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Continuous Cover Forestry and Remote Sensing: A Review of Knowledge Gaps, Challenges, and Potential Directions

Jaz Stoddart[1] · Juan Suarez[2] · William Mason[2] · Ruben Valbuena[3]

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Abstract

Purpose of Review Continuous cover forestry (CCF) is a sustainable management approach for forestry in which forest stands are manipulated to create irregular stand structures with varied species composition. This approach differs greatly from the traditional approaches of plantation-based forestry, in which uniform monocultures are maintained, and thus, traditional methods of assessment, such as productivity (yield class) calculations, are less applicable. This creates a need to identify new methods to succeed the old and be of use in operational forestry and research. By applying remote sensing techniques to CCF, it may be possible to identify novel solutions to the challenges introduced through the adoption of CCF.

Recent Findings There has been a limited amount of work published on the applications of remote sensing to CCF in the last decade. Research can primarily be characterised as explorations of different methods to quantify the target state of CCF and monitor indices of stand structural complexity during transformation to CCF, using terrestrial and aerial data collection techniques.

Summary We identify a range of challenges associated with CCF and outline the outstanding gaps within the current body of research in need of further investigation, including a need for the development of new inventory methods using remote sensing techniques. We identify methods, such as individual tree models, that could be applied to CCF from other complex, heterogenous forest systems and propose the wider adoption of remote sensing including information for interested parties to get started.

Keywords Remote sensing · Continuous cover forestry · Biomass estimation · Individual tree growth models · Forest inventory

Introduction

Continuous Cover Forestry and Its Challenges

As concern for the environment has grown in the past decades, the role of forest management in mitigating the impacts of climate change and biodiversity losses has garnered greater importance. The landmark resolutions for a coordinated international move towards sustainable forest management in the 1990s, the Rio Forest principles [1] and the Helsinki Process [2], promoted a resurgence in interest in 'close-to-nature' forestry and continuous cover forestry (CCF), having initially gained popularity in the early years of the twentieth century with concepts such as the 'Dauerwald' [3–5]. These sustainable silvicultural practices are based around a set of five defining principles: partial harvesting rather than clear-felling; preferential use of natural regeneration rather than planting; developing structural diversity and spatial variability within forests; and fostering mixed species stands and avoidance of intensive site management practices such as soil cultivation, herbicide application, and fertiliser input [6–9]. There is a level of contention over the use of close-to-nature as a term within these practices as the level of human interference within these silvicultural systems can be considered far from natural

✉ Jaz Stoddart
jazstoddart@bangor.ac.uk

1 School of Natural Sciences, Bangor University, Bangor LL57 2DG, UK

2 Forest Research, The Agency of the Forestry Commission, Northern Research Station, Roslin, Midlothian EH25 9SY, Scotland, UK

3 Division of Forest Remote Sensing, Department of Forest Resource Management, Swedish University of Agricultural Sciences (SLU), Skogsmarksgränd 17, 901 83 Umeå, Sweden

[10–12]. The specific silvicultural systems that fall within the definition of CCF include irregular shelterwoods and group and single stem selection (terminology follows Matthews 1989). [7, 13, 14].

The driving forces behind the adoption of CCF are the many environmental advantages CCF presents over clear cutting in traditional uniform even-aged forest monocultures. CCF is recommended by the European Union (EU) Biodiversity Strategy as a beneficial form of forest management for biodiversity [15]. Where transformation to CCF accompanies a transition away from monocultures, the increased tree species diversity provides additional habitats, as tree species richness strongly influences the diversity of forest inhabiting species [16]. Increased diversity of tree species and genetics are important contributing factors to increased resilience, resistance, and capacity for adaptation with respect to climate change [17], pathogens, and pests [18].

The persistence of stands between harvests, characteristic of CCF, has been found to improve multi-functionality of production forests in Fennoscandia and specifically to improve diversity of ectomycorrhizal fungi and herbivorous larvae [19]. CCF also has better retention of late successional forest species—especially shade-tolerant understory plants and bird species assemblages—than traditional clear cutting [20–23]. CCF is thought to be second only to retention forestry with respect to habitat preservation [24], where retention forestry is itself a form of CCF in which dead wood, habitat trees, and trees with larger contributions to diversity are retained during harvesting [24, 25]. The risk and impact of soil erosion, particularly on slopes, are also reduced dramatically by the continued presence of vegetation, and thus, CCF provides greater soil stability and reduces soil losses relative to clear cutting [26]. Additionally, continuous cover reduces the creation of brown edges, which are newly exposed edges in neighbouring stands when a site is clear-felled, that are less resilient to windthrow and particularly susceptible to storms [27]. CCF shows greater windthrow stability and resistance to storms than clear-cut sites [28, 29], and the increased structural complexity of the stands also appears to have a positive impact on wind resilience [29].

In addition to the environmental benefits of CCF, there are also economic considerations surrounding CCF uptake. It can be a smaller financial burden to manage and thin naturally regenerating forest than to establish and tend restocking sites after clear cutting [30, 31], though the regular respacing of some prolific species such as Sitka spruce can itself incur large costs. Natural regeneration also mitigates much of the impact of pests such as the pine weevil [32] which can devastate restocked sites owing to the vulnerable and attractive nature of the seedlings. The products of CCF can also be larger and more valuable than equivalent volumes of even-aged forest. For example, a study by Hanewinkel [33] found that CCF stands produced many more high-value large-sized logs which commanded high timber prices and thus increased the profitability of CCF almost twofold over even-aged stands. However, it should be noted that to produce more valuable timber yields, CCF stands require appropriate management, which is specialist knowledge that many foresters lack and for which there continues to be a significant lack of adequate guidance [7••].

Challenges and Knowledge Gaps in CCF

Whether CCF adoption presents an economic advantage over clear cutting and even-aged forestry is unclear and debated and this is one of many challenges facing the adoption of CCF [7, 31, 34]. From a management perspective, CCF can be a considerably more complex procedure than traditional clear cutting in even-aged stands and this requires specialist knowledge and training for forest managers and harvest workers [7••]. Selective harvesting can limit the use of mechanised felling and extraction machinery which can subsequently drive up costs for labour to manually fell the desired trees and extract the timber without significantly disturbing the stand. Additionally, yields for each harvest are smaller owing to the very nature of selective harvests; thus, it takes a longer time or a greater area to produce yields of equivalent volume to clear felling which can disincentivise investment and adoption.

The timber industries in the majority of the European countries where CCF uptake is increasing are set up to receive near-uniform logs from even-aged monocultures with little variability within their dimensions and properties. However, CCF produces logs of a wider range of diameters and potentially different species with each harvest and thinning [7, 35] and this introduces a need for investment into new equipment and tools which is only justifiable if the supply of these forest products is both predictable and reliable.

Estimating standing stocks and future harvest volumes in CCF is considerably more difficult than in clear-cutting systems as the forest manager must be able to estimate the whole volume of the stand in addition to the volume of exclusively either the harvested or retained stems. Forest managers must map which stems are to be harvested, to subsequently estimate harvest yield and retained stock. This challenge is being addressed by the advent of precision forestry—providing greater volumes of detailed information facilitating targeted interventions aimed at maximising yields of more valuable products—which is inextricably linked to developments in remote sensing.

CCF often requires multiple interventions throughout its growth to maintain the desired forest structures while, in contrast, clear cutting typically requires less active management. Typically, in a clear-cutting system, a monoculture stand of even age will be planted on a previously cleared site, maintained during its growth, and harvested upon reaching the desired size or age. By contrast, CCF is a multi-stage cycle of harvests, regeneration, and growth with no clear demarcation between the end of one cycle and the start of the next. Due to the selective nature of the harvests and varied approaches to CCF, harvests can vary in scale from large group fellings to individual stems as required. To direct harvesting, forest managers may rely upon target diameters (maximum diameters) for a species in each stand to inform when a harvest is due. Alternatively, there is also the reverse-J distribution (J-curve model) for stem diameters which is considered an easily identifiable and achievable distribution within CCF. This method can be used as an indicator of when to harvest and where to concentrate harvests in accordance with which diameter classes are found to be in surplus to maintain the desired forest structure [36, 37].

The constant regeneration, management, and recruitment of understory trees provide a challenge for mapping inventory as there is a need to record the locations and species of trees as well as their development over time. Currently, inventory protocols for CCF are based on relatively labour-intensive manual data collection methodologies [36]. Monitoring regeneration is of particular importance as many forest managers overestimate the likelihood of regeneration at their sites or find the success of regeneration to be less predictable than that of planting [37].

Future yield forecasting and growth modelling are currently significantly under-developed areas of research for CCF and for mixed species stands in general. In the UK, there are currently no models for CCF forecasting [7••] and approaches used in traditional methods of even-aged forestry are inapplicable to CCF, e.g. yield class which is an index of the potential productivity of even-aged stands of trees [7••].

Remote Sensing and CCF

Existing Research

There is currently a dearth of research exploring the application of remote sensing to CCF, despite the general growth of interest in both fields separately in recent years. Searches for literature to include in this review were conducted using Google Scholar and Scopus with search queries comprising keywords used for CCF, the Boolean operator 'AND', and keywords for remote sensing. The keywords used were 'CCF', 'Shelterwood', 'sustainable forestry', 'Dauerwald', or 'close-to-nature' plus 'remote sensing', 'LiDAR', 'earth observation', 'laser scanning', or 'photogrammetry'. Once completed, the returned titles and abstracts of highlighted papers were assessed for relevance, and the few relevant studies were subsequently reviewed.

There is an obvious need for more work specific to the overlap of these subjects to further encourage the adoption of CCF [38–44]. There are a range of remote sensing data sources which could be applied to monitoring CCF; however, they do not all describe the specific forest stand traits. As such, each data source is best suited to monitoring specific traits, ALS for height and canopy cover, TLS for stem structure, and spectral data to monitor photosynthetic capacity.

A selection of key forest metrics and traits and that can be measured operationally by different remote sensing data sources are explored below, in Table 1. The listed traits and remote sensing methods are themselves grouped into categories with shared characteristics. The 'inventory data' traits—tree location, tree height, and diameter at breast height—are all forest traits which are commonly recorded and measured as part of forest inventory activities. 'Structural metrics' describes all measurements of horizontal complexity, such as gap fraction, leaf area index, and percentage cover; as well as vertical complexity, such as foliage height diversity, Gini coefficient of heights, and standard deviation of heights. The 'other CCF traits' are a catch-all category for remaining observable traits of specific interest in CCF. Stem volume is included owing to its potential for yield measurement and forecasting in uneven-aged stands where traditional models are not applicable. Similarly, regeneration is included as it is a defining characteristic of CCF and the capacity to monitor regeneration also has implications for yield measurement and forecasting. Tree species is of interest as CCF can include species mixtures, and so remote identification of species is necessary for stock mapping and monitoring successional development of the forest.

The remote sensing methods, presented in Table 1, are separated by whether they generate 3-dimensional point cloud or 2-dimensional image data. Within the 3-dimensional point cloud generating methods, there are three laser scanning methods and two photogrammetric methods. Photogrammetric data typically also captures optical data owing to the use of optical (camera) sensors for data collection, and it is possible to generate photogrammetric point clouds with images from outside the visible spectrum; however, it is uncommon. The 'optical' 2-dimensional image–based remote sensing method includes a range of methods such as multi-spectral and hyperspectral imaging in addition to specialist imaging methods such as hemispherical photography used in canopy cover measurement [45].

Relevant remote sensing research on CCF, Dauerwald, and shelterwood systems has shown that it may be possible to both monitor the transformation of a traditional stand to CCF and monitor the progression of growth and the associated changes in forest structural type that can be applied to describe CCF stands. At the individual tree level, Bennet et al. [46] describe a novel method of using aerial data

Table 1 Remote sensing data sources and the types of information they can be used to observe operationally in CCF

		Inventory Data			Structural Metrics		Other CCF Traits		
		Tree location	Tree height	Diameter at breast height	Vertical structural complexity	Horizontal structural complexity	Stem Volume	Regeneration	Tree Species
3-Dimensional Point Cloud Data	Aerial Laser Scanning (ALS)	✓ [46-48]	✓ [49-53]	X	✓ [44,49,50,54]	✓ [47,54-56]	✓ [51]	✓ [50,57]	# [58]
	Terrestrial Laser Scanning (TLS)	✓ [59-61]	~ [53,61]	✓ [53,59-62]	✓ [61,63-65]	✓ [63,66,67]	✓ [59, 68, 69]	✓ [59,81]	# [70,71]
	Mobile Laser Scanning (MLS)	✓ [53,60, 72-74]	~ [53,73-75]	✓ [53,60, 72-76]	✓ [77]	✓ [77]	✓ [72, 73]	✓ [72]	# [78]
	Aerial Photogrammetry	✓ [47]	✓ [47, 79,80]	X	X	✓ [47,48]	✓ [79,80]	~ [81]	# [82]
	Below-canopy photogrammetry	✓ [83,84]	X	✓ [83-85]	~ [83,84]	X	X	✓ [83,84]	X
2-Dimensional Image Data	Optical (RGB, multispectral, hyperspectral)	✓ [57,86, 87]	X	X	✓ [88]	✓ [48]	X	X	✓ [51,52,57, 82,86,87, 89]

✓ represents information that can be reliably and directly extracted using this remote sensing data source, ~ represents information which may be extracted using the stated data source but can be subject to complications such as occlusion which may impact or reduce reliability, # represents information which has only been derived from the outputs of the stated data source using machine learning methods, and X indicates that we did not find references that showed this information could be directly and reliably extracted with the stated data source.

from photogrammetry and ALS to detect individual trees with improved detection rates among smaller diameter trees than previous methods, which makes the model applicable to monitoring transformation to CCF. This model relies upon a Bayesian optimisation approach to the parameterisation of the tree detection algorithm; by utilising external datasets they eliminate the requirement for site specific allometric models derived from field data which can also reduce required fieldwork [46]. At the stand level, Stiers et al. [5] used TLS to measure structural complexity within forest and proposed a novel index of structural complexity. This index quantifies stands by their structural type and serves as an indicator of how close a stand is to the CCF 'target structure'. This work has strong similarities to the work of Valbuena et al. who instead used ALS to classify the forest structural types of a stand [49]. Their classification was based upon two more widely used measures of forest structure: Lorenz asymmetry, where greater asymmetry is associated with the idealised 'target structure' (characterised by the reverse-J shape), and the Gini coefficient, a measure of inequality in size (DBH). By integrating these classifications into forest structural types as a guideline, forest managers could make informed decisions about when to harvest within large regions of forest without the need for extensive fieldwork. Annually updated maps of structural types could be used to monitor important processes within CCF systems and inform managers of where regeneration and recruitment are occurring.

Remote Sensing for CCF Inventory Measurement and Stock Mapping

Inventory protocols for CCF currently rely upon labour- and time-intensive fieldwork for data collection with three variations of commonly used protocols across a handful of plots (radii varying from 8 to 15 m depending on protocol) taking one operator a whole working day and complete enumeration of plots taking a day for two operators [90]. By contrast, remote sensing can be used to completely enumerate a plot [91] and collect all protocol relevant data with greater efficiency resulting in faster, more cost-effective data collection [58]. Studies have shown that using terrestrial laser scanning (TLS) and mobile laser scanning (MLS), it is possible to detect and segment up to 100% of the trees within a plot [53] and 97% within 20-m radius of a TLS scanning position, although this falls to 75% at a 40-m radius due to occlusions and decreasing point density [90, 92]. Combining data from TLS multi-scans or using MLS from less than 20 m can mitigate occlusion-based inaccuracy. Consequently, MLS data from within the plots collected with a handheld or backpack-mounted platform would be expected to suffer from less occlusion–based error than data from a vehicle mounted platform on a forest track, such as in Bienert et al. [60].

There is consensus in the literature that both TLS and MLS can be used for the accurate collection of inventory data such as DBH and height. Donager et al. found that TLS had an RMSE of 7.2% for DBH and 2.7% for height, and in the same study, MLS was found to have an RMSE of 8.1% for DBH and 1.6% for height [53]. Hartley et al. similarly found that for MLS-derived DBH and height measurements, they achieved RMSE values of 5.4% and 3.0%, with R^2 values of 0.99 and 0.94 respectively [74]. The accuracies achieved in these studies are very high and for the height measurements are more accurate than those obtainable from the ground with traditional field methods [93]. It can thus be argued that even if there is a potential decrease in accuracy relative to fieldwork, it is likely to be extremely small and can be offset against the speed and efficiency with which data can be collected. It is worth noting that ground-based LiDAR systems can cost tens of thousands of dollars and, while this can be offset against the reduced costs for the labour brought about by greater data collection efficiency, it may not always be financially beneficial.

In addition to improving the efficiency of data collections in existing inventory protocols, there is the potential for the development of novel remote sensing–specific protocols. With remote sensing, it is possible to calculate volumetric measurements of stands or individual trees directly from point clouds [68, 69]. Direct measurement of volumes may allow for estimates with higher accuracies and lower uncertainties. Lowering uncertainty in volume estimates can directly improve sales prices and profits, where the law of conservativeness is used in pricing, as is particularly common in forest products sold for pulp or fuel and the sale of logging rights.

Tree identification and diameter measurement can be approached with remote sensing from either above or below the canopy. Aerial datasets can be used to map trees quite accurately within the overstory as there are many publicly available solutions with tools for tree identification and crown delineation that make use of optical and LiDAR data [46–48]. Tree identification within the understory is also possible from high point density aerial LiDAR datasets. However, in the context of CCF, and owing to occlusion, the precision drops off with smaller trees such as those from regeneration [50]. Below-canopy remote sensing techniques—such as TLS, MLS, and photogrammetry—are better suited to the accurate mapping of regeneration [59, 72, 82–84], and it has been shown in irregular tropical forests that MLS can identify small-diameter understory trees with far greater geospatial positioning accuracy, 6 cm, than methods using aerial data, which had 6-m positioning error [91]. The development of tree detection algorithms for use with below-canopy point clouds is happening rapidly, and there now are several solutions available which can accurately locate, identify, and measure trees and saplings from point cloud data [95–98]. In addition to tree identification, it is also possible to measure metrics such as the straightness of trees and even the calculation of lengths and sizes of logs that can be harvested from below-canopy point clouds [98–100]. Trunk straightness and merchantable log estimation from the integration of remote sensing technology into CCF inventory protocols could potentially allow forest managers to tailor harvests to meet market demands or to list their stocks for sale in advance more accurately.

There continue to be challenges in remotely identifying tree species, as LiDAR data alone appears to be insufficient for species delineation. Current literature suggests that it is possible with the use of deep learning and tree species classification systems and optical remote sensing techniques, and there is evidence that channels in these algorithms can be substituted with LiDAR metrics [101]. These methods could be applied to CCF stands for stock mapping, mapping of inventory with species distributions and abundance [57, 86, 87, 89, 94]; however, for aerial data, occlusion below dense canopy would limit reliability and for terrestrial data, the extent would be limited. Modern ALS methods with laser scanning at angles close to nadir can improve canopy penetration though dense canopy continues to obscure the understory and the close to nadir angled pulses are less likely to reflect off the vertical stem surfaces.

Remote Sensing for CCF Yield Modelling and Forecasting

Beyond improving data collection for existing inventory protocols, remote sensing could be used for the development of new models estimating current biomass yields. Biomass estimation is typically performed with single variable models, such as the model by Asner and Mascaro [102] which uses top of canopy height to predict biomass in each area. However, the variables used in these models cannot describe the irregular horizontal and vertical structure of CCF, as such there is a need for models with variables that better describe the structure of CCF. Remote sensing–informed multivariate models are already being applied to similarly complex irregular forest systems, such as selectively logged tropical forests, and thus, it may be prudent to apply similar approaches to CCF. Various approaches have been proposed that involve other non-height morphological traits of forest ecosystems [43•]—often one of either cover or vertical structural complexities—to make a biomass prediction that would be better applicable to CCF systems [44, 103–106]. One example of note is the 'ecosystem morphological trait' (EMT) framework proposed by Valbuena et al. which is intended to be applicable across a range of diverse and complex ecosystems and across multiple sources of 3D data [43•]. The proposed EMT framework posits that all forest can be fully characterised through use of measures for all three morphological traits of height, horizontal structural complexity, and vertical structural complexity.

In addition to estimating current biomass, there is also the need to predict future biomass yields which requires that biomass estimations be combined with growth models to provide estimates of future biomass. Observed trends of growth are an effective way to create estimates of future growth by simply projecting past patterns of growth forward. The location specificity of observed trends makes them particularly appealing tools for growth forecasting; however, such trends are limited by their specificity to current and historical climatic conditions. Multi-temporal data for tree heights and diameters can be modelled to find trends, and these can be projected forward using individual tree growth models, at both the tree and stand levels. Such multi-temporal data can be used to train individual tree growth models which can be used to simulate growth of individual trees within a stand. Individual tree growth models have historically been successfully applied to traditional uniform age monocultures to model and identify dominant and subdominant trees and responses to management activities such as thinning [107, 108]. The most recent form of the Canadian tree and stand simulator (TASSIII) can model complex systems with multiple species (a limited number for now but including several key timber species) and spatial heterogeneity and thus could be suitable for use in CCF [108]. An earlier iteration of TASS was applied to CCF in the UK by Suarez and found to be useful for modelling the growth of trees in CCF stands [109] and thus with the improvements made in the newer TASSIII could render it a valuable tool for CCF forecasting.

There are other individual tree models that could also be applied to CCF using data from remote sensing sources, such as CAPSIS which is already used to assess the sustainability of harvests by predicting the impacts of harvests on the future growth of trees in the stands [110]. Such insights within CCF could allow forest managers to predict the impacts of management and harvests on a CCF stand. Further development of these predictive tools could inform harvesting approaches and potentially allow managers to influence the future forest products as desired, prioritising the retention of slow growing, high-density timber or alternatively prioritising harvests which create conditions which favour faster growing, high-volume wood for fuel or pulp.

Practicalities of Remote Sensing

To further develop remote sensing tools for CCF, there is a need for a greater appreciation of the potential benefits of remote sensing among foresters, with greater adoption and development of remote sensing techniques for inventory assessment and monitoring. Promoting adoption of remote sensing will require opening communication between existing remote sensing practitioners and interested parties, particularly forest managers, and thus, the intent of this section is to introduce the practicalities of remote sensing.

Getting started with remote sensing can seem technically daunting; however, it does not need to be a challenge; there are multiple ways to approach data collection and processing, varying in their required investment of time and money and from relatively accessible to requiring programming skills.

Below is a list of data acquisition approaches in an order indicative of typical associated costs per unit area, informed by the combined experience of the authors, and descending from most to least expensive.

1. Inventory fieldwork requires operators to travel to the plots and collect data manually which is a relatively slow and inefficient method with low spatial coverage.
2. MLS and TLS require a relatively expensive, specialist equipment and an operator to attend each of the plots and collect the data. However, this method is considerably faster than conventional inventory fieldwork allowing for greater spatial coverage in a day [58, 90, 91].
3. Unmanned aerial vehicle (UAV)–mounted ALS requires an unmanned craft to be flown over a forest at a relatively low altitude collecting high point density data. UAV-mountable laser scanners vary in price but tend to be relatively expensive; however, they are often commercially available. Additional costs are the UAV, which are becoming relatively affordable for the required payload capacities and an operator. Spatial coverage and data collection speed are generally greater than those of ground-based techniques and can vary greatly between quadcopters and fixed-wing UAVs, the latter being capable of larger-scale data collections owing to longer flight times.
4. UAV-mounted photogrammetry has many of the same requirements as UAV-mounted ALS; however, the costs for the UAV and sensors are typically lower. Photogrammetry coverage can be similar to ALS; however, canopy penetration is often greatly reduced.
5. Manned aerial vehicle–mounted ALS requires a plane to be flown over a forest and tends to be performed by third parties that survey areas of interest with contractually stipulated minimum point densities. These companies either perform surveys of their own and sell access to

data they have already collected or may also be commissioned to survey specific areas. This method can be used to collect data over a whole forest in a single survey and thus can be extremely cost-effective when a large spatial coverage is required.

6. Publicly available ALS datasets are provided by some government agencies or bodies at no or low cost. A significant disadvantage of using public datasets is that there is no control of spatial and temporal coverage, there may be limited data for some areas, and the period between surveys may be several years These datasets also tend to have low point densities due to the high altitudes; these ALS datasets are collected from which can be particularly limiting for CCF due to the vertical complexity below the canopy.

Examples include the UK (data.gov.uk), Finland (maanmittauslaitos.fi), Denmark (download.kortforsyningen.dk), Spain (centrodedescargas.cnig.es), and the Netherlands (lists.osgeo.org).

Most of the discussed methods of remote sensing data acquisition produce point clouds which can be processed directly to extract inventory information; photogrammetry first requires conversion of photographs into a point cloud. Point clouds yielded from photogrammetry are not directly equivalent to point clouds yielded from laser scanning primarily due to lower vegetation penetration, and this can restrict their utility, as outlined in Table 1. Solutions for photogrammetric point cloud generation are available within suites of commercially available tools for data acquisition, such as the Pix4D suite, as standalone commercial packages for point cloud generation, like Agisoft Metashape, and even as open-source solutions which are freely available to install, such as WebODM.

Processing point clouds to extract inventory information can be performed in multiple programming languages. However, some of the most comprehensive packages appear in R where lidR [111] is the first choice of many for processing aerial data. For terrestrial data, there are a range of packages with different utilities, such as TreeLS [97], rTLS [112], and FORTLS [113]; some such as ITSMme [98] and aRchi [114] even include tools to produce quantitative structure models of trees. Additionally, there is soon to be a public database of publicly available terrestrial point cloud processing solutions for forestry including information on their function and guidance on their use. It is to be an output of the 3DForEcoTech COST action and was publicised at the Silvilaser conference in 2023 [115, 116]. For those not wishing to use programming, there are standalone software solutions available such as LiDAR360, a commercial solution produced by GreenValley International, which has aerial and terrestrial point cloud–specific forestry packages available; LAStools, a licensable library of executables specific to various processing functions; CloudCompare, an open-source solution with forestry-specific tools available and for which public users and researchers often develop add-ons; and FUSION/LDV, a freely available software for point cloud data analysis and visualisation produced by the United States Department of Agriculture (USDA) Forest Service.

Conclusion

As we have explored, it is evident that there are a host of ways in which remote sensing could be used to address the challenges CCF faces for monitoring and management. It is our belief that there needs to be a concerted effort to further research the ways remote sensing can be applied to CCF. Remote sensing can monitor several parameters relevant to CCF, as shown in Table 1, and thus, it is simply a matter of identifying how monitoring these parameters can inform our management and understanding of CCF that is required. As forests are increasingly being transformed from even-aged stands to irregular CCF systems, there is increasing opportunity to make use of remote sensing in the monitoring and management of the changes in stand structure that characterise the transformation to CCF. Methods such as those already presented by Bennet et al., Stiers et al., and Valbuena et al. [5, 46, 49] will be important contributors to the success of these efforts. Models, such as TASIII and CAPSIS, will similarly become more important over time with the increased availability of multi-temporal CCF datasets allowing the impacts of management and environmental conditions to be seen; providing the data required to inform more accurate yield forecasting models.

The accuracy and precision of remote sensing methods have dramatically improved in the years since CCF began to gain widespread traction and adoption; thus, where CCF historically represented a challenging and complex system to study, it is now well within the capabilities of the technology and the limitation has now become the lack of research into applications of remote sensing for CCF. We invite further research into the topics listed below exploring how the application of remote sensing can improve the management of CCF so that it might become a more easily adopted and managed silvicultural approach.

Topics for further research:

- Development of remote sensing supplemented inventory protocols for improved CCF management
- Stem volume estimation from below-canopy point clouds to improve estimates of standing stocks
- Stem segmentation and marketable timber estimation from below-canopy point clouds

•Application of individual tree growth modelling approaches to CCF yield estimation and forecasting
•Use of multi-temporal remote sensing datasets to develop methods to produce spatially localised growth trends and yield forecasts for CCF
•Improving regeneration prescriptions from localised information about canopy gaps and competition

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Declarations

Conflict of Interest The authors declare that they have no competing interests.

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- •• Of major importance

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