Untangling methodological and scale considerations in growth and productivity trend estimates of Canada's forests

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TOPICAL REVIEW

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Abstract

In view of the economic, social and ecological importance of Canada's forest ecosystems, there is a growing interest in studying the response of these ecosystems to climate change. Accurate knowledge regarding growth trajectories is needed for both policy makers and forest managers to ensure sustainability of the forest resource. However, results of previous analyses regarding the sign and magnitude of trends have often diverged. The main objective of this paper was to analyse the current state of scientific knowledge on growth and productivity trends in Canada's forests and provide some explanatory elements for contrasting observations. The three methods that are commonly used for assessments of tree growth and forest productivity (i.e. forest inventory data, tree-ring records, and satellite observations) have different underlying physiological assumptions and operate on different spatiotemporal scales, which complicates direct comparisons of trend values between studies. Within our systematic review of 44 peer-reviewed studies, half identified increasing trends for tree growth or forest productivity, while the other half showed negative trends. Biases and uncertainties associated with the three methods may explain some of the observed discrepancies. Given the complexity of interactions and feedbacks between ecosystem processes at different scales, researchers should consider the different approaches as complementary, rather than contradictory. Here, we propose the integration of these different approaches into a single framework that capitalizes on their respective advantages while limiting associated biases. Harmonization of sampling protocols and improvement of data processing and analyses would allow for more consistent trend estimations, thereby providing greater insight into climate-change related trends in forest growth and productivity. Similarly, a more open data-sharing culture should speed-up progress in this field of research.

Introduction

Humans have modified their environment substantially, far beyond the natural variability in ecosystem processes (Zalasiewicz *et al* 2011), which has led to the proclamation of a new geological era, the Anthropocene (Crutzen 2002). A recent study located its onset at around the year 1950 (Waters *et al* 2016), after which a strong warming trend in climate was identified globally and particularly at high latitudes (IPCC 2013). In Canada, mean annual temperatures have risen on average by 1.7 °C since 1948, with the strongest increase along the West Coast (Environment Canada 2017). These rising temperatures coincide with an increase of almost 25% in atmospheric CO_2 concentrations, emissions of which are attributable to human activities over the same period (IPCC 2013). Some concerns regarding climate change relate to its potential effects on ecosystems, including forests, that are of major importance for society. Forests cover

nearly 40% of Canada's land surface and play a crucial role in the Canadian economy (Gillis *et al* 2005). Forest ecosystems also offer a large number of societally-relevant functions (Gauthier *et al* 2015), including the sequestration of a significant proportion of anthropogenic carbon emissions (Arneth et al 2010, Kurz *et al* 2013, Le Quéré *et al* 2018).

Concerns about the future of Canadian wood resources have led to a growing number of studies focusing on the assessment and monitoring of forest ecosystem characteristics. Major satellite observation programs began in the early 1980s and have provided information on the effects of environmental change and human activities on the geographical distribution of natural resources (Roy *et al* 2014). Such data allow mapping and monitoring the Earth's surface as a whole, with minimal budgetary considerations and time constraints that would limit spatial field observation campaigns to disparate networks of inventory plots in areas that are easily accessed (Zhang *et al* 2003, Sulla-Menashe *et al* 2016). The quality, accuracy and availability of remotely sensed data has been improving constantly over the last few decades. Moreover, a substantial proportion of these data is now available free of charge (Czerwinski *et al* 2014).

In contrast to remote sensing observations, a more field-based monitoring approach is the network of sample plots that has been established by federal and provincial authorities in Canada through national and provincial forest inventories (Béland *et al* 1992, Gillis *et al* 2005). These plots allow for the estimation of stand biomass through allometric equations that are based upon measurements of tree dimensions and the number of stems per hectare (Lambert *et al* 2005). Plot remeasurement provides information on temporal variation in stand productivity and permits the estimation of future (potential) productivity (Ciais *et al* 2008), an important management tool for adapting silvicultural practices to changing environmental conditions (Gillis 2011). A second field-based approach for studying growth trends relies upon dendrochronology, i.e., the measurement and dating of annual growth rings that allow linking spatiotemporal fluctuations in environmental factors to changes in tree growth rates (e.g., Berner *et al* 2011, Dietrich *et al* 2016, Babst *et al* 2018).

Many studies have focused on quantifying growth and productivity trends in Canadian forests using either one or multiple of these data sources, but reporting very different results. Rising temperatures combined with higher atmospheric CO_2 concentrations have been assumed to improve forest productivity by lengthening the growing season (Eastman *et al* 2013) and increasing carbon assimilation rates (Long *et al* 2004). While several studies had indeed shown mainly positive trends for Canadian forests (Ju and Masek 2016, Hember *et al* 2017), other studies indicated a decreasing trend in growth and productivity rates (e.g., Chen *et al* 2016, Girardin *et al* 2016a). Heat stress that is caused by rising temperatures and an increase in the frequency and intensity of droughts, among other factors, have been suggested as explanations for these downward trends (Hogg *et al* 2005, Zhang *et al* 2008, Michaelian *et al* 2011, Girardin *et al* 2014). The lack of a clear tendency in growth and productivity estimates prevents policy makers from adequately defining annual allowable cuts, and foresters from determining appropriate silvicultural practices that maximize growth rates and forest yields.

Here, we provide an in-depth assessment of methodological aspects that could explain, in part, the contradictory findings of earlier studies. The first section of this paper focuses on the characteristics of the studied variables and spatiotemporal scales. We examine, whether the different methods target comparable ecophysiological processes, and to what extent observational scales and data resolution allow for robust comparisons. We then discuss biases associated with each method and how they may affect the calculation of growth and productivity trends. Finally, we propose the co-integration of the different methods as a means of improving estimates of growth and productivity trends across large forest biomes such as the Canadian forests. We conclude by pointing out the urgent need to adjust some of our established working methods to foster advances in this field of research. We also encourage intensified data sharing through open-access portals.

Methodology

Data sources and definitions

This paper is based upon a systematic review of trends in Canada's forest growth and productivity that were reported in peer-reviewed scientific articles. Articles were searched through the Google Scholar and ISI Web of Knowledge search engines using the following keywords: 'Canadian forest growth,' 'Canadian forest productivity,' 'Canadian forest inventory data,' 'Dendrochronological studies Canada,' 'Forest response to climate change,' 'normalized difference vegetation index (NDVI) trends Canada,' 'Productivity trends Canada,' 'Dendrochronology trends Canada,' 'Biases dendrochronology,' 'Biases forest inventory data,' 'Biases vegetation indices,' 'Uncertainties remote sensing data,' 'Uncertainties productivity calculation,' 'Uncertainties detrending.' Citations within the searched articles were also carefully checked and incorporated if they were relevant (backward search). While this work focuses on growth and productivity trends in Canadian forests, search results from other geographic areas have been retained for the purposes of discussion. In particular, these were studies that mentioned innovative methodological approaches that have rarely been applied in Canadian studies. The search did not include studies of productivity simulations that were derived from predictive models.

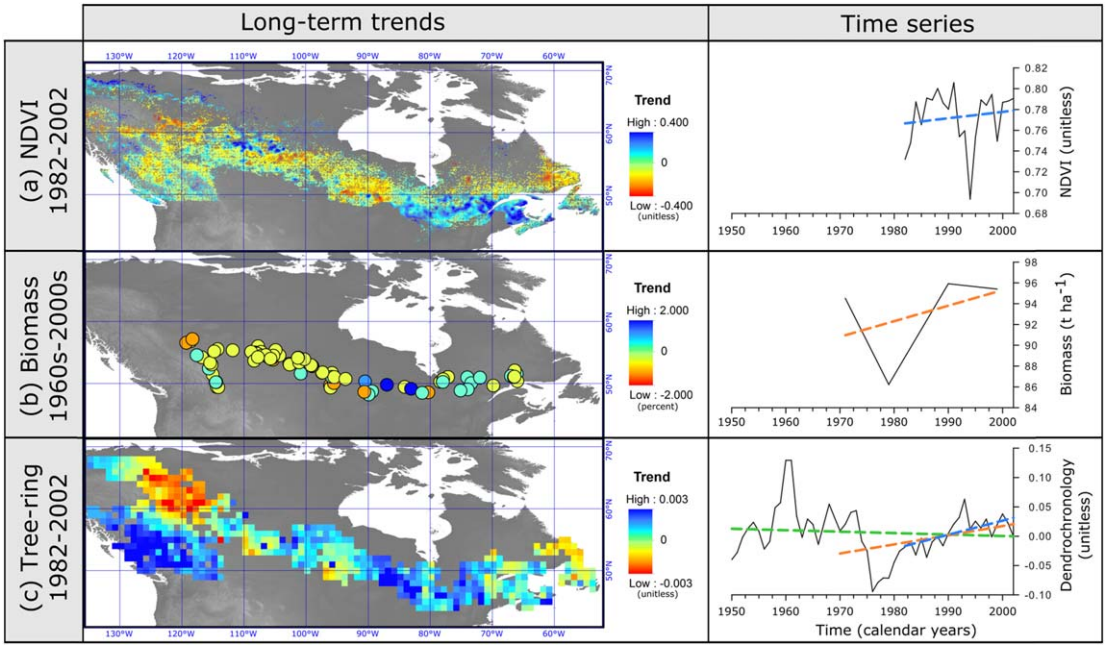

Figure 1. Left: comparison of spatially explicit trends across Canada's boreal forest assessed by (a) remote sensing (GIMMS 3g NDVI, data from Pinzon and Tucker 2014), (b) forest inventory (aboveground biomass, data from Ma *et al* 2012), and (c) dendrochronology (detrended basal area increments, data from Girardin *et al* 2016a). The periods covered by the trend analyses are indicated next to each map. Right: three examples of time series are shown for eastern Canada: (a) averaged NDVI over 50.875° N, 74.21° W, (b) aboveground biomass for 50.96° N, 74.01° W; (c) detrended basal area increments aggregated over 48.94° N, 74.76° W (see original papers for computation procedures). Also shown are linear regressions of values over time (a): 1982–2002 (blue dashed line), (b): 1971–1999 (orange dashed line), (c): 1950–2002 (green dashed line), 1970–2002 (orange dashed line) and 1982–2002 (blue dashed line).

Throughout this systematic review, we shall refer to the terms 'growth' and 'productivity.' Here, we shall use the term 'growth' mainly to refer to secondary growth, i.e., the increase in tree diameter or basal area (e.g., Dietrich *et al* 2016, Girardin *et al* 2016a). Elsewhere, Assman (1970) defined 'forest productivity' as the increase in biomass or volume of wood per unit area and time. Researchers usually calculate this value as the difference in woody biomass between two measurement dates (e.g., Ma *et al* 2012, Hember *et al* 2017). In this paper, we shall use the term 'productivity' to refer to the change in living wood biomass that occurs within a stand or forested area between two measurement dates.

Different variables at different working scales

Interconnected but dissimilar physiological processes

We identified 44 studies that focus on the estimation of Canadian forest growth and productivity trends. Most of these studies rely upon remote sensing data, followed by forest inventory and tree-ring analyses (table 3, see specific examples in figure 1). Across all of these studies, Canadian forests experienced no significant change in growth, with a typical standardized growth rate of −0.52% per year with 95% bootstrapped confidence intervals [−2.27, +0.70] (average taken from $n = 51$ standardized growth rate samples, table 3). Half of the studies report positive trends, whereas the other half shows a decline in growth and productivity. Observed growth trends ranged from $-24.5\%\ \mathrm{yr}^{-1}$ to $+10\%\ \mathrm{yr}^{-1}$ (table 3). Some datasets show similarities, including NDVI from GIMMS 3g (Pinzon and Tucker 2014), aerial biomass inferred from provincial forest inventories, and trends in dendrochronological analyses of Canada's National Forest Inventory database (figure 1). During the late-20th century, the north-westernmost boreal zone showed negative trends, while the southeastern boreal zone displayed positive trends (figure 1). Despite this general tendency, one can see many differences in the signs and magnitudes of the trends within regions, depending upon the data source (table 3). Determining how much of these variable results are due to geography, versus methodological differences, versus random processes (errors) is a daunting task, and necessitates a closer look at the underlying eco-physiological and ecosystem processes that are captured by each of these methods.

Vegetation indices that are derived from remote sensing data are broadly used to approximate plant productivity (Berner *et al* 2011). The most commonly used vegetation indices are the NDVI derived from surface reflectance, and the leaf area index (LAI), estimated from other vegetation indices such as the NDVI on the basis of statistical relationships with field measurements. Vegetated areas typically exhibit NDVI values between 0.1 and 0.7 (Seth *et al* 1994,

Wang *et al* 2005). Similar to spectral reflectance values (Carlson and Ripley 1997), vegetation indices are the expression of how much photosynthetic pigment is present in a given area (Nagai *et al* 2010, Piao *et al* 2014) and refer to 'greening' and 'browning' as seasonal trends in foliage area and pigment density. These indices are assumed to represent the state of the vegetation, its photosynthesis capacity (Myneni *et al* 1997b). In contrast, productivity estimates from forest inventories (typically quantified as aboveground biomass increment, ABI) correspond to stand-level biomass gains and losses between two inventory periods (Chen *et al* 2016, Hember *et al* 2017). These values inherently consider stand regeneration and mortality rates, as well as the stand-level increase in woody biomass of surviving trees (Hember *et al* 2017). Finally, tree-ring width (TRW), which is the most common parameter in dendrochronological studies, corresponds to the annual radial growth of a tree and represents the number and size of cells that are produced during the growing season (Berner *et al* 2011). TRW is often standardized (i.e., 'detrended') to obtain a dimensionless index (tree growth increment (TGI); ring-width index (RWI), a measure of the annual growth anomaly compared to the mean over a given time period (D'Arrigo *et al* 2004), although this step is increasingly being avoided when tree rings are used in an ecological context (Babst *et al* 2018).

Vegetation indices from remote sensing, aboveground biomass increments from forest inventories, and TGIs from dendrochronological studies are reported occasionally to be correlated with one another (Pouliot *et al* 2009, Girardin *et al* 2014, Vicente-Serrano *et al* 2016), but they represent the outcome of different physiological processes. While vegetation indices reflect photosynthetic capacity, growth-based metrics represent increases in woody biomass at different scales (stem: ring-widths or stand: ABI). These different proxies of growth and productivity refer to different processes of plant carbon uptake and use (leaf, stem, roots) and are correlated in a nonlinear fashion (Tateishi and Ebata 2004). RWIs refer mainly to the increase in radial diameter, i.e., secondary growth, and are thus not a direct measure of height growth or stand demographic processes, such as recruitment or mortality. Furthermore, the carbon that is sequestered in a given year will not only ensure the growth of that year, but can additionally sustain the tree's needs in the following years through the storage and remobilization of non-structural carbohydrates (Berner *et al* 2011, Richardson *et al* 2013). Consequently, a reduction in the tree's photosynthetic capacity or an increased carbon consumption for baseline metabolism during a drought year will reduce the carbon that is available for structural growth in the following year. This often leads to a 1 year lag between vegetation indices and radial growth increments (Berner *et al* 2011, Beck *et al* 2013, Seftigen *et al* 2018) and to significant autocorrelation in tree-ring time series (Zhang *et al* 2017). The correlation between remote sensing vegetation indices and tree- or plot-scaled proxies may also depend upon carbon sink strength of different organs (e.g., roots, shoot, needles or leaves) (Rieger *et al* 2017).

On the importance of working scales

Spatial scales

Spatial variability in growth and productivity trends is an important feature of Canadian forests (Girardin *et al* 2011, 2016a), and this variability occurs across latitudinal (Huang *et al* 2010) and longitudinal (Nishimura and Laroque 2011) gradients. Some authors also observed the importance of elevation (Parent and Verbyla 2010) and soil hydraulic regimes (Hember *et al* 2017), thereby emphasizing the role of spatially heterogeneous and temporally non-stationary factors that occur at different geographical scales (Anyomi *et al* 2014). Numerous interactions and feedbacks across time and space prevent analysts from defining clear boundaries between these scales (Miller *et al* 2004, Soranno *et al* 2014, Scholes 2017). As noted by Zhang *et al* (2003) and McMahon *et al* (2010), the different methods of assessing forest growth and productivity do not always operate at the same spatial scale.

Remote sensing often operates at regional scales where some local or stand-specific ecological and environmental processes are not captured as accurately as in field-based assessments (Goetz *et al* 2005, Beck and Goetz 2011, Piao *et al* 2014). Land cover maps allow grouping of the woody vegetation into large forest types (Zhou *et al* 2003), for which different productivity trends have been observed (Goetz *et al* 2005) that are potentially influenced by natural or anthropogenic disturbances (Boisvenue and Running 2006). Negative trends have been reported for areas that have been recently affected by a disturbance, whereas strongly positive trends are characteristic of forest regrowth responses (Hicke *et al* 2002a, Pouliot *et al* 2009, Beck and Goetz 2011, Ju and Masek 2016). Sulla-Menashe *et al* 2018 demonstrated that a large part of positive NDVI trends from remote sensing data could be associated with forest recovery after disturbance. Elimination of areas that were affected by a major disturbance could help improving comparisons between studies, as well as distinguishing the effects of climate change from those that are related to disturbances (e.g., Parent and Verbyla 2010, Beck and Goetz 2011, Sulla-Menashe *et al* 2016, Girardin *et al* 2016a, Hember *et al* 2017). However, algorithm-based identification of disturbed areas is error-prone and caution is warranted when interpreting these data (Sulla-Menashe *et al* 2016).

At the stand level, composition and demography can significantly affect forest productivity (Foster *et al* 2014). In addition to differences between individuals, some authors also have identified species-specific

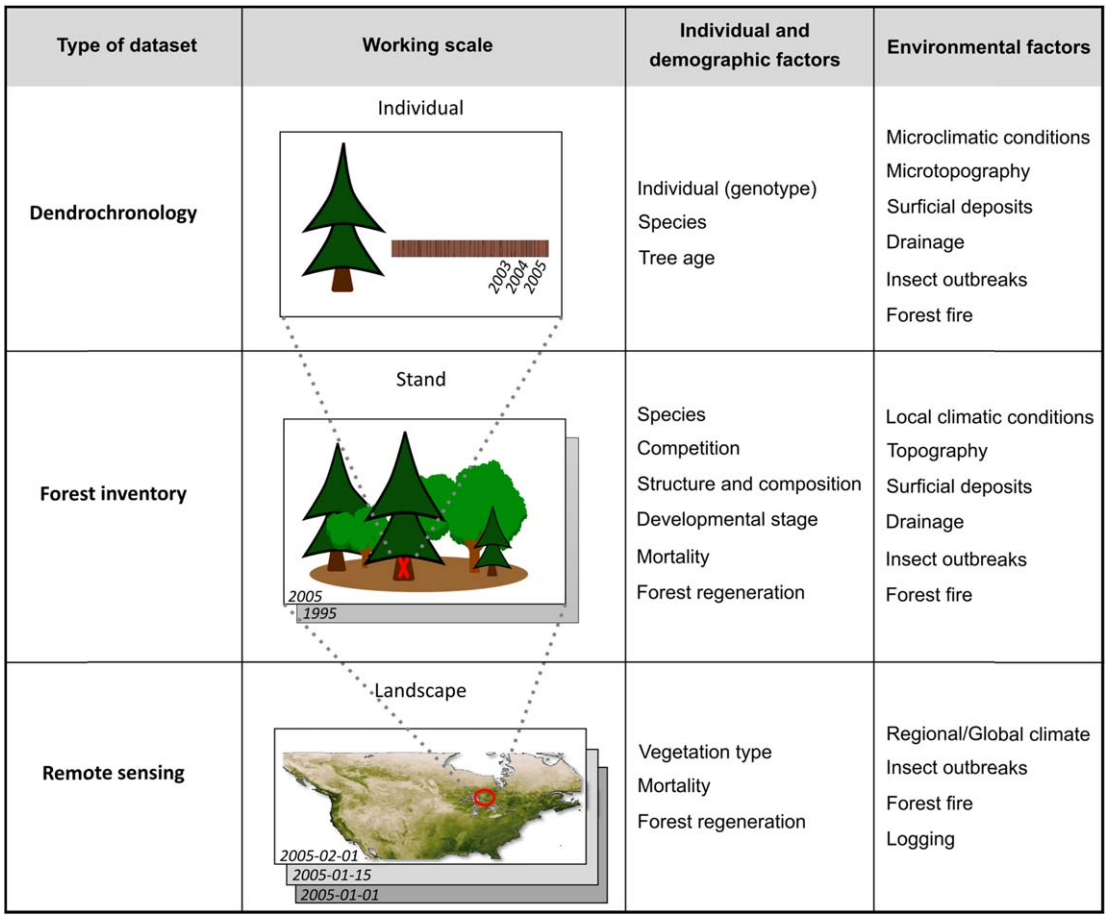

Figure 2. List of factors that could be measured or controlled at the different working scales (individual stem, sample plot/stand, landscape/global).

sensitivity to environmental stresses (Chen *et al* 2016, Wason *et al* 2017, Teets *et al* 2018). Such inter-specific differences are related to physiological thresholds and anatomical properties, such as root system morphology (Hember *et al* 2016), and would lead to different rates of biomass accumulation and growth trends (McMahon *et al* 2010, Girardin *et al* 2016a). Finally, at the finest scale of dendrochronological studies, growth trends of individual trees of the same species may differ even within the same stand (Buras *et al* 2016). This is likely due to demographic and genotypic differences between individuals or differences in microclimatic conditions, topography, soil properties and soil drainage (Wilmking *et al* 2005, Berner *et al* 2011, Brienen *et al* 2012, Girardin *et al* 2012, Girardin *et al* 2014).

Since ecological parameters that influence tree growth and forest productivity cannot be measured or controlled accurately, depending upon the spatial scale (figure 2), comparing trends from methods that operate at different scales is challenging. Therefore, it is risky to extrapolate results that were obtained at fine spatial scales to coarser scales (i.e., upscaling), and *vice versa* (i.e., downscaling) (Scholes 2017). For example, strong positive trends could be observed at the individual tree level, while the stand could experience lower or even negative trends resulting from a lack of regeneration or an increase in mortality rates (Hogg *et al* 2005, McMahon *et al* 2010, Groenendijk *et al* 2015). Similarly, an increase in vegetation cover could result in increasing values of vegetation indices over time, without a simultaneous improvement of tree growth rates (Mekonnen *et al* 2016). In this regard, one should proceed with caution when merging and interpreting results from several datasets based on different spatial scales.

Time scales

Growth and productivity trends are also temporally heterogeneous (Girardin *et al* 2016b, Hember *et al* 2017) (figure 1) and temporal scales differ between the three observation methods. First, remote sensing data have been available since the early 1980s (see table 1). The recording frequency varies from one week to one month for the most commonly used datasets (see table 1). Vegetation indices are usually rescaled to a monthly or annual step (e.g., Zhou *et al* 2001). In contrast, data from forest inventories have been available over the last 50 years on a 5- or 10-year time step (Hember *et al* 2017). Environmental conditions at the time of sampling are known; hence, each inventory campaign provides a snapshot of the

Table 1. Spatial and temporal resolution and period covered by the most frequently used remote sensing datasets.

Dataset	Spatial resolution	Period covered	Temporal resolution	Notes
AVHRR GIMMS	1 km/8 km	1978–now	Weekly/Bi-monthly	These products are derived from AVHRR data for which there are several sensor versions: 1 (1978), 2 (1981), 3 (1998) http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html. Data correction methods differ between the three datasets.
AVHRR PAL	8 km	1981–2001	10 day/monthly	
AVHRR FASIR	0.08°/0.25°/0.5°/1°	1982–1999	10 day/monthly	
Terra-MODIS	250 m/500 m/1 km	2000–now	16 day	https://terra.nasa.gov/about/terra-instruments/modis
GIMMS LAI3g	0.08°	1981–2004	Bi-weekly	These products are derived from a merging of MODIS and AVHRR data http://modis.cn/globalLAI/GLOBMAP_LAI_DescriptionV1.pdf; http://glcf.umd.edu/data/lai/
GLOBMAP LAI	8 km, 0.08°	1981–now	Bi-monthly (1981–2000), 8 day (2000–2015)	
GLASS LAI	1 km, 0.05°/5 km	1981–2012	8 day	
LandSat TM/ ETM+	30 m	1982–now	16 day	Landsat 4 (1982), 5 (1984), 7 (1999), Landsat 8 since 2013 https://lta.cr.usgs.gov/products_overview/

sampled stands at a specific point in their life history (Biondi 2000, Bowman *et al* 2013). The temporal resolution of forest inventory data is coarse and does not allow visualizing inter-annual growth variations, e.g., following extreme climate events (Hember *et al* 2017). Finally, working with ring-width data allows analysts to assess inter-annual or seasonal growth variation of boreal species over the tree's lifespan (Berner et al 2011, Bowman *et al* 2013). However, tree rings in pre-instrumental times were formed in an unknown and uncontrolled environment (e.g., during the Little Ice Age, which ended in 1850), differing from current environmental conditions (Cook and Pederson 2011, Bowman *et al* 2013, Rieger *et al* 2017). Ring-width data, as well as remote sensing data, are available at a very fine timescale, which could also reduce the ability to detect subtle changes in growth due to a higher noise level (Verbesselt *et al* 2010).

The direction and magnitude of trends may also depend on time-series length and their start and end dates (Lloyd and Bunn 2007, Hember *et al* 2017) (figure 1). Trends from half century-long series (e.g., 1950–2002; Girardin *et al* 2016a) that reflect a multi-decadal change in growth and productivity rates will not necessarily agree with those obtained from shorter time-series (e.g., 1984–2012; Ju and Masek 2016), which provide information on more recent changes. This would be particularly true in the context of a sudden reversal of trends, such as has been noted in some Canadian regions between the late 1980s and early 1990s (Wang *et al* 2011, Girardin *et al* 2014; see figure 1).

The spatiotemporal specificities of each observation method allow scientists to test for a large number of ecological assumptions. Forest ecologists rely on the very fine time resolution and wide geographical coverage of satellite data to observe continuous patterns of productivity trends across the landscape, and to formulate hypotheses about the potential link with other geographically-varying ecological phenomena, such as changes in the pattern of natural disturbances or in the phenology of woody species (Goetz *et al* 2007, Beck and Goetz 2011). Besides, the spatial unit of forest inventory data, i.e. the forest stand, makes them better suited to test more applied and forest industry-oriented hypotheses, for example regarding the best combination of stand structure and composition to maintain the highest yields under a warming climate (Millar *et al* 2007). Lastly, the individually-scaled ring-width data allow to quantify the between-tree heterogeneity in the growth response to environmental gradients occurring within a population (Buras *et al* 2016), and to link this heterogeneity with tree's growing conditions or morpho-physiological traits (Rozas and Olano 2013). However, despite their respective strengths, each of these three methods has its own weaknesses for assessing trends in tree growth and forest productivity.

Biases and uncertainties

Limitations of remote sensing data

Multiplicity of vegetation indices

The open availability of remote sensing data has led to a plethora of vegetation indices, each with its own calculation process. Because different vegetation indices are based upon different wavelengths, they do not convey the same information (Czerwinski *et al* 2014). Also, because of their remote nature, vegetation indices can be influenced by several environmental characteristics. For example, soil characteristics, such as soil colour, brightness and texture, or slope, are known to affect NDVI values (Raynolds *et al* 2013, Pattison *et al* 2015), especially in sparsely-vegetated (Czerwinski *et al* 2014) and mountainous terrain (Kerr and Ostrovsky 2003). Finally, NDVI is prone to saturation when focusing on highly productive areas (Pattison *et al* 2015), leading to less precise estimates of biomass changes in the most productive forests and possibly obscuring significant trends (Berner *et al* 2011). Since compiled NDVI time series are easily accessible (Ichii *et al* 2002), other existing and potentially more accurate indices are rarely used, such as the enhanced vegetation index (Baret and Guyot 1991, Czerwinski *et al* 2014, Jin *et al* 2016, Sulla-Menashe *et al* 2016, Karkauskaite *et al* 2017).

Spatial resolution

The limited spatial resolution of remote sensing time-series (table 1) may affect the trend accuracy of vegetation indices. The vegetation index value that can be attributed to a given pixel corresponds to the whole photosynthetic signal of the pixel (Olthof *et al* 2009, Berner *et al* 2011), and the detected trend will mostly be representative of foliage and productivity variation of the dominant species (Chen *et al* 2016), regardless of whether it is a tree species or not (Berner *et al* 2011). The influence of the type and amount of vegetation can be particularly problematic at high latitudes, where spurious positive trends that are observed in sparsely-forested areas (e.g., Guay *et al* 2014) could be due to an expansion of the understory vegetation (Berner *et al* 2011). Myneni *et al* (1997b) recommended that the type of vegetation cover be considered when using NDVI data. A lag between leaf expansion and photosynthetic capacity of broadleaved species is often proposed to explain the nonlinear relationship between vegetation index values and leaf area values of a given area (Nagai *et al* 2010). These resolution-dependent uncertainties may partly explain the largest proportion of positive trends for remote sensing-based studies compared to field observations (68% and 35%, respectively; figure 3(a)).

Data quality

Data quality is crucial for detecting trends that result from subtle environmental changes, such as climatic gradients (Pouliot *et al* 2009, Guay *et al* 2014).

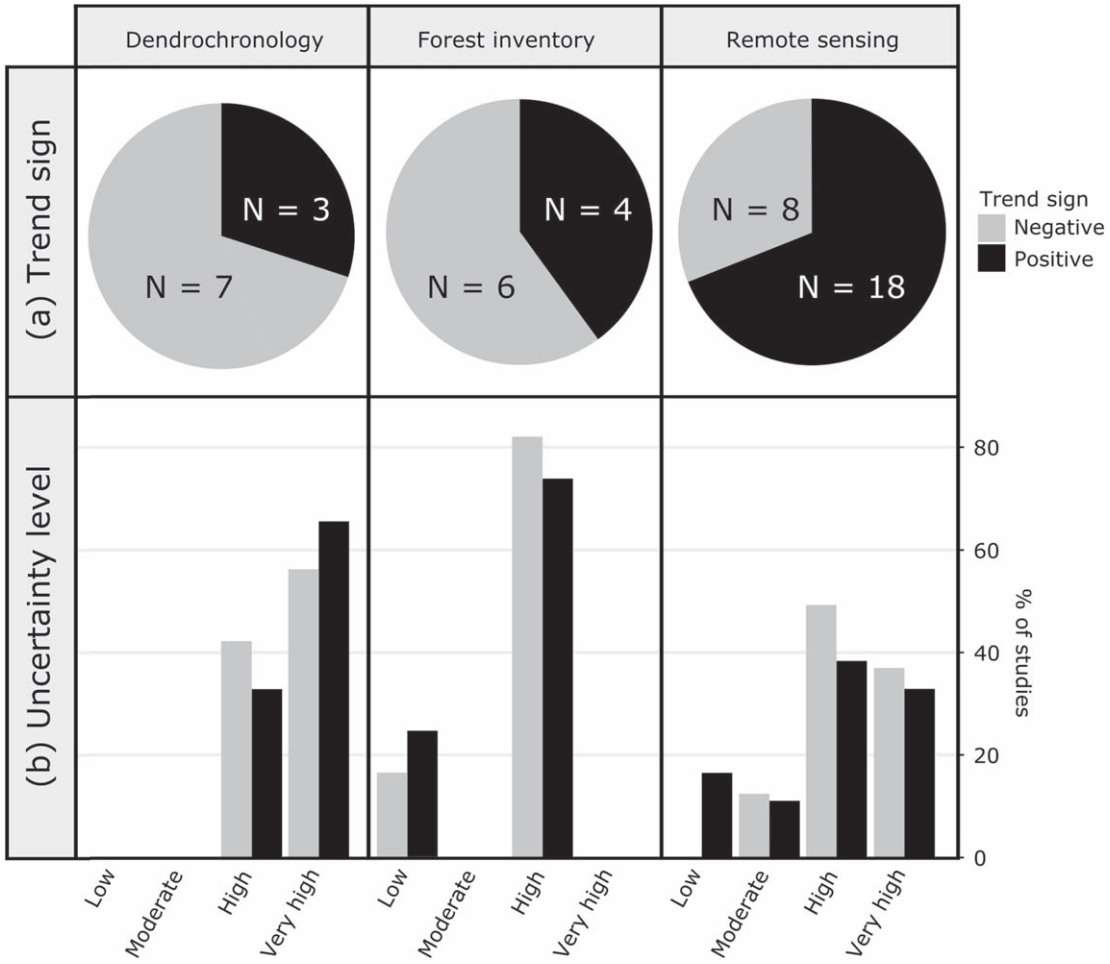

Figure 3. (a) Percentage of studies reporting positive (black) or negative (grey) growth and productivity trends for Canadian forests, by observational method (see table 1 for references). Pseudo-replication was considered as follows: in the case of two different studies published by the same author, the most recent study was selected; Chen and Luo (2015), Zhou *et al* (2001) and Ichii *et al* (2002) have been excluded. In the case of different results from the same study, with the same method and the same geographical area, but with different datasets, the sign of the average trend was considered (Zhu *et al* 2016). In the case of different results, with the same method, from the same study, but for different geographical areas, the trend corresponding to the widest geographical area (Chen *et al* 2014), or to the boreal forest (Goetz *et al* 2005, Bunn and Goetz 2006) was considered. In the case of two different results from the same study but with different methods, the two trends were retained (Berner *et al* 2011, Hember *et al* 2012, Bond-Lamberty *et al* 2014, Girardin *et al* 2014, Boisvenue *et al* 2016). Also shown is the number of studies taken into account by observational method and trend sign. (b) Percentage of studies according to their level of uncertainty, by observational method and trend sign. For information about the attribution of uncertainty levels, see the subsection 'Uncertainty assessment'.

Remote sensing data are prone to quality loss through environmental perturbations, mechanistic limitations, or sensor degradation (see figure 2 in Babst *et al* 2010). The main source of environmental perturbations are snow and cloud cover (Fensholt and Proud 2012). While the effect of snow cover can be avoided when focusing on snow-free seasons, cloud cover is a persistent concern, particularly for Landsat records of northeastern and western Canada (Roy *et al* 2008, Pouliot *et al* 2009). Cloud contamination induces artificially low NDVI values and could be responsible for the negative trends that have been observed for the Arctic region (Parent and Verbyla 2010). Existing algorithms that are used to remove cloudy pixels automatically (Sulla-Menashe *et al* 2016) are suboptimal (Slayback *et al* 2003). Removal of cloudy pixels also lowers the number of observations (Parent and Verbyla 2010, Fraser *et al* 2011, Ju and Masek 2016) and, thus, affects the capacity to detect significant trends (Pattison *et al* 2015). Uncertainties that are associated with sensor mechanics and post-recording corrections are related, among other things, to a lack of calibration, orbital drift, differences in viewing geometries, and to the use of different algorithms for atmospheric corrections (e.g., Roy *et al* 2008, Chen *et al* 2014). Because of these mechanistic limitations and error-prone correction algorithms, different data sources and sensors can provide differing NDVI values for the same geographical area (Sulla-Menashe *et al* 2016). This lack of robustness constrains the possibility of cross-studies comparisons (Fensholt *et al* 2009, Fensholt and Proud 2012, Raynolds *et al* 2013, Zhu *et al* 2016), as well as merging data from multiple sensors (Girardin *et al* 2016b), particularly for the Arctic region (Raynolds *et al* 2013).

Spatial heterogeneity and sampling biases

Effects of a non-random sampling strategy

Soil properties and vegetation types within ecological units are often heterogeneous (Lands Directorate 1986, Marshall *et al* 1999), and an incomplete representation of such heterogeneous conditions in analyses of Canadian forest trajectories may induce biases. Since field sampling is expensive and time-consuming (Vicente-Serrano *et al* 2016), forest inventory campaigns tend to target commercial species within intact, productive and mature forests (Hember *et al* 2012). Thus, the least productive (forested peat bogs or xeric forests) and the least accessible (mainly high-latitude areas) stands are underrepresented when considering these field-based observations (Boisvenue *et al* 2016). Dendrochronological studies, in contrast, often focus on the most climate-sensitive trees, i.e., individuals growing at the edges of their distribution range (Kaufmann *et al* 2004, D'Arrigo *et al* 2014, Charney *et al* 2016). This may explain the heterogeneity of trends from studies that are based upon plot inventories and dendrochronology (table 3, figure 3(a)).

Within a sample plot, the largest dominant/co-dominant and healthy trees are usually targeted for tree-ring or stem analyses (Duchesne and Ouimet 2008, Bowman *et al* 2013). This non-random selection of a subpopulation could bias the resulting growth trends. Sampling only the largest trees in recently regenerated stands, such as fast-growing trees, is referred to as 'big tree selection bias' in the scientific literature (Nehrbass-Ahles *et al* 2014, Groenendijk *et al* 2015, Brienen *et al* 2017). The resulting growth trends would be artificially high and unrepresentative of the entire population (Brienen *et al* 2012). In contrast, the selected living trees in the oldest stands could have experienced the slowest growth, especially for species with a short life expectancy, including most of boreal species. This selection of old, slow-growing individuals (Nehrbass-Ahles *et al* 2014) would lead to artificial negative growth trends (Brienen *et al* 2012). This is referred to as 'slow growth survivorship bias' or 'productivity survivorship bias' in the literature (Bowman *et al* 2013). Senescent trees would also artificially lower growth trends, which is referred to as 'pre-death slow growth bias' (Bowman *et al* 2013, Groenendijk *et al* 2015, Cailleret *et al* 2017). Also, trees that died prior to sampling are usually not accounted for when building chronologies (Swetnam *et al* 1999). This results in a loss of reliability and a biomass underestimation going back in time (Dye *et al* 2016), which is referred in the literature to as the 'fading record problem,' and could lead to apparent increasing growth rates.

Demographic biases, such as those discussed above, can lead to biased estimates of tree growth and forest productivity (Foster *et al* 2014) potentially exceeding by 150%–200% the average trend experienced by the whole population (Nehrbass-Ahles *et al* 2014). Therefore, there is a need to consider past demography when studying growth dynamics and variation in forest biomass (Hember *et al* 2016), especially through the sampling of deadwood and snags (Girardin *et al* 2011, Gennaretti *et al* 2014, Groenendijk *et al* 2015). A combination of dendrochronological data and simulated past biomass increments can permit accounting for growth rates of dead trees (Foster *et al* 2014). However, this approach does not account for abrupt and large mortality events, but instead relies upon the representativeness of the available dendrochronological data (Foster *et al* 2014).

Spatiotemporal fluctuation of inventory plot network

Analyses of repeated forest stand measurements have important advantages over other methods in that they enable the assessment of effects of stand dynamics, such as mortality and regeneration, together with competition for resources on productivity (Wilmking *et al* 2004, Foster *et al* 2014, Hember *et al* 2017). Since old stands exhibit lower productivity trends than mature and young stands (Girardin *et al* 2012, Chen *et al* 2016, Girardin *et al* 2016b), the use of the age of the oldest tree or time-since-disturbance as proxies for stand age are ecological parameters that are necessary for explaining productivity trends. Yet this variable can rarely be obtained because either the lifespan of trees is shorter than the typical stand-replacing disturbance return interval (and therefore, a minimum age is assigned to the stand), or age is estimated from core samples that are collected at breast height (1.3 m) or 1 m height, which can lead to an underestimation of tree age of up to 30% with shade-tolerant species (Marchand and DesRochers 2016). Other challenges include the effects of natural or anthropogenic disturbances that are superimposed upon ecological gradients (Girardin *et al* 2008) and stands that are, unfortunately, rarely resampled after disturbances (e.g. Hember *et al* 2012, Zhang *et al* 2015, Dietrich *et al* 2016, Hember *et al* 2017). A standard practice is the translocation or addition of new, non-disturbed stands to the initial inventory network (Hember *et al* 2012, Bowman *et al* 2013). Hence, post-disturbance recovery of productivity cannot be compiled. The resulting modification in the distribution of site quality, competition intensity, climatic conditions and age classes could induce further spurious negative productivity trends or mask positive trends (Bowman *et al* 2013, Hember *et al* 2017). To avoid uncertainties that are linked with these spatiotemporal fluctuations in the plot network, researchers need to consider only plots that were sampled from the first inventory campaign to the last one (Duchesne and Ouimet 2008, Ma *et al* 2012). This strategy leaves very few plots for analysis; for example, Ma *et al* (2012) retained less than 1% of the available plots in their study, in part, because of this criterion. Nevertheless, an important problem remains: random mass mortality events that are induced by natural disturbances are not considered (Körner 2003, Vanderwel *et al* 2013), which could

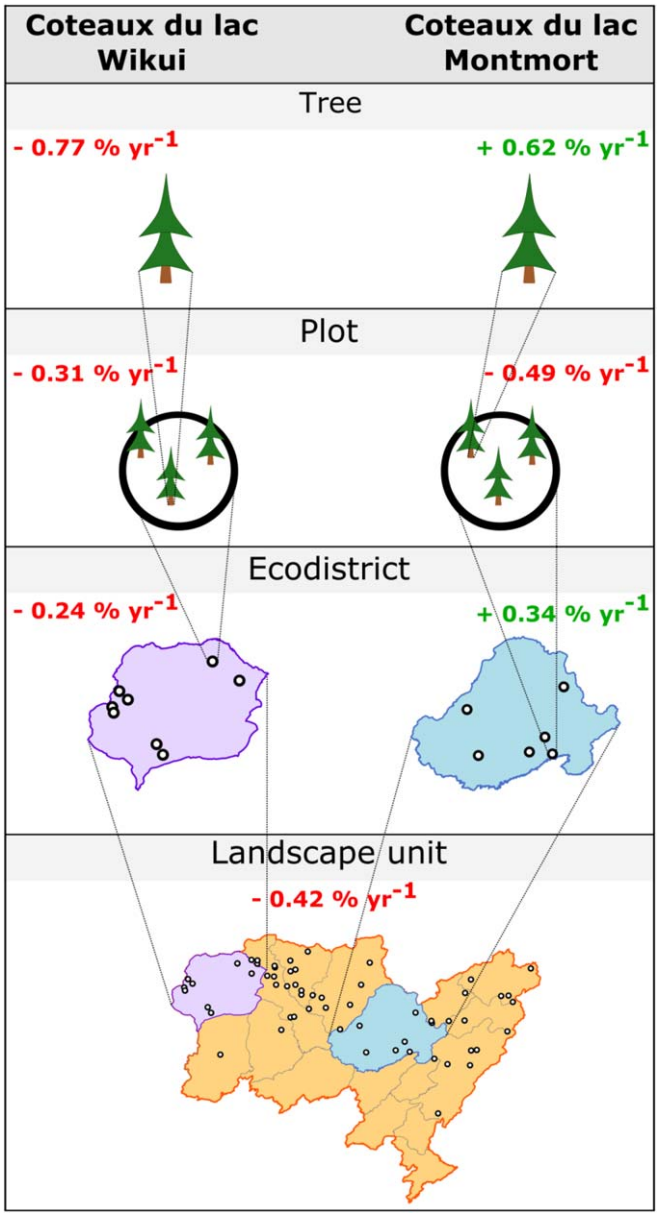

Figure 4. Illustration of some concerns resulting from data aggregation, using a subset of data from the Quebec's Northern Ecoforest Inventory program to infer black spruce 1980–2005 growth trends (in % of change per year) according to the working scale, from the individual tree to the landscape unit. Examples are provided for two different ecological districts within the landscape unit 'Lac Robineau' (50.48–51.60N, 73.75–76.25W).

result in underestimation of mortality rates and overestimation of the increase in aboveground biomass over time (Fisher *et al* 2008).

Uncertainties resulting from data processing

Spatiotemporal data aggregation

When working with large datasets, data rescaling, i.e., aggregation of data at a broader scale than the original scale, is a common practice that represents a trade-off between the amount of available information and its relevance to the study's purpose. Rescaling data at coarser spatial and temporal scales eases the interpretation and visualization of the results, but it also results in the loss of strong spatiotemporal variability in growth and productivity trends. Figure 4 illustrates how the direction of growth trends could vary when computed from chronologies successively aggregated at upper spatial scales. We utilized a subset of stem-analysis data from Quebec's Northern Ecoforest Inventory program, a network of 400 m^2 sampling plots located in unmanaged forests (Létourneau *et al* 2008, Girardin *et al* 2012, Ols *et al* 2018). Individual ring-width series of black spruce (*Picea mariana* [Mill.] BSP) trees within Quebec's landscape unit 'Lac Robineau' (50.48–51.60N, 73.75–76.25W; $n = 94$ trees, up to $n = 3$ trees per plot were sampled) were detrended following Girardin *et al* (2016a) to obtain annually-resolved chronologies of growth coefficients. The detrended chronologies were then successively aggregated from the tree level to the plot level,

ecological district and landscape unit by computing the median values per calendar year, and growth trends were computed over the period 1980–2005 as the regression coefficient between median chronologies and calendar years (as in Girardin *et al* 2016a). For illustration purposes, we highlight the very different results obtained from two distinct ecological districts regarding the direction of growth trends (figure 4). Sampling within the 'Coteaux du lac Wikui' ecological district suggested a decline in the growth of black spruce trees regardless of the working scale, consistent with the negative trend observed for the whole landscape unit. By contrast, sampling within the 'Coteaux du lac Montmort' ecological district revealed trends with reversed signs from one scale to another. Similarly, rescaling of vegetation indices when dealing with different spatiotemporal resolutions leads to an 'ecological fallacy' (Robinson 1950), i.e., making inferences about individuals based upon aggregate data and *vice versa*, and the broader 'ecological inference' problem (King 2013), *viz.,* the difficulty of detecting significant trends (Slayback *et al* 2003, Fensholt *et al* 2009, Verbesselt *et al* 2010). Moreover, Chen and Cihlar (1996) and Chen *et al* (2014) highlighted differences in the way that vegetation indices are aggregated. Indeed, some authors consider either a maximum (e.g., Nagai *et al* 2010) or an average value (e.g., Chen *et al* 2014) at an annual or monthly timescale, or over the growing season of the trees (e.g., Slayback *et al* 2003). These differences would diminish the correlation between remote sensing indices and field data (Chen and Cihlar 1996), thereby leading to less reliable and less comparable trends.

Allometric estimation

Allometric estimation is the extrapolation of some tree-or stand-level parameters that are difficult to measure directly (e.g., volume), based upon their strong statistical correlation with tree characteristics that are easily measured in the field, such as diameter at breast height. Thus, field measurements extending from local to national scales (Case and Hall 2008) are used to determine these relationships and to parameterize allometric equations, which are widely used to estimate stand productivity from forest inventory data (Lambert *et al* 2005, Wang 2006). Local equations are rarely developed because of the costs and logistics of field sampling. The number of field measurements remains low even for national equations. For example, the most widely used national equations that were devised by Lambert *et al* (2005) (e.g., Hogg *et al* 2008, Chen *et al* 2016) are based on relatively few field samples, with some provinces having very few measurements (see figure 2 in Lambert *et al* 2005). Even if one could assess the reliability of such parametric models *via* fit statistics, some concerns remain when extrapolating these models to broader scales without considering the whole set of ecological variables accounting for the variability in biomass within stands and regions. Since the heterogeneity of growing conditions increases with geographical extent, the use of a wide scale-parameterized equation (e.g., ecological region) also implies some uncertainties when results are to be analysed at a fine scale (Wayson *et al* 2015). Furthermore, biomass estimates from allometric equations rarely consider juvenile trees and belowground biomass, which leads to less accurate estimates (Keller *et al* 2001), particularly for slow-growing boreal stands (Bond-Lamberty *et al* 2002).

Estimate accuracy also relies upon the structure of allometric equations. Because of sampling issues, some variables that could improve estimation accuracy (Lambert *et al* 2005, Wang 2006), such as tree height, site quality index, ground-level stem diameter or stand age, are rarely considered (Bond-Lamberty *et al* 2002, Lambert *et al* 2005, Wang 2006, Case and Hall 2008). The use of well-documented tree-growth metrics from forest inventories could be a solution to the lack of field samples for parameterization. Despite these various sources of uncertainty, very few studies have tried to evaluate the accuracy of biomass estimates, because of the scarcity of field measurements (Wayson *et al* 2015). According to Bond-Lamberty *et al* (2002), the biomass of small or large trees would be underestimated, while the biomass of medium-sized trees would be overestimated when using allometric equations. Theoretically, when averaged over several trees of various sizes, these errors should cancel one another and lead to acceptable population-level values. In practice, since these errors are cumulative, biases from allometric equations could result in large uncertainties. Moreover, warmer weather conditions could alter allometric relationships as a result of modified carbon allocation strategies (Hasibeder *et al* 2015), leading to potential under- or over-estimations when inferring a future stand's aboveground biomass.

Detrending

Inter-annual variation in TRW is the result of multiple ecological and environmental processes. Detrending is a method of standardizing TRW data to remove unwanted (e.g., geometric) trends that can mask the desired environmental signal that is preserved in the measurements. As a standard procedure in dendrochronological analyses (Hember *et al* 2012, Sullivan *et al* 2016), detrending eliminates long-term growth trends that are induced, for example, by a tree's biology (tree size and local genotype; Savolainen *et al* 2007) and stand demography (age, competition). Numerous detrending methods have been developed over the years (Peters *et al* 2015), with the underlying aim of improving the retention of environmental signals. Depending upon the statistical procedure, several authors have observed differences in the magnitude and direction of growth trends that are derived from detrended series (Peters *et al* 2015, Sullivan *et al* 2016, Girardin *et al* 2016a). The most commonly used

Table 2. A preliminary assessment of uncertainty rates attributed to different biases, depending on the sign of the observed trend. The aim of this table is to provide some idea of the magnitude for each uncertainty rate. See the subsection 'Uncertainty assessment' for information on the rate attribution.

Bias		Data type	Uncertainty for positive trend	Uncertainty for negative trend
Non-random selection of the stands, and temporal fluctuation of plot network		Forest inventory plots	30%	30%
Non-random selection of the trees		Tree-ring	30%	30%
Detrending	Conservative	Tree-ring	20%	30%
	RCS/BAC/SCI	Tree-ring	10%	15%
	GAMM	Tree-ring	5%	5%
Use of allometric equations		Forest inventory plots	30%	30%
Resampling			20%	20%
Vegetation indices		Remote sensing	10%	10%
Spatial resolution	1–8 km	Remote sensing	30%	30%
	30–250 m	Remote sensing	10%	10%
Atmospheric contamination of the satellite signal and calibration errors		Remote sensing	5%	15%
Fire and insect outbreaks		Remote sensing	10%	10%

detrending method (i.e., fitting a curve through the time series) apparently eliminates part of the long-term signal and would be responsible for the lack of significant growth trends in many studies (Peters *et al* 2015). Regional curve standardization (RCS) and its derivatives (Helama *et al* 2016), which is seen as a potential solution to reduce detrending biases (Briffa and Melvin 2011), could induce artificially negative growth trends, according to Groenendijk *et al* (2015) and Brienen *et al* (2017). Sullivan *et al* (2016) observed a trend reversal when applying this method to chronologies that were averaged by size class. These negative biases are related to the trend detection step, which could partly explain the high percentage of dendrochronological studies reporting negative trends (70%, figure 3(a)), compared to remote sensing (31%) and forest inventory-based studies (60%). A recent detrending method that is based on mixed generalized additive models (GAMM), which was used by Fajardo and McIntire (2012), Camarero *et al* (2015) and Girardin *et al* (2016a), considered linear trends such as growth trends, together with nonlinear trends such as those linked with tree age and size (Peters *et al* 2015). GAMM could reduce detrending biases. Yet uncertainties remain about which part of the signal is exactly excluded or preserved from raw chronologies (Nehrbass-Ahles *et al* 2014), and which biases from collinear effects between variables could persist.

Uncertainty assessment

We have described above some of the most frequently reported biases, which could lead to erroneous conclusions about recent trends in tree growth and forest productivity. Therefore, one must deal with uncertainties that result from the inherent nature of remotely sensed data, from the sampling strategy, or from data processing prior to trend estimation. A quantification of these uncertainties could allow some confidence thresholds to be determined, thereby attributing some weight to the conclusion of the studies (Wayson *et al* 2015, Alexander et al 2018). According to Wayson *et al* (2015), uncertainties that are associated with allometric equations are responsible for up to 30% of the variability in productivity trends. This value and the qualitative information that is disseminated by other studies provide a preliminary assessment of the magnitude of uncertainties that are associated with the other sources of bias. We determined the uncertainty rates as follows.

First, remote sensing-specific biases are resolution-dependent. Uncertainties resulting from the use of coarse-grain datasets would be of similar magnitude to allometric estimations, and would decrease at finer resolutions. Thanks to correction algorithms, environmental or mechanistic noise would result in lower levels of uncertainty, especially when positive trends are detected (e.g., Sulla-Menashe *et al* 2016). The saturation phenomenon that is associated with NDVI datasets only weakens positive trends without changing their sign (Pattison *et al* 2015), but it would lead to a low level of uncertainty. Since most studies partly remove disturbed areas (e.g., Parent and Verbyla 2010, Beck and Goetz 2011), forest regrowth would only weakly affect productivity trends. In contrast, a non-random sampling strategy could lead to substantial uncertainty of magnitude similar to that imposed by allometric equations (Nehrbass-Ahles *et al* 2014, Alexander *et al* 2018). Furthermore, data processing for trend detection would affect growth trends, depending upon the method that is used. According to Sullivan *et al* (2016), the most commonly used detrending methods would lead to a higher level of uncertainty. In contrast, more recent methods, such as RCS and GAMM-based detrending, would be associated with lower levels of uncertainty (Peters *et al* 2015). Lastly, data rescaling should result in uncertainties of intermediate magnitude. A summary of the uncertainty rates that can be attributed to each source of bias is

presented in table 2. One can see that uncertainty rates estimated here remained in the same order of magnitude whatever the observational method (tables 2 and 3). However, attribution of these different rates, although partly based on the literature review, remains highly subjective.

An overall uncertainty rate was computed for each of the referenced studies, as the sum of uncertainty rates (i.e., values in table 2) potentially affecting the results that were reported in the study (table 3, last column). For example, Dietrich *et al* (2016) suggested that results could be biased both by stand- and tree-level sampling biases (both 30% uncertainty rates), and by biases from RCS detrending (15% uncertainty rate for the detection of negative trends), which leads to the assignment of an overall 75% uncertainty rate. These uncertainty rates were finally segregated into four classes, i.e. four levels of uncertainty, as follows: a 'low' level of uncertainty was attributed to studies whose uncertainty rate is below 40%, a 'moderate' level of uncertainty to studies whose rate is comprised between 40% and less than 60%, a 'high' level of uncertainty to studies whose rate is comprised between 60% and less than 80%, and a 'very high' level of uncertainty in the case of studies whose rate is equal to or above 80%. Based on this classification, one can see that a substantial proportion of trends reported in the literature, whatever their direction or the observational method they originated from, is subject to a 'high' or 'very high' level of uncertainty (figure 3(b)). As a guideline for forest ecologists, the approach we proposed remains voluntarily illustrative and uncertainty rates will have to be improved before using them to correct previously assessed trends. Given that some biases may cancel out or amplify one another, further field-based quantification is needed.

Co-integration and a multidisciplinary approach

Make these approaches complementary, not contradictory

When studying growth and productivity trends of Canadian forests, one might think that the use of a given observational method would provide a more accurate assessment of recent trend directions than other methods. Yet the response of the forest ecosystem to global change depends upon multiple interactions and feedbacks that occur at different spatial and temporal scales (Pouliot *et al* 2009). A disturbance occurring at a given scale will have repercussions at the other scales. When studying the forest ecosystem as a whole, one should simultaneously consider all working scales, which involves the combination of all available methods, *viz.*, dendrochronology, forest inventory data and remote sensing observations (Berner *et al* 2011, Girardin *et al* 2014, Boisvenue *et al* 2016, Girardin *et al* 2016a). Merging data from different approaches would allow for cross-validation (Nagai *et al* 2010, Bowman *et al* 2013, Czerwinski *et al* 2014), facilitating the determination of representative growth trajectories for the entire Canadian forest (Boisvenue *et al* 2016).

Co-integration of different observational methods

Different spatiotemporal coverages of the three observational methods that are discussed throughout this paper are currently complicating comparisons between studies. The comparison of the three different approaches would first benefit from the study of a common period of time. As discussed in the section *Different variables at different working scales*, different time windows (table 3), as well as a trend reversal from the early 1980s (Wang *et al* 2011, Girardin *et al* 2014; see also figure 1), reduce the possibility for cross-validation of the results. Historical growing conditions could affect current tree growth (Baral *et al* 2016), but recent growth rates would be more representative of current directions of Canadian forests. Thus, a recent time window, e.g., 1981 to the present, would be an appropriate choice when studying growth trajectories. In particular, only the last 30 years of growth are to be considered when estimating growth trends from ring-width series of centuries-old trees because of the potentially compensation effect of older tree-rings leading to trend estimates that are not reflective of recently occurring changes in growth rates.

Second, studies focusing specifically on the post-disturbance recovery of productivity through the measurement of seedlings and saplings are scarce (Van Bogaert *et al* 2015). To improve our knowledge regarding current and future growth directions, data that are available on the growth of young trees from studies comparing different developmental stages (e.g. Chen *et al* 2016) or comparisons of height growth rates of trees based upon time-since-disturbance (e.g., Fantin and Morin 2002, Gamache and Payette 2004, Andalo et al 2005, Leroy *et al* 2016, Marchand and DesRochers 2016) must be merged into a meta-analysis. Given that no transformation is applied (raw data), sampling height values from stem-analysis data that are taken from permanent sample plots are free from the uncertainties that are associated with dendrochronological data or with allometric estimates. A few sources of bias could originate from approximations of heights of sampling when cutting the radial sections. Thus, the time interval that is necessary to reach a given height can be extracted and used as a proxy for recent changes in primary growth rates, thereby complementing the information on radial growth that is provided by RWIs. As an applied case study, figure 5 provides an example of cross-validation between two data sources. Figure 5(a) displays height-growth curves from stem-analysis data of 1878 black spruce trees from Quebec's Northern Ecoforest Inventory program (Létourneau *et al* 2008). In figure 5(b),

Table 3. Signs and values of growth and productivity trends from studies the areas of which include all or part of the Canadian territory (non-exhaustive list). (a) Trends that are based on a visual interpretation of the maps provided by the authors are indicated with an asterisk (*). (b) The determination of the last column ('Uncertainty') is explained in the subsection 'Uncertainty assessment'. The value reported here corresponds to the sum of all uncertainty rates assessed to the specified reference. NA for the growth trend ratio means that no quantitative value was available in the associated reference.

Observational method	Trend sign (a)	Standardized rate (% per year)	Geographic area	Studied period	Dataset origin	Ecological process	Reference	Uncertainty (b)
Remote sensing	Negative *	NA	Northern Hemisphere	1982–2008	AVHRR GIMMS + MODIS	Productivity	Beck and Goetz (2011)	45
Remote sensing	Negative	−24.5	Northwest Territories	1982–2008	AVHRR GIMMS	Productivity	Berner *et al* (2011)	75
Remote sensing	Negative *	−4	World	1981–2006	AVHRR GIMMS 8 km	Productivity	de Jong *et al* 2011	65
Remote sensing	Negative *	−1	Northern Hemisphere	1994–2002	GIMMS 1°	Productivity	Angert *et al* (2005)	65
Remote sensing	Negative *	−1	World	1982–2009	GIMMS	Productivity	Zhu *et al* (2016)	85
Remote sensing	Negative *	−1	World	1982–2009	GLOBMAP	Productivity	Zhu *et al* (2016)	85
Remote sensing	Negative *	−0.45	Northwestern America	1982–2011	AVHRR GIMMS 8 km	Productivity	Chen *et al* (2014)	85
Remote sensing	Negative *	−0.3	Canada	1981–2003	AVHRR GIMMS	Productivity	Goetz *et al* (2005)	85
Remote sensing	Negative *	−0.3	Northwestern America	1982–2006	AVHRR GIMMS 8 km	Productivity	Wang *et al* (2011)	65
Remote sensing	Negative	−0.2	Quebec	1981–2011	AVHRR GIMMS3g 9 km	Productivity	Girardin *et al* (2014)	75
Remote sensing	Negative *	−0.06	Northern Hemisphere	1982–2003	AVHRR GIMMS + MODIS	Productivity	Bunn and Goetz (2006)	85
Remote sensing	Positive *	0.06	Northern Hemisphere	1982–2003	AVHRR GIMMS + MODIS	Productivity	Bunn and Goetz (2006)	75
Remote sensing	Positive	0.06	Canada	1984–2011	Landsat TM L1T	Productivity	Sulla-Menashe *et al* 2018	35
Remote sensing	Positive *	0.2	World	1983–2005	AVHRR GIMMS + MODIS	Productivity	Zhang *et al* (2008)	95
Remote sensing	Positive *	0.3	Canada	1981–2003	AVHRR GIMMS	Productivity	Goetz *et al* (2005)	75
Remote sensing	Positive *	0.47	Northwestern America	1982–2011	AVHRR GIMMS 8 km	Productivity	Chen *et al* (2014)	75
Remote sensing	Positive *	0.56	World	1982–1999	AVHRR GIMMS	Productivity	Zhou *et al* (2001)	75
Remote sensing	Positive *	0.6	World	1984–2012	Landsat + AVHRR GIMMS 8 km	Productivity	Ju and Masek (2016)	35
Remote sensing	Positive *	0.75	World	1982–1999	GIMMS + Pathfinder PAL	Productivity	Nemani *et al* (2003)	85
Remote sensing	Positive	0.92	Saskatchewan	1984–2012	Landsat	Productivity	Boisvenue *et al* (2016)	45
Remote sensing	Positive *	0.94	Northwestern America	1982–1998	AVHRR GIMMS	Productivity	Hicke *et al* (2002b)	85
Remote sensing	Positive	0.97	Northern Hemisphere	1982–1999	AVHRR GIMMS + FASIR 1° + Pathfinder 1°	Productivity	Slayback *et al* (2003)	75
Remote sensing	Positive *	1	Northern Hemisphere	1982–1991	GIMMS 1°	Productivity	Angert *et al* (2005)	55
Remote sensing	Positive *	1	Canada	1985–2006	AVHRR GIMMS 1 km	Productivity	Pouliot *et al* (2009)	75

Table 3. (Continued.)

Observational method	Trend sign (a)	Standardized rate (% per year)	Geographic area	Studied period	Dataset origin	Ecological process	Reference	Uncertainty (b)
Remote sensing	Positive	1.25	Yukon, northern Quebec	1986–2006	AVHRR 1 km + Landsat 30 m	Productivity	Olthof *et al* (2009)	35
Remote sensing	Positive *	1.4	World	2000–2009	MODIS	Productivity	Zhao and Running (2010)	85
Remote sensing	Positive *	1.7	Northern Hemisphere	1981–1991	AVHRR GIMMS + Pathfinder	Productivity	Myneni *et al* (1997a)	75
Remote sensing	Positive *	2.4	World	1982–2009	GLASS LAI	Productivity	Zhu *et al* (2016)	75
Remote sensing	Positive *	2.5	World	1982–1990	AVHRR Pathfinder	Productivity	Kawabata *et al* (2001)	85
Remote sensing	Positive	3.75	Alberta	1982–2011	AVHRR GIMMS	Productivity	Jiang *et al* (2016)	75
Remote sensing	Positive *	8	Northern Hemisphere	1981–2000	AVHRR GIMMS	Productivity	Piao *et al* (2006)	75
Remote sensing	Positive *	10	Northern Hemisphere	1982–1999	AVHRR GIMMS	Productivity	Zhou *et al* (2003)	75
Remote sensing	Positive	NA	World	1982–1990	Pathfinder AVHRR	Productivity	Ichii *et al* (2002)	75
Remote sensing	Positive *	NA	World	1982–2000	AVHRR Pathfinder	Productivity	Tateishi and Ebata (2004)	55
Forest inventory	Negative	−20.8	Northwest Territories, Alberta, British Columbia, Saskatchewan, Manitoba, Ontario	2000–2005	Permanent sample plots	Productivity	Hogg *et al* (2008)	60
Forest inventory	Negative	−4.78	Alberta, Saskatchewan	1958–2011	Permanent sample plots	Productivity	Chen and Luo (2015)	60
Forest inventory	Negative	−2.61	Alberta, Saskatchewan, Manitoba, Ontario, Quebec	1963–2008	Permanent sample plots	Productivity	Ma *et al* (2012)	60
Forest inventory	Negative	−1	Alberta, Saskatchewan	1958–2011	Permanent sample plots	Productivity	Chen *et al* (2016)	60
Forest inventory	Negative	−0.64	British Columbia, Alberta, Saskatchewan, Manitoba	1958–2009	Permanent sample plots	Growth	Zhang *et al* (2015)	30
Forest inventory	Negative	−0.4	Manitoba	1999–2012	Permanent sample plots	Productivity	Bond-Lamberty *et al* (2014)	60
Forest inventory	Negative	−0.38	Ontario	1950–1989	NFBI	Productivity	Peng *et al* (2002)	60
Forest inventory	Positive	0.35	British Columbia	1959–1998	Permanent sample plots	Productivity	Hember *et al* (2012)	60
Forest inventory	Positive	0.55	British Columbia	1959–1998	Permanent sample plots	Growth	Hember *et al* (2012)	30
Forest inventory	Positive	1	Canada	1961–2011	Permanent sample plots	Productivity	Hember *et al* (2017)	60
Forest inventory	Positive	1.2	Saskatchewan	1984–2012	Permanent sample plots	Productivty	Boisvenue *et al* (2016)	60

Table 3. (Continued.)

Observational method	Trend sign (a)	Standardized rate (% per year)	Geographic area	Studied period	Dataset origin	Ecological process	Reference	Uncertainty (b)
Dendrochronology	Negative	−4	Ontario	1872–1999	Wood cores	Growth	Dietrich *et al* (2016)	75
Dendrochronology	Negative	−2.2	Northwest Territories	1982–2008	Wood cores	Growth	Berner *et al* (2011)	60
Dendrochronology	Negative *	−1	Northern Hemisphere	1951–2005	Chronologies	Growth	Tei *et al* (2017)	90
Dendrochronology	Negative	−0.9	Quebec	1950–2005	Permanent sample plots	Growth	Girardin *et al* (2012)	90
Dendrochronology	Negative	−0.1	Canada	1950–2002	Permanent sample plots	Growth	Girardin *et al* (2016a)	65
Dendrochronology	Negative	−0.086	Quebec	1950–2007	Permanent sample plots	Growth	Girardin *et al* (2014)	90
Dendrochronology	Positive	0.55	Saskatchewan, Manitoba	1950–1994	Wood cores	Growth	Brooks *et al* (1998)	90
Dendrochronology	Positive	0.57	Manitoba	1912–2000	Temporary sample plots	Growth	Girardin *et al* (2011)	70
Dendrochronology	Positive	1.4	Manitoba	1999–2012	Wood cores	Growth	Bond-Lamberty *et al* (2014)	90
Dendrochronology	Negative	NA	Northern Hemisphere	1902–2002	Chronologies	Growth	Lloyd and Bunn (2007)	90

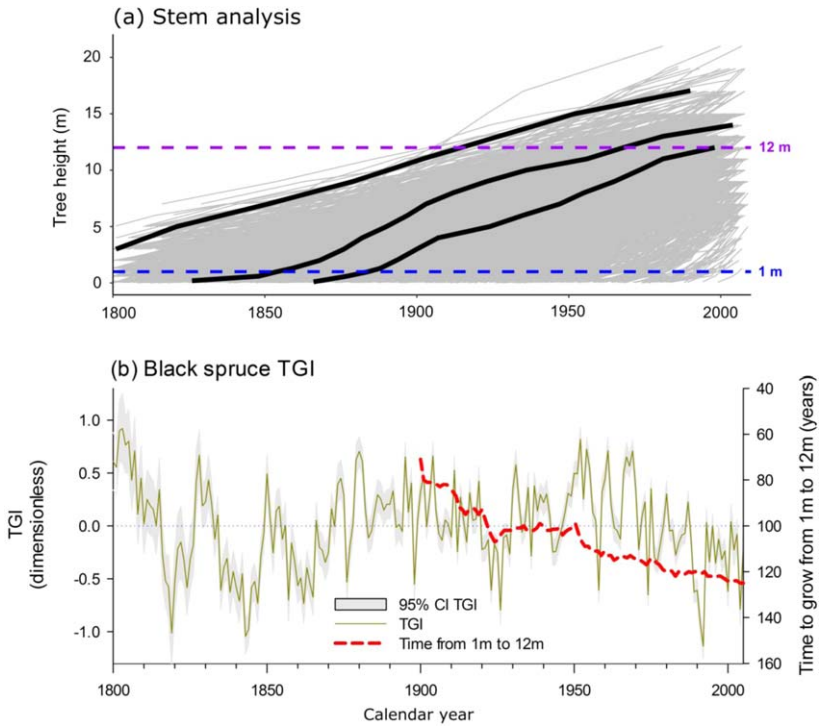

Figure 5. Cross-validation of forest growth trajectories using a combination of two different approaches. (a) Height-growth curves for *Picea mariana* trees north of the limit of commercial forests. (b) Time for a black spruce tree to grow from 1 to 12 m in height, superimposed on regional black spruce tree growth index (TGI, a unitless value computed as the average of detrended tree-ring width measurements) chronology, (data from Girardin *et al* 2014).

the time that was required for a black spruce tree to grow from 1 to 12 m was superimposed upon detrended mean annual basal area increments (BAIs) that were based on 200 plot-level chronologies (data from Girardin *et al* 2014). The time to grow from 1 to 12 m was computed as the difference between the age at which the tree reached the sampling height (calendar year attributed to the stem-section's ring of cambial age 1, minus calendar year attributed to the oldest tree-ring of the tree) and the age when reaching a height of 1 m. The two different approaches displayed a similar pattern of growth declines throughout the 20th century.

Given their broad geographical extent, remote sensing data must be used first to assess the geographical variation of productivity trends of forest ecosystems, as a general overview. Since suboptimal targeting of forested areas can bias productivity trends, the use of maps that include not only forest cover, but also site characteristics (rather than land use or land cover maps) is advised to locate forested stands accurately and to exclude non-forested regions. These maps can facilitate the linking of remote sensing-based trends with ecological parameters, for example, to differentiate trends between stands of different ages or compositions. For an even more accurate comparison with inventory- and tree-ring-based studies, one must target only pixels including field-sampled areas (e.g., Berner *et al* 2011, Girardin *et al* 2014). In a second step, forest inventory data must be used to target stands of interest, for example, to study the specific response of stands to climate change according to their age or density. Last, dendrochronological and height-growth data can be used to cross-validate trends at stand- and individual-levels, and to specify whether the observed trends are due to changes in stand demography (i.e., mortality rate or recruitment efficiency) or to modifications of individual growth rates.

Need for improvements

To improve comparisons between studies relying on forest inventory data and to increase the quantity of potentially usable data for meta-analyses, standardization of sampling protocols appears necessary (Peters *et al* 2015, Chen *et al* 2016). This is the particular goal of establishing Canada's National Forest Inventory program, which is a systematic or random sampling strategy that is applied across Canada's forests. Measurement of as many environmental variables as possible that are undertaken through this inventory will help determine potential drivers of growth trajectories.

Open datasets through public repositories (e.g. DRYAD[7], PANGEA[8]) have the potential to accelerate advances in environmental sciences (Wolkovich *et al* 2012), especially in the field of forest ecology where large datasets are highly valuable for global-

[7] https://datadryad.org.
[8] https://pangaea.de/.

scale studies (Soranno *et al* 2014). The collaborative effort that was initiated by the International Tree-Ring Data Bank[9] (NOAA, Boulder, CO, USA) to centralize and make available all data from dendrochronological studies (Grissino-Mayer and Fritts 1997) should be strengthened with data that have been collected from national and provincial forest inventories, together with unpublished data contributed by research laboratories (Babst *et al* 2017). Some authors highlight the lack of a systematic assessment of data quality (Goetz *et al* 2005, Gleckler *et al* 2008, Ju and Masek 2016), which is necessary to quantify trend accuracy. To this end, it would be a wise systematic strategy to include detailed metadata when sharing datasets, especially information regarding sampling methods and known biases (Daly 2006). Open data and metadata will also facilitate the attribution of a rate of uncertainty to the computed trends, notably through the dissemination of the size of the sampled population (e.g. number of pixels effectively accounted for, size of the area for which a positive versus a negative trend was observed) of remote sensing-based studies. Because of improved knowledge about what is already available and what is still lacking, data sharing could also stimulate data collection worldwide (Wolkovich *et al* 2012). Making data sharing a standard requirement for scientific publication (Whitlock *et al* 2016) could thus help filling the gap between studies whose primary aim is to assess forest growth and productivity from direct observations and studies more specific to other research fields, such as ecophysiology or genetics.

The trend detection step is an important source of uncertainty in dendrochronological studies. Most currently used detrending methods were developed with a view to reconstructing past climatic conditions from inter-annual to multi-centennial variations in growth rates; they are not necessarily appropriate to quantify and assess long-term growth trends. More flexible statistical methods that are capable of retaining both long- and short-term growth trends would allow analysts to adapt detrending procedures to these emerging objectives. Because trees respond individually to environmental gradients, the trend detection step should be performed at the individual scale. The challenge for unbiased detrending is to accurately distinguish and remove the proportion of long-term trend that is induced only by the tree's biology (age and size), and to retain the signal that originates from both environment and climate. Currently, the GAMM-based approach seems the most appropriate method because it allows for some control over what trend is being removed from the raw chronology, given the possibility for including some environmental variables. An approach that permits the determination of an average biologically-induced growth trend at the individual scale, such as the C-method that was developed by Biondi and Qeadan (2008) for shade-intolerant species, also seems promising. Some work should be done to adapt this method (i.e., the underlying mathematical equations) for slow-growing boreal species. Dendroecologists are increasingly attempting to move away from detrending, for example, by using BAI instead of TRW or by combining TRW data with inventories (Evans *et al* 2017). Pending these improvements, the suggestion of Peters *et al* (2015) and Girardin *et al* (2016a) to test and compare different detrending methods for cross-validating the resulting growth trends is meaningful. This comparison should be supplemented by an assessment of the effects of coring or harvesting height on the accuracy of the detrending step (Autin *et al* 2015).

[9] https://ncdc.noaa.gov/data-access.

Conclusions

Throughout this systematic review, we have highlighted several elements that contribute to the divergences observed in growth and productivity trends of Canadian forests. By the different working scales and physiological processes considered, observational methods utilized when assessing forest trajectories are suitable to test a broad range of ecological hypotheses, both from an applied and a more theoretical standpoint. Concurrently, these differences prevent an accurate comparison between studies. Trend calculation is also affected by several biases that are inherent to these methods, which further contributes to the observed variation in growth and productivity trends. Because the biases for over- and underestimation are comparable across these methods (table 2), we cannot attribute contrasting results from growth or productivity trend estimates simply to these scale and methodological concerns. The inability either to control or to measure some ecological or disturbance-related processes when working at a broad geographical scale is an additional difficulty that impedes the comparison, cross-validation, and joint use of datasets from multiple observational methods.

Several improvements would help clarify the current and future trajectories of forest communities. We argue that we must work towards generalizing growth trends that are inferred from dendrochronological studies and productivity trends from forest inventories. In proceeding in this manner, one must be careful about sampling biases and the degree to which plot networks are representative of the focal area. Better sampling strategies (Nehrbass-Ahles *et al* 2014, Babst *et al* 2017), together with integration of remote sensing (e.g. Jucker *et al* 2017) or forest inventory data (Evans *et al* 2017), could help. A co-integration approach is a means of emphasizing the respective advantages of each method, while limiting their respective disadvantages. The study of a recent and common period of time, a better targeting of the data, a focus on recently regenerated stands, and a hierarchical use of different types of data would provide a better idea of changes that have recently occurred in growth and

productivity rates of forest ecosystems. Finally, harmonized sampling protocols, together with a revision of some empirical, but out-dated data processing procedures and a generalization of open datasets would improve the accuracy of the resulting trends.

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