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SCATTERING MECHANISM MODELS IN POLARIMETRIC SAR: A BRIEF REVIEW

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Abstract
Polarimetric Synthetic Aperture Radar (PolSAR) has emerged as a powerful tool in remote sensing due to its ability to capture detailed scattering information under all-weather, day-and-night conditions. Understanding scattering mechanisms is essential for accurate interpretation of PolSAR data across various applications, including urban area classification, forest canopy analysis, and environmental monitoring. This review provides a comprehensive overview of key scattering mechanism models, focusing on the Freeman-Durden Three-Component Model, Cloude-Pottier Decomposition, and Yamaguchi Four-Component Model. Each model's theoretical basis, strengths, limitations, and real-world applications are critically discussed. The review highlights common challenges such as ambiguity in oriented urban structures and volume scattering overestimation. Furthermore, the potential of integrating advanced computational techniques, including artificial intelligence (AI) and machine learning (ML), to improve model robustness is emphasized. This work aims to serve as a foundational reference for future research on enhancing scattering mechanism models in PolSAR data analysis.

Keywords: PolSAR, Scattering, Decomposition, Urban, Forest

Introduction

Synthetic Aperture Radar (SAR) and Polarimetric Synthetic Aperture Radar (PolSAR) systems have become essential tools in the field of remote sensing, owing to their capability to acquire high-resolution images regardless of weather conditions or time of day. Unlike optical sensors, SAR systems utilize microwave signals, which allow them to penetrate clouds, vegetation canopies, and other atmospheric interferences. PolSAR, an advanced form of SAR, records the polarization states of both transmitted and received signals, providing detailed information about the scattering behavior and physical properties of surface and volumetric targets. The ability of PolSAR to capture this additional polarimetric information makes it particularly suitable for complex scene analysis, including land cover classification, vegetation monitoring, urban infrastructure mapping, and maritime surveillance.

Recent advancements in SAR and PolSAR technologies have significantly enhanced their application potential across various fields. Researchers have demonstrated their effectiveness in tasks such as semantic segmentation, object detection, and environmental monitoring. For instance, Shi et al. (2021) introduced a novel encoder-decoder framework specifically designed for semantic segmentation of high-resolution SAR images from the Gaofen-3 (GF-3) sensor, contributing to object-level interpretation [1]. Similarly, Tu et al. (2021) applied full-polarization GF-3 imagery for synergetic classification of coastal wetlands, achieving higher accuracy and better temporal resolution [2]. In the context of urban target recognition, Garg et al. (2021) utilized deep learning models to minimize misclassification in highly vegetated and structurally complex urban environments [3]. Further advancements include ship detection techniques, such as the super-pixel-based neighbourhood covariance matrix proposed by Zhang et al. (2021) and a scattering characteristic-aware detection network developed by Gao et al. (2023). Additionally, Geng et al. (2022) introduced a hypergraph neural network approach to leverage spatial and polarimetric features for improved PolSAR image classification [4], [5], [6].

The foundation of these applications lies in a fundamental understanding of scattering mechanisms. Scattering in SAR systems results from interactions between the radar signal and target surfaces, which can involve mechanisms such as surface scattering, double-bounce scattering, volume scattering, and more complex phenomena like helix scattering. Accurately decomposing and interpreting these scattering contributions is crucial for reliable image classification, target recognition, parameter inversion, and environmental monitoring. Studies such as Chen et al. (2021) emphasize the importance of multiple-bounce analysis for river water level monitoring, while DEMİRCİ et al. (2021) demonstrated the value of polarimetric decompositions in enhancing target discrimination [7], [8]. Applications in agriculture and forestry, such as plant height estimation (Wang et al., 2022) and soil moisture retrieval (Zhang et al., 2022), further highlight the significance of understanding scattering mechanisms [9], [10].

Beyond target recognition, scattering models are vital for analyzing urban and natural environments to support sustainable development and ecosystem management. For example, Maranesi et al. (2021) utilized SAR-based forest monitoring services for assessing green areas, while Tao et al. (2021) investigated urban carrying capacities to balance development with ecological sustainability [11], [12]. Other studies have focused on groundwater modeling (Semyachkov et al., 2022), change detection (Choi et al., 2022), and air pollution effects on urban vegetation (Dwijendra et al., 2023) [13], [14], [15]. Despite these advances, challenges such as orientation ambiguities in urban areas, volume scattering overestimation, and model generalizability persist . Therefore, the aim of this review paper is to present a comprehensive overview of prominent scattering mechanism models used in PolSAR data analysis. This paper critically examines the theoretical basis, applications, strengths, and limitations of key models—including the Freeman-Durden three-component model, Cloude-Pottier decomposition, and Yamaguchi four-component model. Additionally, it explores recent advancements, discusses their applications in urban and natural settings, and highlights potential future directions, such as integrating machine learning techniques to improve model performance and adaptability.

3. Scattering Mechanism Models

One of the key challenges in Polarimetric Synthetic Aperture Radar (PolSAR) data analysis is accurately interpreting the backscattered signal by identifying the dominant scattering mechanisms responsible for the observed returns. Scattering mechanisms are essential for understanding the interactions between the radar signal and various surface or volume features. Over the years, several decomposition models have been developed to analyze these mechanisms, each providing a unique approach to separating and interpreting surface, double-bounce, and volume scattering components. This section presents an overview of widely-used scattering models, starting with the Freeman-Durden Three-Component Model.

3.1 Freeman-Durden Three-Component Model

The Freeman-Durden Three-Component Model is one of the most fundamental and widely adopted model-based decomposition techniques in PolSAR data analysis. Originally introduced by Freeman and Durden in 1998, this model decomposes the total observed scattering power into three physically interpretable scattering components: surface scattering, double-bounce scattering, and volume scattering. Each of these mechanisms represents specific interactions between the incident radar wave and ground targets—surface scattering typically occurs on smooth surfaces, double-bounce scattering is observed in vertical structures such as urban areas or tree trunks, and volume scattering is common in vegetation canopies or randomly oriented scatterers.

The model's mathematical formulation is based on representing the observed covariance matrix as a linear combination of the three elementary scattering mechanisms, each associated with specific scattering matrices and power contributions. This decomposition is non-iterative, computationally efficient, and physically meaningful, making it highly suitable for operational remote sensing applications, including land cover classification, forest structure analysis, and urban mapping.

In recent years, numerous researchers have focused on enhancing the Freeman-Durden model to address its limitations and improve decomposition accuracy. One of the key challenges is the overestimation of volume scattering, particularly in urban areas with oriented buildings or anisotropic targets. Addressing this, Inderkumar et al. (2021) proposed

modifications in hybrid-polarimetric SAR data decomposition to better allocate depolarized power, reducing the misclassification of volume scattering in complex environments [16].
Similarly, Hou et al. (2021) introduced a two-stage Hybrid Compact Polarimetric (HCP) SAR decomposition approach that adapts the Freeman-Durden model to compact polarimetric SAR data [17]. Their method identifies dominant scattering mechanisms at the pixel level while maintaining the model's interpretability and enhancing its adaptability to HCP datasets, which are increasingly used in spaceborne SAR missions due to their reduced data volume.
To further address the limitations of conventional decomposition methods, Wang et al. (2021) developed an adaptive decomposition framework incorporating a dipole aggregation model [18]. This approach fits the PolSAR data to an independent volume scattering mechanism, minimizing negative powers and enhancing adaptability across varying land cover types. Likewise, Ramya et al. (2021) demonstrated the practical application of coherence-based decomposition using the Freeman-Durden model for scattering characterization in Uttarakhand, India, showing its effectiveness in diverse terrains [19].
Advancements in optimization techniques have also contributed to refining the Freeman-Durden model. Ainsworth et al. (2022) presented an L1 regularization-based decomposition approach, ensuring non-negative scattering powers by imposing sparsity constraints. This enhancement not only improves the stability of decomposition results but also eliminates the occurrence of physically implausible negative powers [20].
Vegetation parameter retrieval is another critical application area where the Freeman-Durden model has shown significant relevance. Yin et al. (2022) applied an adaptive weighted learning mechanism to PolSAR data, improving the estimation of vegetation contributions in soil moisture inversion tasks [21]. Their study emphasized the importance of selecting appropriate decomposition descriptors to isolate vegetation effects from underlying soil signals.
In forestry applications, Hu et al. (2023) combined C-band and L-band SAR data with the Freeman-Durden decomposition model to improve aboveground biomass estimation [22]. By integrating decomposition features with non-parametric models and advanced feature selection techniques, their approach demonstrated enhanced accuracy in forest parameter retrieval, underlining the model's utility in environmental monitoring.
More recently, Wang et al. (2023) proposed an optimal polarization three-component target decomposition method based on semi-definite programming, further improving decomposition stability and interpretability by solving optimization problems to allocate scattering powers optimally [18]. Additionally, Zhu et al. (2024) evaluated the relationship between polarization observation variables from the Freeman-Durden decomposition and forest canopy height, illustrating the model's effectiveness in studying biophysical forest parameters such as carbon stocks and canopy structure [23].
Overall, the Freeman-Durden Three-Component Model remains a cornerstone in SAR and PolSAR data analysis due to its simplicity, computational efficiency, and physical interpretability. Continuous refinements and adaptations to hybrid polarimetric data, optimization techniques, and machine learning frameworks have further expanded its applicability across diverse remote sensing tasks. However, challenges such as handling oriented urban structures, mitigating volume scattering overestimation, and extending the model to novel datasets necessitate ongoing research and model evolution.

3.2 Cloude-Pottier Decomposition

The Cloude-Pottier decomposition is one of the most fundamental and widely utilized eigen-based decomposition techniques in polarimetric SAR (PolSAR) analysis. Introduced by Cloude and Pottier in 1997, this model provides a statistical approach to decomposing the scattering matrix based on eigenvalue and eigenvector analysis of the coherency or covariance matrix. Unlike model-based decompositions (such as Freeman-Durden), which rely on predefined physical scattering models, the Cloude-Pottier method is data-driven and does not assume specific scattering mechanisms. Instead, it characterizes the scattering behavior of targets using three key parameters: Entropy (H), Alpha (α) angle, and Anisotropy (A).
The Entropy (H) parameter measures the randomness of the scattering process, with low entropy indicating well-defined scattering (e.g., surface scattering) and high entropy suggesting complex or random scattering (e.g., volume scattering). The Alpha angle (α) provides information about the dominant scattering mechanism, ranging from surface (low α) to double-bounce (mid α) to volume scattering (high α). Anisotropy (A) quantifies the relative importance of the secondary scattering mechanisms when entropy is high. This decomposition framework is particularly powerful for classifying targets in natural and urban environments, as it offers a compact representation of scattering behavior while retaining physical interpretability.
Numerous studies have applied and refined the Cloude-Pottier decomposition to enhance its utility in specific remote sensing applications. For instance, Weiß et al. (2021) utilized a dense time series of VV-polarized Sentinel-1 C-band SAR data to analyze wheat fields near Munich, Germany. Although their study focused on backscatter analysis, it highlights the importance of understanding temporal variations in scattering behavior, which the Cloude-Pottier decomposition effectively captures when applied to multi-temporal PolSAR datasets [24]. Similarly, Jiao et al. (2021) demonstrated the value of time-series SAR data for monitoring crop growth, emphasizing the relevance of polarimetric parameters, such as entropy and alpha angle, for tracking vegetation changes in conjunction with optical indices like NDVI [25].
In addition, the Cloude-Pottier decomposition has been enhanced through regularization techniques to address stability and robustness issues. Ainsworth et al. (2022) introduced an L1 regularization-based approach for model-based PolSAR decomposition, ensuring nonnegative power allocations and improving performance across various scattering conditions [20]. While primarily applied in the context of Freeman-Durden decomposition, such regularization techniques can complement eigen-based methods like Cloude-Pottier to enhance parameter retrieval accuracy.
Advanced methods integrating polarimetric interferometry (PolInSAR) coherence have also been explored to refine decomposition performance. Di et al. (2024) proposed incorporating repeat-pass PolInSAR coherence information into

target decomposition, enhancing algorithm stability across different temporal baselines [26]. This improvement is particularly relevant in applications such as forest height estimation and land cover classification, where coherence information augments the interpretation of scattering mechanisms over time.
In the urban context, orientation angle estimation is crucial to improving decomposition accuracy, especially in environments with strong double-bounce or dihedral scattering from buildings. Kobayashi et al. (2024) addressed this by proposing a rotated dihedral model to estimate the orientation angles of urban structures, which, when combined with Cloude-Pottier parameters, enhances target classification and urban mapping accuracy [27].
Beyond terrestrial applications, the versatility of polarimetric decomposition has been demonstrated in other domains. For instance, Qiao et al. (2024) presented a novel snow depth retrieval technique based on polarization decomposition, enhancing the DM-RVoG model by integrating decorrelation optimization [28]. This shows the broader applicability of polarimetric decomposition concepts, including those rooted in the Cloude-Pottier framework, to diverse environmental monitoring tasks.
Interestingly, studies in materials science and optics, such as Levitsky et al. (2021) and Zhang et al. (2023), while not directly related to SAR, highlight similar decomposition principles (e.g., spinodal decomposition, mode distortion analysis) applied in different physical contexts [9], [29]. These parallels underscore the fundamental nature of decomposition techniques in interpreting complex systems across scientific fields.
Despite its strengths, the Cloude-Pottier decomposition faces challenges such as ambiguity in low-entropy regions and sensitivity to noise. Recent research focuses on integrating this model with machine learning techniques and temporal coherence information to overcome these limitations and improve classification robustness.
In summary, the Cloude-Pottier decomposition remains a cornerstone in PolSAR data analysis, offering a statistical, physically meaningful framework for characterizing scattering mechanisms. Its adaptability across various land cover types, temporal scales, and environmental conditions makes it highly valuable. Continuous improvements through integration with interferometric data, regularization techniques, and orientation correction models ensure its relevance in modern SAR applications, including agriculture, forestry, urban mapping, and cryosphere monitoring.

3.3 Yamaguchi Four-Component Model

The Yamaguchi Four-Component Decomposition Model is a significant advancement over traditional three-component models, designed to provide a more comprehensive interpretation of the scattering mechanisms present in Polarimetric Synthetic Aperture Radar (PolSAR) data. Developed by Yamaguchi et al. in 2005, this model extends the Freeman-Durden decomposition by adding a helix (or cross-polarized) scattering component to account for asymmetric and complex scattering behaviors, particularly in urban environments with oriented buildings or rough surfaces [30].
The model decomposes the total backscattered signal into four physically meaningful components: surface scattering, double-bounce scattering, volume scattering, and helix scattering. The inclusion of the helix component distinguishes the Yamaguchi model from earlier approaches, enabling better characterization of targets exhibiting asymmetric scattering properties due to target orientation or structural complexity [31]. This is particularly beneficial when dealing with built-up areas, forested regions with varying canopy geometries, and complex terrain features.
Several studies have focused on improving and applying the Yamaguchi Four-Component Model across different domains. For instance, Kuznetsov et al. (2020) investigated scattering processes in a non-terrestrial context, analyzing the formation of drift-pair bursts in plasma environments [32]. Their study suggested that the trailing components of such bursts are a result of turbulent reflection and anisotropic scattering, highlighting the broader relevance of multi-component scattering analysis, akin to the principles underlying the Yamaguchi model.
In the realm of agriculture, Xie et al. (2022) validated the effectiveness of the Physically Constrained General Model-Based Decomposition (PCGMD) method for crop classification [33]. Their results demonstrated that while traditional four-component decompositions like the Yamaguchi model offer valuable insight into scattering behavior, incorporating additional physical constraints significantly improves classification accuracy. The study emphasized how understanding and precisely modeling volume and double-bounce scattering contributions are crucial for differentiating various crop types, especially when complex vegetation structures are involved.
In maritime applications, Gao et al. (2023) introduced the Ship-4SD decomposition model, specifically designed for ship detection in fully polarized SAR images [6]. This model builds upon the Yamaguchi framework by refining the decomposition process to handle scattering characteristics unique to ship structures, such as strong double-bounce and helix scattering signatures caused by metallic surfaces and complex ship geometries. Their results showed that the Ship-4SD model achieved superior precision in various datasets, demonstrating the robustness of the Yamaguchi approach when tailored for specific applications [34].
Forestry studies have also benefited from the Yamaguchi model. Hu et al. (2023) explored its application in improving forest aboveground biomass (AGB) estimation by integrating both C-band and L-band SAR data [35]. They emphasized the importance of feature selection based on scattering mechanisms, leveraging the model's capability to distinguish between volume scattering from forest canopies and double-bounce effects from tree trunks and ground interactions. By combining decomposition parameters with non-parametric regression models, they achieved higher accuracy in estimating forest biomass, highlighting the Yamaguchi model's significance in ecological monitoring and carbon stock assessment.
Moreover, Ainsworth et al. (2022) proposed incorporating L1 regularization techniques in model-based PolSAR decomposition, which can be adapted to the Yamaguchi model framework to ensure nonnegative scattering powers and improve robustness against noise and model misfit [20]. This highlights ongoing efforts to address inherent challenges such as overestimation of certain scattering components, particularly volume scattering, in urban areas with oriented buildings.

Despite its wide applicability, the Yamaguchi Four-Component Model is not without limitations. One key issue is the ambiguity in interpreting oriented urban structures, which may lead to inaccurate allocation of power between double-bounce and helix components. Researchers continue to refine the model by incorporating orientation angle compensation techniques and optimization strategies to enhance its adaptability across varying terrain and target conditions.
The Yamaguchi Four-Component Model remains a pivotal tool in PolSAR data analysis, offering enhanced interpretability of complex scattering scenarios compared to earlier models. Its application spans diverse fields such as crop classification, forest biomass estimation, ship detection, and even plasma scattering studies, underscoring its versatility [36]. Ongoing advancements, including integration with machine learning techniques, regularization methods, and physically constrained models, continue to improve its effectiveness and broaden its applicability in both natural and urban environments.

Table 1: Summary of key scattering mechanism models used in SAR and PolSAR data analysis.

Model Name	Main Components	Advantages	Limitations	Key References
Freeman-Durden Three-Component Model	**Surface, Double-bounce, Volume**	**Simple, physically interpretable, widely used**	**Overestimation of volume scattering in complex targets**	**Freeman & Durden (1998); Ramya et al. (2021); Inderkumar et al. (2021)**
Yamaguchi Four-Component Model	**Surface, Double-bounce, Volume, Helix**	**Better accuracy for urban and oriented structures**	**Sensitive to orientation angle, complex computation**	**Yamaguchi et al. (2005); Xie et al. (2022); Gao et al. (2023)**
L1 Regularization Model	**Optimal component selection using regularization**	**Ensures non-negative powers, robust to scattering variations**	**Requires tuning, computational cost**	**Ainsworth et al. (2022)**
PCGMD Model (Physically Constrained)	**Data-driven, General Decomposition**	**High accuracy in crop and vegetation classification**	**Needs careful parameter selection**	**Xie et al. (2022)**
Dipole Aggregation Model	**Surface, Volume with Adaptive Dipole Aggregation**	**Reduces negative powers, adapts to different targets**	**Application-dependent, requires validation**	**Wang et al. (2021)**

4. Applications
The versatility of Synthetic Aperture Radar (SAR) and Polarimetric SAR (PolSAR) technologies has opened up a wide array of practical applications across various domains, including urban area classification, forest canopy analysis, disaster monitoring, agriculture, and environmental management. The ability of SAR systems to operate under all-weather conditions and provide detailed information about surface and volumetric scattering mechanisms makes them indispensable tools in modern remote sensing [37]. This section reviews key application areas of scattering mechanism models, emphasizing recent advancements and their impact on enhancing classification accuracy and environmental monitoring.

4.1 Urban Area Classification
Urban environments are characterized by complex structures, including buildings, roads, and various man-made surfaces, which pose significant challenges in remote sensing analysis. The unique scattering behavior of these features, often involving strong double-bounce and helix scattering mechanisms, makes SAR data particularly useful for urban area classification.
Recent studies have demonstrated the effectiveness of SAR and PolSAR data in identifying urban land cover and infrastructure patterns. Todar et al. (2021) examined the seasonality effect on impervious surface detection using Sentinel-1 SAR and Sentinel-2 optical imagery, highlighting how the integration of SAR data enhances the temporal resolution and robustness of urban classification models [38]. Their results showed that SAR data, particularly when fused with optical sensors, could reliably detect seasonal variations in urban impervious surfaces.
Similarly, Nicolau et al. (2021) assessed the capability of C-band SAR data to distinguish modified land uses in a heavily disturbed Amazon forest, emphasizing SAR's utility in monitoring urban encroachment and land use changes in sensitive ecosystems [39]. In agricultural and peri-urban regions, Adrian et al. (2021) demonstrated the successful fusion of Sentinel-1 SAR and optical data for crop type mapping, showcasing the broader applicability of SAR in both rural and urban contexts [40].
Kraatz et al. (2021) further emphasized the importance of SAR time series analysis by comparing L-band and C-band SAR data for active crop area mapping, showing high classification accuracy and temporal stability [41]. Their study reinforced the advantage of dense SAR time series for capturing dynamic land use patterns, essential for urban expansion monitoring.

Additionally, Hu et al. (2021) proposed an approach that combines Sentinel-1 SAR and Sentinel-2 optical imagery to improve urban land cover classification, effectively leveraging complementary data sources to overcome the limitations of single-sensor systems [42]. Furthermore, Garg et al. (2021) applied advanced deep learning models for semantic segmentation of PolSAR data, demonstrating how machine learning algorithms can exploit polarimetric features, such as entropy and alpha angle, for accurate urban target classification, even in structurally complex environments [3].
These studies collectively highlight the potential of SAR and PolSAR technologies, particularly when integrated with optical data and advanced algorithms, in providing reliable and precise classification of urban areas, contributing to effective urban planning, infrastructure monitoring, and sustainable development.

4.2 Forest Canopy Analysis
Another prominent application of SAR and PolSAR data lies in forest canopy analysis, including the estimation of forest structure, canopy height, and aboveground biomass (AGB). Forest environments typically involve complex volume scattering mechanisms, making polarimetric decomposition models, such as Freeman-Durden and Yamaguchi, essential tools for accurate characterization [43].
Wang et al. (2021) introduced an innovative model-based PolSAR decomposition scheme incorporating a random thin disk model to differentiate between scattering behaviors of deciduous and coniferous forests [18]. By accounting for the unique scattering properties of various vegetation types, their approach enhanced the accuracy of forest structure interpretation.
At a broader scale, the NASA AfriSAR Campaign conducted by Fatoyinbo et al. (2021) exemplified the integration of airborne SAR and LiDAR measurements to assess tropical forest structure and biomass [44]. The campaign provided crucial data to support current and future space missions aimed at monitoring forest ecosystems, emphasizing the value of multi-sensor approaches in canopy analysis.
Santoro et al. (2021) advanced biomass retrieval methods by incorporating allometric equations into the Water Cloud Model, improving the estimation of forest stem volume using L-band SAR data in Sweden [45]. This highlights how model refinements combined with SAR data can reduce uncertainties in forest parameter retrieval.
In boreal forests, Blomberg et al. (2021) evaluated P-band TomoSAR data for biomass estimation, demonstrating that suppressing ground backscatter signals enables more accurate retrieval of aboveground biomass, even with limited tomographic resolution [46]. Similarly, Luca et al. (2022) integrated Sentinel-1 SAR, Sentinel-2 optical data, and machine learning algorithms for land cover mapping in Mediterranean forests, emphasizing the correlation between polarimetric decomposition parameters and canopy structure [47].
Verhegghen et al. (2022) showcased the potential of combining Sentinel-1 SAR and Sentinel-2 optical sensors to map tree cover in East Africa, focusing on the integration of open-access data and tools for establishing national forest monitoring systems [37]. Chen et al. (2022) expanded on this by integrating LiDAR data with multi-sensor imagery to reduce uncertainty in object-based forest AGB estimation, particularly in heterogeneous mountainous regions.
Additionally, Almeida et al. (2022) assessed canopy height mapping in the Atlantic Forest of Brazil by integrating Sentinel-1, Sentinel-2, airborne LiDAR, and machine learning techniques, demonstrating the effectiveness of a multi-sensor, data-fusion approach [48]. More recently, Kacic et al. (2023) utilized complementary sensors, including GEDI LiDAR, Sentinel-1, and Sentinel-2, to generate detailed forest structure products across Germany, allowing for dynamic analysis of forest ecosystems [36].
These advancements underline the critical role of SAR and PolSAR data in enhancing forest monitoring and resource management. Through the integration of polarimetric decomposition models, machine learning algorithms, and multi-sensor data fusion, researchers can achieve more accurate assessments of forest canopy structure, biomass, and overall ecosystem health.

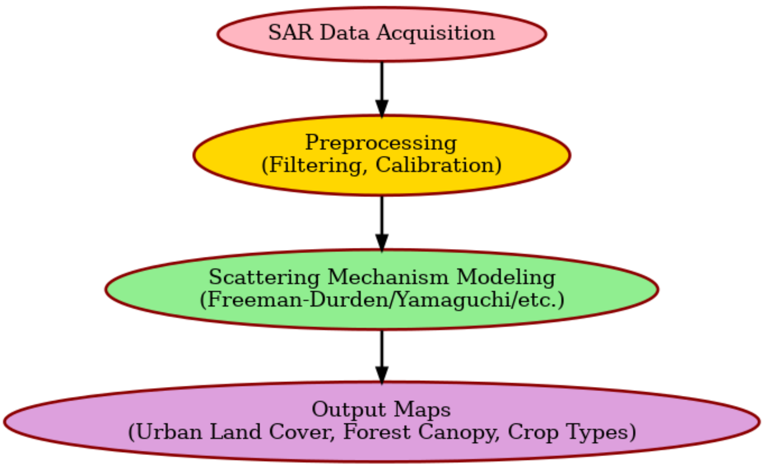

Figure 1: Workflow of SAR data processing for urban and forest classification.

5. Challenges & Future Prospects

While scattering mechanism models such as Freeman-Durden, Cloude-Pottier, and Yamaguchi have significantly advanced PolSAR data interpretation, several challenges persist that limit their accuracy and applicability in complex environments. One key limitation is the ambiguity in oriented urban structures, particularly in areas with buildings exhibiting varying orientation angles [43]. Traditional decomposition models often misclassify double-bounce and helix scattering components in such cases, leading to inaccuracies in urban land cover mapping. Additionally, a common issue encountered is the overestimation of volume scattering, especially in urban and forested areas where volume scattering contributions may overlap with surface or double-bounce scattering, reducing classification reliability [44].
To address these challenges, there is a growing need for model improvements that incorporate orientation compensation techniques, optimization-based approaches, and more adaptive parameter estimation. Moreover, the integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques presents promising avenues for enhancing scattering model performance [49]. Deep learning models, when combined with physical decomposition outputs, can learn complex patterns and reduce misclassification, particularly in heterogeneous environments. Recent studies have already demonstrated the potential of AI/ML in improving target recognition, urban classification, and forest parameter retrieval using PolSAR data.
Looking forward, future research should focus on developing hybrid models that blend physical scattering theories with data-driven learning frameworks, allowing for greater adaptability across diverse datasets and terrain types. Furthermore, incorporating temporal SAR datasets and multi-sensor fusion approaches will improve robustness, particularly for dynamic environmental monitoring. Advancements in computational techniques and cloud-based processing will also facilitate large-scale applications, supporting sustainable development, urban planning, and ecosystem management [50].

Conclusion

Scattering mechanism models play a pivotal role in the interpretation of Polarimetric Synthetic Aperture Radar (PolSAR) data, providing insights into surface, double-bounce, volume, and helix scattering behaviors across diverse natural and urban environments. This review presented an overview of three widely used decomposition models—Freeman-Durden Three-Component Model, Cloude-Pottier Decomposition, and Yamaguchi Four-Component Model—highlighting their principles, strengths, and application areas. These models have proven highly effective in various fields, including urban area classification, forest canopy analysis, agriculture, and maritime surveillance.
However, despite their effectiveness, challenges such as ambiguity in oriented urban structures and volume scattering overestimation remain. These limitations underline the need for continuous refinement of existing models, incorporating techniques such as orientation compensation and optimization-based approaches. Additionally, the integration of Artificial Intelligence (AI) and Machine Learning (ML) algorithms offers significant potential to enhance model adaptability, reduce misclassification, and improve overall analysis accuracy.
Future research should focus on the development of hybrid, data-driven, and physics-based models that combine the strengths of conventional decomposition frameworks with advanced computational techniques. Such efforts will ensure more accurate and efficient utilization of PolSAR data in addressing global challenges related to urbanization, forest management, environmental monitoring, and sustainable development.

References:

[1] X. Shi, S. Fu, J. Chen, F. Wang, and F. Xu, "Object-Level Semantic Segmentation on the High-Resolution Gaofen-3 FUSAR-Map Dataset," *IEEE J Sel Top Appl Earth Obs Remote Sens*, vol. 14, 2021, doi: 10.1109/JSTARS.2021.3063797.

[2] C. Tu *et al.*, "Synergetic classification of coastal wetlands over the yellow river delta with gf-3 full-polarization sar and zhuhai-1 ohs hyperspectral remote sensing," *Remote Sens (Basel)*, vol. 13, no. 21, 2021, doi: 10.3390/rs13214444.

[3] R. Garg, A. Kumar, N. Bansal, M. Prateek, and S. Kumar, "Semantic segmentation of PolSAR image data using advanced deep learning model," *Sci Rep*, vol. 11, no. 1, 2021, doi: 10.1038/s41598-021-94422-y.

[4] X. Zhang, J. Xu, Y. Chen, K. Xu, and D. Wang, "Coastal wetland classification with gf-3 polarimetric sar imagery by using object-oriented random forest algorithm," *Sensors*, vol. 21, no. 10, 2021, doi: 10.3390/s21103395.

[5] J. Geng, R. Wang, and W. Jiang, "Polarimetric SAR Image Classification Based on Feature Enhanced Superpixel Hypergraph Neural Network," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, 2022, doi: 10.1109/TGRS.2022.3220409.

[6] G. Gao, C. Zhang, L. Zhang, and D. Duan, "Scattering Characteristic-Aware Fully Polarized SAR Ship Detection Network Based on a Four-Component Decomposition Model," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, 2023, doi: 10.1109/TGRS.2023.3336300.

[7] X. Chen, Y. Zheng, J. Peng, and M. Floris, "Monitoring river water level using multiple bounces of bridges in SAR images," *Advances in Space Research*, vol. 68, no. 10, 2021, doi: 10.1016/j.asr.2021.08.006.

[8] Ş. Demirci and C. Özdemir, "An investigation of the performances of polarimetric target decompositions using GB-SAR imaging," *International Journal of Engineering and Geosciences*, vol. 6, no. 1, 2021, doi: 10.26833/ijeg.665175.

[9] L. Zhang, X. Lv, and R. Wang, "Soil Moisture Estimation Based on Polarimetric Decomposition and Quantile Regression Forests," *Remote Sens (Basel)*, vol. 14, no. 17, 2022, doi: 10.3390/rs14174183.

[10] Y. Wang, S. Fang, L. Zhao, and X. Huang, "Estimation of maize plant height in North China by means of backscattering coefficient and depolarization parameters using Sentinel-1 dual-pol SAR data," *Int J Remote Sens*, vol. 43, no. 6, 2022, doi: 10.1080/01431161.2022.2054294.

[11] W. Yu and T. Tao, "Scenario Simulation for the Urban Carrying Capacity Based on System Dynamics Model in Shanghai, China," *Sustainability (Switzerland)*, vol. 14, no. 19, 2022, doi: 10.3390/su141912910.
[12] M. Maranesi, M. Picchiani, … C. C.-E. G., and undefined 2021, "MAFIS-Multiple Actors Forest Information System: EO+ AI+ ODC for scalable forest monitoring services," *ui.adsabs.harvard.edu*, Accessed: Mar. 20, 2025. [Online]. Available: https://ui.adsabs.harvard.edu/abs/2021EGUGA..2316539M/abstract
[13] A. I. Semyachkov and K. Al Semyachkov, "Digital model of groundwater technogenesis as an element of sustainable development of the urban environment," *Sustainable Development of Mountain Territories*, vol. 14, no. 3, 2022, doi: 10.21177/1998-4502-2022-14-3-362-369.
[14] Y. Choi, D. Yang, S. Han, and J. Han, "Change Target Extraction Based on Scale-Adaptive Difference Image and Morphology Filter for KOMPSAT-5," *Remote Sens (Basel)*, vol. 14, no. 2, 2022, doi: 10.3390/rs14020245.
[15] N. K. Acwin Dwijendra *et al.*, "Investigating the Effects of Air Pollution on Plant Species Resistance in Urban Areas," *Health Scope*, vol. 12, no. 1, 2023, doi: 10.5812/jhealthscope-129786.
[16] K. Inderkumar, A. Kumar, and R. K. Panigrahi, "Three-Component Decomposition of Hybrid-Polsar Data With Volume Scattering Models," *IEEE Access*, vol. 9, 2021, doi: 10.1109/ACCESS.2021.3106151.
[17] W. Hou, F. Zhao, X. Liu, and R. Wang, "General Two-Stage Model-Based Three-Component Hybrid Compact Polarimetric SAR Decomposition Method," *IEEE J Sel Top Appl Earth Obs Remote Sens*, vol. 14, 2021, doi: 10.1109/JSTARS.2021.3065431.
[18] Y. Wang *et al.*, "An Improved Urban Area Extraction Method for PolSAR Data Using Eigenvalues and Optimal Roll-Invariant Features," *IEEE J Sel Top Appl Earth Obs Remote Sens*, vol. 17, 2024, doi: 10.1109/JSTARS.2024.3372504.
[19] M. N. S. Ramya and S. Kumar, "PolInSAR coherence-based decomposition modeling for scattering characterization: A case study in Uttarakhand, India," *Science of Remote Sensing*, vol. 3, 2021, doi: 10.1016/j.srs.2021.100020.
[20] T. L. Ainsworth, Y. Wang, and J. Sen Lee, "Model-Based Polarimetric SAR Decomposition: An L1Regularization Approach," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, 2022, doi: 10.1109/TGRS.2021.3083511.
[21] Q. Yin, J. Li, Y. Zhou, D. Xiang, and F. Zhang, "Adaptive weighted learning for vegetation contribution in soil moisture inversion using PolSAR data," *Int J Remote Sens*, vol. 43, no. 9, 2022, doi: 10.1080/01431161.2022.2088259.
[22] L. Chen *et al.*, "Improved Object-Based Estimation of Forest Aboveground Biomass by Integrating LiDAR Data from GEDI and ICESat-2 with Multi-Sensor Images in a Heterogeneous Mountainous Region," *Remote Sens (Basel)*, vol. 14, no. 12, 2022, doi: 10.3390/rs14122743.
[23] H. Zhu, B. Zhang, W. Song, Q. Xie, X. Chang, and R. Zhao, "Forest Canopy Height Estimation by Integrating Structural Equation Modeling and Multiple Weighted Regression," *Forests*, vol. 15, no. 2, 2024, doi: 10.3390/f15020369.
[24] T. Weiß, T. Ramsauer, T. Jagdhuber, A. Löw, and P. Marzahn, "Sentinel-1 backscatter analysis and radiative transfer modeling of dense winter wheat time series," *Remote Sens (Basel)*, vol. 13, no. 12, 2021, doi: 10.3390/rs13122320.
[25] X. Jiao, H. McNairn, and L. Dingle Robertson, "Monitoring crop growth using a canopy structure dynamic model and time series of synthetic aperture radar (SAR) data," *Int J Remote Sens*, vol. 42, no. 17, 2021, doi: 10.1080/01431161.2021.1938739.
[26] Z. Ye, J. Long, T. Zhang, B. Lin, H. L.- Plants, and undefined 2024, "L-Band Synthetic Aperture Radar and Its Application for Forest Parameter Estimation, 1972 to 2024: A Review," *mdpi.comZ Ye, J Long, T Zhang, B Lin, H LinPlants, 2024•mdpi.com*, Accessed: Mar. 20, 2025. [Online]. Available: https://www.mdpi.com/2223-7747/13/17/2511
[27] C. Kobayashi, H. Yamada, … R. S.-I. S. on, and undefined 2024, "Orientation angle estimation of buildings and streets in urban areas using PolSAR data," *ieeexplore.ieee.orgC Kobayashi, H Yamada, R Sato2024 International Symposium on Antennas and Propagation (ISAP), 2024•ieeexplore.ieee.org*, Accessed: Mar. 20, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10846314/
[28] H. Qiao *et al.*, "A Novel Method for Snow Depth Retrieval Using Improved Dense Medium RVoG Model," *IEEE J Sel Top Appl Earth Obs Remote Sens*, vol. 17, 2024, doi: 10.1109/JSTARS.2023.3342993.
[29] A. Levitsky, S. A. Schneider, E. Rabkin, M. F. Toney, and G. L. Frey, "Bridging the thermodynamics and kinetics of temperature-induced morphology evolution in polymer/fullerene organic solar cell bulk heterojunction," *Mater Horiz*, vol. 8, no. 4, 2021, doi: 10.1039/d0mh01805h.
[30] T. Wang, Z. Suo, J. Ti, B. Yan, H. Xiang, and J. Xi, "A Unitary Transformation Extension of PolSAR Four-Component Target Decomposition," *Remote Sens (Basel)*, vol. 16, no. 6, 2024, doi: 10.3390/rs16061067.
[31] T. Zhang *et al.*, "PolSAR Ship Detection Using the Superpixel-Based Neighborhood Polarimetric Covariance Matrices," *IEEE Geoscience and Remote Sensing Letters*, vol. 19, 2022, doi: 10.1109/LGRS.2021.3090368.
[32] A. A. Kuznetsov, N. Chrysaphi, E. P. Kontar, and G. Motorina, "Radio Echo in the Turbulent Corona and Simulations of Solar Drift-pair Radio Bursts," *Astrophys J*, vol. 898, no. 2, 2020, doi: 10.3847/1538-4357/aba04a.
[33] Q. Xie *et al.*, "Crop Classification Based on the Physically Constrained General Model-Based Decomposition Using Multi-Temporal RADARSAT-2 Data," *Remote Sens (Basel)*, vol. 14, no. 11, 2022, doi: 10.3390/rs14112668.
[34] X. Shi and F. Xu, "LAND COVER SEMANTIC SEGMENTATION OF HIGH-RESOLUTION GAOFEN-3 SAR IMAGE," in *International Geoscience and Remote Sensing Symposium (IGARSS)*, 2021. doi: 10.1109/IGARSS47720.2021.9553435.

[35] Y. Hu, Y. Nie, Z. Liu, G. Wu, and W. Fan, “Improving the Potential of Coniferous Forest Aboveground Biomass Estimation by Integrating C- and L-Band SAR Data with Feature Selection and Non-Parametric Model,” *Remote Sens (Basel)*, vol. 15, no. 17, 2023, doi: 10.3390/rs15174194.

[36] P. Kacic, F. Thonfeld, U. Gessner, and C. Kuenzer, “Forest Structure Characterization in Germany: Novel Products and Analysis Based on GEDI, Sentinel-1 and Sentinel-2 Data,” *Remote Sens (Basel)*, vol. 15, no. 8, 2023, doi: 10.3390/rs15081969.

[37] A. Verhegghen, K. Kuzelova, V. Syrris, H. Eva, and F. Achard, “Mapping Canopy Cover in African Dry Forests from the Combined Use of Sentinel-1 and Sentinel-2 Data: Application to Tanzania for the Year 2018,” *Remote Sens (Basel)*, vol. 14, no. 6, 2022, doi: 10.3390/rs14061522.

[38] S. A. Samadi Todar, S. Attarchi, and K. Osati, “Investigation the seasonality effect on impervious surface detection from Sentinel-1 and Sentinel-2 images using Google Earth engine,” *Advances in Space Research*, vol. 68, no. 3, 2021, doi: 10.1016/j.asr.2021.03.039.

[39] A. P. Nicolau, A. Flores-Anderson, R. Griffin, K. Herndon, and F. J. Meyer, “Assessing SAR C-band data to effectively distinguish modified land uses in a heavily disturbed Amazon forest,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 94, 2021, doi: 10.1016/j.jag.2020.102214.

[40] J. Adrian, V. Sagan, and M. Maimaitijiang, “Sentinel SAR-optical fusion for crop type mapping using deep learning and Google Earth Engine,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 175, 2021, doi: 10.1016/j.isprsjprs.2021.02.018.

[41] S. Kraatz *et al.*, “Comparison between dense l-band and c-band synthetic aperture radar (Sar) time series for crop area mapping over a nisar calibration-validation site,” *Agronomy*, vol. 11, no. 2, 2021, doi: 10.3390/agronomy11020273.

[42] B. Hu *et al.*, “Improving urban land cover classification with combined use of sentinel-2 and sentinel-1 imagery,” *ISPRS Int J Geoinf*, vol. 10, no. 8, 2021, doi: 10.3390/ijgi10080533.

[43] G. De Luca, J. M. N. Silva, S. Di Fazio, and G. Modica, “Integrated use of Sentinel-1 and Sentinel-2 data and open-source machine learning algorithms for land cover mapping in a Mediterranean region,” *Eur J Remote Sens*, vol. 55, no. 1, 2022, doi: 10.1080/22797254.2021.2018667.

[44] T. Fatoyinbo *et al.*, “The NASA AfriSAR campaign: Airborne SAR and lidar measurements of tropical forest structure and biomass in support of current and future space missions,” *Remote Sens Environ*, vol. 264, 2021, doi: 10.1016/j.rse.2021.112533.

[45] M. Santoro, O. Cartus, and J. E. S. Fransson, “Integration of allometric equations in the water cloud model towards an improved retrieval of forest stem volume with L-band SAR data in Sweden,” *Remote Sens Environ*, vol. 253, 2021, doi: 10.1016/j.rse.2020.112235.

[46] E. Blomberg, L. M. H. Ulander, S. Tebaldini, and L. Ferro-Famil, “Evaluating P-Band TomoSAR for Biomass Retrieval in Boreal Forest,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 5, 2021, doi: 10.1109/TGRS.2020.3020775.

[47] M. Banic, L. Zatti, M. Liscidini, and J. E. Sipe, “Two strategies for modeling nonlinear optics in lossy integrated photonic structures,” *Phys Rev A (Coll Park)*, vol. 106, no. 4, 2022, doi: 10.1103/PhysRevA.106.043707.

[48] C. Torres de Almeida *et al.*, “Canopy Height Mapping by Sentinel 1 and 2 Satellite Images, Airborne LiDAR Data, and Machine Learning,” *Remote Sens (Basel)*, vol. 14, no. 16, 2022, doi: 10.3390/rs14164112.

[49] X. Yan, J. Li, A. R. Smith, D. Yang, T. Ma, and Y. Su, “Rapid Land Cover Classification Using a 36-Year Time Series of Multi-Source Remote Sensing Data,” *Land (Basel)*, vol. 12, no. 12, 2023, doi: 10.3390/land12122149.

[50] T. T. Aragaw and G. Gnanachandrasamy, “Evaluation of groundwater quality for drinking and irrigation purposes using GIS-based water quality index in urban area of Abaya-Chemo sub-basin of Great Rift Valley, Ethiopia,” *Appl Water Sci*, vol. 11, no. 9, 2021, doi: 10.1007/s13201-021-01482-6.