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Carbon Direct | Meta

Integrating Meta's Canopy Height Map into Forest Carbon Methodologies

A tactical guidebook

August 2025



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Acronyms

ACR: American Carbon Registry

AGB: above-ground biomass

AI: artificial intelligence

ARR: afforestation, reforestation, and revegetation

CHM: canopy height map

GEDI: Global Ecosystem Dynamics Investigation

IFM: improved forest management

MAE: mean absolute error

MMRV: measurement, monitoring, reporting, and verification

NAIP: National Agriculture Imagery Program (United States)

NDFI: Normalized Difference Fraction Index

NDVI: Normalized Difference Vegetation Index

NEON: National Ecological Observatory Network (United States)

RS: remote sensing

SI: stocking index

VCM: voluntary carbon market

VVBs: validation and verification bodies

Foreword

As Meta develops artificial intelligence tools for a more connected world, we also see an opportunity to apply our research to help advance global climate mitigation efforts. We recognize that forests are key to supporting these global goals as well as our own ambition to achieve net-zero emissions across our value chain in 2030. To enhance the scientific understanding of these ecosystems, we launched an open source map of forest canopy height at a submeter resolution, allowing the detection of individual trees at a global scale. We continue advancing our research, applying high-resolution satellite imagery, artificial intelligence, and our computational resources to our vision of ultimately strengthening forest restoration and conservation project monitoring, particularly in carbon projects where remote sensing technologies can help scale project development and enhance integrity.

In order to identify opportunities to improve our research and help practitioners effectively apply our research in carbon projects, we are pleased to collaborate with Carbon Direct to develop this guidebook on integrating remote-sensing based map products like ours into carbon market methodologies. This guidebook is intended to help bridge the gap between novel research and the practical application of that research in carbon project development and monitoring.

When applied thoughtfully, we believe AI research and remote-sensing tools, particularly those that are open source, have the potential to revolutionize the transparency and accessibility of the carbon market. To achieve meaningful results to mitigate climate at scale, tools like our map of forest canopy height must be reliable and accessible. Remote sensing can drive trust within the market, and research like ours can drive access to information that has been previously unavailable or prohibitively expensive, especially for new and small-scale project developers. We hope this guidebook provides useful insights to unlock the potential of our research and the broader application of remote sensing to forests and land use. We look forward to building upon our work to support a more reliable and accessible carbon market to help us achieve our global climate goals.

Reza Rastegar
Senior Manager of Research Science

Meta

Executive summary

Forests are a cornerstone of global climate mitigation efforts due to their critical role in sequestering carbon. Ensuring the credibility and integrity of forest carbon projects requires measurement, monitoring, reporting, and verification (MMRV) that is accurate, scalable, and cost-effective. Developers and registries increasingly use remote sensing (RS) technologies, especially high-resolution, data-driven approaches, to meet these demands. Meta leveraged its internal artificial intelligence (AI) and computer vision expertise, along with its extensive computational resources, to develop an open-source, deep learning model (hereafter referred to as "Meta's model") that estimates tree canopy height globally with submeter resolution. Meta's high-resolution estimates of canopy height provide new insights into forest structure over large areas. Developers and registries can use Meta's model to advance their MMRV workflows.

Meta asked Carbon Direct to evaluate the strengths and limitations of its model for forest carbon project applications. This guidebook highlights how Meta's model addresses traditional RS limitations, such as low spatial resolution and high acquisition costs, by using deep learning techniques to combine optical and lidar data. Developers can now access submeter-resolution insights to better manage small parcels, heterogeneous forest features, and dynamic changes in forest cover, while reducing their dependency on expensive field data.

This guidebook offers developers and registries tactical guidance on how to work with Meta's model and canopy height map.

This guidebook provides practical advice for developers and registries on how to apply Meta's model and companion canopy height map (CHM) to forest carbon project development and MMRV. These tools offer exciting opportunities to enhance project planning and feasibility, dynamic baselining, and reversals monitoring. Developers and registries could apply Meta's model and CHM to many forest carbon methodologies, and to many forest management activities beyond carbon projects, but this guidebook focuses specifically on three major methodologies that incorporate dynamic baselining: Verra's VM0045 v1.1,[1] Verra's VM0047 v1.0,[2] and American Carbon Registry's (ACR's) improved forest management (IFM) v2.1.[3] Notably, while RS offers significant potential to improve many aspects of

1. Verra. 2024. VM0045 Methodology for Improved Forest Management Using Dynamic Matched Baselines from National Forest Inventories, v1.1. Verra. [accessed 2025 Jun 12]. https://verra.org/methodologies/methodology-for-improved-forest-management/.

2. Verra. 2023. VCS Methodology VM0047 Afforestation, Reforestation, and Revegetation, v1.0. [accessed 2025 Jun 12]. https://verra.org/wp-content/uploads/2023/09/VM0047_ARR_v1.0-1.pdf.

3. American Carbon Registry. 2024. Improved Forest Management (IFM) on Non-Federal U.S. Forestlands. ACR. [accessed 2025 Jun 12]. https://acrcarbon.org/methodology/improved-forest-management-ifm-on-non-federal-u-s-forestlands/.

forest carbon project MMRV, not all methodologies allow it to be used in the same ways. We examine where and how RS in general, and Meta's tools in particular, can be integrated into each of these methodologies:

- **VM0045 v1.1, a global IFM methodology:** VM0045 v1.1 permits RS for project feasibility assessment and reversals monitoring, but not for dynamic baselining. Developers can use Meta's CHM and underlying AI model to identify strategic parcels based on high biomass and structural heterogeneity, delineate project boundaries in complex or mixed landscapes, and monitor forest disturbances such as selective logging or windthrow at fine spatial scales.

- **VM0047 v1.0, a global afforestation, reforestation, and revegetation (ARR) methodology:** VM0047 v1.0 requires RS for dynamic baselining using a stocking index (SI) and allows RS for project planning, feasibility, and reversals monitoring. Meta's AI model could serve as a higher-fidelity, open-source SI to overcome the saturation limitations of traditional vegetation indices like the Normalized Difference Vegetation Index (NDVI).[4] It could also help developers identify eligible parcels with low forest cover for ARR activities, especially in narrow or fragmented landscapes such as riparian corridors, and support fine-scale reversals monitoring by detecting canopy disturbance.

- **ACR's IFM v2.1, a US-based IFM methodology:** ACR's IFM v2.1 requires RS for dynamic baselining through comparable properties analysis and permits RS for project planning, feasibility, and reversals monitoring. Developers can use Meta's CHM and AI model to quantify merchantability and stand structure metrics when matching project parcels with comparable properties. Developers could also use these tools for enhancing estimates of harvest intensity in baseline control plots, particularly for detecting selective or low-intensity logging, and for improving disturbance monitoring in complex forests where moderate-resolution RS data may be insufficient.

This guidebook offers developers and registries tactical guidance on how to work with Meta's model and CHM. It includes practical information and considerations on how to leverage the model to make custom time series of canopy height, when to preprocess high-resolution imagery for use in the model, when to conduct local validation to ensure crediting integrity, and how to work with the model's limitations. Importantly, we recommend that, where Meta's model is used to deduce changes over time (e.g., height growth), the mean absolute error (MAE) should be low enough to detect statistically significant trends. This means that the MAE should be significantly lower than the expected height growth over the time interval of interest.

4. United States Geological Survey. c2025. Landsat Normalized Difference Vegetation Index. [accessed 2025 Jun 12]. https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index.

Looking forward, while Meta's CHM and AI model present exciting opportunities to improve the transparency, rigor, and accessibility of forest carbon markets, broader industry efforts are needed. Standardizing model validation practices, clarifying acceptable uncertainty thresholds, and investing in user-friendly RS data platforms will be crucial steps toward realizing the full potential of high-resolution RS tools such as Meta's. These efforts will be beneficial to carbon credit development and to sustainable forest management more generally.



Tropical forest after rain. Source: Adobe Stock.

Introduction and purpose of this guidebook

Forests play a critical role in global climate mitigation due to their ability to store vast amounts of carbon and act as carbon sinks. As a result, forest management has become the dominant source of carbon removal in the voluntary carbon market (VCM). To ensure the credibility and integrity of these projects, accurate MMRV of forest carbon is essential—particularly for demonstrating real, additional, and long-term carbon benefits.

Forest carbon project developers increasingly rely on RS data and analytical approaches for MMRV.[5] Local data and place-based ecological knowledge remain critical for a nuanced understanding of forests. However, RS data have the potential to enhance reporting transparency and inform data-driven, scientifically rigorous approaches for scaled forest carbon project analysis. There is interest in and momentum for integrating RS into project feasibility and MMRV, but developers and registries lack clear guidance on how to apply appropriate RS tools and best practices to meet forest carbon project goals. We discuss this in detail in the companion piece to this guidebook, *Remote Sensing for Forest Carbon: Challenges, Opportunities, and a Path Forward*. Developers and registries require deep and practical insights into how novel datasets can support key aspects of project development and evaluation.

> **Developers and registries require deep and practical insights into how novel datasets can support key aspects of project development and evaluation.**

Meta's Every Tree Counts initiative produced a high-resolution (one meter) global CHM with an underlying AI model infrastructure,[6] both of which are open source and freely available.[7] These tools represent an exciting step forward. They leverage RS to provide new insights into forest structural attributes that are useful for forest carbon project development. In this guidebook, we provide project developers with a breakdown of Meta's CHM and underlying AI model, as well as technical guidance on using these tools in the context of three common forest carbon methodologies:

5. This process is often referred to as digital MMRV, which leverages RS technologies, analytics, and digital platforms to enhance the transparency, accuracy, and efficiency of carbon project monitoring and reporting.

6. Meta's model is based on vision transformers, a cutting-edge form of deep learning AI for image processing.

7. Tolan J, Couprie C, Brandt J, Spore J, Tiecke T, Johns T, Nease P. 2024 Ap 22. Using Artificial Intelligence to Map the Earth's Forests. Meta Sustainability. [accessed 2025 Jun 12]. https://sustainability.atmeta.com/blog/2024/04/22/using-artificial-intelligence-to-map-the-earths-forests/.

Verra's VM0045 v1.1,[8] Verra's VM0047 v1.0,[9] and ACR's IFM v2.1.[10] Finally, we highlight practical considerations and limitations for developers or registries who are considering integrating Meta's model and datasets into their project analysis frameworks.

RS for forest carbon project development

Accurately characterizing forest structural attributes, such as canopy height and above-ground biomass (AGB), is important for forest conservation and forest carbon MMRV. RS technologies are critical tools for this work, offering scalable and cost-effective alternatives or complements to traditional field surveys. In this context, RS refers to the science and technology of obtaining information about forest ecosystems without direct physical contact, typically using sensor technologies on satellites, aircraft, or drones. RS data comes from optical, radar, and lidar sensors, each of which contribute unique insights and face their own respective limitations. Optical sensors are capable of acquiring data over broad temporal and spatial domains, and often provide freely available access to data and more comprehensively processed data products. Some imagery acquisition programs such as Landsat[11] have been operating since the 1970s, providing imagery data decades into the past. A common criticism of optical data, however, is that it cannot be used to accurately characterize forest structure (e.g., canopy height or carbon stocks) by itself and is also unable to provide observations in cloudy conditions. Radar data is capable of penetrating deeper into forest canopies and can operate in cloudy conditions or at night, but provides limited insight into forest structural attributes for MMRV applications. Aerial lidar data uses laser pulses from sensors onboard aircraft to provide highly accurate measurements of forest structure with high spatial resolution. However, these data are spatially discontinuous resulting in large gaps in coverage, are often acquired at only a single point in time, and are costly to acquire.

To overcome these data-specific constraints, Meta applied multi-sensor fusion techniques to enable tree canopy height estimation at high spatial resolution and broad spatial coverage. These techniques are based on AI—specifically deep learning architectures, including convolutional neural networks and vision transformers. Deep learning architectures have the ability to model spatial context and long-range dependencies, making them particularly well-suited to learn from high-resolution imagery. This allows for more accurate and spatially continuous predictions of forest structure. Meta's deep learning architecture leverages the strengths of globally available, consistently updated optical

8. Verra. 2024. VM0045 Methodology for Improved Forest Management Using Dynamic Matched Baselines from National Forest Inventories, v1.1. Verra. [accessed 2025 Jun 12]. https://verra.org/methodologies/methodology-for-improved-forest-management/.

9. Verra. 2023. VCS Methodology VM0047 Afforestation, Reforestation, and Revegetation, v1.0. [accessed 2025 Jun 12]. https://verra.org/wp-content/uploads/2023/09/VM0047_ARR_v1.0-1.pdf.

10. American Carbon Registry. 2024. Improved Forest Management (IFM) on Non-Federal U.S. Forestlands. ACR. [accessed 2025 Jun 12]. https://acrcarbon.org/methodology/improved-forest-management-ifm-on-non-federal-u-s-forestlands/.

11. Landsat satellites capture multispectral data, supporting applications such as land use monitoring, agriculture, forestry, water management, and climate change studies. The current satellites, Landsat 8 and Landsat 9, offer high-quality imagery across multiple spectral bands with a 16-day revisit time for each satellite.

Meta's model has the potential to overcome some of the barriers that have limited the application of remote sensing to forest carbon project development.

imagery[12] and pairs it with the highly accurate, yet geographically and temporally limited, structural information that aerial lidar provides. The output is a submeter-resolution estimate of forest height for a single time point at a global scale, with the opportunity to produce multi-temporal estimations at project and regional scales.

Meta's model has the potential to overcome some of the barriers that have limited the application of RS to forest carbon project development. As an open-source model, it could help provide increased access to data products that are otherwise prohibitively expensive, especially for small-scale developers. Developers and registries could use Meta's model, along with existing optical imagery, to obtain canopy height estimates with high temporal resolution. Additionally, the model's very high spatial resolution means that developers could use it to manage and monitor projects with heterogeneous forest features, such as riparian corridors or forest management units with varying management objectives. If validated with high-quality field data, Meta's model could improve predictive accuracy and help address the core challenges of data availability, resolution, and coverage. This ability could pave the way for more reliable and accessible MMRV in forest carbon projects.

Meta's CHM and global dataset

Meta leveraged its internal AI and computer vision expertise, along with its extensive computational resources, to develop its CHM. The model's submeter spatial resolution presents a variety of novel applications and specific use cases that we discuss further in the sections below. Meta's deep learning architecture produces CHMs at higher spatial resolution than prior studies. This is partly because it uses high-resolution imagery, with a spatial resolution of 0.59 meters.[13] Prior global canopy height models were trained on Landsat (30 meter resolution) or Sentinel-2[14] (10 meter resolution) imagery, which have coarser spatial resolution.[15, 16] Meta used its AI model to generate a global, spatially continuous CHM (hereafter referred to as the "2020 CHM") from a mosaic of cloud-free images that represent one snapshot in time. Not all locations on

12. Maxar Technologies. c2025. Maxar Intelligence & Maxar Space Systems. [accessed 2025 Jun 12]. https://www.maxar.com/home.

13. Tolan J, et al. 2024. Very high resolution canopy height maps from RGB imagery using self-supervised vision transformer and convolutional decoder trained on aerial lidar. 2024. Remote Sensing of Environment. 300:113888. doi:10.1016/j.rse.2023.113888.

14. Sentinel-2 is a European Earth observation satellite mission, part of the Copernicus Programme, designed to provide high-resolution optical imagery for land monitoring. It carries a multispectral instrument that captures data in 13 spectral bands, supporting applications like vegetation health assessment, soil and water monitoring, and disaster management.

15. Lang N, Jetz W, Schindler K, Wegner JD. 2023. A high-resolution canopy height model of the Earth. Nat Ecol Evol. 7(11):1778–1789. doi:10.1038/s41559-023-02206-6.

16. Potapov P, Li X, Hernandez-Serna A, Tyukavina A, Hansen MC, Kommareddy A, Pickens A, Turubanova S, Tang H, Silva CE, et al. 2021. Mapping global forest canopy height through integration of GEDI and Landsat data. Remote Sensing of Environment. 253:112165. doi:10.1016/j.rse.2020.112165.

Meta's deep learning architecture produces canopy height models at higher spatial resolution than prior studies.

Earth can be imaged in a cloud-free state in the same year, so depending on the pixel location, the image date could be from between 2009 and 2020, but 80% of the pixels have an image taken between 2018 and 2020.[17] Both the 2020 CHM and Meta's underlying AI model are open source and available for public use,[18] which means that users can choose to work with the ready-to-use 2020 CHM or use the AI model to create custom CHMs at any time point, in any location where suitable high-resolution imagery exists **(figure 1**).

At a high level, there are four key steps for working with Meta's 2020 CHM and underlying AI model:

1. Identify the required application by reading the *RS in forest carbon methodologies* and *Applications of Meta's AI model and 2020 CHM for key project activities* sections of this guidebook.
2. Determine, based on the required application and time period of interest, if the 2020 CHM can be used as is or if Meta's underlying AI model is needed to create custom CHMs for other points in time. If the user would like to use Meta's estimates of canopy height going forward over the project lifetime, they will need to work directly with Meta's model and input high-resolution imagery of the project location.
3. Browse[19] and download the required data via Amazon Web Services[20] or Jupyter[21] notebook[22] for a specific area of interest if the 2020 CHM is sufficient for the application. If the user needs to work directly with Meta's AI model, then they will use the Meta-hosted Jupyter notebook[23] to upload imagery and generate custom CHMs for the time period of interest.
4. See the *Practical considerations and limitations* section of this guidebook for further technical guidance on how to work with Meta's model and 2020 CHM.

A key advantage of Meta's model is that it can use multiple, different image sources to make high-resolution canopy height estimations. This versatility is partly due to the use of AI and computer vision technology that was trained on millions of satellite images to help the model learn spatial patterns on

17. The dataset does not cover Antarctica or Greenland.

18. Tolan et al., 2023. Global Canopy Height. Google Earth Engine. [accessed 2025 Jun 12]. https://meta-forest-monitoring-okw37.projects.earthengine.app/view/canopyheight.

19. Tolan et al., Global Canopy Height.

20. Meta and World Resources Institute. 2024. High Resolution Canopy Height Maps. [accessed 2025 Jun 12]. https://registry.opendata.aws/dataforgood-fb-forests/.

21. Jupyter. 2025. Project Jupyter. [accessed 2025 Jun 12]. https://jupyter.org.

22. GitHub. 2025. HighResCanopyHeight. [accessed 2025 Jun 12]. https://github.com/facebookresearch/HighResCanopyHeight/blob/main/notebooks/download_chm.ipynb.

23. GitHub. 2025. HighResCanopyHeight. [accessed 2025 Jun 12]. https://github.com/facebookresearch/HighResCanopyHeight/blob/main/notebooks/run_chm_model.ipynb.

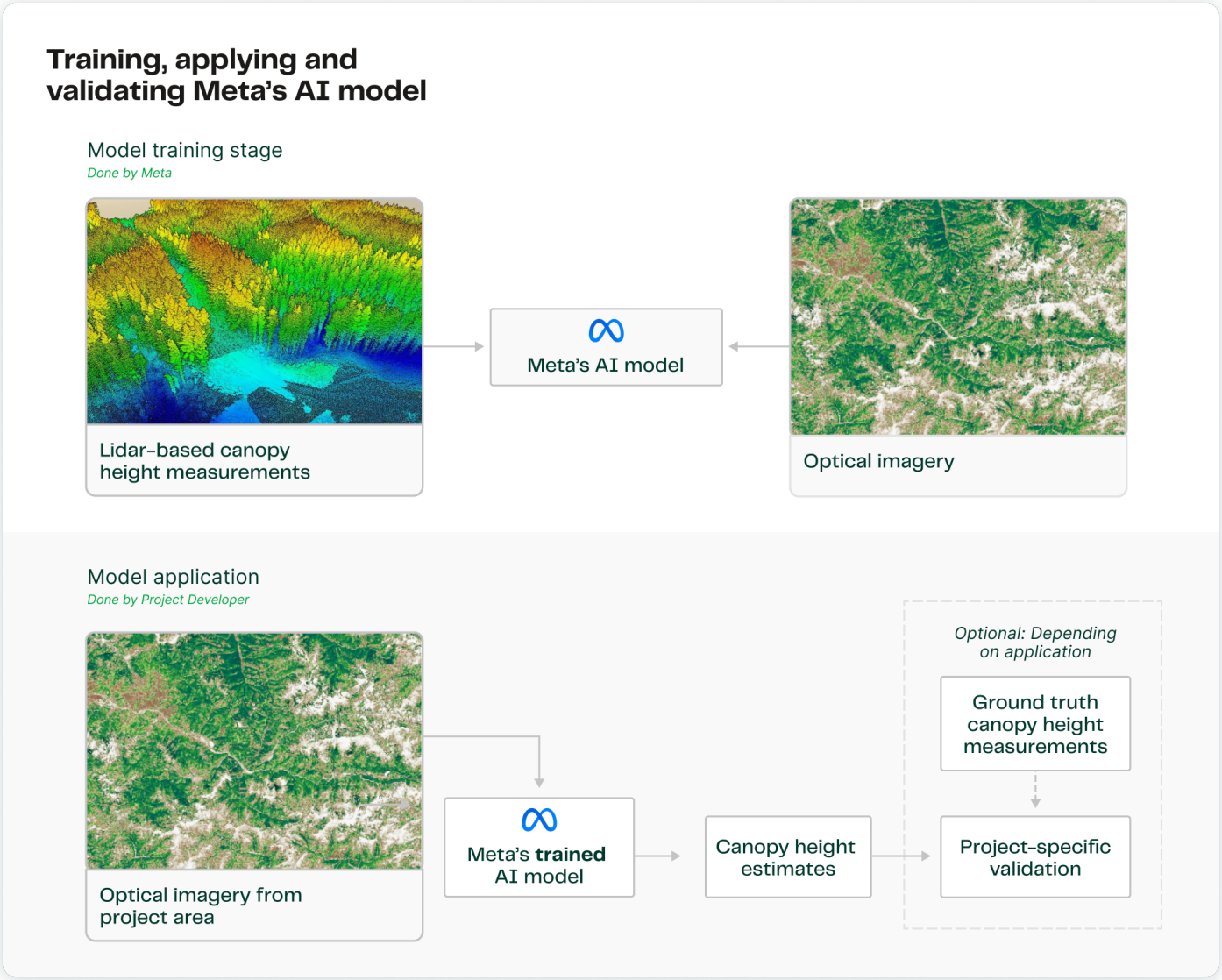


Figure 1. Process flow and data types for how Meta trained its model (top panel), and how developers can apply and validate Meta's model to estimate tree canopy height in their project area. Source: Carbon Direct.

the landscape. The model's versatility and training give it a uniquely advanced ability to recognize features like tree crowns and shadows in much the same way as a human would interpret an image. The model is able to use spatial context (e.g., "this long shadow is associated with that tall tree") to learn how to estimate canopy height. Meta trained the model to estimate canopy heights using Maxar optical imagery[24] and aerial lidar data from the National Ecological Observatory Network (NEON) in the United States (US). Although the NEON lidar training data was only available for sites within the US, Meta's model can consistently detect key landscape features across broad geographic areas in varying ecological contexts (**figure 2**). Meta validated the model using a test set of NEON sites in coastal California, and in Brazil. Meta did not use these sites to train the model. Meta used lidar data

24. Maxar Technologies. c2025. Maxar Intelligence & Maxar Space Systems. [accessed 2025 Jun 12]. https://www.maxar.com/home.

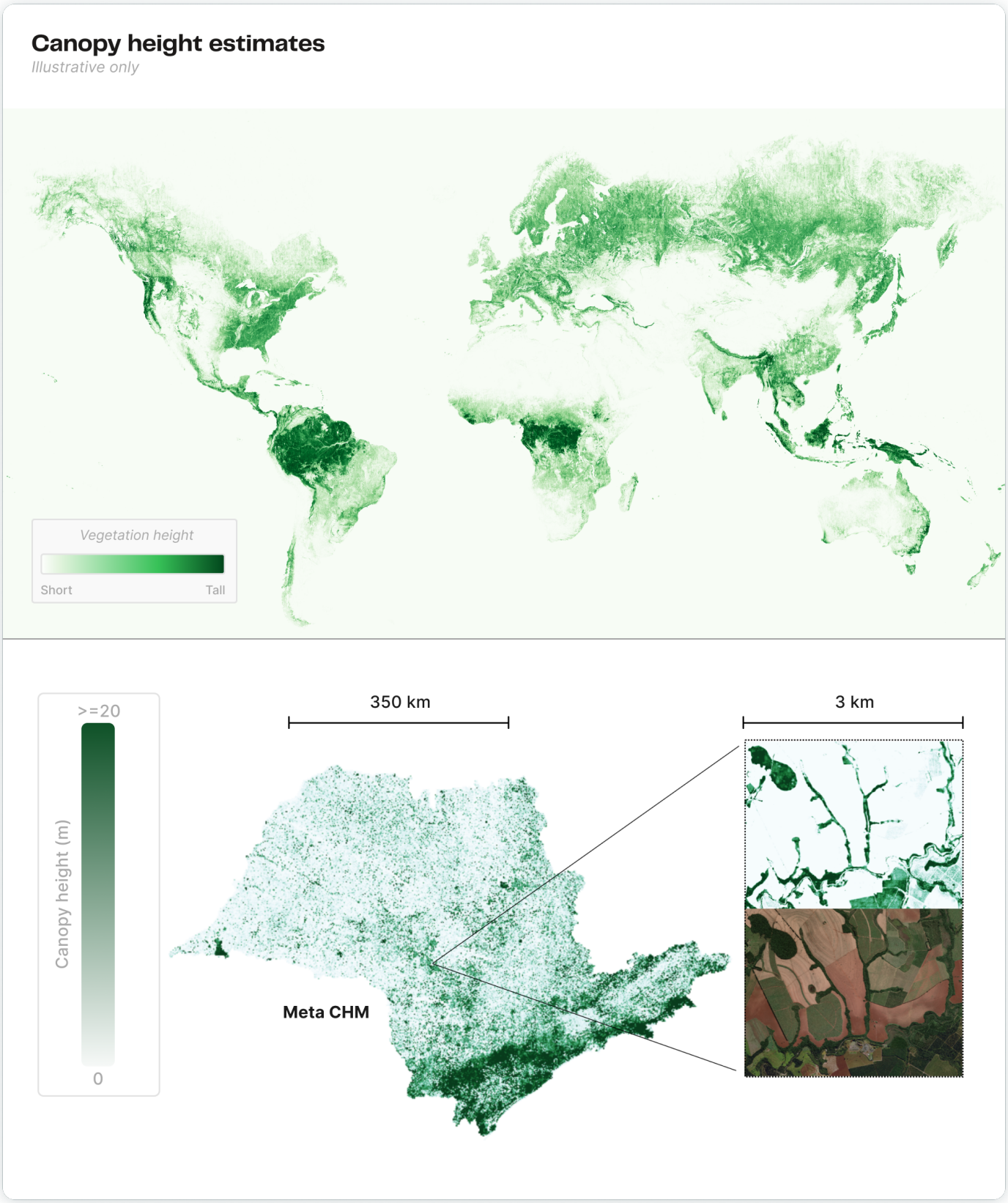


Figure 2. Estimates of canopy height from Meta's 2020 CHM at the global scale (top), and zoomed into smaller 350-km and 3-km scales (bottom) to show high spatial resolution. Source: Meta.

from the Global Ecosystem Dynamics Investigation (GEDI)[25] instrument onboard the International Space Station to provide additional, final calibration to canopy height estimates and to help the model perform better in multiple forest types globally. See the Appendix of this guidebook for technical details on how Meta created, trained, and used its model to create the 2020 CHM.

Although Meta's model represents a significant step forward in creating global estimates of tree canopy height, it has limitations. Project developers seeking to use the model in the near term should understand these limitations. The model's estimation uncertainty, or error, varies depending on the forest type, geographic location, and the type of data used to validate the model. The way this uncertainty varies over geographic space is important for developers and registries to consider when applying these tools to their project area. A local validation exercise may be needed depending on the project location and the model's specific application.

Model validation is the process of evaluating how well a trained model performs on unseen data (i.e., data not used during model training) by quantifying the difference between the model's estimate and the true value (i.e., the error). Meta's AI model is relatively well validated in the US context because Meta tested it against NEON data taken in multiple forest types within the US (spanning coniferous, broadleaf deciduous, and tropical forests that were not used for model training). This exercise revealed that Meta's model had a MAE of 2.8 meters across these US-based forests, meaning that the canopy height estimates from the model were usually within this range of the actual canopy height. However, when compared to aerial lidar data from São Paulo State, Brazil the model had a MAE of 5.1 meters. Although these errors represent a promising improvement over prior global CHMs,[26] the tendency for errors to be different in different forest types (e.g., US versus Brazil) means that local validation could be needed in some areas, especially where canopy height estimates would directly affect credit issuance.

Unfortunately, developers, registries, validation and verification bodies (VVBs), and buyers have not yet reached broad consensus on how much error is too much for specific applications, so error evaluation is still largely up to the discretion of project stakeholders on an ad hoc basis. We discuss this broader industry issue in detail in the companion piece to this guidebook, *Remote Sensing for Forest Carbon: Challenges, Opportunities, and a Path Forward*. We discuss more practical considerations and limitations of Meta's 2020 CHM and underlying AI model in the *Practical considerations and limitations* section of this guidebook.

25. A particularly influential example of spaceborne lidar data is NASA's Global Ecosystem Dynamics Investigation (GEDI) mission, which is freely available throughout many areas of the globe. These data are highly valuable for global and regional forest carbon estimates, but are sample-based (i.e., not spatially continuous, covering 4% of Earth's surface, and limited to +/- 52° latitude) and have a relatively coarse spatial resolution (i.e., 25 meters). These technical limitations mean that these data are unsuitable for measuring individual tree heights on their own, but it can still be used to calibrate higher-resolution canopy height models that are already trained.

26. Lang N, Jetz W, Schindler K, Wegner JD. 2023. A high-resolution canopy height model of the Earth. Nat Ecol Evol. 7(11):1778–1789. doi:10.1038/s41559-023-02206-6.

Remote sensing in forest carbon methodologies

Overview of methodologies

VCM forest carbon project methodologies are evolving rapidly and increasingly integrating RS and digital MMRV frameworks, creating new opportunities for innovation in RS and modeling. The scope of this integration encompasses not just RS data (e.g., spectral indices), but more advanced data products, such as maps of AGB that are derived from a combination of RS data, field data, and modeling (often machine learning models). Verra and ACR are two leading carbon credit registries that develop standards and methodologies for forest carbon offset projects. They play a central role in ensuring that carbon credits represent real, additional, and verifiable emissions reductions and removals. Both registries' forestry carbon methodologies increasingly incorporate RS data and RS-derived data products to improve MMRV. Some registries (e.g., Isometric and Ecosystem Restoration Standard) are bringing RS analyses in-house, but Verra and ACR still largely require developers to conduct their own RS analyses. Verra's VM0047 v1.0 methodology applies to ARR projects while Verra's VM0045 v1.1 methodology and ACR's IFM v2.1 apply to IFM projects.

Developers can incorporate RS data and analytical methods into three key project stages: (1) project planning and feasibility, (2) dynamic baselining, and (3) reversals monitoring. Regardless of the methodology used, most developers use RS in the project planning and feasibility stage to identify suitable parcels to include in the project. Developers use geographic information (e.g., landcover, elevation) and information from satellite imagery (e.g., SIs, soil moisture, structural data) to identify and strategically place project area boundaries. In order to demonstrate parcel eligibility for VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1, developers can use satellite imagery, spectral indices, or RS-derived land cover products to prove that historical forest cover and land use meet each methodology's unique requirements. Projects under all three methodologies may choose to use RS data for reversals monitoring including detecting forest disturbance from fire, windthrow, pests, or disease.

Developers can incorporate remote sensing data and analytical methods into three key project stages: project planning and feasibility, dynamic baselining, and reversals monitoring.

VM0045 v1.1, VM0047 v1.0, and ACR's IFM 2.1 have been the earliest methodologies hosted on

major registries to explicitly incorporate dynamic baseline approaches into their carbon accounting frameworks. Prior to the incorporation of dynamic baselines, projects evaluated their project performance against a static baseline scenario, such as a fixed deforestation rate (for IFM) or the assumption of zero forest regeneration (for ARR). Static baselines fail to adapt to real-world ecological, economic, or policy changes, which can lead to systematic overcrediting. Projects establish a dynamic baseline by comparing carbon stock changes within project areas to control plots outside the project boundary, which serve as performance benchmarks and are not subjected to the carbon management activities. When projects determine control plot locations, RS data are used to maximize their similarity to the project area, in terms of ecological and historical land management conditions.

Because the data driving annual performance benchmarks and comparisons between project plots and control plots are reflective of real-world landscape conditions, they can integrate shifts in socioeconomic conditions and policy directives. This reduces risks related to regulatory additionality. National and regional economic conditions, as well as forest policy, are likely to shift during a project's crediting period. If not accounted for, these shifts could result in inaccurate baseline estimates. Using regional RS data can enhance the transparency and credibility of baseline estimates. RS data is reflective of national and regional policy shifts to reduce or increase forest harvesting, compliance with these laws, and the economic conditions that influence forest loss pressure. Compared to traditional static baselines, dynamic baselines that are regionally contextual and consistently updated provide a more credible basis for assessing project impacts and avoiding overcrediting.

Using regional remote sensing data can enhance the transparency and credibility of baseline estimates. Remote sensing has become critical to the process of developing and monitoring projects that utilize dynamic baselines.

Increasing criticisms of project additionality, over-crediting, and market credibility have largely driven the adoption of dynamic baselines. Using a dynamic baseline generally requires estimating changes in carbon stocks at hundreds to thousands of locations both inside and outside the project boundaries, making labor- and cost-intensive field measurements infeasible. RS data has therefore become critical to the process of developing and monitoring projects that utilize dynamic baselines. While both Verra's and ACR's updated methodologies rely on the same general principles for developing a dynamic baseline, each methodology has a unique approach (**table 1**).

Table 1. Role of RS in forest carbon methodologies

	VM0045 v1.1	VM0047 v1.0	ACR's IFM v2.1
Description	Global IFM methodology[27] that uses national or sub-national forest inventory data[28] as control plots, with FIA[29] data specified as the data source for US-based projects	Global ARR methodology that requires the use of a RS-based SI[30] to compare project performance relative to matched control plots	IFM methodology for non-federal forestland in the US that requires RS data to quantify harvest intensity and merchantability in matched control plots
Dynamic baseline update frequency	Project and control plots must be measured at or before the project start date. Project plots must be remeasured at least every five years and control plots at least every 10 years.	SI for project and control plots must be measured 10–8 years prior to project initiation (t = -10 to t = -8), again 8–1 years prior to project initiation (t = -8 and t = -1), and at project initiation. SI must then be monitored annually for both project and control plots. Project and control plots must be remeasured in the field at least once every five years after the project start date. The performance benchmark must be updated based on annual SI data every five years or at every verification, whichever comes first.	Initial field inventory in the project area must occur at or before project initiation. For projects using a comparable properties analysis to identify baseline harvest intensity, harvest intensity must be calculated for five consecutive years within the 10 years prior to validation. The baseline must then be assessed at least once every five years.
Required RS applications	None	**Dynamic baselining** • Use RS for identifying control plots. • Use RS for calculating SIs for project and control plots.	**Dynamic baselining (if using the comparable properties analysis)** • Use RS for calculating baseline harvest intensity using comparable property analysis.[31] • Use RS for assessing merchantability and for matching comparable properties to the project area.
Permitted RS applications	Project planning (e.g., project area delineation) and feasibility Reversals monitoring (before and during project)	Project planning (e.g., project area delineation) and feasibility Reversals monitoring (before and during project)	Project planning (e.g., project area delineation) and feasibility Reversals monitoring (before and during project)
Applications where field data is required (i.e., RS can't be used on its own)	Field data required for determining baseline carbon stocks in project area Field data required for monitoring forest carbon stock change in project area for credit issuance	Field data required for determining baseline carbon stocks in project area Field data required for monitoring forest carbon stock change in project area for credit issuance	Field data required for determining baseline carbon stocks in project area Field data required for monitoring forest carbon stock change in project area for credit issuance
Guidance on use of AI models	No specific guidance on the use of AI models or AI-derived data products Not explicitly prohibited	No specific guidance on the use of AI models or AI-derived data products Not explicitly prohibited	Provides a framework and approval process for developers to use for internally developed forest loss models that can incorporate AI algorithms[32]

27. VM0045 v1.1 is global, but national forest inventories used for control points need to be approved by Verra.

28. National or sub-national forest inventory datasets for projects outside of the US require approval from Verra.

29. This is data from the US Forest Service's Forest Inventory and Analysis program.

30. A remotely sensed SI is used to compare carbon accrual in the project area to carbon accrual (if any) in the control plots. The SI must be correlated with forest carbon and is intended to serve as a proxy for forest carbon. Project developers may use a variety of SIs that differ in their suitability for this purpose.

31. The "comparable property analysis" is ACR's term for the analysis used to determine the dynamic baseline at a property that has similar underlying ecological conditions and historical management, but is not included in the project activities.

32. At the time of this writing, ACR is close to releasing a more comprehensive framework to guide the use of remote sensing for its methodologies.



Aerial view of a landscape in Coorg, India. Source: Adobe Stock.

RS in VM0045 v1.1

Verra's VM0045 v1.1 is a global IFM methodology. While it does not require the use of RS, this methodology permits RS use for some project activities, such as planning and determining feasibility, assessing parcel eligibility, and monitoring for reversals. Of the three methodologies we examine here, VM0045 v1.1 presents the least opportunity for incorporating RS data into dynamic baselining

Required RS applications:

- None

Permitted RS applications:

- Project planning and feasibility
- Reversals monitoring

Dynamic baselining: VM0045 v1.1 does not allow developers to use RS for dynamic baselining analysis. Instead, developers conduct field measurements in permanent project plots (located within the project area) and compare these measurements to matched permanent baseline plots (located outside the project area) within national or sub-national forest inventory plots. For US-based projects, developers are required to locate control plots within the US Forest Service's Forest Inventory and Analysis (FIA) program plots.[33] For international projects, developers must locate control plots within national or sub-national forest inventory plots, subject to Verra approval and based on designated criteria for inclusion of forest inventory data. Matching is based on proximity and other criteria Verra has designated, which are intended to develop and dynamically evaluate the project baseline. VM0045 v1.1 requires developers to monitor project plots according to standard field protocols, choose control plots in the same ecoregion as the project plots, and track individual stems within the project plots.

Project planning, feasibility and reversals monitoring: VM0045 v1.1 does not explicitly require or prohibit the use of RS data for reversals monitoring within the project area, meaning a developer could design a monitoring plan that utilizes RS data for monitoring reversals from disturbance (e.g., fire, windthrow, logging). Likewise, VM0045 v1.1 does not prohibit or require the use of RS for determining project feasibility or assessing parcel eligibility.

33. United States Forest Service. 2023 Jan 13. Forest Inventory and Analysis. [accessed 2025 Jun 12]. https://research.fs.usda.gov/programs/fia.



Aerial view of a tropical forest. Source: Adobe Stock.

RS in VM0047 v1.0

Verra's VM0047 v1.0 is a global ARR methodology. It requires RS for dynamic baselining and permits its use in other project activities such as planning and determining feasibility, assessing parcel eligibility, and monitoring for reversals.

Required RS applications:

- Dynamic baselining (area-based approach)

Permitted RS applications:

- Project planning and feasibility
- Reversals monitoring

Dynamic baselining: Developers using the VM0047 v1.0 methodology must prove that carbon accumulation in the project area is additional to carbon accumulation in a baseline scenario, and there is ample opportunity to use RS for this purpose. Our discussion of the use of RS for dynamic baselining in VM0047 v1.0 applies to the "area-based approach," not the "census-based approach." The census-based approach is used for stands that are one hectare or smaller in size.[34] In these stands, additionality is quantified by counting individual trees and assuming zero carbon accrual in the baseline scenario. The census-based approach does not use a dynamic baseline or require the use of RS.

For larger stands, VM0047 v1.0 uses an area-based approach to quantify a project's dynamic baseline. RS is used to help select control plots that have underlying ecological conditions and historical land management practices that are similar to the project area. Control plots are located outside of the project area and are not subjected to project activities. Verra requires that developers use RS-based SIs to help compare changes in the project area to control plots. An SI is an RS-derived variable such as a vegetation index or an estimate of forest structure (e.g., AGB) that is intended to serve as a proxy for forest carbon stocks. The methodology does not specify what metric to use for the SI, although it does require that the chosen metric have a significant correlation with AGB, as evidenced by published or peer-reviewed studies. Once developers identify and match control plots to project sites, they must perform a time-series analysis to compare changes in the SI in the control

34. On May 14, 2025, Verra released v1.1 of its VM0047 methodology, which allows projects to use RS data to measure pre-existing biomass in some cases and introduces changes to parcel eligibility for the census-based approach. Due to the timing of the release, we did not include an analysis of this update in this report.

plots over time. This analysis covers the 10-year period prior to project initiation in order to determine a "performance benchmark," or the expected change in baseline SI in the absence of the carbon project. Developers must also take field measurements of carbon stocks at plots within the project area (e.g., using forest inventory plots), but do not need to take field measurements in control plots.

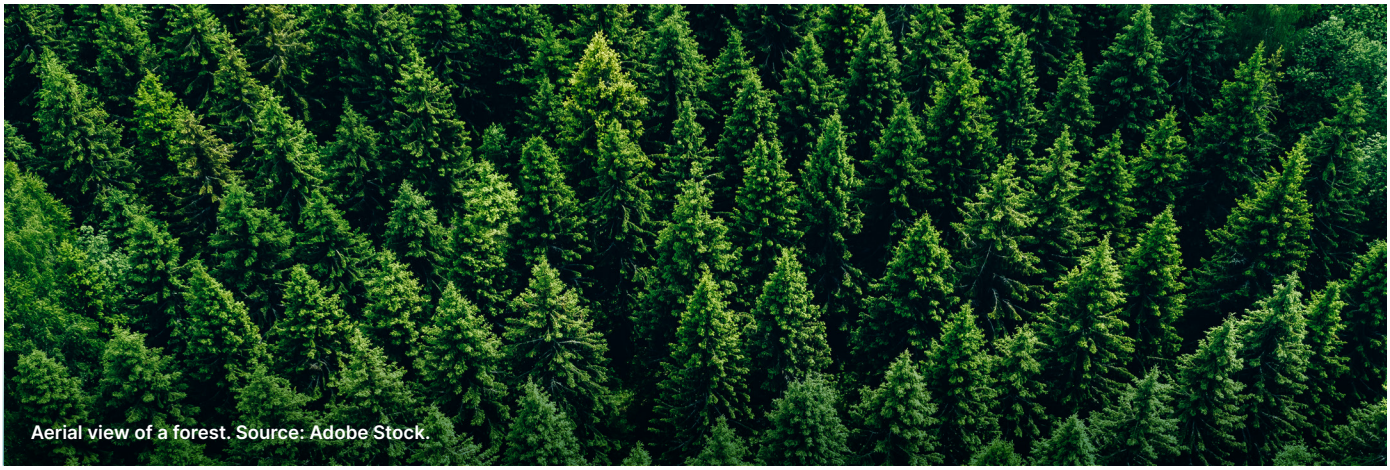
VM0047 v1.0 includes limited data requirements and minimal guidance on RS methods, which allows developers flexibility when developing a dynamic baseline. However, this flexibility can come at the expense of clarity on best practices. Verra suggests using metrics such as the Normalized Difference Fraction Index (NDFI)[35] from Landsat imagery or average canopy height derived from lidar data, but does not offer specific guidance around datasets or procedures to calculate these metrics. The methodology does lay out requirements on the resolution of the data. VM0047 v1.0 requires the spatial resolution of the data to be at least 30 meters and the temporal resolution to be at least annual. Developers should also use imagery from a consistent time of year to minimize seasonal variation. Historical data needs to be available at a minimum of three time points: (1) between 10–8 years prior to project initiation (t = -10 to t = -8), (2) between 8–1 years prior to project initiation (t = -8 to t = -1), and (3) at project initiation.[36] While setting the minimum spatial resolution to 30 meters allows developers to use readily accessible data sources, such as Landsat imagery, it may not be detailed enough for small-scale parcels or project activities that take place along narrow riparian corridors. Additionally, NDFI and other spectral indices, such as NDVI,[37] are prone to saturation at high levels of biomass, which makes it difficult to accurately measure biomass change as forests mature, particularly after canopy closure. While more sophisticated metrics could be used as an SI, such as RS-based estimates of AGB, these datasets are often expensive and may have high uncertainty depending on the region of interest.

Project planning, feasibility, and reversals monitoring: VM0047 v1.0 does not explicitly require or prohibit the use of RS data for reversals monitoring within the project area, meaning a developer could design a monitoring plan that utilizes RS data for reversals monitoring via disturbance (e.g., fire, windthrow, logging). Likewise, VM0047 v1.0 does not prohibit the use of RS for determining project feasibility or parcel eligibility. Under the census-based approach, if pre-existing woody biomass was cleared in the project area in the 10-year period prior to project initiation, developers must demonstrate that it was not cleared with the intention of altering the baseline scenario in order to prove that the project area is eligible under the methodology's rules. To prove this, developers may use RS data or other documentation to demonstrate that the clearing was a result of natural disturbance.

35. Combining spectral and spatial information to map canopy damage from selective logging and forest fires. 2005. Remote Sensing of Environment. 98(2–3):329–343. doi:10.1016/j.rse.2005.07.013.

36. Verra. 2023. VCS Methodology VM0047 Afforestation, Reforestation, and Revegetation, v1.0. [accessed 2025 Jun 12]. https://verra.org/wp-content/uploads/2023/09/VM0047_ARR_v1.0-1.pdf.

37. United States Geological Survey. c2025. Landsat Normalized Difference Vegetation Index. [accessed 2025 Jun 12]. https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index.



Aerial view of a forest. Source: Adobe Stock.

RS in ACR's IFM v2.1

ACR's IFM v2.1, a US-focused IFM methodology, incorporates a dynamic baseline framework and provides details on acceptable RS approaches and datasets for dynamic baselining. This methodology provides more specific instructions than VM0047 v1.0 regarding appropriate RS data and approved sources. It gives developers the flexibility to bring their own data to ACR for approval or utilize a baseline procedure that is not subject to dynamic baseline evaluation and, therefore, does not require RS data. ACR's IFM v2.1 permits the use of RS in other project activities such as planning and determining feasibility, assessing parcel eligibility, and monitoring for reversals.

Required RS applications:

- Dynamic baselining (for comparable properties analysis matching)

Permitted RS applications:

- Project planning and feasibility
- Reversals monitoring

Dynamic baselining: One of the primary steps in establishing a baseline for ACR's IFM v2.1 methodology is determining the baseline harvest intensity. This methodology allows developers to set a project's baseline harvest intensity using one of three approaches: (1) using a historical baseline derived from pre-existing, long-term forest management plans, (2) establishing a removals-only baseline, or (3) using an RS-based comparable properties analysis.[38] Baseline harvest intensities established using pre-existing forest management plans or a removals-only baseline are not subject to dynamic baseline evaluation. However, other components of the baseline, such as legality and operability, are dynamically evaluated regardless of which method was used to derive the baseline harvest intensity. Here, we focus on the comparable properties analysis approach because it requires leveraging RS data.

To conduct a comparable properties analysis, ACR's IFM v2.1 requires developers to use RS-derived similarity matching to identify comparable properties within a 150-mile radius of the project area. Matching is based on RS data such as forestland acreage, distance from project area, slope, elevation, AGB, forest cover type, and merchantability. The methodology identifies specific sources of RS data

38. ACR IFM v2.1, Section 4.1.3.2.

as pre-approved, such as the European Space Agency's Global Forest Above Ground Biomass dataset for AGB[39] and the US Geological Survey's National Land Cover Database[40] for forest cover type. In order to assess merchantability on comparable properties, ACR suggests using the ETH Zurich's Global Sentinel-2 10-meter CHM.[41] Notably, it also allows Meta's 2020 CHM as an acceptable data source to assess merchantability, but states that the high resolution of the dataset may make it more computationally intensive to use. Once a developer selects a comparable property, they can derive a historical harvest intensity using either management records or RS data. The developer must then redo the comparable properties analysis at each full verification. In sum, developers may choose to use methods other than the comparable properties analysis to determine baseline harvest intensity, but if they choose to use a comparable properties analysis, they are required to use RS for property matching.

There is one major limitation of the RS procedure developers use to identify baseline harvest intensity under the comparable property analysis method. This is the fact that the suggested data sources lack sensitivity to low-intensity or partial harvests. The methodology specifically mentions the Global Land Analysis & Discovery[42] and the Landscape Change Monitoring System[43] datasets, both of which are publicly available and regularly updated. However, one downside of these datasets is their lack of ability to detect partial harvests. To account for this, the methodology instructs developers to assume 100% biomass removal where forest loss is detected using these datasets. In order to detect partial harvests, such as thinning, developers would need to use a higher-resolution dataset.

ACR's IFM v2.1 also includes examples of RS procedures using datasets the methodology identifies as appropriate. These examples can help developers overcome a lack of experience or technical expertise when they are conducting these analyses. In order to help a developer implement a comparable properties analysis, ACR also provides a full example of the process utilizing mostly publicly available data. This example can help project developers, especially those new to the methodology or without in-house technical expertise, overcome the barriers to incorporating RS data into their process.

Project planning, feasibility, and reversals monitoring: ACR's IFM v2.1 does not explicitly require or prohibit the use of RS data for reversals monitoring within the project area, meaning a developer could design a monitoring plan that utilizes RS data for reversals monitoring via disturbance (e.g., fire, windthrow, logging). Likewise, ACR's IFM v2.1 does not prohibit the use of RS for determining project feasibility or parcel eligibility.

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39. Santoro M, Cartus O. 2024. ESA Biomass Climate Change Initiative (Biomass_cci): Global datasets of forest above-ground biomass for the years 2010, 2015, 2016, 2017, 2018, 2019, 2020 and 2021, v5.01. :8977 Files, 663753418058 B. doi:10.5285/BF535053562141C6BB7AD831F5998D77. [accessed 2025 Jun 12]. https://catalogue.ceda.ac.uk/uuid/bf535053562141c6bb7ad831f5998d77.

40. United States Geological Survey. 2018. National Land Cover Database. [accessed 2025 Jun 12]. https://www.usgs.gov/centers/eros/science/national-land-cover-database.

41. Lang N, Jetz W, Schindler K, Wegner JD. 2023. A high-resolution canopy height model of the Earth. Nat Ecol Evol. 7(11):1778–1789. doi:10.1038/s41559-023-02206-6.

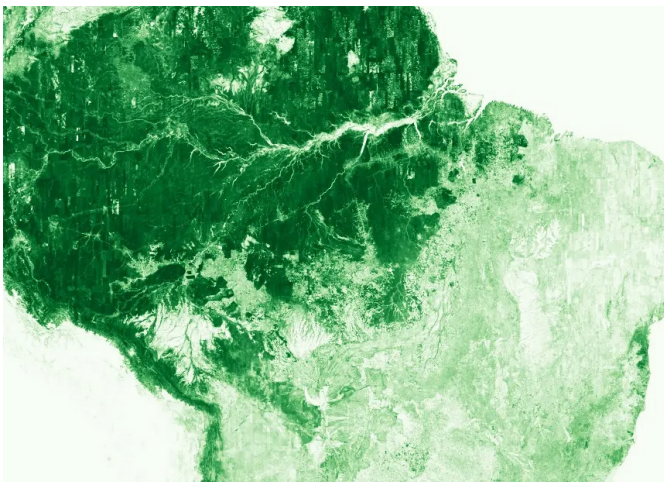
42. Global Land Analysis & Discovery. c2025. [accessed 2025 Jun 12]. https://glad.umd.edu/.

43. United States Forest Service. 2025. Landscape Change Monitoring System (LCMS). [accessed 2025 Jun 12]. https://data.fs.usda.gov/geodata/rastergateway/LCMS/index.php.

Applications of Meta's AI model and 2020 CHM for key project activities

Here we discuss how Meta's AI model and 2020 CHM could be applied to the three key stages of carbon project development: (1) project planning and feasibility, (2) dynamic baselining, and (3) reversals monitoring. Meta's 2020 CHM dataset is freely and publicly available for exploration[44] and download.[45] This dataset can be used in its current form where forest structural attributes are only needed for a snapshot in time that is reflective of 2020.[46] The underlying model that generated this dataset is open source and capable of estimating canopy height from a wide variety of high-resolution imagery sources. This introduces the possibility of developing CHMs with higher temporal resolution in targeted areas and widens the scope of applications. Throughout our discussion of applications below, we note where the 2020 CHM may be suitable, versus where users would need to apply Meta's deep learning model to high-resolution imagery from the desired time points. This discussion is summarized in **table 2**.

Meta's 2020 CHM dataset is freely and publicly available for exploration and download.



Detail of Meta's global CHM. Source: Meta.

44. Tolan et al., 2023. Global Canopy Height. Google Earth Engine. [accessed 2025 Jun 12]. https://meta-forest-monitoring-okw37.projects.earthengine.app/view/canopyheight.

45. Meta and World Resources Institute. 2024. High Resolution Canopy Height Maps. [accessed 2025 Jun 12]. https://registry.opendata.aws/dataforgood-fb-forests/.

46. The exact image date will vary between 2009 and 2020 depending on the pixel location. However, 80% of pixels have an image date between 2018 and 2020.

Table 2. Applications of Meta's 2020 CHM and AI model to forest carbon methodologies*

Project stage	Use case	Meta's 2020 CHM[47]	Meta's AI model[48]	VM0047 v1.0	VM0045 v1.1	ACR's IFM v2.1
Project planning and feasibility	Identify strategic parcels (e.g., for biodiversity benefits)	⚠	✔	✔	✔	✔
	Delineate project boundaries	⚠	✔	✔	✔	✔
	Stratify project area	⚠	✔	✔	✔	✔
	Quantify pre-existing forest cover to assess parcel eligibility	⚠	✔	✔	✔	✔
Dynamic baselining	Use canopy height as an SI	✖	✔	✔	✖	✖
	Support ex ante projections of carbon accumulation	✖	✔	✔	✖	✖
	Use estimated merchantability as a matching variable when identifying control plots	⚠	✔	✖	✖	✔
	Estimate harvest intensity in control plots	✖	✔	✖	✖	✔
Reversals monitoring and field data QA/QC	Monitor forest disturbance	✖	✔	✔	✔	✔
	Augment field data with estimates of tree height	⚠	✔	✔	✔	✔
	Conduct quality control of field data	⚠	✔	✔	✔	✔
	Use as an input variable for estimating AGB	⚠	✔	✔	✔	✔

* The symbols used in this table indicate the following:

- A ✔ symbol indicates the applicability of Meta's 2020 CHM and underlying AI model to a specific use case and methodology.
- A ⚠ symbol indicates where Meta's 2020 CHM could be used if the time period of interest overlaps with Meta's 2020 CHM or if the user doesn't need a specific time period.
- A ✖ symbol indicates that Meta's model and 2020 CHM are not applicable.

47. The applicability of Meta's CHM to use cases depends on temporal alignment between project needs and the existing dataset.

48. Applying Meta's CHM to these cases requires users to provide their own input imagery for the model, for the area and time period of interest.

Project planning and feasibility

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Identify strategic parcels: The project planning and design stage of IFM projects involves surveying large areas of forestland to identify areas with desirable forest structure for IFM. Meta's 2020 CHM provides detailed insights into size class distributions, maximum individual tree heights, and tree density. These insights can help identify areas with large carbon stocks, a history of logging, or high conservation value. For example, quantifying structural heterogeneity is important for predicting biodiversity benefits and mapping old-growth stands. Meta's AI model and 2020 CHM can do this with greater granularity than prior global CHMs because of its higher spatial resolution. This allows developers to gain deeper insight into more subtle features of forest structure such as the prevalence of canopy gaps and understory structure. This fine-scale forest structure information is required to map habitat suitability for a wide range of organisms.[49] Where these insights are needed for points in time beyond 2018–2020, Meta's AI model can be applied to high-resolution imagery from the time points of interest. For ARR projects under VM0047 v1.0, Meta's 2020 CHM and AI model can help developers identify areas that have been deforested and currently have low forest cover to ensure that reforestation efforts are deployed in the right places.

Meta's 2020 CHM provides detailed insights into size class distributions, maximum individual tree heights, and tree density.

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Delineate project boundaries: Project area delineation often requires identifying non-forest features to exclude from the project. High-resolution imagery can be used on its own to identify many non-forest features such as roads, buildings, and fields, but it is not always sufficient to distinguish between different types of vegetation (e.g., distinguishing between shrubs and trees). Meta's dataset could be particularly useful for identifying non-forest features in cases where raw high-resolution imagery is not available or where visual interpretation of high-resolution imagery (e.g., on Google Earth) cannot sufficiently distinguish between trees, shrubs, other non-woody vegetation, and other landscape features.

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Stratify project area: All three methodologies identify project area stratification as an important tool for ensuring that field data are statistically representative. Developers commonly stratify

49. Hyde P, Dubayah R, Walker W, Blair B, Hofton M, Hunsaker C. 2006. Mapping forest structure for wildlife habitat analysis using multi-sensor (LiDAR, SAR/InSAR, ETM+, Quickbird) synergy. Remote Sensing of Environment. 102(1–2):63–73. doi:10.1016/j.rse.2006.01.021.

project activity areas by vegetation type and/or biomass, and choose proxies for biomass so that estimates of mean carbon stock dynamics capture variation across forest age, local soil conditions, or historical land use legacies.[50] Meta's 2020 CHM could serve as a useful data layer for project area stratification in contexts where developers expect canopy height differences among the strata to remain the same between the 2018–2020 time period and the project's time period of interest. This could be particularly applicable when developers are aiming for stratification to capture differences over soil and topographic gradients (e.g., valleys versus ridges) in areas where human disturbance has been minimal. In cases where project area stratification is required on a more dynamic landscape, developers could apply Meta's AI model to high-resolution imagery at the project's preferred time point.

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Quantify pre-existing forest cover to assess parcel eligibility: IFM projects utilizing Verra's VM0045 v1.1 methodology must demonstrate that their project area qualifies as promoting "forests remaining forests." While the methodology does not explicitly define "forest," Meta's 2020 CHM and underlying AI model can be used to quantify tree cover in the project area to meet this eligibility criteria. ARR projects using VM0047 v1.0's census-based approach must prove that pre-existing forest cover was less than 10% for 10 years prior to project inception. Because this requires reporting on forest structure for more than one point in time,

Meta's AI model is especially useful for projects that want to reforest riparian corridors, which are often smaller than what is detectable using moderate-resolution datasets.

Meta's model must be applied to high-resolution imagery over multiple time periods. The high spatial resolution of Meta's AI model makes it especially useful for distinguishing between eligible and non-eligible parcels that are too small to analyze using more widely available datasets with moderate resolution (e.g., 10–30 meters). This is especially useful for projects that want to reforest riparian corridors, which are often smaller than what is detectable using moderate-resolution datasets. IFM projects using ACR's IFM v2.1 methodology must occur on forestland. The methodology defines forestland as being at least one acre in size, having at least 10% tree cover or equivalent stocking (or formerly having such tree cover), and not currently being developed for non-forest uses. Meta's 2020 CHM or underlying AI model could be used to prove that a parcel meets these requirements. Like in VM0047 v1.0, for small or irregularly-shaped parcels, the Meta model's submeter resolution data would be useful in demonstrating eligibility where existing moderate-resolution imagery is insufficient.

50. Goodbody TRH, Coops NC, Queinnec M, White JC, Tompalski P, Hudak AT, Auty D, Valbuena R, LeBoeuf A, Sinclair I, et al. 2023. sgsR: a structurally guided sampling toolbox for LiDAR-based forest inventories. Forestry: An International Journal of Forest Research. 96(4):411–424. doi:10.1093/forestry/cpac055.

Dynamic baselining

Relevant to VM0047 v1.0

Use canopy height as an SI: Projects using VM0047 v1.0's area-based approach must use an RS-based SI to assess project performance compared to statistically matched control plots that are outside the project area. However, developers, registries, and domain experts have found that freely available, open-source SIs are often insufficient for distinguishing between areas with medium or high levels of biomass. These reports align with scientific findings that optical vegetation indices saturate (i.e., become unable to quantify forest structure) in areas with medium and high levels of biomass.[51] Meanwhile, biomass data products that could serve as more robust SIs are often cost prohibitive. In scenarios where Meta's AI model can be applied to a time series of high-resolution imagery covering the project area and control plots, the resulting time series of CHMs has the potential to serve as a more robust and accessible SI than current open-source and commercially available options. Where project interventions assist natural regeneration, it is especially important for developers to understand what the baseline is for unassisted natural regeneration. Meta's model is well positioned to do this. It could provide a time series of canopy height growth for naturally regenerating forest in control plots that developers can compare to canopy height growth in the project areas. There are a number of important technical considerations stakeholders should take into account when using Meta's model for these purposes. We discuss these further in the *Practical considerations and limitations* section of this guidebook.

Meta's model is well positioned to convert historical imagery to a time series of canopy height growth, which can help make ex ante projections of carbon accumulation.

Relevant to VM0047 v1.0

Support ex ante projections of carbon accumulation: Understanding natural growth and recovery rates after disturbance helps project developers create ex ante projections of biomass accumulation. However, many developers do not have access to these data and cannot make estimates based on existing moderate-resolution, multispectral imagery. Meta's model is well positioned to convert historical imagery to a time series of canopy height growth, which can help make ex ante projections of carbon accumulation.

Relevant to ACR's IFM v2.1

Estimate merchantability to use as a matching variable when identifying control plots: IFM projects using the ACR's IFM v2.1 methodology's comparable properties analysis must compare the merchantability of stands in the project area to prospective comparable properties. Meta's model is particularly well suited for this because it can be

51. Gao Si, Zhong R, Yan K, Ma X, Chen X, Pu J, Gao Sicong, Qi J, Yin G, Myneni RB. 2023. Evaluating the saturation effect of vegetation indices in forests using 3D radiative transfer simulations and satellite observations. Remote Sensing of Environment. 295:113665. doi:10.1016/j.rse.2023.113665.



Summer forest fire. Source: Adobe Stock.

used to quantify the range of tree sizes in a forest on a finer scale than is possible using moderate-resolution imagery (e.g., Landsat). This allows project developers to identify areas with higher-value timber (i.e., taller, more merchantable), versus lower-value stands that are at an earlier stage of regrowth after a recent harvesting event.

Relevant to ACR's IFM v2.1

Estimate harvest intensity in control plots: Developers of IFM projects under ACR IFM v2.1 must track project performance relative to a baseline scenario, on comparable properties where forests are managed according to a standard approach. Most developers currently use moderate-resolution RS data (e.g., Sentinel-2) to quantify harvest intensity in the baseline scenario. However, some harvest regimes (e.g., selective logging or thinning) are challenging, if not impossible, to detect using moderate-resolution RS data because changes in forest structure occur at a finer scale than these data can reflect. Submeter resolution canopy height data from Meta's 2020 CHM and underlying AI model are uniquely positioned to improve the effectiveness of estimating harvest intensity in forests where selective logging and thinning occurs. Although this application is particularly relevant to estimating baseline harvest rates for IFM projects, it also has broader applications for monitoring reversals from disturbance, as discussed below.

Reversals monitoring and other applications

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Monitor forest disturbances: It is critical for IFM and ARR project developers to monitor for reversals from forest disturbance. Meta's tools are particularly well suited for gaining higher-resolution insights into disturbance. Developers often use moderate-resolution, multispectral data sources (e.g., Landsat, Sentinel-2) for disturbance monitoring. However, in tropical regions with rapid vegetation recovery after disturbance, it can be difficult to detect disturbance

> **Meta's tools are particularly well suited for gaining higher-resolution insights into disturbance.**

using these data sources. This is because it can be hard, using optically-derived data products, to distinguish between intact tree canopies (i.e., that were not disturbed) and thick post-disturbance regrowth (e.g., shrubs). Meta's AI model provides more direct estimates of canopy height at a much higher spatial resolution. If applied to a time series of high-resolution imagery in the project area, Meta's model could facilitate more robust insights into where and when disturbances occur in these highly productive forests. Moderate-resolution imagery, such as imagery from Landsat, can be an effective tool for monitoring deforestation from clear cuts (where all trees in a relatively large area are removed). However, moderate-resolution RS data can be ineffective when developers are attempting to detect more subtle forms of forest degradation, such as when understory trees or only a small percentage of high-value trees are removed. Meta's submeter resolution data is especially well positioned to be used for detecting selective logging because it reflects small changes at the scale of individual trees.

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Augment field data with estimates of tree height: Tree height is a required parameter in many allometric equations. However, height can be difficult to measure in the field where trees are dense and/or very tall, which can dramatically increase the cost and labor intensiveness of field



Aerial view of Amazonian rain forest. Source: Adobe Stock.

campaigns. When the project's required time period for tree height data overlaps with 2018–2020, then project developers could use Meta's 2020 CHM to provide or augment tree height data, enhance field measurement efficiency, and support allometric modeling. However, depending on a stand's prevailing canopy characteristics and how well individual trees are mapped in field inventory plots, it may not be possible for developers to identify individual trees and species or directly link these observations to field data.

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Conduct quality control of field data: Where there is uncertainty about whether field plots are representative of the broader project area, developers can use Meta's 2020 CHM and underlying AI model to assess representativeness. Specifically, it can help developers determine whether field plots are distributed across the full range of canopy height classes found in the project region. Developers can also use the CHM data to support quality control, leveraging it to detect location errors in the field plot data. More broadly, having access to spatially continuous canopy height data enables developers to cross-check against field measurements and identify potential issues. For example, large mismatches between field-measured and predicted canopy height may reveal geolocation errors or mislabeling of field plots—insights that can help developers prioritize resurvey or data validation efforts.

Having access to spatially continuous canopy height data enables developers to cross-check against field measurements and identify potential issues.

Relevant to VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1

Use as an input variable for estimating AGB: Meta's 2020 CHM and underlying AI model can serve as a valuable tool in broader modeling efforts to estimate AGB from a combination of field data, optical data (e.g., Landsat), and other data sources. Canopy height is a strong predictor of AGB[52] and provides a key structural variable that complements spectral information. By integrating spatially explicit, high-resolution canopy height data with satellite imagery, climate data, or field-based allometric models, developers can make AGB predictions that are more accurate and spatially consistent.

52. Su Y, Schwartz M, Fayad I, García M, Zavala MA, Tijerín-Triviño J, Astigarraga J, Cruz-Alonso V, Liu S, Zhang X, et al. 2025. Canopy height and biomass distribution across the forests of Iberian Peninsula. Sci Data. 12(1):678. doi:10.1038/s41597-025-05021-9.

Practical considerations and limitations

When project developers choose to work with Meta's 2020 CHM or underlying AI model, they should first consider if the time period of the data required for the project extends beyond the 2018–2020 timeframe of the 2020 CHM. If it does, then developers will need to work with Meta's underlying AI model directly. Secondly, if a project developer is following a methodology that requires them to apply RS data to a specific project stage, and the required application directly affects credit issuance, we recommend doing a local validation exercise.

Figure 3 provides a high-level overview of the key decisions and workflow involved in using Meta's CHM and underlying AI model.

Local validation: If a project developer is following a methodology that requires application of RS data to a specific project stage, and the required application directly affects credit issuance then we recommend doing a local validation exercise. This recommendation applies to both the 2020 CHM and situations where the developer generates their

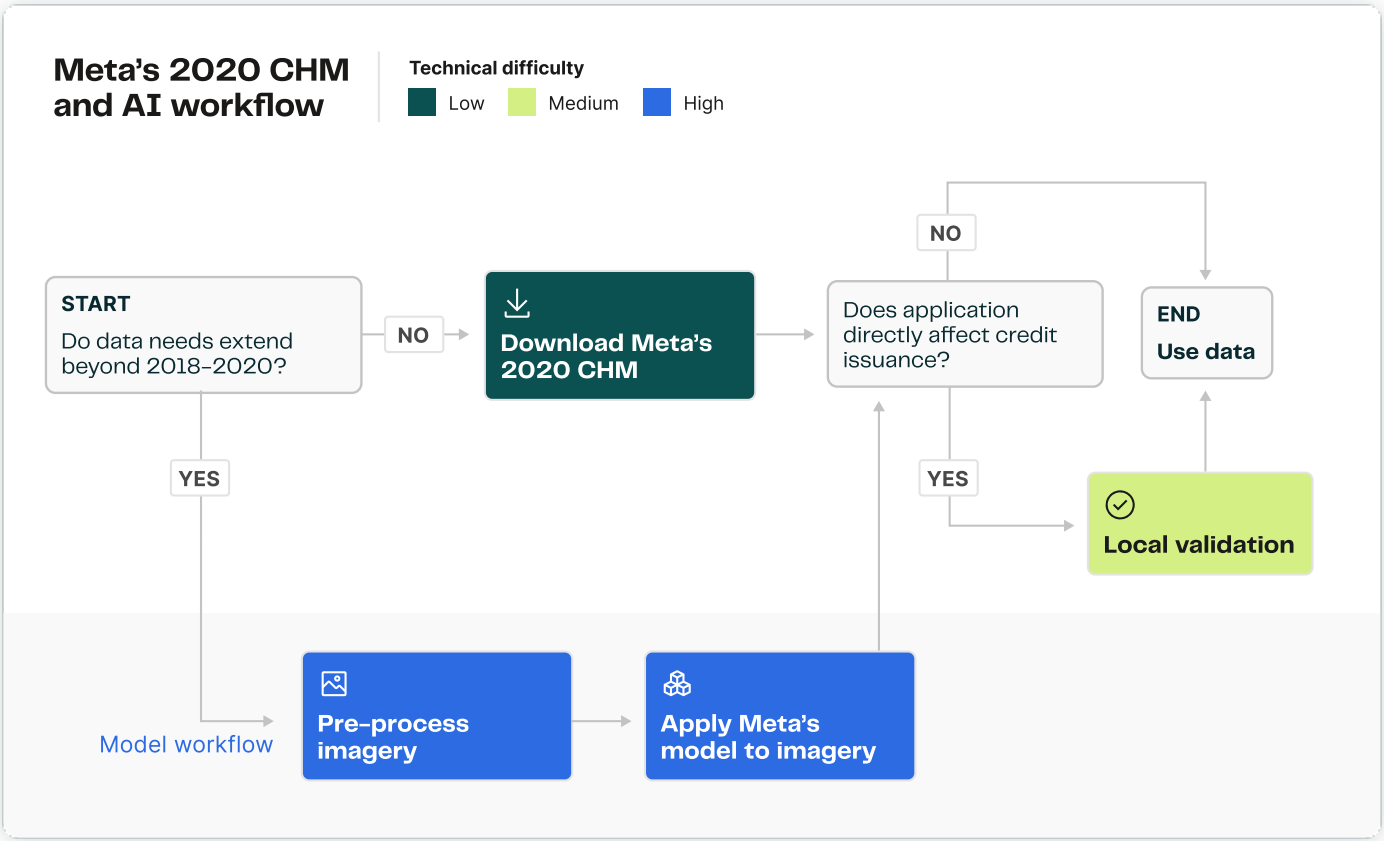


Figure 3. Key decisions and workflow for using Meta's 2020 CHM and underlying AI model. Note: In the model workflow, see **table 3** to determine if imagery pre-processing is needed for your imagery source. Source: Carbon Direct.

own CHM using Meta's AI model along with project-relevant, high-resolution imagery. Although the 2020 CHM has been globally calibrated using GEDI data, it has only been regionally validated with aerial lidar data in California and Brazil. Further, the 2020 CHM has only been validated with field inventory data in Brazil. This level of validation is likely sufficient for applications where the 2020 CHM is used to understand broad patterns and relative differences in canopy height within a project area in a specific region. However, for applications where the absolute canopy height values are critical to the objective (e.g., as an input to a biomass model that would affect credit issuance), then we recommend that the dataset is validated with local field data or aerial lidar.

For example, if a developer plans to use Meta's model results as an SI under VM0047 v1.0, we recommend first performing local validation using project-specific field data. This would involve collecting canopy height data from the field, within the project boundary, and quantitatively evaluating the model's performance against these field data using a statistic such as MAE. We do not provide thresholds on what acceptable errors are here, because this depends on the specific application. Also, industry stakeholders across registries, purchasing organizations, and academia have not aligned on such thresholds. (See our companion piece to this guidebook, Remote Sensing for Forest Carbon: Challenges, opportunities, and a path forward, for a deeper discussion of this barrier and our proposed recommendations for mitigation). In lieu of providing a quantitative error threshold, we recommend that, where Meta's model is used to deduce changes over time (e.g., height growth), the MAE should be low enough to detect statistically significant trends. This means that the MAE should be significantly lower than the expected height growth, over the time interval of interest.

Users of the dataset should check the imagery date for the pixels in a specific area of interest to ensure that the image date aligns with their needs.

It is important to keep in mind that the 2020 CHM was created using a multi-year, cloud-free image mosaic, which means that it is a reflection of the state of the world in different years depending on the pixel. The years used for this mosaic range from 2009-2020, with 80% of the images taken between 2018 and 2020. Users of the dataset should check the imagery date[53] for the pixels in a specific area of interest to ensure that the image date aligns with their needs. It is possible that one area of interest could have multiple underlying image dates. Given that Meta's model is sensitive to variables that change with image date (discussed below), errors may vary systematically across these image dates. Pixels imaged on the same date can share the same direction and magnitude of bias, so errors are

53. Tolan et al., 2023. Global Canopy Height. Google Earth Engine. [accessed 2025 Jun 12]. https://meta-forest-monitoring-okw37.projects.earthengine.app/view/canopyheight.

not independent Gaussian draws at each pixel.[54] Developers should consider this when interpreting uncertainty over spatial aggregations of pixels.

Pre-processing high-resolution imagery: There are several important practical considerations developers should keep in mind when using Meta's AI model (**table 3**). First, all input imagery is required to have data in the red, green, and blue bands. Second, Meta's deep learning model has a uniquely advanced ability to recognize features like tree crowns and shadows in much the same way as a human would interpret an image. Therefore, the input imagery used with Meta's AI model must be of sufficiently high spatial resolution for those features to be identifiable. We recommend using input imagery with a native spatial resolution of 0.5–1.0 meters. Meta tested the model with high-resolution (1 meter) imagery from the National Agriculture Imagery Program (NAIP),[55] high-resolution Maxar imagery (0.5 meter), and imagery with even higher-resolution imagery down to 20 centimeters. Meta has not conducted a systematic exploration of how errors in its model vary with imagery source or native spatial resolution, but these prior tests serve as a guide for the range of spatial resolutions we recommend testing. Regardless of the native spatial resolution of the input imagery, it will need to be resampled to a ground sampling distance of 0.59 meters because this is what the model was originally trained on. Third, the input imagery will likely need to be color balanced so that it is compatible with the model.

Applying Meta's AI model to bespoke imagery: Meta's model is currently available on GitHub[56] and can be accessed via a Jupyter[57] notebook.[58] The notebook allows users to point the model to their pre-processed imagery and then use the model to convert the imagery into local CHMs. When users apply Meta's model to an imagery time series, it is important to keep in mind that Meta's canopy height predictions are affected by differences in atmospheric conditions, view angle, and other variables that change with the image date. While this phenomenon is not specific to Meta's model, it can nevertheless create systematic biases linked to imagery dates. These biases can pose challenges to constructing a time series or evaluating errors within an area of interest. When constructing a time series, we recommend that users apply smoothing splines to the time series to help distinguish directional trends in canopy height from noise associated with changing atmospheric conditions or view angles. Working with a time series can be computationally expensive because of the added temporal dimension. For this reason, we recommend using a cloud-based computing infrastructure for subsequent data exploration and analysis.

54. A Gaussian draw refers to a value randomly sampled from a normal (Gaussian) distribution, which is defined by a mean and standard deviation. When errors are considered independent Gaussian draws, it implies that each error is an uncorrelated random value drawn from the same normal distribution, with no spatial or temporal dependence.

55. National Agriculture Imagery Program. c2022. NAIP Hub Site. [accessed 2025 Jun 12]. https://naip-usdaonline.hub.arcgis.com/.

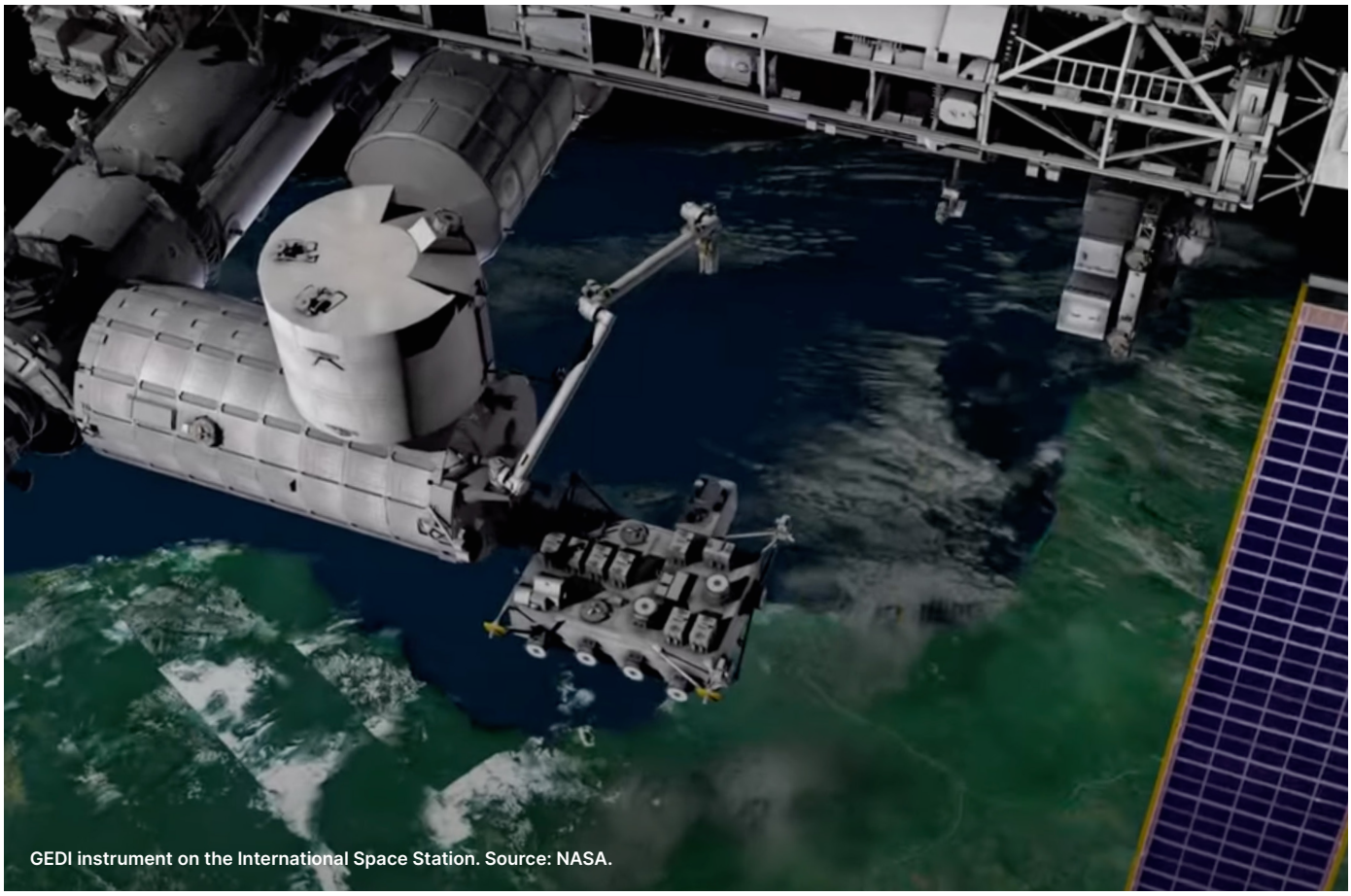
56. GitHub. 2025. HighResCanopyHeight. [accessed 2025 Jun 12]. https://github.com/facebookresearch/HighResCanopyHeight/blob/main/notebooks/download_chm.ipynb.

57. Jupyter. 2025. Project Jupyter. [accessed 2025 Jun 12]. https://jupyter.org.

58. GitHub. 2025. HighResCanopyHeight. [accessed 2025 Jun 12]. https://github.com/facebookresearch/HighResCanopyHeight/blob/main/notebooks/run_chm_model.ipynb.

Table 3. Pre-processing considerations for using high-resolution imagery with Meta's AI model

Dataset	Ground sampling distance	Color balancing	Has been tested with Meta's model
Maxar[59]	0.59 meters, no pre-processing required	No pre-processing required	Yes
National Agriculture Imagery Program (NAIP),[60] operated by USDA	One meter, needs to be upsampled to 0.59 meters	Use of Meta's NAIP-tuned model[61] required.	Yes
Pleiades,[62] operated by Airbus	0.5 meters, needs to be downsampled to 0.59 meters	No pre-processing required	Yes
SkySat,[63] operated by Planet	0.5 meters, needs to be downsampled to 0.59 meter	Pre-processing and user experimentation required	No, lower native resolution may make this perform worse than other imagery.



GEDI instrument on the International Space Station. Source: NASA.

59. Maxar. c2025. High-resolution Satellite Imagery. [accessed 2025 Jun 12]. https://www.maxar.com/maxar-intelligence/products/satellite-imagery.

60. National Agriculture Imagery Program. c2022. NAIP Hub Site. [accessed 2025 Jun 12]. https://naip-usdaonline.hub.arcgis.com/.

61. Meta and World Resources Institute. 2024. High Resolution Canopy Height Maps. [accessed 2025 Jun 12]. https://registry.opendata.aws/dataforgood-fb-forests/.

62. Airbus. c2025. High resolution remote-sensing satellite imagery. [accessed 2025 Jun 13]. https://space-solutions.airbus.com/imagery/optical-radar-satellite-imagery/.

63. SkySat. 2025 May 1. Planet Documentation. [accessed 2025 Jun 13]. https://docs.planet.com/data/imagery/skysat/.

Conclusions and future opportunities

Meta's 2020 CHM and underlying AI model are well positioned to support forest carbon projects. These tools have a wide array of applications for projects using methodologies such as Verra's VM0045 v1.1, Verra's VM0047 v1.0, and ACR's IFM v2.1. Most notably, they offer the following opportunities:

- **Identifying parcels for inclusion in projects:** The submeter spatial resolution of Meta's 2020 CHM enables users to quantify canopy height with finer detail than previously available global CHMs could provide. This can help developers identify strategic parcels for inclusion in forest carbon projects.
- **Using canopy height as an SI:** Meta's AI model has exciting potential to be used as a more robust, open-source SI for ARR projects, compared to commonly used vegetation indices such as NDVI and NDFI.
- **Monitoring changes in forest structure:** Because it is trained on high-resolution imagery, Meta's AI model can be used to detect subtle changes in forest structure. This can help developers quantify harvest intensity under selective logging regimes or forest degradation.
- Beyond their compliance with VM0045 v1.1, VM0047 v1.0, and ACR's IFM v2.1, Meta's tools are well positioned to support forest managers in monitoring REDD+ projects[64] and complying with a wide range of regulations such as Brazil's Forest Code,[65] the US National Forest Management Act,[66] certification with the Forest Stewardship Council,[67] and others.

The submeter spatial resolution of Meta's 2020 CHM and underlying AI model makes them especially useful for developers planning and monitoring forest management activities along riparian corridors, biodiversity corridors, and other small or irregularly shaped features that are hard to detect with moderate-resolution imagery. These capabilities extend the utility of these tools beyond forest carbon project development to forest management more broadly. In some contexts, Meta's AI model has the ability to delineate tree crowns due to its submeter spatial resolution. With sufficient testing, these capabilities could be used to count and monitor individual trees in agroforestry projects and other sparsely forested ecosystems. The model's submeter spatial resolution may also pave the way for detailed characterization of tree crown shapes.

64. United Nations Framework Convention on Climate Change. c2025. What is REDD+?. [accessed 2025 Jun 13]. https://unfccc.int/topics/land-use/workstreams/redd/what-is-redd.

65. Government of Brazil. 2012. Lei nº 12.651 de 25 de maio de 2012. [accessed 2025 Jun 13]. https://www.gov.br/mj/pt-br/acesso-a-informacao/atuacao-internacional/legislacao-traduzida/lei-no-12-651-de-25-de-maio-de-2012-senasp_eng-docx.pdf.

66. United States Forest Service. 2022 Apr 22. History of Forest Planning. [accessed 2025 Jun 13]. https://www.fs.usda.gov/managing-land/planning-rule/history.

67. Forest Stewardship Council United States. c2025. Certification. [accessed 2025 Jun 13]. https://us.fsc.org:443/en-us/certification.

If combined with other data (e.g., hyperspectral), these characterizations could unlock more accurate classification of tree species, forest types, and landscape features such as riparian zones.

Stakeholders that apply Meta's 2020 CHM and AI model to forest carbon project development are taking part in a broader effort to increase the reliability, accessibility, and transparency of RS tools for forest carbon MMRV. Realizing the full potential of Meta's model in this context involves certain challenges. Developers need technical expertise, validation data, and computational resources to take full advantage of the model's suite of capabilities. Additionally, users need clear regulatory guidance on how to account for uncertainty in RS data and deep learning models. These challenges are not unique to Meta's tools. They are shared across similar models and data products and provide an exciting opportunity for a coordinated, multi-stakeholder, solutions-oriented effort at forming consensus on best practices for their use. In our companion piece, *Remote Sensing for Forest Carbon: Challenges, Opportunities, and a Path Forward*, we make specific recommendations for addressing these challenges and for building consensus across registries, developers, and verification bodies while avoiding overly prescriptive standards that could slow innovation. We recommend standardizing how model uncertainty is evaluated and reported. We also recommend aligning on what constitutes suitable validation data sources and error metrics. Further, we advocate for developing a centralized, user-friendly data portal that integrates benchmarking datasets and RS tools, enabling broader accessibility and reducing technical burdens. These solution pathways will help the industry leverage Meta's model, and many other exciting technologies like it, to the fullest extent possible. By pursuing these solutions collectively, the industry can unlock the full promise of RS for forest carbon projects and ensure that innovations like Meta's model can help shape a more reliable, accessible, and transparent future for forest carbon MMRV.



Sunrise over river in Summer. Source: Adobe Stock.

Appendix: Training and validating Meta's global CHM

The forestry research community has been working to develop high-resolution CHMs with global coverage for many years. One recent example is the CHM developed by Lang et al.[68] They trained an ensemble of convolutional neural networks to estimate canopy height, based on both imagery from Sentinel-2 (including optical, near-infrared, and short-wave infrared bands) and lidar-derived canopy height reference data from the GEDI mission. Because the Sentinel-2 data has a 10-meter ground sampling distance, the resulting CHM has a spatial resolution of 10 meters. Lang et al.'s model achieves a root mean square error of 6.0 meters, with a bias of 1.3 meters.

Tolan et al.[69] developed Meta's CHM and made several important modifications to Lang et al.'s approach. First, they use a vision transformer model architecture, which has shown better performance than convolutional neural networks on many computer vision tasks, to extract relevant features from satellite imagery with high spatial resolution. They pre-trained the vision transformer encoder on 18 million satellite images. They used images from the Maxar Vivid2 dataset (with a ground sampling distance of 0.59 meters at the equator), and used a self-supervised approach. Next, they trained a dense transformer model on top of the features extracted by the vision transformer encoder to predict canopy height, using a supervised learning approach. For this, CHM data (based on aerial lidar from NEON) served as the reference data. Because the NEON data are entirely from the US, the resulting model was not initially capable of performing well globally. To address this, Tolan et al. trained a separate, relatively shallow, convolutional neural network on GEDI data (with sparse but global coverage) to produce a "rescaling factor." They used this rescaling factor in post-processing to rescale the aerial lidar-trained model predictions.

To validate the accuracy of the model's canopy height estimates, the Meta team generated submeter-resolution CHMs of California and São Paolo, Brazil using cloud-free, 0.59-meter Maxar imagery taken between 2017 and 2020. They compared the results with aerial lidar-based reference CHMs. The team tested several variations of the model. The best version achieved an average root mean square error of 4.4 meters (at 0.59-meter spatial resolution), although this value varied significantly across jurisdictions.

Meta openly released its CHMs and trained AI model, so that they can be used by researchers, project developers, and others in many different

68. Lang N, Jetz W, Schindler K, Wegner JD. 2023. A high-resolution canopy height model of the Earth. Nat Ecol Evol. 7(11):1778–1789. doi:10.1038/s41559-023-02206-6.

69. Tolan J, et al. 2024. Very high resolution canopy height maps from RGB imagery using self-supervised vision transformer and convolutional decoder trained on aerial lidar. 2024. Remote Sensing of Environment. 300:113888. doi:10.1016/j.rse.2023.113888.

contexts. Those wishing to generate high-resolution CHMs covering new regions or new time periods, must obtain high-resolution satellite imagery, pre-process it, and input the imagery to the trained model. The model will then produce a pixel-by-pixel estimate of canopy height for each image. In order to quantify the model's performance characteristics in new contexts, users must conduct careful validation of a sample of these results against reference data (e.g., aerial lidar-derived CHMs).



Aerial view of Amazonian rain forest with fog. Source: Adobe Stock.

Glossary

Allometric equation: A mathematical model relating easily measured tree dimensions (e.g., diameter, height) to variables that are harder to measure (e.g., biomass). These equations are specific to particular species or sites and are critical for estimating forest carbon stocks.

Calibration: The process of aligning the predictions of a model with observed, ground-truth measurements to ensure that the model's outputs are as accurate as possible for the context in which it is calibrated.

Carbon project methodology: A standardized, science-based framework that defines how a carbon project should be designed, implemented, monitored, and verified to quantify the greenhouse gas reductions or removals it claims to generate.

Data product: Processed dataset in a standardized format (e.g., GeoTIFF, NetCDF), often including metadata, that may be derived from remotely sensed data or a combination of remotely sensed data, field data, and modeling.

Forest structural attributes: Variables that describe different dimensions of forest structure including above-ground biomass, tree canopy height, and tree density. These attributes are used to find suitable areas for forest carbon projects, to monitor disturbances, and to estimate project performance. Above-ground biomass can be used to estimate forest carbon stocks.

Forest type: A classification of forests based on dominant tree species, composition, and environmental conditions (e.g., tropical rainforest, temperate deciduous forest). Types are defined by factors like canopy structure, leaf longevity, and climate.

Ground truthing: The process of validating a remote sensing inference with field observations that are assumed to be the source of truth.

Model: A mathematical or computational structure that represents the relationships between inputs and outputs based on underlying patterns in data. Models can range from simple formulations, like regression models that fit linear or nonlinear relationships between variables, to highly complex architectures such as deep learning models and vision transformers that learn hierarchical and abstract representations from large-scale datasets.

Remote sensing: The science of acquiring information about Earth's surface or other objects without physical contact, using sensor technologies on satellites, aircraft, or drones. It includes passive (e.g., reflected sunlight) and active (e.g., radar, lidar) methods to detect surface properties.

Reversal: The unintentional or intentional release of previously sequestered carbon (e.g., via logging, fire, or other disturbance).

Spatial and temporal resolution: Spatial resolution is the ground area represented by one pixel (e.g., 30 meters for Landsat). Finer spatial resolution captures smaller features. Temporal resolution is the frequency of data acquisition (e.g., daily for MODIS). High temporal resolution tracks dynamic changes.

Validation: Assessing model performance by comparing model estimates with independent ground-truth data.

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