6554	1.17	98.77%
Testing	6554	1.37	98.41%

In order to further analyze the accuracy of PWV_{VR} , PWV_{VR} , and PWV_{ERA5} at ZXS (the radiosonde in the northern of the virtual radiosonde network), BOI (the radiosonde station in the central of the virtual radiosonde network), and EPZ (the radiosonde station in the south of the virtual radiosonde network) were selected to compare with the PWV_{RAD} , respectively. The root mean square error (RMS), mean, and standard deviation (STD) were calculated, respectively. The correlations between PWV_{ERA5} and PWV_{RAD} , and PWV_{VR} and PWV_{RAD} , were analyzed, respectively. The statistical results are listed in Table 4.

Table 4. PWV of virtual radiosonde station network (PWV_{VR}) accuracy analysis.

Station	Latitude (°)	Longitude (°)	Geodetic Height (m)	Parameter	PWV _{ERA5} and PWV _{RAD} (mm)	PWV _{VR} and PWV _{RAD} (mm)
ZXS	53.9	-122.79	601	RMS STD MEAN CORREL	2.16 1.85 1.11 0.98	1.75 1.75 0.05 0.99
BOI	43.56	-116.21	874	RMS STD MEAN CORREL	0.93 0.91 -0.11 0.98	0.72 0.72 -0.08 0.99
EPZ	31.86	-106.7	1252	RMS STD MEAN CORREL	1.02 0.97 0.31 0.98	0.79 0.79 0.04 0.99



Figure 4. Learning effect of multilayer perceptron (MLP) neural network (the horizontal axis is the PWV of the radiosonde station, the vertical axis is the PWV of machine learning, and the oblique line is the fitting line).

According to the statistics, compared with the RMS, STD, and mean of the difference between PWV_{ERA5} and PWV_{RAD}, those of the difference between PWV_{VR} and PWV_{RAD} at the three radiosonde stations were reduced by 21.37%, 14.95%, and 69.95%, respectively, with particularly obvious improvement in the mean value. This shows that the system error between PWV_{ERA5} and PWV_{RAD} could be greatly reduced by establishing a virtual radiosonde station network, so that the accuracy of PWV_{ERA5} can be improved. It can be seen from the above statistical results that the accuracy of PWV_{VR} was obviously better than that of PWV_{ERA5}. Therefore, PWV_{VR} could be used to replace the PWV_{RAD} value of the radiosonde station to calculate Δ PWV.

3.2. Detection of Change of Particulate Matter Based on ΔPWV

Firstly, based on PWV_{VR} in the Rocky Mountain region of the United States, the Δ PWV of each GNSS station at hour 0 (UTC) each day was obtained, and the mean of Δ PWV of each period before, during, and after the fire was calculated. The variation of the mean of Δ PWV in different fire stages was analyzed, and the statistical results were listed in Table 5.

As is listed in Table 5, the mean of Δ PWV at each GNSS station was higher than that before the fire, which was mainly due to the significant increase in Δ PWV caused by a large amount of particulate matter generated during the fire. The Δ PWV before the wildfire of the seven GNSS stations was higher than that after the wildfire, such as QUIN. This was mainly due to the rainy season from January to April every year. After the fire, there was less rainfall in the dry season in this area. Due to the special climatic factors, the Δ PWV in the seven GNSS stations was higher in the early period than in the later period of the wildfire. The Δ PWV of the three GNSS stations, including STFU in the later stage of fire, was larger than that in the earlier stage, possibly because the three GNSS stations were located at the junction of the Coast Mountains and Tehachapi Mountains, with no high mountains blocking them. Under the influence of the Pacific humid airflow all year round [45], and because the GNSS stations on both sides were close to the fire burning area, the particles after the fire remained in the air for a long time.

Table 5. Statistics of mean of the difference (Δ PWV) between the PWV of virtual radiosonde stations network and GNSS-derived LPWV in different fire periods (mm).

GNSS	Before Fire	During Fire	After Fire
QUIN	2.42	3.51	2.36
GOLD	3.67	4.50	2.90
GOL2	3.63	4.44	2.88
FVPK	1.84	3.57	1.24
SLAC	1.76	4.11	1.42
TIBB	1.57	4.02	1.42
UCSF	3.87	6.25	3.47
STFU	1.80	3.69	2.50
CSST	1.05	3.33	2.79
EOCG	0.98	2.21	2.47

There were four air quality monitoring stations distributed in the study area. San Jose only provided PM2.5 data, while the other three stations provide PM10 and PM2.5 data. This paper determined statistics on PM10 data of the four air quality stations according to the maximum value, average value, and STD before and after the fire. The results are listed in Table 6, from which it can be concluded that PM10 was maximum at the time of fire occurrence. The PM10 concentration after the wildfire was higher than that before the wildfire, which was consistent with the change trend of wildfire, indicating that PM10 data could be used to characterize the change of wildfire.

Air Station	Parameter	Before Fire	During Fire	After Fire
	STD	10.09	38.77	15.83
San Jose	MEAN	25.53	58.08	36.20
	MAX	57.00	180.00	85.00
	STD	15.21	26.01	14.75
Los Angeles	MEAN	43.82	68.38	55.38
	MAX	94.00	159.00	90.00
	STD	10.19	29.77	19.31
Fresno	MEAN	23.07	69.71	32.61
	MAX	59.00	164.00	79.00
	STD	7.52	10.72	8.16
Las Vegas	MEAN	18.84	32.72	20.66
	MAX	57.00	67.00	43.00

Table 6. The PM10 statistics of air quality stations in different fire periods ($\mu g/m^3$).

In order to analyze the relationship between Δ PWV and PM more directly, the variation trend of Δ PWV and PM2.5 at the SLAC station and STFU station in different fire periods was studied. The two GNSS stations were close to the San Jose Air Quality Station, and the PM2.5 data of San Jose Air Quality Station were taken to characterize the change of fire. The monthly mean of Δ PWV at the two GNSS stations and the monthly mean of PM2.5 at the air quality station were analyzed. The results are shown in Figure 5, where the red box is the time of fire occurrence.



Figure 5. Comparison of monthly mean values of Δ PWV and PM2.5 at SLAC and STFU stations (the fire period is in the box).

As is shown in Figure 5, before the fire, Δ PWV and PM2.5 of the two GNSS stations were small with steady change. Since May, PM2.5 and Δ PWV were on the rise. From August to October, when fires broke out on a large scale, PM2.5 reached the peak, and Δ PWV also rose rapidly to the peak, both changing dramatically. After October, the PM2.5 and the Δ PWV showed a trend of rapid decline, and then stabilized after November. As can be seen from the above results, Δ PWV was highly consistent with the change of PM2.5, and the change of PM2.5 could be detected by Δ PWV.

3.3. Analysis of the Detection of Wildfires by ΔPWV Based on SSA

However, due to the complex composition of water vapor, the ΔPWV may also be affected by other factors. Therefore, ΔPWV was decomposed by SSA to obtain the ΔPWV principle component (ΔPWV_{PC}), and the effects of other factors (except particulate matter) on ΔPWV were reduced as much as possible. The window length selected in this study was 90.

In order to select the principal component, firstly, the eigenvalue contribution rate was analyzed. As shown in Figure 6, the results show that the eigenvalue contribution rate of the first RC in the Δ PWV decomposition results was more than 87%. Theoretically, most of the signals contained in the Δ PWV were caused by particles, so this result was reasonable.



Figure 6. Eigenvalue contribution rate.

This paper, respectively, took the first one to ten order RCs as ΔPWV_{PC} and analyzed the correlation between each ΔPWV_{PC} and PM10. The results show that it could achieve

the best effect when the first RCs were taken as ΔPWV_{PC} . Therefore, the first RCs of the decomposition results were taken as ΔPWV_{PC} . The undecomposed ΔPWV and ΔPWV_{PC} were analyzed for correlation with PM10 data, respectively, and the results are listed in Table 7.

GNSS	Correlation Coefficient between Δ PWV and PM10	Correlation Coefficient between ΔPWV_{PC} and PM10
GOL2	0.11	0.53
GOLD	0.12	0.55
STFU	0.21	0.46
SLAC	0.19	0.43
TIBB	0.25	0.49
UCSF	0.22	0.45
QUIN	0.10	0.58
CSST	0.35	0.56
EOCG	0.19	0.55
FVPK	0.21	0.59

Table 7. Correlation comparison between PM10 data and Δ PWV before and after reconstruction.

As is listed in Table 7, by using SSA to extract the principle components, the correlation coefficient between ΔPWV_{PC} and PM10 was 209.65% higher than the correlation between ΔPWV and PM10. It could be concluded that after SSA reconstruction, the influence of non-particulate matter on ΔPWV was significantly reduced, and the contribution rate of particulate matter to ΔPWV was significantly increased.

Taking QUIN, CSST, EOCG, and FVPK as examples, the correlation analysis of Δ PWV_{PC} in different periods of fire with PM10 and PM2.5 was conducted, respectively. The statistical results are listed in Table 8.

GNSS	Fire Period	PM10	PM2.5
	Before the fire	0.082	-0.525
QUIN	During the fire	0.413	0.310
	After the fire	0.309	-0.007
	Before the fire	0.027	0.175
CSST	During the fire	0.418	0.321
	After the fire	0.377	0.295
	Before the fire	0.117	0.257
EOCG	During the fire	0.412	0.281
	After the fire	-0.164	-0.202
	Before the fire	0.045	0.182
FVPK	During the fire	0.346	0.310
	After the fire	-0.260	-0.064

Table 8. The correlation analysis of ΔPWV principle component (ΔPWV_{PC}).

As is listed in Table 8, the correlation coefficient between ΔPWV_{PC} and PM10 and PM2.5 increased significantly when fire occurred, which indicates that ΔPWV based on the virtual radiosonde station network was feasible to detect the change of particulate matter. Additionally, it was also effective to detect the change of particulate matter. In addition, the correlation coefficient between PM10 and ΔPWV increased the most, indicating that in the particulate matter produced by the fire, the content of PM10 was larger than that of PM2.5.

4. Conclusions

The study took the 2020 California wildfires as an example, and the data of doy 001 to 366 in 2020 from 10 GNSS stations were calculated to obtain LPWV. A new method base on Δ PWV to detect the changes of particulate matter in the atmosphere during the

2020 California wildfires was proposed. The results showed that the variation trend of Δ PWV was highly consistent with that of particulate matter data, with a high correlation between them.

The specific conclusions are as follows:

- (1) The virtual radiosonde station network in the Rocky Mountain region was constructed based on the MLP neural network. The accuracy of PWV_{VR} was significantly higher than that of PWV_{ERA5}, and the system deviation between PWV_{ERA5} and PWV_{RAD} could be greatly reduced.
- (2) The Δ PWV at fire occurrence was significantly higher than that at early and late stages of fire occurrence, showing the same change pattern with particulate matter.
- (3) The ΔPWV_{PC} was obtained by decomposing and reconstructing ΔPWV with the SSA method. The correlation coefficient between ΔPWV_{PC} and particulate matter data was significantly improved, showing that the decomposition and reconstruction of ΔPWV by SSA can significantly increase the contribution rate of particulate matter to ΔPWV . At the same time, the correlation coefficient between ΔPWV_{PC} and particulate matter data matter data was significantly higher during the fire occurrence period than before and after the fire occurrence.

In conclusion, the Δ PWV method based on the virtual radiosonde station network could effectively detect the change of particulate matter and, thus, provides a new technology and method for wildfire detection.

Author Contributions: J.G.: Conceptualization, Methodology, Funding acquisition; R.H.: Data curation, Software, Writing—original draft preparation. M.Z.: Validation, Investigation, Writing—reviewing and editing. X.J.: Software, Validation. G.L.: Supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the National Natural Science Foundation of China (grant nos. 41774001, 41374009), SDUST Research Fund (grant no. 2014TDJH101), and Autonomous and Controllable Special Project for Surveying and Mapping of China (grant no. 816–517).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The GNSS observation data used in our work can be freely accessed at https://www.sonel.org/ Access date: 6 September 2021. The PWV_{RAD} data were obtained from http://weather.uwyo.edu/upperair/sounding.html Access date: 6 September 2021. The PWV_{ERA5} data were obtained from https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis--era5-single--levels?tab=form Access date: 6 September 2021. The air quality monitoring data were obtained from https://aqicn.org/data-platform/register/ Access date: 6 September 2021. The forest fire information was obtained from https://firms.modaps.eosdis.nasa.gov/map/ Access date: 6 September 2021.

Acknowledgments: We are very grateful to SONEL for providing the GPS data. We are very grateful to the ECMWF and the University of Wyoming for providing the PWV data. We thank NASA for providing the wildfire information. We are very grateful to the global air quality data platform for providing the PM data. We thank the Massachusetts Institute of Technology (MIT), Scripps Institution of Oceanography (SIO), and Harvard University for providing GAMIT/GLOBK software. This research was supported by the National Natural Science Foundation of China (grant numbers 41774001) and the SDUST Research Fund (grant number 2014TDJH101).

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

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