



Land Surface Clustering Based GNSS-R Soil Moisture Retrieval Algorithm

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ABSTRACT

We propose a GNSS-R soil moisture (SM) retrieval algorithm based on land surface clustering using the twin satellites A/B of BuFeng-1 (BF-1). Similar to other semi-empirical algorithms, this algorithm incorporates vegetation and roughness parameters. However, it introduces empirical clustering as an alternative to quantitative calculations. Vegetation and roughness, recognized as significant factors influencing GNSS scatter signals, are utilized to categorize the land surface into distinct classes. The opportunity observations of spaceborne GNSS-R present a challenge in obtaining a sufficient number of valid observations within a grid cell at the theoretical spatial resolution of approximately 3.5 km to 20 km over land. This limitation hampers the establishment of robust empirical relationships. Consequently, our algorithm avoids pixel-by-pixel fitting and instead establishes empirical relationships between SM and GNSS-R observations within each class. A global comparison between the algorithm's results and the 36-km soil moisture product from the Soil Moisture Active Passive (SMAP) mission reveals a correlation coefficient (R) of 0.82 and an unbiased root mean square error (ubRMSE) of $0.070 \text{ cm}^3 \cdot \text{cm}^{-3}$.

RESULTS

BF-1 SM results exhibit great agreement with SMAP SM products in low vegetation cover areas, boasting a high correlation coefficient of 0.82 and a low ubRMSE of $0.07 \text{ cm}^3/\text{cm}^3$.

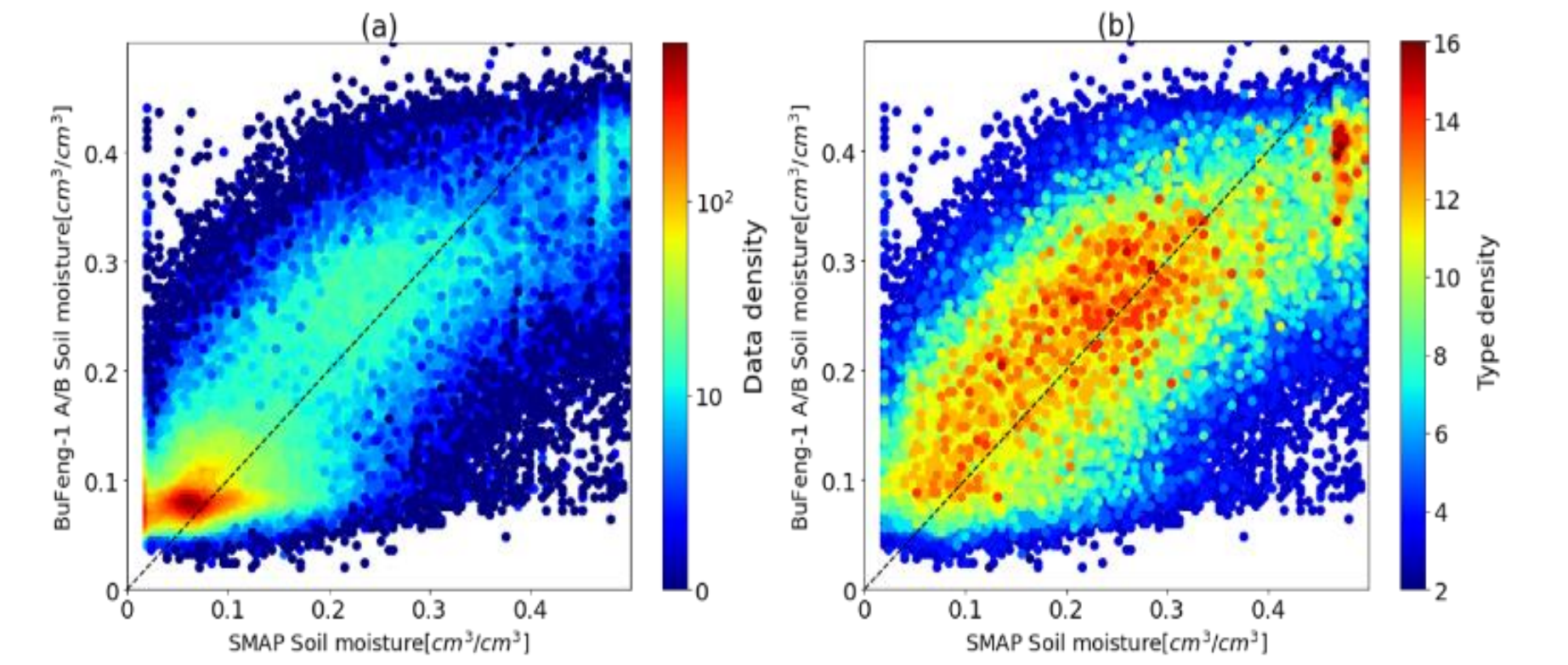


Figure 1. Land clustering results for different type numbers. (a) Distribution of VO and RC (the clustering basis); (b) IGBP land type; (c)~(g) The top 17 types of area ratio in 20/50/100/200/500-types-clustering

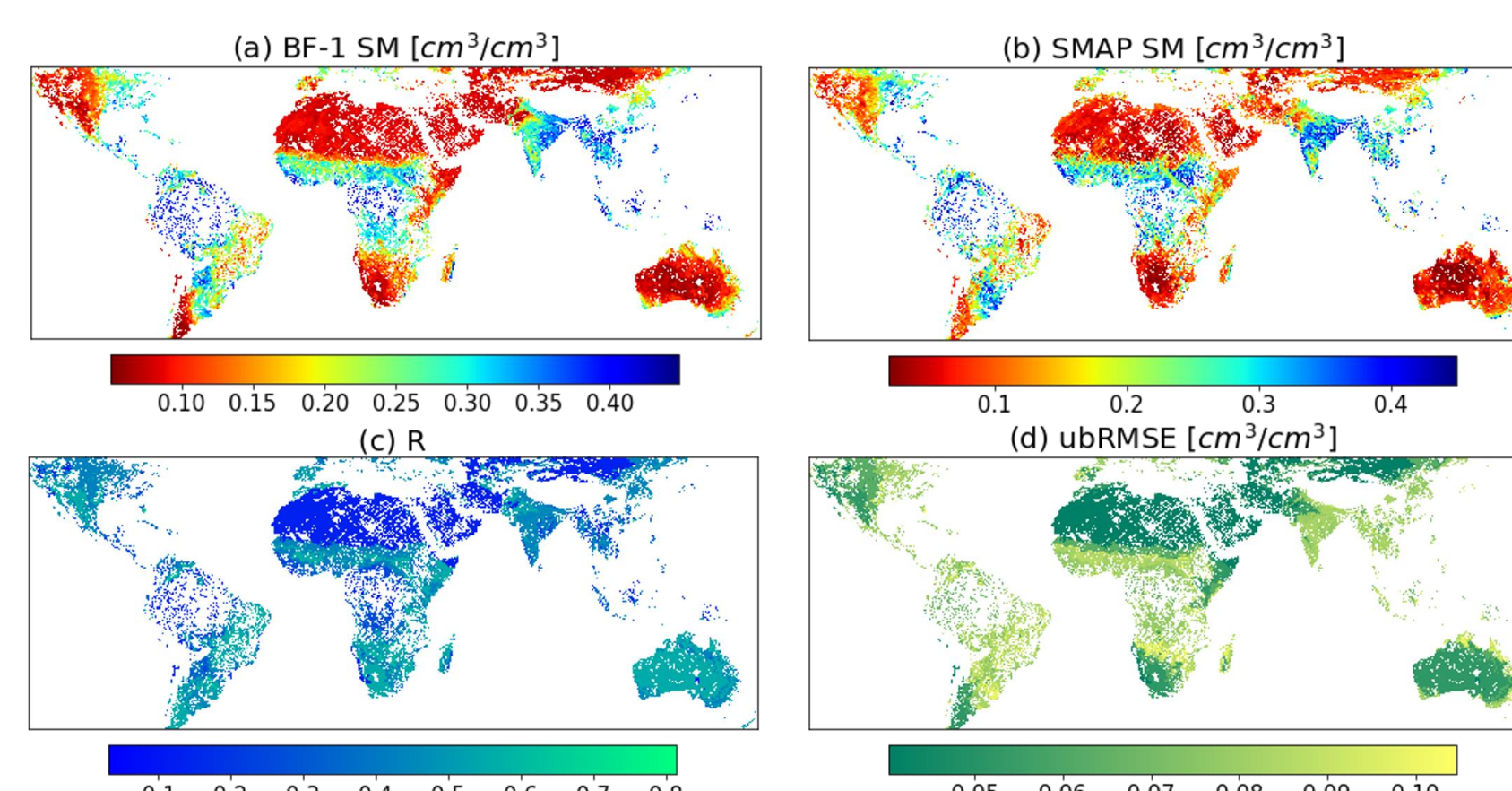


Figure 2. Comparison of the BF-1 soil moisture (SM) and SMAP SM. (a) BF-1 36 km global SM; (b) SMAP 36 km global SM; (c) The R value between SMAP SM and BF-1 SM; (d) ubRMSE between SMAP SM and BF-1 SM.

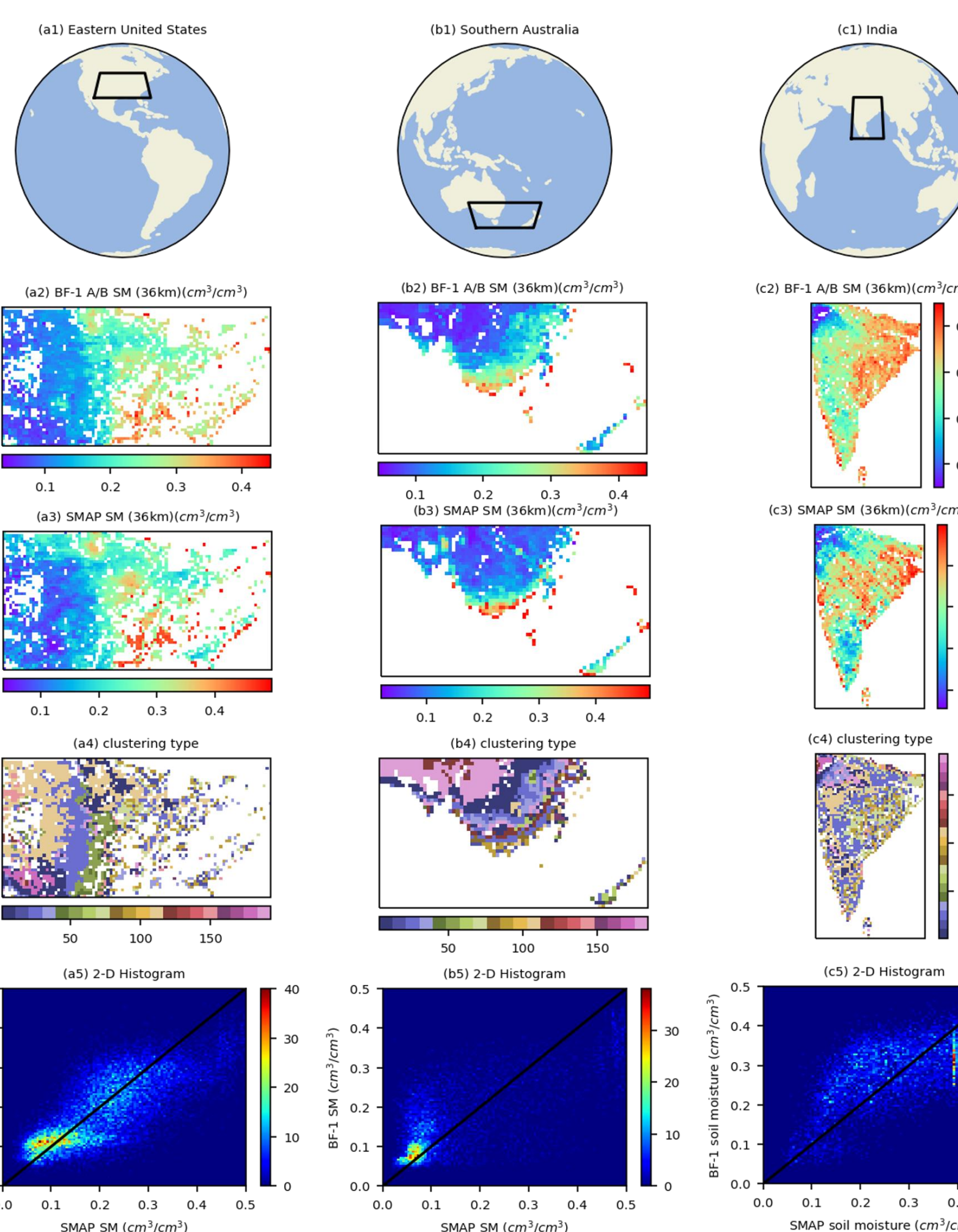
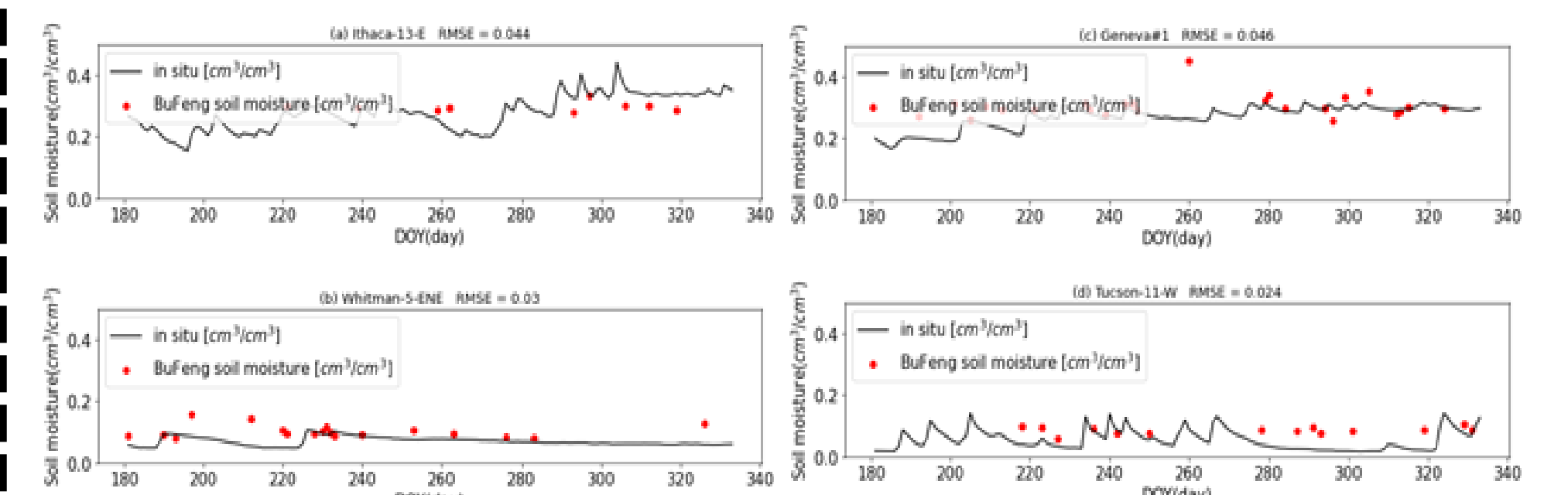


Figure 3. Retrieval of different regions in the world (a) Southern Australia; (b) Eastern US; (c) India. No.1~5 indicate the (1) Regions extent; (2) BF-1 SM; (3) SMAP SM; (4) clustering type; (5) 2-D histogram

■ The correlation of BF-1 SM and SMAP SM colored by (a) data density and (b) type density.

Upon comparison with ISMN station SM data, an optimal RMSE as low as $0.036 \text{ cm}^3/\text{cm}^3$ is achievable under ideal conditions.



■ Four ISMN stations (a)Ithaca-13-E; (b)Whitman-5-ENE; (c)Geneva#1; (d)Tucson-11-W; SM and BF-1 SM retrieval for 5 months.

CONCLUSIONS

This study introduces a novel approach for SM retrieval using land surface clustering based on critical parameters such as roughness coefficient and vegetation opacity. The proposed method overcomes the limitations of previous linear and property-based techniques. **Global retrieval accuracy compared with SMAP SM products is great, with a correlation coefficient of 0.82 and ubRMSE of $0.07 \text{ cm}^3/\text{cm}^3$.** Classification quality and the ESR-SM correlation jointly influence retrieval outcomes. Comparison with ISMN station SM data reveals the potential for achieving an optimal RMSE of $0.036 \text{ cm}^3/\text{cm}^3$ under ideal conditions. This work demonstrates the capability of BF-1 soil moisture observation and provides a promising avenue for accurate global SM retrieval using spaceborne GNSS-R.

DISCUSSION

In the classification process, we focus solely on the primary influencing factors (VO and RC). While vegetation effects exhibit intra-annual variations, they were not considered due to the limited data time span in this study. Additionally, surface types with small sample size are unavoidable through automated classification methods. To address this, manual classification techniques are being considered for category merging and refinement.

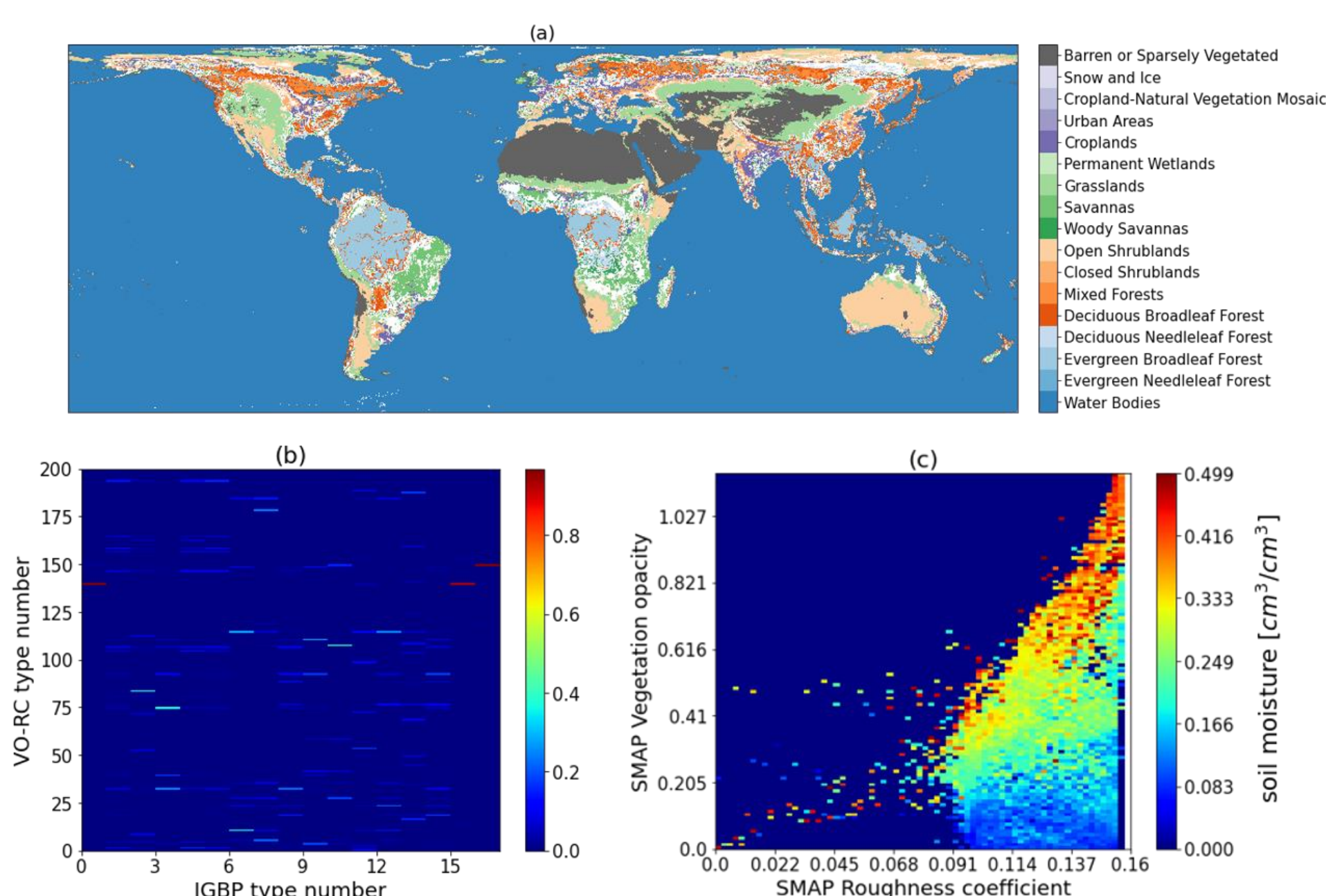
INTRODUCTION

Using BuFeng-1 (BF-1) [1], we present a novel method for global SM retrieval using land surface clustering based on critical parameters like roughness coefficient and vegetation opacity. This approach overcomes the limitations of previous linear and property-based methods. Validation with SMAP data and in situ measurements demonstrates the effectiveness of our algorithm.

METHODS

1. Land Surface Clustering Method

We introduce a novel approach for SM retrieval by utilizing land surface clustering based on critical parameters: roughness coefficient (RC) and vegetation opacity (VO). We use averaged RC and VO for five months to cluster land surfaces, employing the K-Means++ algorithm..



2. SM Retrieval via Linear Regression

The method utilizes linear regression to connect GNSS-R reflectivity and SM in each land type.

