The Impact of Radiometric Terrain Normalization (γ^0) on Burned Area Mapping Accuracy Using Sentinel-1 data

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***Abstract* — This study evaluates the impact of angular-based radiometric terrain normalization (RTN) on burned area mapping using Sentinel-1 SAR data and the Normalized Radar Burn Ratio (NRBR) index. We compare the performance of NRBR calculated with standard sigma nought (σ^0) and with gamma nought (γ^0) corrected via an angular-based RTN model implemented in Google Earth Engine. A U-Net deep learning model was used to delineate burned areas in Portugal and California. Results show that NRBR without RTN achieved better accuracy in Portugal, suggesting potential overcorrection effects in moderate terrain. In California, RTN slightly improved overall accuracy and reduced commission errors, although omission errors remained high. These findings indicate that while RTN enhances radiometric consistency, its impact on burned area detection with NRBR is limited, likely because the NRBR formulation itself already mitigates topographic effects through pre/post-fire ratios.**

***Keywords* — burned area mapping, radar index, sentinel-1, wildfire monitoring.**

I. INTRODUCTION

Wildfires are increasingly destructive natural hazards, affecting ecosystems, biodiversity, and human infrastructure while emitting large amounts of carbon (Bowman et al., 2017). As fire regimes intensify due to climate change and land-use shifts, accurate and timely burned area mapping is essential for mitigation and recovery (Bowman et al., 2017). While optical satellite sensors such as Sentinel-2 offer high-resolution vegetation information, their effectiveness is limited under cloud or smoke conditions. In contrast, Synthetic Aperture Radar (SAR) sensors like Sentinel-1 provide all-weather imaging capabilities, making them particularly valuable for wildfire monitoring in adverse environment conditions.

Radar-based indices such as the Normalized Radar Burn Ratio (NRBR) have demonstrated significant potential for detecting fire-induced structural changes in vegetation (Tarazona et al., 2025; Tarazona and Mantas, 2025; Tarazona and Mantas, 2026). However, one of the key challenges in SAR-based wildfire analysis is the influence of topography on backscatter intensity. The side-looking geometry of SAR systems introduces distortions such as layover, foreshortening, and shadowing in mountainous or hilly regions, which can lead to inaccurate detection of burned areas if not corrected (Vollrath et al., 2020).

Radiometric Terrain Normalization is a critical preprocessing step that aims to mitigate these terrain-induced effects by adjusting radar backscatter according to local incidence angle and slope orientation. Traditionally, angular-based correction methods have been employed, such as those based on incidence angle normalization (e.g., Hoekman (1990); as used in Vollrath et al. (2020)). These methods assume simplified models of terrain–sensor interaction, such as isotropic volume scattering, and are especially suited for vegetated surfaces. Vollrath et al. (2020) proposed an operational, empirically-based RTN model that has been widely implemented in cloud computing platforms like Google Earth Engine (GEE), enabling large-scale analysis.

In this study, we aim to assess whether applying angular-based radiometric terrain normalization (γ^0) using the model 1 of Vollrath et al. (2020) improves burned area detection accuracy when using the NRBR index, compared to using the uncorrected sigma nought (σ^0) backscatter.

II. STUDY AREA AND DATA

A. Study area and ground truth data

The study focuses on two distinct fire-prone regions Portugal and California (Fig. 1). In both cases, 50×50 km grid tiles were used to evaluate burned area predictions. The Portuguese area (mean and standard deviation of slope: 11 and 7.5 respectively), located in Castelo Branco, Coimbra, and Guarda districts, represents Mediterranean forests heavily affected by large fires (e.g., 217,000 ha burned in 2017). The Californian are (mean and standard deviation of slope: 10 and 11 respectively) covers typical chaparral and shrubland ecosystems with frequent high-intensity wildfires. These regions differ in vegetation, climate, and fire regimes, providing contrasting conditions to evaluate the impact of applying RTC using gamma nought (Vollrath et al., 2020) versus sigma nought backscatter products on burned area detection.

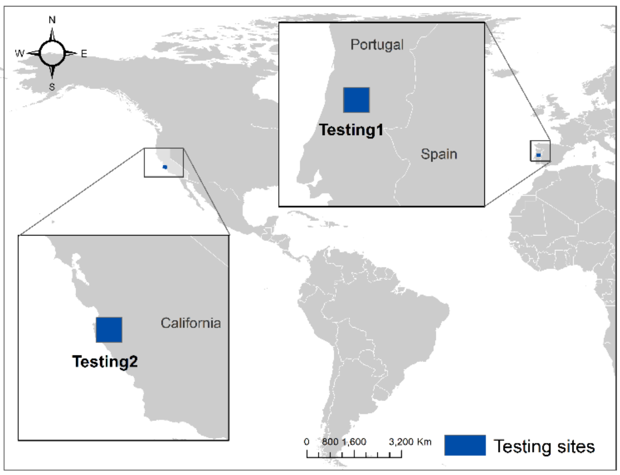

Fig. 1. Study areas in central Portugal (Testing 1) and California (Testing 2), each represented by 50×50 km testing grids.

To validate burned area predictions, official reference datasets were obtained from national geospatial agencies.

For Portugal, we used annual burned area perimeters provided by the Direção-Geral do Território through the Sistema Nacional de Informação Geográfica (Direção-Geral do Território, 2024). For California, burned area perimeters were sourced from the California Department of Forestry and Fire Protection (CALFIRE, 2024). These datasets are based on semi-automated classifications using optical satellite imagery (Landsat and Sentinel-2), often combined with vegetation indices and field observations. All reference data were rasterized at 10-meter resolution to ensure consistency with the Sentinel-based predictors used in this study.

B. *Sentinel-1 C data*

This study uses Sentinel-1 C-band Synthetic Aperture Radar (SAR) data acquired from the GEE platform. The dataset consists of Ground Range Detected (GRD) products in Interferometric Wide (IW) mode, with dual-polarization (VV and VH) at 10-meter spatial resolution. Standard GEE preprocessing steps were applied, including thermal noise removal, radiometric calibration, and terrain correction to sigma nought (σ^0). Data from ascending relative orbits were used for both regions: orbit 147 for Portugal and orbit 35 for California. The pre-fire and post-fire periods were defined as October 15 – December 15 of 2016 and 2017 for Portugal, and of 2019 and 2020 for California.

III. METHODOLOGY

C. *Brief review of Radiometric Terrain Normalization*

Radiometric terrain normalization is a fundamental preprocessing step for Synthetic Aperture Radar (SAR) imagery, particularly in topographically complex regions. The side-looking geometry of SAR sensors introduces distortions in backscatter intensity due to variations in local terrain slope and incidence angles, which can obscure true land surface properties. Without correction, these geometric effects may lead to misinterpretations of land cover or biophysical parameters.

The radar backscatter coefficient, denoted as σ^0 (sigma naught), represents the normalized radar cross-section and is defined as:

$$\sigma^0 = \frac{P_{scattered}}{P_{incident}} / A \tag{1}$$

where $P_{scattered}$ is the power returned to the sensor, $P_{incident}$ is the incident power, and A is the illuminated ground area.

In practice, σ^0 is calibrated and converted from decibels (dB) to linear power scale (i.e., de-logarithmised).

In rugged terrain, σ^0 is influenced not only by surface characteristics but also by geometric factors such as the incidence angle θ_i and slope orientation (α, ϕ), where α represents the steepness of the terrain slope, measured in degrees from the local horizontal plane and ϕ indicates the Orientation of the steepest slope, measured in degrees from true north (0° = North, 90° = East, 180° = South, 270° = West). Foreslopes facing the sensor typically exhibit stronger backscatter, while backslopes appear darker due to reduced effective illumination. To address these distortions, we employ an angular-based radiometric correction (Vollrath et al., 2020) (Fig. 2), specifically their Model 1 (Hoekman, 1990), which assumes volume scattering, a suitable approximation for vegetated surfaces. The correction involves two key steps. First, the original σ⁰ values are converted to γ^0 by normalizing for the incidence angle:

$$\gamma^0 = \sigma^0 / \cos\theta_i \tag{2}$$

This step accounts for the natural decrease in backscatter intensity with increasing incidence angle. Second, a terrain-dependent adjustment is applied to compensate for slope-induced variations in scattering volume. The corrected backscatter γ_f^0 is computed as:

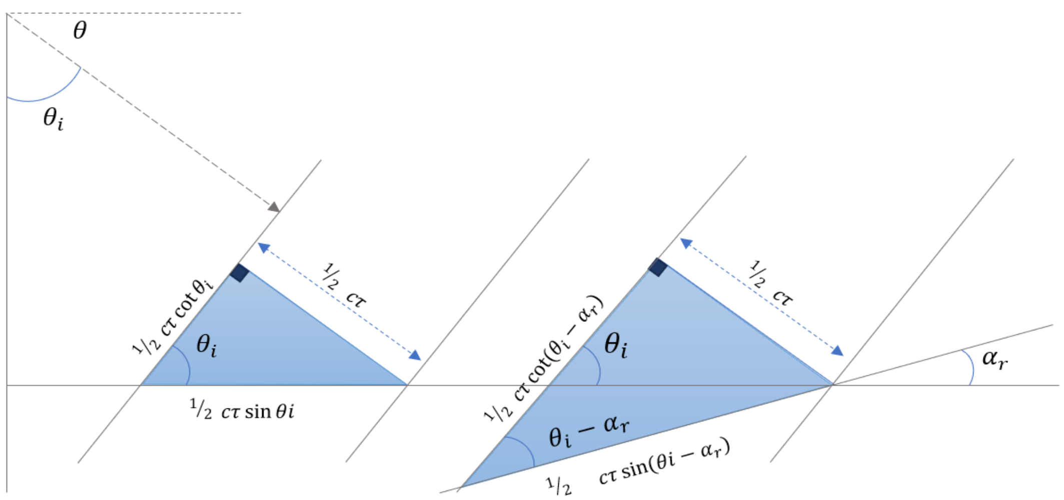

Fig. 2. Range resolution cell geometry in two scenarios: flat terrain (left) and sloped terrain (right). The slope angle α (or α_r) modifies the cell geometry. The incidence angle θ_i relates to the look angle by θ_i = 90° − θ. The range resolution is ½ cτ, where c is the speed of light and τ the pulse duration. On slopes, the resolution cell size changes according to ($\theta_i - \alpha_r$). This figure is adapted from Hoekman (1990).

$$\gamma_f^0 = \gamma^0 \frac{\tan(\theta_i - \alpha_r)}{\tan(\theta_i)} \quad (3)$$

where α_r represents the slope steepness in the range direction. A technical explanation of Fig. 1 and demonstration of Equation (3) is detailed:

a) Volume Scattering Assumption:

- The terrain is modeled as an opaque volume with isotropic scatterers of constant density.
- Backscatter is proportional to the illuminated volume within the resolution cell.

b) Illuminated Volume Calculation:
Flat terrain (left triangle in Fig.1):

$$V_{flat} \propto 1/2c\tau \cot\theta_i$$

Tilted terrain (right triangle):

$$V_{tilted} \propto 1/2c\tau \cot(\theta_i - \alpha_r)$$

c) Backscatter Ratio: The correction factor is the ratio of volumes to normalize tilted-terrain backscatter to flat-terrain conditions:

$$\gamma_f^0 = \gamma^0 \frac{V_{flat}}{V_{tilted}} = \gamma^0 \frac{1/2c\tau \cot\theta_i}{1/2c\tau \cot(\theta_i - \alpha_r)}$$

Simplifying

$$\gamma_f^0 = \gamma^0 \frac{1/\tan\theta_i}{1/\tan(\theta_i - \alpha_r)}$$

Therefore,

$$\gamma_f^0 = \gamma^0 \frac{\tan(\theta_i - \alpha_r)}{\tan(\theta_i)} \quad \text{(as the Eq. 3)}$$

While this approach effectively reduces radiometric disparities across slopes, certain limitations should be noted. The volume scattering assumption may not hold for urban areas or bare soils, where surface scattering - Model 2 (Ulander, 1996) would be more appropriate. Additionally, the correction tends to overcorrect backscatter values for slopes steeper than 35°, as noted in the original study. Despite these constraints, the method significantly improves the consistency of SAR backscatter over varied terrain, facilitating more reliable land surface analysis. This normalization aligns with CEOS Analysis-Ready Data (ARD) standards, supporting large-scale applications in platforms like Google Earth Engine.

In the Vollrath et al. (2020) paper, the depression angle θ is used, so the equation is different; but if it were simplified to the incidence angle, Eq. 3 is demonstrated.

D. *The Normalized Radar Burn Ratio*

The NRBR index was used to enhance burned area detection using Sentinel-1 SAR data (Tarazona et al., 2025). NRBR combines VV and VH polarizations to highlight fire-induced structural changes in vegetation. It is calculated as the normalized difference between pre- and post-fire Radar Burn Ratios of VH and VV backscatter values, expressed in power units. Burned areas typically produce negative NRBR values due to decreased VH backscatter and relatively stable or increased VV backscatter after fire events. This index mitigates speckle noise and reduces topographic effects by relying on temporal backscatter changes, as proposed in Tarazona et al. (2025). All NRBR (Eq. 4) calculations were implemented within Google Earth Engine using pre- and post-fire Sentinel-1 imagery.

$$\text{NRBR}=\frac{RBR_{VH} - RBR_{VV}}{RBR_{VH} + RBR_{VV}} \quad (4)$$

where, RBR_{VH} and RBR_{VV} are the Radar Burn Ratio calculated for VH and VV polarizations in power units. NRBR values range from −1 to 1 (approximately).

E. *Preparing sigma and gamma nought within GEE*

To prepare radar backscatter data for burned area detection, both sigma nought (σ^0) and gamma nought (γ^0) products were processed within GEE. Sentinel-1 backscatter data is originally provided in decibel (dB) units in GEE; therefore, all images were first converted to linear power units. Gamma nought (γ^0) was computed using the angular-based radiometric terrain correction method proposed by Vollrath et al. (2020), specifically applying Model 1, which assumes volume scattering and is recommended for vegetated surfaces. This approach accounts for terrain-induced radiometric distortions, enabling a direct assessment of whether the use of γ^0 improves burned area predictions compared to standard σ^0 backscatter data.

Terrain parameters, including slope, aspect, and terrain orientation (facing towards or away from the sensor), were derived within GEE using the SRTM 30-meter Digital Elevation Model, which was resampled to 10-meter resolution to match the Sentinel-1 backscatter data.

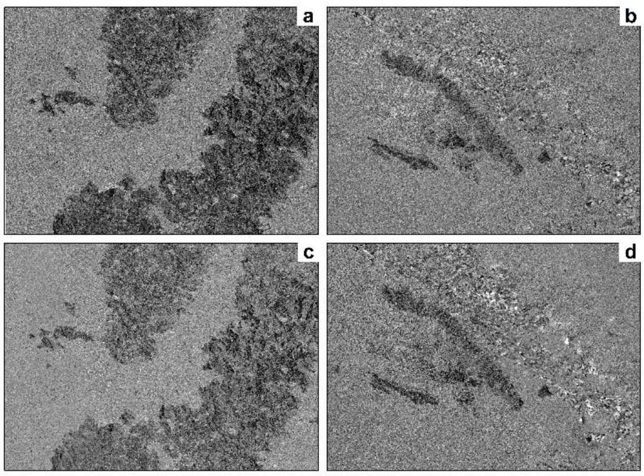

Fig. 3. Comparison of NRBR index without (top) and with (bottom) radiometric terrain normalization. Left panels (a, c) correspond to a region in Portugal; right panels (b, d) to California.

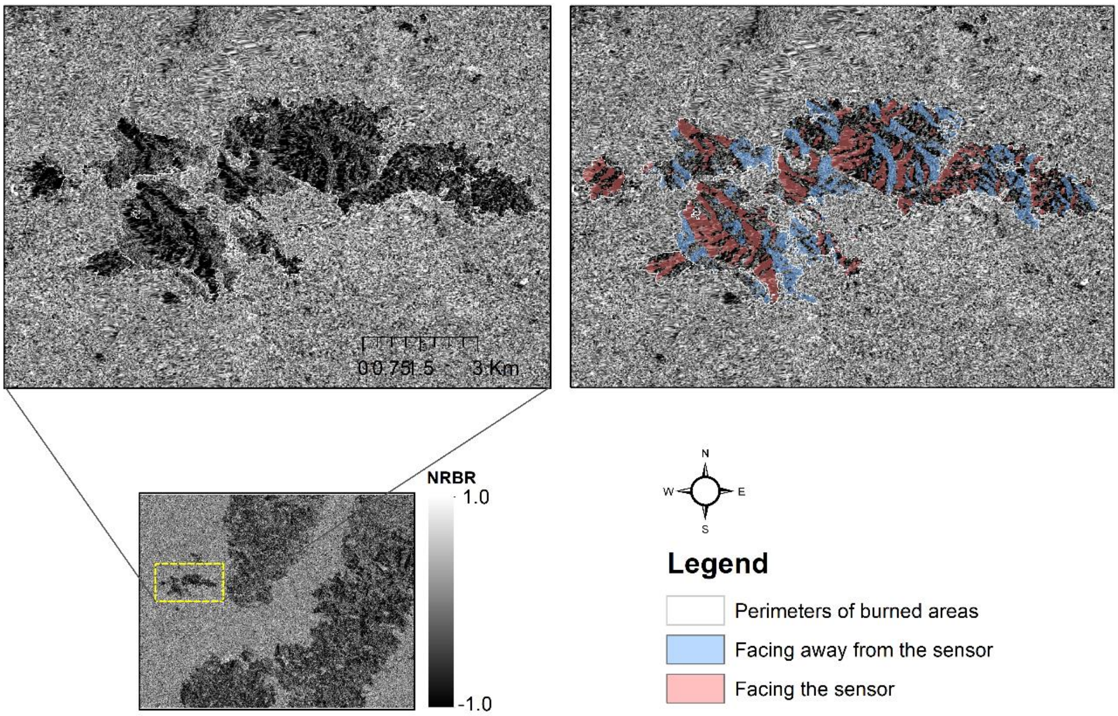

Fig. 4. Detailed view of a portion of the Portugal tile, highlighting burned regions based on slope orientation. Red indicates slopes facing the sensor, blue indicates slopes away from the sensor. Darker tones correspond to slopes facing the sensor.

F. *General Architecture Overview*

We employed a U-Net convolutional neural network (Ronneberger et al., 2015) with an encoder-decoder architecture and skip connections for burned area segmentation. Dropout regularization (20%) was applied throughout the network to mitigate overfitting. The model was trained on 256×256-pixel patches, addressing significant class imbalance since burned pixels typically constitute only a small fraction of each scene.

To handle this imbalance, we used a combined loss function integrating Categorical Cross-Entropy and Dice Loss, where the Dice Coefficient term enhances segmentation performance for the minority burned class. This approach reduces the model's tendency to bias predictions toward the background class. The model was trained using the NRBR index. Without retraining, we applied the pretrained model to assess its transferability to two independent test regions: central Portugal and California.

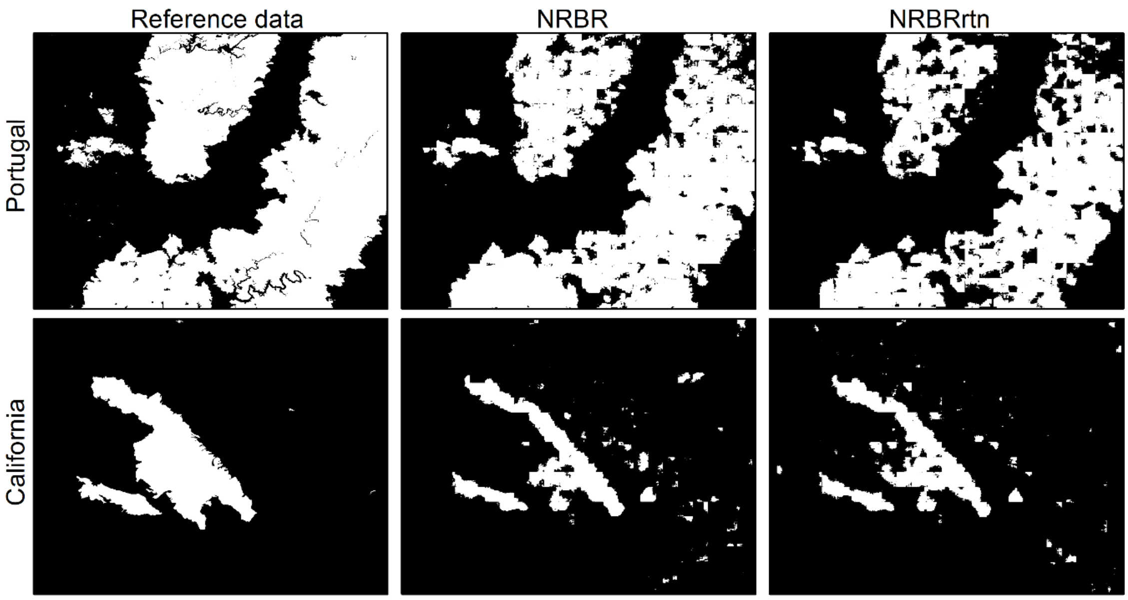

Fig. 5. Burned area estimation for NRBR and NRBR applying RTN.

Table I. ACCURACY METRICS FOR NRBR and $NRBR_{rtn}$ (with Radiometric Terrain Normalization)

		OA	IoU	DC	OE	CE
Portugal	NRBR	0.949	0.811	0.896	0.143	0.019
	$NRBR_{rtn}$	0.934	0.757	0.861	0.210	0.015
California	NRBR	0.947	0.516	0.680	0.415	0.014
	$NRBR_{rtn}$	0.956	0.584	0.737	0.400	0.010

G. Accuracy assessment metrics

Model performance was assessed using four per-pixel evaluation metrics: Overall Accuracy (OA), Intersection over Union (IoU), Dice Coefficient (DC), and Omission (OE) and Commission Errors (CE). OA measures the global classification correctness, while IoU and DC evaluate segmentation performance—particularly effective for imbalanced burned area detection due to their sensitivity to minority-class accuracy. OE and CE quantify under-detection (missed burns) and over-detection (false positives), respectively. All metrics were derived by comparing the model's predicted burned area masks against ground-truth reference datasets.

$$\mathrm{OA} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FN+FP}} \quad (4)$$

$$\mathrm{IoU} = \frac{\mathrm{TP}}{\mathrm{TP+FP+FN}} \quad (7)$$

$$\mathrm{OE} = \frac{\mathrm{FN}}{\mathrm{FN+TP}} \quad (8)$$

$$\mathrm{CE} = \frac{\mathrm{FP}}{\mathrm{FP+TP}} \quad (9)$$

$$\mathrm{DC} = \frac{\mathrm{2TP}}{\mathrm{2TP+FP+FN}} \quad (10)$$

IV. Results

Burned area detection was evaluated using NRBR with and without RTN across two contrasting study sites. The results revealed a mixed performance of RTN depending on terrain and fire conditions.

In Portugal where vegetation is dense, the NRBR without RTN outperformed the RTN-corrected version across all accuracy metrics (Fig. 5 and Table I). The model achieved an OA of 0.949, an IoU of 0.811, and a DC of 0.896, with relatively low OE of 14.3% and CE of 1.9%. Applying RTN (NRBRrtn) resulted in a decline in all metrics, with IoU dropping to 0.757 and DC to 0.861. This suggests that, in this region, the RTN correction may have introduced noise or inconsistencies, possibly due to overcorrection on steep slopes or vegetation structure mismatches with the volume scattering assumption. In contrast, results in California show that applying RTN provided some slightly improvements, particularly in OA (from 0.947 to 0.956) and DC (from 0.680 to 0.737), as well as a slight reduction in CE (from 0.014 to 0.010). However, OE remained high in both cases (OE: 41.5% without RTN vs. 40.0% with RTN), indicating that burned area underdetection persisted regardless of the correction. These results suggest that RTN using γ^0 may help slightly in complex terrain like California (where terrain is moderately rugged more than Portugal), but its benefits are still limited.

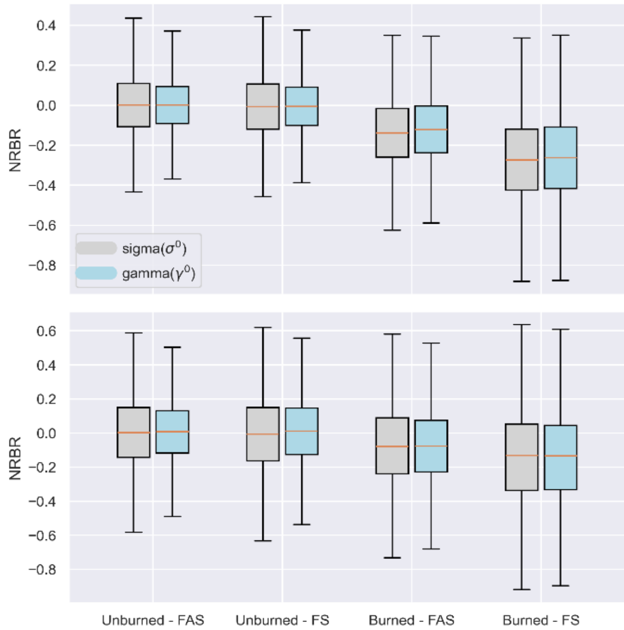

Fig. 6. Boxplots of NRBR values for slopes facing the sensor (FS) and facing away from the sensor (FAS), comparing unburned and burned areas. Gray boxes correspond to no RTN, and blue boxes to RTN-corrected values.

To further investigate terrain effects, Fig. 6 compares NRBR values over burned and unburned areas for slopes facing the sensor and facing away from the sensor. Without RTN, NRBR values on FAS slopes showed greater variability and overlap between burned and unburned classes. RTN narrowed these distributions, especially on backslopes, suggesting improved radiometric consistency. However, this geometric correction did not consistently translate into better classification accuracy, especially in Portugal. The limited benefit by using RTN to improve burned area mapping may be related to the fact that the NRBR formulation inherently reduces topographic effects by using ratios before and after fire events. This ratio-based approach helps minimize static geometric distortions, meaning that the benefit of applying additional terrain normalization may be limited or even cancelled out (Tarazona et al., 2025).

The angular-based RTN model used here, while operational, may be limited by its simplifications in complex terrain. The method assumes volume scattering and corrects based on local incidence angle, but does not fully account for the relationship between map and radar geometry (e.g., layover, foreshortening) or compute the true locally illuminated area projected in the slant-range plane. Future work should investigate whether more rigorous radiometric terrain correction methods, such as the area-integration approach proposed by Small (2011) for generating terrain-flattened gamma naught, could yield greater accuracy improvements.

Even though, results indicate that radiometric terrain normalization may improve the radiometric consistency of SAR backscatter, but does not guarantee improved burned area detection performance, at least by using the NRBR index. Its effectiveness may depend on regional terrain complexity, fire severity, and vegetation type as well.

V. CONCLUSION

Our findings suggest that the effectiveness of the angular-based RTN model is region-dependent and influenced by terrain complexity, vegetation structure, and fire characteristics. In addition, the limited improvement observed with RTN may also be attributed to the inherent formulation of NRBR, which reduces topographic effects by computing ratios of pre- and post-fire backscatter. This temporal normalization naturally mitigates static geometric distortions, thereby diminishing the additional benefit of terrain correction. While angular-based RTN can improve radiometric consistency, especially on backslopes, it does not necessarily translate into improved burned area detection performance when using NRBR.

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