Reconstruction of Global 9 km, 8-day SMAP Surface Soil Moisture Dataset during 2015-2020 by Spatio-temporal Fusion

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Abstract

Soil moisture, a crucial property for Earth surface research, has been applied widely in various studies. The Soil Moisture Active Passive (SMAP) global products at 36 km and 9 km (called P36 and AP9 in this research) have been published from April 2015. However, the 9 km AP9 product was retrieved from the active radar and L-band passive radiometer, and the active radar failed in July 2015. In this research, the virtual image pair-based spatio-temporal fusion model was coupled with a spatial weighting (VIPSTF-SW) to simulate the 9 km AP9 data after failure of the active radar. The method makes full use of all the historical AP9 and P36 data available between April and July 2015. As a result, 8-day composited 9 km SMAP data at the global scale were produced from 2015 to 2020, by downscaling the corresponding 8-day composited P36 data. The available AP9 data and in-situ reference data were used to validate the predicted 9 km data. Generally, the predicted 9 km SMAP data can provide more spatial detail than P36 and are more accurate than the existing EP9 product. The VIPSTF-SW predicted 9 km SMAP data are an accurate substitute for AP9, and will be made freely available to support research and applications in hydrology, climatology, ecology, and many other fields at the global scale.

1 Introduction

Soil moisture is considered to be a significant property in a range of models including those in applied ecosystem cycling [1, 2], water resources [3], drought monitoring [4, 5] and soil evaporation studies [6, 7]. Sensors installed on the ground are one of the earliest solutions to measure soil moisture, and can acquire real-time in-situ data. These in-situ data provide accurate measurements of soil moisture, and they are commonly regarded as a ground reference for quantitative evaluation of soil moisture predicted by other platforms (e.g., satellite sensors) [8-10]. However, in-situ data are commonly spatially sparse: that is, observations are provided only at the limited sensor locations available. Furthermore, the high economic and labor costs further hamper development of this measurement approach, especially for large area monitoring [11]. In contrast, satellite sensors can provide spatially continuous soil moisture data with large spatial coverage (i.e., including at the global scale). Therefore, the soil moisture data acquired by satellite sensors have been used widely in practical applications [12].

The Soil Moisture Active Passive (SMAP) satellite supported by the National Aeronautics and Space Administration (NASA) was launched in January 2015 and started to provide data in April 2015. The SMAP product is always considered as a type of dataset with greater accuracy than the other soil moisture products [13-15], as exhibited in Table 1. For the SMAP satellite, two sensors, including an L-band active radar (1.26 GHz) and a passive radiometer (1.41 GHz), are carried by to measure global surface soil moisture at a fine temporal resolution [16]. As a result, a spatially complete global soil moisture map can be acquired every 2-to-3 days. The SMAP data are published at spatial resolutions of 36 km (called P36 in this paper), 9 km (called AP9 in this paper), and 3 km, which are retrieved using the passive radiometer observation, the combined active radar and passive radiometer, and the active radar observation, respectively [17, 18]. However, the on-board active radar operated only for approximately 3 months (13 April 2015 to 07 July 2015) and failed on 08 July 2015. Subsequently, directly retrieved SMAP soil moisture data at 3 km and 9 km were not provided.

Table 1. Information of some commonly used soil moisture products.

<table>
<thead>
<tr>
<th>Satellite/Sensor/Product</th>
<th>Gridded Spatial resolution</th>
<th>Temporal resolution</th>
<th>Launched time (mm-yyyy)</th>
<th>Reference</th>
</tr>
</thead>
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</table>
To cope with the failure of the active radar, the enhanced SMAP passive 9 km soil moisture product (called EP9 in this paper) was created to extend the 9 km soil moisture data. The EP9 data were retrieved using interpolated brightness temperature based on the single-channel algorithm [25, 26]. Although both EP9 and AP9 are at the same 9 km spatial resolution, AP9 has been observed to contain more spatial details than EP9. To increase the spatial details, another product at 3 km/1 km spatial resolution was published by NASA, using C-band synthetic aperture radar from Sentinel-1 A/B to substitute the defunct L-band active radar on-board SMAP, that is, the SMAP/Sentinel1 L2 soil moisture product (called SM_SP in this paper). Nevertheless, the temporal resolution of Sentinel-1 A/B is coarser than SMAP due to the narrow swath [27-29].

In recent years, a variety of methods have been developed to downscale the 36 km soil moisture data (i.e., P36) from the passive radiometer of SMAP. Zhao et al. [9] developed an ensemble learning-based random forest model to downscale the 36 km SMAP product to 1 km, in which 1 km optical and thermal infrared MODerate resolution Imaging Spectroradiometer (MODIS) observations were used as auxiliary data. Likewise, Hu et al. [30] incorporated finer spatial resolution visible and shortwave-infrared data (such as land surface temperature (LST), normalized difference vegetation index (NDVI) and brightness temperature (TB)) in a random forest model to downscale the 36 km SMAP data. Wei et al. [31] proposed a gradient boosting decision tree method to downscale the P36 data to 1 km, coupled with a large number of soil moisture indices derived from MODIS and a digital elevation model (DEM). On the other hand, spatial interpolation-based methods have also been developed for downscaling the P36 data. Based on the well-established area-to-point regression kriging (ATPRK) method [32, 33], a geographically weighted version proposed by Jin et al. [34] replaces the original linear regression in ATPRK to account for spatial non-stationary in downscaling. Wen et al. [35] further extended the geographically weighted version with a self-adaptive window in regression modeling. In addition, similar methods have also been developed for coarse soil moisture data acquired by other sensors, such as the European Space Agency’s Soil Moisture Climate Change Initiative (CCI) [36], Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) [37] and Advanced Microwave Scanning Radiometer 2 (AMSR-2) [38].

All of the aforementioned methods require auxiliary data (e.g., NDVI, TB, LST, and DEM) at finer spatial resolution. The auxiliary data are acquired by other sensors and influence the accuracy of downscaling directly. In particular, a key issue is that the auxiliary data acquired from other sources represent different physical meanings. Thus, the spatial texture of the fine spatial resolution auxiliary data may not be highly correlated with that of the fine spatial resolution SMAP.
data. Moreover, auxiliary data acquired by optical sensors can be contaminated easily by cloud
and haze, leading to spatially incomplete data and increased uncertainty in the downscaling
predictions [39].

Jiang et al. [18] first proposed to extend the 9 km SMAP product (i.e., AP9) by fusing the P36
product with the available AP9 data. As the baseline data, the 8-day (the last eight days of working
active radar in the three months) global P36 and AP9 were considered as the known image pair of
the fusion model, which was used to downscale the P36 data on other days (i.e., between 8 July
2015 and 12 April 2017) to 9 km. Jiang et al. [18] provided a pioneering study blending AP9 data
for downscaling P36 data. However, two issues remain to be addressed. Firstly, only a single image
pair was used in spatio-temporal fusion in Jiang et al. [18]. The image pair plays a crucial role in
spatio-temporal fusion, as the included fine spatial resolution image provides indispensable
information for predicting the target image at the same fine spatial resolution on other days.
Generally, the accuracy of spatio-temporal fusion tends to be greater when more image pairs are
considered [40]. Thus, it is worthwhile to use more image pairs for downscaling the P36 product.
Secondly, only two years (from July 2015 to April 2017) of AP9 data were produced in Jiang et
al. [18]. It is worthwhile to create longer time-series AP9 data at the global scale, which can be
applied straightforwardly by researchers, for example, in hydrology, meteorology, climatology and
ecology.

In this paper, we created a long time-series, 8-day composited soil moisture product at 9 km,
and at the global scale, by spatio-temporal fusion of P36 and available AP9 data. We tackled
directly the two issues mentioned above. Firstly, we considered multiple image pairs in the fusion
of P36 and AP9. The use of multiple AP9-P36 pairs is feasible, as the AP9 data are available from
13 April 2015 to 07 July 2015 and there are about 10 AP9 images (8-day composited) in total, with
each providing full cover at the global scale. The composited period is the same as the well-known
8-day composited MODIS products to facilitate the post-applications where MODIS data are
required. Secondly, 9 km global soil moisture data were produced over five years (from July 2015
to August 2020). The new product will be made publically available to support global research in
hydrology and other related fields.

2 Data and methods

2.1. Data

2.1.1. Satellite sensor data

Three Level 3 SMAP products with global coverage were applied in this research, including
P36, AP9 and EP9. Different versions of the SMAP product were released by NASA due to
continuous optimization of the SMAP products through time. In this research, the Version 6 P36
and Version 3 AP9 and EP9 were considered. It should be noted that there are no substantial
changes between different versions and only one version was used for each SMAP product. Thus,
the difference in data version was neglected in this research. Two groups of experiments with
disparate periods were designed. Specifically, the period of Experiment 1 is the same as that of
AP9 (i.e., 14 April 2015 to 07 July 2015), while the period of Experiment 2 is after the failure of
AP9 (i.e., 12 July 2015 to 19 August 2020). In addition, regional SM_SP data at 3 km were also
used in this research. Details of the used SMAP data are listed in Table 2. The data can be acquired
freely from the National Snow and Ice Data Center (NSIDC, https://nsidc.org/).

Table 2. The satellite products of soil moisture used in the study
In-situ soil moisture data

The in-situ data are soil moisture data measured on the ground, and have been used widely as reference for evaluating the accuracy of soil moisture products retrieved from satellite sensor data [41-43]. The in-situ data are provided freely by the International Soil Moisture Network (ISMN, https://ismn.earth/en/). The soil moisture observation networks are set up across the entire globe by several institutions with different sensors for various purposes. Accordingly, the networks have different measurement periods and one or more observation depths in some cases [44-47]. Thus, based on the availability of the in-situ data at the given periods, different networks were considered in Experiments 1 and 2 in this research. Additionally, two networks (i.e., Fort Cobb and Little Washita) in Oklahoma, USA were used for the regional comparison, which are provided by the U.S. Department of Agriculture, Oklahoma State University, and the Oklahoma Climatological Survey. The location of the in-situ data is exhibited in Figure 1. It should be stressed that only topsoil moisture (< 0.05 m) can be retrieved effectively from L-band radiometers (with ~1.4 GHz frequency and ~21 cm wavelength), since they cannot penetrate deep soil [48-50]. Therefore, the measured depths of the in-situ data selected for validation are less than 0.05 m. In addition, for some points, parts of the in-situ data are missing along the time-series, which were excluded for consideration in the experiments. The locations of the used in-situ data are listed in Table 3.
Figure 1. Locations of the in-situ data (a) Experiment 1. (b) Experiment 2. (c) Case study at the regional scale in the Discussion.

Table 3. Details of the in-situ data

<table>
<thead>
<tr>
<th>Section</th>
<th>Network</th>
<th>Number of in-situ points</th>
<th>Location</th>
<th>Depth (m)</th>
<th>Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1</td>
<td>AMMA-CATCH</td>
<td>3</td>
<td>Benin, Niger, Mali</td>
<td>0.05-0.05</td>
<td>CS616</td>
</tr>
<tr>
<td></td>
<td>CTP_SMTMN</td>
<td>14</td>
<td>China</td>
<td>0.00-0.05</td>
<td>5TM</td>
</tr>
<tr>
<td></td>
<td>DAHRA</td>
<td>1</td>
<td>Senegal</td>
<td>0.05-0.05</td>
<td>ThetaProbe-ML2X</td>
</tr>
<tr>
<td></td>
<td>FLUXNET-AMERIFLUX</td>
<td>2</td>
<td>USA</td>
<td>0.00-0.00</td>
<td>ThetaProbe-ML2X</td>
</tr>
<tr>
<td></td>
<td>FR_Aqui</td>
<td>3</td>
<td>France</td>
<td>0.05-0.05</td>
<td>ThetaProbe-ML2X</td>
</tr>
</tbody>
</table>
The virtual image pair-based spatio-temporal fusion (VIPSTF) method provides a flexible framework for spatio-temporal fusion, by creating a virtual image pair (VIP) that blends the information from multiple image pairs [40]. Accordingly, two versions were derived, including spatial unmixing-based VIPSTF (VIPSTF-SU) and spatial weighting-based VIPSTF (VIPSTF-SW). VIPSTF-SW has been demonstrated to be the more accurate in [40]. Thus, this method was used to extend the AP9 data by fusion of P36 and existing AP9 time-series data. Specifically, the predicted AP9 is expressed as follows:

$$\text{AP9}_{\text{T}_t} = \text{AP9}_{\text{VIP}} + \Delta \text{AP9}$$

(1)

where $\text{AP9}_{\text{T}_t}$ is the predicted 9 km SMAP data at time $T_t$, $\text{AP9}_{\text{VIP}}$ is the AP9 image in the VIP and $\Delta \text{AP9}$ is the 9 km increment image predicted using a spatial weighting scheme.

The $\text{AP9}_{\text{VIP}}$ image is produced with a linear combination of the multiple known AP9 images:

$$\text{AP9}_{\text{VIP}} = \sum_{i=1}^{n} a_i \text{AP9}_{\text{T}_i} + b$$

(2)

where $a_i$ is a transformation coefficient for the $i$-th image $\text{AP9}_{\text{T}_i}$, $b$ is a constant, and $n$ is the number of known AP9 images. In Experiment 1, each of the 10 scenes was predicted in turn, using the other 9 scenes. Therefore, $n$ was set to 9 in Experiment 1. In Experiment 2, all the 10 scenes were used as the inputs. Thus, $n$ was set to 10 in Experiment 2. Based on the assumption of scale
Invariance [40, 51], the optimal coefficient set (i.e., \(a_i\) and \(b\)) is estimated based on the linear regression model fitted between the corresponding P36 images:

\[
P_{36 \_T_i} = \sum_{i=1}^{n} a_i \ P_{36 \_T_i} + b + \Delta P36
\]  

(3)

In Eq. (3), \(P_{36 \_T_i}\) is the \(i\)-th known P36 image, and \(\Delta P36\) refers to the residual image. The optimal coefficient set is predicted using the least squares fitting method. The 9 km increment image \(\Delta AP9\) is predicted based on the following spatial weighting scheme:

\[
\Delta AP9(x_0, y_0) = \sum_{i=1}^{s} w_i \Delta P36(x_i, y_i)
\]  

(4)

where \((x_i, y_i)\) is the spatial location of the similar pixels surrounding the center pixel \((x_0, y_0)\), \(w_i\) refers to a weight calculated according to the distance between the center pixel and the \(i\)-th surrounding similar pixel, and \(s\) is the number of surrounding similar pixels [52]. \(s\) was set to 5 in this research. Note that the \(\Delta P36\) image needs to be interpolated to 9 km in advance to match the spatial resolution of AP9, and the bicubic interpolation was employed in this paper for this purpose. Figure 2 shows the whole process of VIPSTF-SW for fusion of P36 and AP9.

Figure 2. Flowchart representing VIPSTF-SW for fusion of P36 and AP9.

2.3. Validation strategy

The predicted SMAP soil moisture data at 9 km spatial resolution were validated with either real AP9 data or in-situ data, or both. Specifically, for Experiment 1, both the real AP9 and in-situ data were applied for validation of the predicted AP9 data. For Experiment 2, however, only the in-situ data were used, as the real AP9 data were not available in the period (i.e., 12 July 2015 to 19 August 2020). For the evaluation using the real AP9 data, the pixels of AP9 data were used.
directly for evaluation, considering the spatial resolution (i.e., 9 km) is consistent. For the
evaluation using in-situ data, the average in-situ data at the level of networks were used for
validation to reduce the measurement errors caused by the numerous stations. Specifically, the
corresponding pixel of each measuring station was extracted from the satellite-derived soil
moisture data based on their locations. Then, the soil moisture values of the extracted pixels were
averaged as the measured value and compared with the data of corresponding network. In addition
to the spatial evaluation (i.e., evaluation was performed on the map at each time in turn), the
temporal evaluation (i.e., evaluation was performed on each pixel with temporal profile in turn)
was also implemented.

Six quantitative evaluation indices were employed for accuracy assessment in this research,
including the correlation coefficient (CC), root mean squared error (RMSE), bias (Bias), unbiased
root mean squared error (ubRMSE), relative global-dimensional synthesis error (ERGAS) [53] and
universal image quality index (UIQI) [54]. For validation using real AP9 data in Experiment 1, all
six indices were utilized for accuracy assessment. With respect to the validation based on the use
of the in-situ data in both Experiments 1 and 2, ERGAS and UIQI were not considered, as these
two indices are calculated based on spatially complete reference data, rather than spatially sparse
in-situ data.

\[
CC = \frac{\text{Cov}(S_w, S_q)}{\sqrt{\text{Var}(S_w) \text{Var}(S_q)}}
\]

\[
\text{RMSE} = \sqrt{E[(S_w - S_q)^2]}
\]

\[
\text{ubRMSE} = \sqrt{E\left\{\left(\frac{(S_w - E(S_w)) - (S_q - E(S_q))}{\sqrt{\text{Var}(S_q)}}\right)^2\right\}}
\]

\[
\text{Bias} = E(S_w) - E(S_q)
\]

\[
\text{ERGAS} = 100 \frac{h}{l} \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left(\frac{\text{RMSE}}{E(S_w)}\right)^2}
\]

\[
\text{UIQI} = \frac{4E(S_w)E(S_q)\text{Cov}(S_w, S_q)}{(E(S_w)^2 + E(S_q)^2)(\text{Var}(S_w) + \text{Var}(S_q))}
\]

where \(S_w\) represents the real soil moisture data (i.e., either AP9 or in-situ data) and \(S_q\) represents
the predicted data. In addition, Cov is the covariance function, E means the expectation, Var
represents the variance, \(h\) and \(l\) are the fine and coarse spatial resolution (i.e., \(h < l\)), and \(N\) means
the number of bands.

3. Experiments and results

The experimental design is shown in Figure 3. In Experiment 1, each of the 10 8-day
composited AP9 data were predicted, in turn, with the other nine AP9 data as known images for
fusion. The acquisition times for the AP9 data are shown in Table 4. Accordingly, all data in
Experiment 1 (i.e., P36, AP9, EP9 and in-situ data) were composited to produce 8-day composited
data for testing. Meanwhile, the composited data of AP9 and P36, that is, the 10 known AP9-P36
image pairs, were also applied in Experiment 2. For clarity, we denoted the AP9 data predicted
using VIPSTF-SW as VIPSTF-SW9 (i.e., \(\text{AP9}_T\) in Eq. (1)). The published EP9 and P36 were
used as benchmark data to show the advantage of VIPSTF-SW9. In Experiment 2, the VIPSTF-SW9 data were produced, in turn, from 12 July 2015. Again, all data in Experiment 2 (i.e., P36, EP9 and *in-situ* data) were composited with the same rule.

![Figure 3. The experimental design for Experiments 1 and 2.](image)

### 3.1. Experiment 1

#### 3.1.1. Validation based on AP9 data

The results at $T_5$ and $T_{10}$ are shown as examples in Figure 4, where four sub-figures are also zoomed to aid comparison. It is seen clearly that the available EP9 data are visually smooth, even though they contain more spatial details than the original P36 data. Compared with the EP9 data, the VIPSTF-SW9 predictions reproduce more spatial heterogeneity and are closer to the reference AP9 data. Table 5 lists the quantitative evaluation VIPSTF-SW9 and EP9 results for the
predictions made 10 times, where the real AP9 data are used as reference. By referring to the real
AP9 data, there are obvious differences between the accuracies of VIPSTF-SW9 and EP9 data for
all 10 cases. The VIPSTF-SW9 data have an average CC of 0.968, which is 0.095 larger than that
of EP9. Furthermore, the average UIQI and ERGAS of VIPSTF-SW9 are 0.118 larger and 5.465
smaller than those of EP9, respectively. Both the average RMSE and ubRMSE of VIPSTF-SW9
are 0.41 smaller than those of EP9. In addition, The VIPSTF-SW9 data have an average Bias of
0.002, which is closer to the reference than that of EP9. The advantage of VIPSTF-SW9 over EP9
is also illustrated by the spatial bias in Figure 5.

The critical reason for the difference between VIPSTF-SW9 and EP9 is that the latter is
produced using only interpolated brightness temperature without auxiliary fine spatial resolution
information. In contrast, the VIPSTF-SW9 data are produced by taking the known fine spatial
resolution AP9 data into account comprehensively.
Table 4. The time of the 8-day composited soil moisture data in Experiment 1

<table>
<thead>
<tr>
<th>Data</th>
<th>$T_1$</th>
<th>$T_2$</th>
<th>$T_3$</th>
<th>$T_4$</th>
<th>$T_5$</th>
<th>$T_6$</th>
<th>$T_7$</th>
<th>$T_8$</th>
<th>$T_9$</th>
<th>$T_{10}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>06-19-2015</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>06-28-2015</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>07-07-2015</td>
</tr>
</tbody>
</table>

Note: The expression for the date is mm/dd/yyyy. We did not collect the P36 and AP9 data on 05-13-2015 and 06-16-2015 since they are unavailable.

Table 5. Statistical metrics for the accuracy of VIPSTF-SW9 and EP9 data (AP9 as reference)

<table>
<thead>
<tr>
<th>CC</th>
<th>UIQI</th>
<th>ERGAS</th>
<th>RMSE</th>
<th>Bias</th>
<th>ubRMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_1$</td>
<td>0.949</td>
<td>0.886</td>
<td>0.949</td>
<td>0.863</td>
<td>7.083</td>
</tr>
<tr>
<td>$T_2$</td>
<td>0.960</td>
<td>0.878</td>
<td>0.960</td>
<td>0.855</td>
<td>6.401</td>
</tr>
<tr>
<td>$T_3$</td>
<td>0.960</td>
<td>0.880</td>
<td>0.959</td>
<td>0.853</td>
<td>6.454</td>
</tr>
<tr>
<td>$T_4$</td>
<td>0.969</td>
<td>0.870</td>
<td>0.968</td>
<td>0.843</td>
<td>5.500</td>
</tr>
<tr>
<td>$T_5$</td>
<td>0.976</td>
<td>0.874</td>
<td>0.975</td>
<td>0.849</td>
<td>4.838</td>
</tr>
<tr>
<td>$T_6$</td>
<td>0.978</td>
<td>0.872</td>
<td>0.978</td>
<td>0.847</td>
<td>4.617</td>
</tr>
<tr>
<td>$T_7$</td>
<td>0.976</td>
<td>0.869</td>
<td>0.976</td>
<td>0.846</td>
<td>4.725</td>
</tr>
<tr>
<td>$T_8$</td>
<td>0.974</td>
<td>0.862</td>
<td>0.973</td>
<td>0.839</td>
<td>4.936</td>
</tr>
<tr>
<td>$T_9$</td>
<td>0.972</td>
<td>0.871</td>
<td>0.971</td>
<td>0.850</td>
<td>5.132</td>
</tr>
<tr>
<td>$T_{10}$</td>
<td>0.971</td>
<td>0.871</td>
<td>0.970</td>
<td>0.850</td>
<td>5.228</td>
</tr>
<tr>
<td>Ave</td>
<td>0.968</td>
<td>0.873</td>
<td>0.968</td>
<td>0.850</td>
<td>5.491</td>
</tr>
</tbody>
</table>
Figure 4. Soil moisture predictions for Experiment 1. (a) P36\_T5. (b) AP9\_T5 (Reference). (c) EP9\_T5. (d) VIPSTF-SW9\_T5. (e) P36\_T10. (f) AP9\_T10 (Reference). (g) EP9\_T10. (h) VIPSTF-SW9\_T10.
3.1.2. Validation based on the in-situ data in Experiment 1

The in-situ soil moisture data were measured continuously from fixed sensors and considered as the reference for validation in this experiment. As shown in Figure 6, the accuracy at each time of the 10 cases is provided. Among the official products (i.e., P36, AP9, EP9 data), at each time, the real AP9 data have the greatest consistency with the in-situ data in Experiment 1. This is because the AP9 data are collaboratively retrieved from the active radar and passive radiometer. However, the other data are not directly derived from the active radar with reliable support to the prediction of 9 km data. Therefore, the accuracy of the other official products is smaller than that of the AP9 data. Besides, the accuracy of predicted VIPSTF-SW9 dataset is similar to that of the AP9 data. Although the average accuracy and stability of VIPSTF-SW9 data are slightly smaller than those of the real AP9 data (see, for example, the box charts of Figure 6), the predicted VIPSTF-SW9 data still have a more accurate performance than the EP9 and P36 data.
3.2. Experiment 2

3.2.1. 9 km SMAP data predicted during 2015-2020

The 10 8-day composited image pairs (AP9-P36) in Experiment 1 were applied to produce the VIPSTF-SW9 data after the failure of AP9 (i.e., from July 2015 to August 2020) in Experiment 2. For Experiment 2, a total of 230 global VIPSTF-SW9 maps were produced from 12 July 2015 to 19 August 2020 (marked as 2015193 to 2020225). Due to the continuous absence of P36 from 20 June 2019 to 22 July 2019, VIPSTF-SW9 predictions from 2019169 to 2019201 are unavailable. The repository holding the predicted 5-year product of global VIPSTF-SW9 data is available at https://doi.org/10.6084/m9.figshare.14634276. As shown in Figure 7, we exhibit all VIPSTF-SW9 data in 2016 (46 scenes). For convenience of visual inspection, a sub-region of both VIPSTF-SW9 and the original P36 data is shown in Figures 8 and 9. It can be seen clearly that the predicted VIPSTF-SW9 data present more spatial details than P36, revealing the advantages of the VIPSTF-SW9 data. In addition, the composited products for each quarter (i.e., three months) from 2015 to 2020 are displayed in Figure A1.
Figure 7. The predicted 8-day VIPSTF-SW9 data in 2016.
Figure 8. The 8-day composited P36 data in 2016 (a sub-region is used for convenience of visualization).
Figure 9. Dynamic changes of 8-day composited VIPSTF-SW9 for 2016.
3.2.2. Validation based on the in-situ data in Experiment 2

As shown in Figure 10, the results in Experiment 2 were evaluated using the in-situ data, as the real AP9 data were unavailable for the five years. The in-situ data in the whole year of 2019 were selected for validation. Note that the P36 and EP9 data were not available from 2019169 to 2019201. Noticeably, there are differences in the accuracies of the results between Experiments 1 and 2. The main reason is that the 9 km data in the two experiments were predicted in completely different periods. It is observed that the VIPSTF-SW9 data are more accurate than that of the P36 and EP9 data. Moreover, the accuracy of the EP9 time-series is close to that of P36. This is because the spatial details acquired from the available AP9 data were injected into VIPSTF-SW9 data by spatio-temporal fusion. Inversely, P36 and EP9 data were retrieved from coarse and interpolated brightness temperature of SMAP, respectively, without prior spatial details.

![Figure 10](image)

In addition to the spatial evaluation above, the accuracy was also evaluated in the temporal domain. That is, the temporal file of each network was compared with that of the in-situ time-series at the same location. As shown in Table 6, the results of all 11 networks are provided, and the average of all results at each network is also provided for comparison. It can be observed that VIPSTF-SW9 data present the greater performance than the P36 and EP9 data for almost all networks. Checking the average results, the VIPSTF-SW9 data have the largest mean CC of 0.787, which are 0.014 and 0.017 larger than that of the P36 and EP9 data. The mean RMSE of VIPSTF-
SW9 data is 0.008 smaller than that of the P36 and EP9 data. Meanwhile, the mean Bias of the VIPSTF-SW9 data is -0.006, which is much closer to the reference (i.e., in-situ data) than that of the P36 and EP9 data (with a Bias of -0.025).

Table 6. Statistical metrics for accuracy evaluation of the soil moisture data in the temporal domain in Experiment 2 (the in-situ data as reference).

<table>
<thead>
<tr>
<th>Network</th>
<th>Dataset</th>
<th>CC</th>
<th>RMSE</th>
<th>Bias</th>
<th>ubRMSE</th>
</tr>
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<tbody>
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<td>P36</td>
<td>FR_Aqui</td>
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<td>0.076</td>
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</tr>
<tr>
<td>P36</td>
<td>EP9</td>
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<td>-0.061</td>
<td>0.023</td>
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<tr>
<td>P36</td>
<td>VIPSTF-SW9</td>
<td>0.954</td>
<td>0.039</td>
<td>-0.024</td>
<td>0.031</td>
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<tr>
<td>P36</td>
<td>HOBE</td>
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<td>0.040</td>
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<td>P36</td>
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<td>0.037</td>
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<tr>
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<td>-0.052</td>
<td>0.037</td>
</tr>
<tr>
<td>P36</td>
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<td>-0.006</td>
<td>0.010</td>
</tr>
<tr>
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<td>-0.003</td>
<td>0.009</td>
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<td>-0.004</td>
<td>0.036</td>
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<td>P36</td>
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<td>-0.051</td>
<td>0.033</td>
</tr>
<tr>
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<td>VIPSTF-SW9</td>
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<td>P36</td>
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<td>0.039</td>
<td>0.036</td>
</tr>
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<td>EP9</td>
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<td>0.053</td>
<td>-0.047</td>
<td>0.023</td>
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<td>VIPSTF-SW9</td>
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</tr>
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<tr>
<td>P36</td>
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<td>-0.051</td>
<td>0.043</td>
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<td>VIPSTF-SW9</td>
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<td>0.041</td>
<td>-0.006</td>
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<td></td>
</tr>
</tbody>
</table>

4 Discussion

4.1. The advantage of using multiple image pairs in the spatio-temporal model

Jiang et al. [18] used a single image pair in their spatio-temporal model for downscaling P36. For spatio-temporal fusion of reflectance images, the use of multiple image pairs has been demonstrated to be more beneficial than use of a single image pair [40]. It is necessary to further examine whether this scheme is also more advantageous for spatio-temporal fusion of the SMAP.
data investigated in this paper. To this end, the performances of both single and multiple image pairs were compared here. For the single image pair case, each of the AP9-P36 image pairs was considered as the known data in VIPSTF-SW, in turn, for downscaling the other nine coarse P36 data. The multiple image pairs case is exactly the same as that in Experiment 1. The accuracies of both cases are shown in Figure 11. As shown in Figure 11, for any prediction time, the average accuracies of using multiple image pairs are obviously greater than that of using a single image pair. This validates rigorously the advantage of using multiple image pairs in this paper over the scheme of using a single image pair in Jiang et al. [18].

Figure 11. Accuracies of using different image pairs in the spatio-temporal fusion model ($T_i$-based means the image pair at $T_i$ was used to predict the data at the other nine times. Multiple-based means all nine image pairs were used to predict the data at the remaining one time).
4.2. Which data are closer to the true soil moisture?

For a given spatial location, the availability of the in-situ data varies across time. Since in this research we sought to maximize the number of in-situ data for evaluation of the predictions, the spatial distributions of the in-situ data in Experiments 1 and 2 are not consistent. To further discuss the reliability of the products in a continuous period, the common in-situ data in both Experiments 1 and 2 were used. The in-situ data from 174 stations and nine networks were collected. The averages of the in-situ data at the station level were calculated for evaluation. As shown in Figure 12, three main points can be observed. Firstly, the time-series of AP9 and VIPSTF-SW9 are the most similar to the in-situ data. Secondly, the time-series of P36 and EP9 are highly similar, and both are more different from the in-situ data than AP9 and VIPSTF-SW9 (i.e., the soil moisture values of P36 and EP9 are much larger than of the other datasets). Thirdly, AP9 and VIPSTF-SW9 are close to each other, as seen in the results for Experiment 1. This further supports the possibility of using the VIPSTF-SW9 data instead of the AP9 data after the failure of AP9.

4.3. Regional comparison of derived VIPSTF-SW9 and SM_SP data

The derived VIPSTF-SW9 data were compared with the SM_SP data at a regional scale, that is, in Oklahoma, USA in 2019. The daily SM_SP data were compositied into 8-day temporal resolution to match that of the VIPSTF-SW9 data. The in-situ data at two independent networks (i.e., Fort Cobb and Little Washita) were used as the reference. As shown in Figure 13, the time-series of derived VIPSTF-SW9 data is more similar to the reference than that of SM_SP. Moreover, there exist many gaps in the time-series of SM_SP data. The main reason is that the available SM_SP data are cooperatively derived from SMAP and Sentinel-1, which have disparate revisit orbits, and swath width (the width of Sentinel-1 is much smaller than that of SMAP). Therefore,
the spatio-temporal distribution of effective SM_SP data is irregular, leading to great uncertainty in the data composition process of the SM_SP data. As shown in Figure 14, there exist many gaps in the composited SM_SP data. Generally, compared with the SM_SP product, the VIPSTF-SW9 data are more suitable for applications at large spatio-temporal scale.

Figure 13. Time-series of the VIPSTF-SW9 and SM_SP data in Oklahoma, USA (the in-situ data as the reference).

Figure 14. The VIPSTF-SW9 and SM_SP dataset in Oklahoma, USA. (a) VIPSTF-SW9_2019009. (b) VIPSTF-SW9_2019033. (c) SM_SP_2019009. (d) SM_SP_2019033.
4.4. Uncertainty in residual correction for VIPSTF-SW9

Residual correction aims to make the predicted fine spatial resolution image consistent with the original coarse data (i.e., perfect coherence). The well-established ATPRK method can achieve reliable residual correction to preserve perfectly the observed coarse images [55]. Thus, this method was also applied to SMAP downscaling, producing 9 km SMAP data with perfect coherence with the original P36 data. The data in Experiment 1 were used for testing, and the predicted 9 km fine SMAP data were denoted as ATPRK9. The accuracies of the 9 km predictions are shown in Table 7. It is seen that the accuracy of ATPRK9 is similar to EP9, but obviously less than for VIPSTF-SW9. Since ATPRK9 has perfect coherence with P36, the results suggest that it is not necessary to preserve the original 36 km information in predicting AP9. To further investigate the relation between AP9, VIPSTF-SW9 and P36, both AP9 and VIPSTF-SW9 data were upscaled to 36 km. As the reference at 36 km, the upscaled AP9 data were used to evaluate the upscaled VIPSTF-SW9 and P36 data, as shown in Table 8 and Figure 15. We find that there exist obvious differences between P36 and the upscaled VIPSTF-SW9, and the latter is closer to the upscaled AP9. Consequently, it is not beneficial to perform residual correction for VIPSTF-SW9 due to the inherent gap between AP9 and P36.
Table 7. Statistical metrics for the ATPRK9 results (AP9 as reference)

<table>
<thead>
<tr>
<th></th>
<th>CC</th>
<th>UIQI</th>
<th>ERGAS</th>
<th>RMSE</th>
<th>Bias</th>
<th>ubRMSE</th>
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<td>ATPRK9-T1</td>
<td>0.879</td>
<td>0.873</td>
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<tr>
<td>ATPRK9-T2</td>
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<td>0.081</td>
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<td>0.083</td>
</tr>
<tr>
<td>ATPRK9-T4</td>
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<td>0.833</td>
<td>12.072</td>
<td>0.093</td>
<td>0.002</td>
<td>0.093</td>
</tr>
<tr>
<td>ATPRK9-T5</td>
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<td>0.861</td>
<td>10.953</td>
<td>0.084</td>
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<td>ATPRK9-T7</td>
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<td><strong>11.090</strong></td>
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<td><strong>-0.004</strong></td>
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<tr>
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<td><strong>-0.007</strong></td>
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<td><strong>0.968</strong></td>
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<td><strong>0.002</strong></td>
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Table 8. Statistical metrics for P36 and upscaled VIPSTF-SW9 data (upscaled AP9 as reference)

<table>
<thead>
<tr>
<th></th>
<th>CC</th>
<th>UIQI</th>
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<th>RMSE</th>
<th>Bias</th>
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<td><strong>P36</strong></td>
<td><strong>upscaled VIPSTF-SW9</strong></td>
<td><strong>P36</strong></td>
<td><strong>upscaled VIPSTF-SW9</strong></td>
<td><strong>P36</strong></td>
<td><strong>upscaled VIPSTF-SW9</strong></td>
<td><strong>P36</strong></td>
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<tr>
<td><strong>T1</strong></td>
<td>0.883</td>
<td>0.984</td>
<td>0.842</td>
<td>0.983</td>
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<tr>
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<td>0.980</td>
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<td>0.988</td>
<td>0.843</td>
<td>0.987</td>
<td>37.884</td>
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<td><strong>T4</strong></td>
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<td>0.986</td>
<td>0.833</td>
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<td>0.994</td>
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<td><strong>0.828</strong></td>
<td><strong>0.990</strong></td>
<td><strong>37.951</strong></td>
<td><strong>8.703</strong></td>
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4.5. Uncertainty in the soil moisture data

There exists inevitable uncertainty in soil moisture data. The uncertainties are mainly two-fold. Firstly, there is uncertainty in the spatial support of the in-situ data, which are measured by fixed stations and almost at the point scale. However, the SMAP data are composed of pixels with regular spatial coverage. The signal of each SMAP pixel represents the convolution of soil moisture over a much wider area (e.g., 9 km by 9 km in AP9, but potentially much larger than this due to the point spread function effect). Therefore, the mismatch in the spatial scale between the in-situ data and the SMAP data leads to uncertainty in accuracy evaluation. Secondly, vegetation commonly covers the topsoil in many regions and the interference of vegetation can increase the uncertainty of soil moisture prediction, especially for satellite soil moisture products that are captured from above the vegetation. To reduce the uncertainty caused by the cover of vegetation, Yang et al. [56] acquired satellite sensor images in periods when the soil was bare to reduce the effect of vegetation. However, this method is unsuitable for studies at the global scale. Furthermore, surface soil moisture retrieved from satellite sensors can be inevitably affected by the vegetation water content. The vegetation optical depth (VOD) data derived from several sensors can reflect the water content in vegetation to some extent. Therefore, with the continuous development of the VOD data, it is expected that the use of such type of data can reduce the uncertainties in soil moisture retrieval [57, 58].

5 Conclusion

In this research, we produced 9 km, 8-day composited soil moisture data at the global scale from 2015 to 2020. The advanced VIPSTF-SW method was applied to produce the data, and 10, 8-day, composited image pairs (AP9-P36) from 14 April 2015 to 07 July 2015 were used as model inputs. The experimental results show that the predicted VIPSTF-SW9 data are more accurate than predictions from EP9 (the alternative published by NASA), based on the evaluation of the available AP9 data. Meanwhile, VIPSTF-SW9 can provide more detailed spatial information than EP9 as
well as the original P36. Moreover, the predicted VIPSTF-SW9 data are also closer to the available
\textit{in-situ} data than EP9 and P36 in term of evaluation based on both spatial and temporal domains.
The use of using multiple image pairs in the VIPSTF-SW method is a preferable choice than the
single image pair scheme. Consequently, we conclude that the predicted VIPSTF-SW9 data are an
accurate substitute for AP9 data for monitoring surface soil moisture after the failure of the SMAP
active radar.

\textbf{Data Availability}

The SMAP data are available through NSIDC (https://nsidc.org/). The \textit{in-situ} data are available
through ISMN (https://ismn.earth/en/). The produced VIPSTF-SW9 data are publicly available at
https://doi.org/10.6084/m9.figshare.14634276.

\textbf{Authors' Contributions}

H.Y. and Q.W. designed the research; H.Y. analyzed the data, wrote the original manuscript,
and produced the dataset; Q.W., W.Z., X.T., and P.A. provided direction and comments on earlier
drafts. All authors edited and approved the final manuscript; Q.W. provided the funding to support
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There is no financial conflicts and interests to manuscript.

\textbf{Conflict of Interest}

The authors declare no conflicts of interest relevant to this study.

\textbf{Appendix}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{Appendix.pdf}
\caption{Soil moisture maps for different quarters from 2015 Q3 to 2016 Q4.}
\end{figure}
Figure A1. The predicted VIPSTF-SW9 data for each quarter from 2015 to 2020 (Q1 to Q4 represents the first to the fourth quarters of a year).

References


