A review of progress and applications in wood quality modelling

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# Abstract

Purpose of review

Producing wood of the right quality is an important part of forest management. In the same way that forest growth models are valuable decision support tools for producing desired yields, models that predict wood quality in standing trees should assist forest managers to make quality-influenced decisions. A challenge for wood quality (WQ) models is to predict the properties of potential products from standing trees, given multiple possible growing environments and silvicultural adjustments. While much research has been undertaken to model forest growth, much less work has focussed on producing wood quality models. As a result, many opportunities exist to expand our knowledge.

Recent findings

There has been an increase in the availability and use of non-destructive methods for wood quality assessment in standing trees. In parallel, a range of new models have been proposed in the last two decades, predicting wood property variation, and as a result wood quality, using both fully empirical (statistical) and process-based (mechanistic) approaches.

Summary

We review here models that predict wood quality in standing trees. Although other research is mentioned where applicable, the focus is on research done within the last twenty years. We propose a simple classification of WQ models, first into two broad groupings: fully empirical and process-based. Comprehensive, although not exhaustive, summaries of a wide range of published models in both categories are given. The question of scale is addressed with relevance to the range of possibilities which these different types of models present. We distinguish between empirical models which predict stand or tree-level wood quality and those which predict within-tree wood quality variability. In this latter group are branching models (variation up the stem) and models predicting pith-to-bark clear-wood wood property variability. In the case of process-based models, simulation of within-tree variability, and specifically, how that variability arose over time, is always necessary. We discuss how wood quality models are, or should increasingly be, part of decision support systems that aid forest managers and give some perspectives on ways to increase model impact for forest management for wood quality.

## Keywords

Cambial model; Xylogenesis; Projection model; Model ensembles; LiDAR; Within-tree variability

# Introduction

Producing wood of the right quality, in addition to merely maximising yield, is an increasingly important goal in forest management [1–4]. To match forest growth and management to planned forest products, however, it is necessary to be able to know something about both the future quantity and quality of the wood within the standing resource [5,6]. As such, a modeller or manager may ask several questions.

* What will the effects be of environment and forest management decisions on tree growth and wood properties?
* How will these wood properties influence the wood quality?
* Can we reliably predict how changes will occur in a stand of growing trees in the future?

Being able to predict the quality of potential products from standing forests, given an almost infinite set of possible growing environments and silvicultural adjustments, remains one of the great challenges for forest modellers in the coming decades. To fully evaluate management alternatives, a view of both wood quantity and quality implications is required [7].

In the area of forest growth and yield, scientists have a long history of modelling using advanced mathematical approaches [7,8]. When looking at the published literature, however, it is evident that wood quality (WQ) modelling lags forest growth modelling. A recent Web of Science analysis[[1]](#footnote-1) returned 11,869 results for the phrase “forest growth model”, compared to only 2,151 for “wood quality model”. Based on an analysis of publications over time, however, there has been a rapid increase in articles with this topic since approximately 20001.

To give perspective on work in this broad area, we summarise and discuss here research progress in WQ modelling in the last two decades on models that predict wood properties in standing trees with a view to the quality of wood formed into final products. Our focus is on work that describes models using environmental/time-based predictors. We do not explore the wide body of literature that reports WQ differences in general, or which deals with genetic correlations with wood quality traits. We take the term “wood quality” to incorporate a set of wood properties in the bole of the tree which qualify it for a particular product. That is, although wood from one tree with certain properties may be suitable for one product (e.g., pulp), it would be poor quality for another (e.g., clear veneer). We focus on those properties of wood that are inside the stem, and in this review do not address work done to model quality issues arising from poor stem form or visible defects and the resultant losses in product recovery.

Our approach to selecting literature was pragmatic. As a point of departure, publications in the primary, peer-reviewed literature returned with a search phrase including “wood quality” + “model/s” using Clarivate’s Web of Science[[2]](#footnote-2) were considered. Those publications which dealt specifically with research in which one or more wood property was used for predictive modelling in standing trees (not just measured or considered in an analysis, as per the scope defined above), was included. From this baseline, additional aspects pertaining to wood quality modelling were added to the narrative. A limited number of references are included from between 1990 and 2001 when they are either important pieces of work in the field, or necessary to ensure clarity and context. In addition, some foundational publications on cambial modelling published sixty years ago are also cited.

Given that models allow us to continually test and evaluate what we know (or think we know) and summarise what we do not [7], it was our goal that this overview would contribute to a better perspective on where progress has already been made and to target research activity in the future.

# Having your trees and the data too

The lag in WQ modelling compared to growth modelling research is possibly because the variables required for predicting volume yield from a standing forest (e.g., height, tree diameter, stand density) can be measured cheaply, multiple times and with relative ease. WQ data, on the other hand, although long-studied [9], are harder and more expensive to obtain and may require the destruction of the tree. As such, it is likely that a major factor in the advancement of WQ modelling in recent years has been the development of several technologies for non-destructively measuring wood properties in standing trees at high spatial, and sometimes temporal, resolution [5,6,10]. Wood density is the most common property measured, as it is relatively easy to obtain and linked to many aspects of tree survival and wood product quality [11,12]. However, tools have also been developed for a multitude of other quality-related variables, including cell morphological properties and wood chemical and physical properties [5,6,12–14].

Some instruments have been developed for predicting tree-level and log-level wood density using penetrative depth or acoustic velocity, such as Pilodyn (Hylec Controls[[3]](#footnote-3)) or ST300 (ABB[[4]](#footnote-4)), respectively, as well as ultrasonic techniques [6,15].

Other methods provide within-tree wood property data, usually pith-to-bark variability, from wood samples. These data are key for modelling wood formation and wood quality variability over time. A good example is the SilviScan system, developed by Robert Evans and colleagues at the Australian CSIRO [16,17]. SilviScan remains a reference technology against which many other systems and approaches are compared [6]. Researchers have also effectively used technologies such X-ray CT scanning to derive data on wood density as well as fibre/tracheid/vessel dimensions in 3-D [18–21]. Recently, CT scanning has even been used for visualisation of the cambial zone [22] which has great potential for calibrating detailed, process-based WQ models. Other interesting methods for rapid cambial zone characterisation include block-based fluorescence imaging [23], eliminating the need for time-consuming sample embedding and sectioning. The use of near infra-red spectroscopy, and especially when applied using customised scanning systems allowing for pith-to-bark trends, has made it possible to get detailed pith-to-bark information about properties like pulp yield, cellulose and lignin content and even propensity for non-recoverable collapse [24,25].

A third type of technology provides pith-to-bark information without requiring a wood sample to be taken, such as resistance drilling (Rinntech Resistograph and IML Power drill or “Resi”). The use of the Resi tool for rapid assessment of standing tree and log density and stiffness has been a subject of increasing research in Australia and in New Zealand in recent years [1,26]. Multiple sawmill studies in *Pinus radiata* have demonstrated strong relationships between Resi data collected from standing trees preharvest and the board volume and quality [27] and is an important part of evolving WQ modelling research in Australia.

Although they involve destroying the tree (to obtain a full disc sample) two other options are worth noting. The first is the Scion DiscBot system[[5]](#footnote-5) in New Zealand which is capable of measuring a wide range of wood quality variables [5]. The second is the use of ultrasonic velocity estimates on whole discs which rapidly gives within-tree information, but at fairly coarse resolution [28].

# Model scale and resolution

There can be a confusing discrepancy between the variation in wood properties (e.g., fibre wall thickness from pith to bark) and the environmental drivers of the observed effects, which are of varying duration and intensity. This problem was, in fact, a basis for the development of early modelling concepts which sought to clarify dendroclimatology relationships [9]. The question is: exactly *when* did a particular portion of wood form?

Consequently, the literature on site and silviculture effects on pith-to-bark variation sometimes seems contradictory. Downes and Drew [29] attempted to explain some of the sources of confusion by discussing how the average rate of growth can be the net effect of markedly different rates of growth over the life of a tree. Accordingly, two trees of the same age and species can have very different wood properties. This averaging effect also applies at the sub-annual level so that correlations between ring width and wood density can produce confusing results [30]. Models of WQ, particularly those that deal explicitly with processes of wood formation, provide a platform to make sense of these interpretive difficulties.

## Scaling for impact

Wood property and quality models cover scales from the forest to the cell, and from annual timesteps to seconds. Models that predict fundamentally at a fine scale (e.g., cell or tissue) may not, however, be the best predictor of WQ outcomes at stand or regional scales [13]. Model selection should consider the scale at which processes of wood formation occur, as well as the scale at which final predictions will be interpreted. Is it necessary to model wood density variation at the cell level if a stand-level ranking of stiffness grade is all that is required? Probably not.

Technology advances are also playing a growing role in defining model scale and scalability. Remote sensing systems are becoming important in scaling model outputs from WQ models. In forest plots where wood property variation is driven by forest structure, aerial and terrestrial laser scanning (ALS and TLS) show great promise as tools for scaling wood properties predictions to stand scale [31,32]. Statistical descriptors of forest structure obtained from ALS data have been linked to wood properties measured in sample plots to produce landscape-level predictions of wood properties variation [31,33–35]. Despite these advances, however, explicit consideration of the known drivers of variation in wood properties remains scarce in multi-scale models, which may limit the degree to which they can be generalized. Nevertheless, because the accuracy of such models depends largely on the quality of field reference data [36], fusion of TLS and ALS data can facilitate the transferability of predictions across multiple scales [32,37].

# Approaches to modelling WQ

Forest growth models are generally classified according to type, spatiotemporal resolution, stochasticity and distance dependence [2 ; p 13] (Figure 1). In attempting to group WQ models we have focussed here on the first two aspects. For WQ models we can distinguish between process-based (mechanistic) and empirical. We can then further consider models at varied levels of scale, and two broad groups emerge. First, models that resolve processes at the tree or stand level only, predicting WQ variables such as pulp yield per hectare at those levels directly. Second, we consider models which resolve within-tree variability, outputs of which are often scaled-up to the tree or stand level. In this second category, three groups can be distinguished: branching/knot models, pith-to-bark “clear-wood” models and models of secondary change. Of the models that predict within-tree variation in clear-wood properties, we deal with two broad types: those that take a projection-type approach (with some expression of cambial age as the major independent modelling variable) and those that take a process-based approach (which model finer-scale physiological and developmental processes).

## Empirical models

### Models of stand- and tree-level variables

A variety of empirical models exist to derive WQ from a multitude of tree, stand and environmental variables. Work by Moore et al. [38] in *Picea sitchensis* (Sitka spruce) is a good example of research at this scale in which multiple regression was used to explain 45% of the variation in dynamic modulus of elasticity (MOE) as a function of yield class, elevation, latitude, longitude and initial spacing. Lenz et al. [39] used various modelling techniques in Canadian *Picea glauca* to explore effects of environment on wood properties, revealing that maximum temperature, degree days, geographic location, tree height, and tree diameter were most important. In New Zealand *Pinus radiata*, 13 variables were linked to dynamic MOE, of which minimum temperature in March and tree slenderness (tree height/diameter) correlated most strongly [40]. Interestingly, stem slenderness and average winter temperature, along with average leaf area index (LAI), were also the best variables for explaining MOE in New Zealand Cupressus lusitanica [41].

More recently, machine-learning approaches are finding application in WQ modelling. For example, the regional-scale models of wood density, microfibril angle (MFA) and MOE in *Eucalyptus nitens* developed in Tasmania, Australia, with respect to tree characteristics, plantation age, environmental and climatic variables used an implementation of the Random Forest ensemble learning method [42]. Also in Tasmanian *E. nitens*, mixed-effects (ME) models were successfully developed for predicting wood density as a function of tree size, temperature, and precipitation extremes and for wood stiffness using tree slenderness, height, density and various site variables [43]. Another method, the use of classification and regression trees (CART), was a useful method for modelling a range of pulp characteristics using the sapwood and heartwood proportion in *Acacia melanoxylon* [44]. Predictions at the stand/regional level based on environmental variables and silvicultural practices provide a valuable method of mapping properties relevant for wood quality at a scale that is relevant to strategic planning.

### Branching and knot models

When linked back to forest growth models, empirical approaches to predict branch and knot distributions and sizes perform well [45], and this approach is commonly used. Trincado and Burkhart [46] linked branching algorithms to outputs from individual tree growth models, which gave promising results in *Pinus taeda*. In Benjamin et al. [47], a combination of modelling techniques were used in *Picea mariana* in Canada to capture the positive relationship between available growing space and crown size and branch size.

Non-linear ME models are some of the best options for modelling branches because they are nested at individual whorl, tree, and stand levels [48]. A set of non-linear models to predict branch and knot positions and diameter in *Picea mariana*, for example, gave good results [49]. Using non-linear ME models, maximum branch diameter was modelled from stand basal area, tree height and crown length for multiple Canadian forest species (conifers and hardwoods) [50]. Diao et al. [51] developed a stochastic model to predict development of topology in eucalypts. This work, unusual in that it was focussed on *Eucalyptus* spp. (*E. grandis x E. urophylla*) successfully predicted growth and branching as a function of probabilities of activity in apical and lateral buds [51]. Zubizarreta-Gerendiain and Fernández [52] successfully used stochastic Markov chains to model branch sizes in clusters in *P. radiata* (a polycyclic species). Other authors have taken a more process-based approach to predict branch numbers, such as the PipeQual modelling work done mainly in *Picea abies* [53]*.*

Some branching models work in a hierarchical way, linking to forest growth models. The New Zealand-developed TreeBLOSSIM model, for example, which was linked to forest growth and yield simulators to predict branching patterns up the stem, is a useful tool for forest management decision support in *P. radiata* (Figure 2b) [54]. Another branching model, linked to the individual tree model ORGANON, was developed by Osborne [55], and also applied to *P. menziesii*.

To provide insights about WQ, however, branching models must translate into knot models. The implementation of non-linear models, at least for the pith-to-bark pattern of branch trajectories, is generally suitable when knots are seen in longitudinal stem sections, particularly with increasing age and depth into the crown [55]. The TreeBLOSSIM modelling system provides a link between tree and branch growth and wood properties (Figure 2c) [56] and enables simulation of the effects of thinning and stand density on branches and knots [57]. Using data from trees of a range of ages, some branching models offer the possibility to simulate branch development over multiple years [58,59]. By assuming that the characteristics of a branch become that of the knot embedded by the next annual growth ring of the tree stem, such models can produce knot development predictions. However, in the absence of longitudinal data to describe branch ontogeny, these representations can be overly simplistic and unrepresentative of the true complexity of knot morphology. Techniques like TLS can help. Researchers looking at *Pinus sylvestris* in Canada found TLS a potentially excellent source of branching parameters as inputs into wood quality models [60]. Longitudinal data can also be obtained through X-ray CT scanning [49,61,62], facilitating the development of dynamic models capable of simulating knot ontogeny using the predictions of tree growth models as input.

### Prediction of pith-to-bark variability using projection-type models

Many empirical approaches aim to model wood property variability from pith to bark. Non-linear models of varying complexity have been widely and successfully employed by a number of authors, generally predicting changes in properties (e.g., wood density) over time, where time or age (often called “cambial age”) is represented frequently as ring number from pith, or by years [63]. Depending on the wood property being measured, different models may better capture the variability better than one single type [64]. In the last decade increasing use has been made of ME approaches that more fully account for hierarchical structures in these data [65]. Newton [66], for example, used ME with cross-validation, while research in *Betula platyphylla* found that a ME logarithmic model worked well [67]. Generalised additive mixed models (GAMM) have also proved to be a viable simulation method for differentiating between intrinsic and extrinsic control of wood properties [68]. A summary of models is given in Table 1 which, although not exhaustive, gives a wide overview of some key studies in the last two decades, in which projection-type wood quality models have been developed for a wide range of species. Notably, however, softwood species are far more represented, and wood density has been the most modelled variable.

Table 1: A summary of some key studies in the last two decades that have developed models of wood density (WD), microfibril angle (MFA), modulus of elasticity (MOE) and other properties using a projection approach with ring number, cambial age or a relative expression of distance from pith as primary predictor. Note that in studies where MOE is predicted, this is usually derived from WD and MFA.

| Authors | Species | Predicted variables | Predictor variables (in addition to age/ring number) |
| --- | --- | --- | --- |
| Antony et al. [69] | *Pinus taeda* | MOE | Stand density |
| Antony et al. [70] | *Pinus taeda* | WD | Fertilizer application |
| Auty et al. [65] | *Pinus sylvestris* | MFA | ring width |
| Beets et al. [71] | *Pseudotsuga menziesii* | WD | Temperature |
| Dahlen et al. [72] | *Pinus taeda* | Tracheid length, width | Position up the stem, region |
| Erasmus et al. [73] | *Pinus patula* | Stem straightnessMFAWD | Stand density |
| Erasmus et al. [74] | *Pinus patula* | MFAWD | Stand density |
| Erdene-Ochir et al. [67] | *Betula platyphylla* | Wood fiber length, vessel element length, basic & air-dry WD | - |
| Gardiner et al. [75] | *Picea sitchensis* | WD | Ring width |
| Gogoi et al. [76] | *Pinus kesiya* | WD | Distance from pith, ring width and growth rate |
| Guilley et al. [77] | *Quercus petraea* | WD | region, silviculture, site quality |
| Jordan et al. [78] | *Pinus taeda* | MFA | Position up the stem |
| Kimberley et al. [79] | *Pinus radiata* | WD | Position up the stem, site |
| Lundqvist et al. [68] | *Picea abies* | Tracheid dimensionsTracheid number | Climatic variables |
| Moore et al. [80] | *Pinus radiata* | Spiral grain | Region, Position up the stem |
| Moore et al. [81] | *Pinus radiata* | MFA | Position up the stem |
| Newton [66] | *Pinus banksiana, Picea mariana* | WD, MFA, MOE, fibre coarseness, tracheid wall thickness, tracheid radial and tangential diameters and specific surface area | Tree size |
| Nezu et al. [64] | *Shorea macrophylla* | wood fiber length, wood fiber wall thickness, WD, vessel element length, vessel frequency, vessel diameter wood fiber diameter | Diameter growth |
| Filipescu et al. [82] | *P. menziessii* | WD | Stand density, average temperature from March to May, total precipitation from April to August |
| Sarkhad et al. [83] | *P. sylvestris*, *P. sibirica*, *P. obovata*, and *L. sibirica* | tracheid length, MFA, WD, and shrinkage | - |
| Todoroki et al [84] | *Cupressus lusitanica, C. macrocarpa, Chamaecyparis nootkatensis x Cupressus macrocarpa* | WD, MFA | Taxon, ring width, aspect. |
| Vega et al. [85] | *Eucalyptus nitens* | WD, MOE | Region |
| Xiang et al. [86] | *Picea mariana* | WD | Position up the stem |

The transition from so-called juvenile (or corewood) to mature wood (or outerwood), and the subsequent size of the juvenile core in proportion to total stand volume, is an important part of pith-to-bark variability [87]. Juvenile wood is almost invariably of a lower quality. Therefore, to estimate the fraction of juvenile wood, much research has focussed on establishing this boundary. That is not a simple task because the transition is seldom clear or abrupt. A number of authors have modelled the transition using empirical approaches [88–93], generally with reasonable success. Modelling approaches need to take into account that the transition between juvenile and mature wood may be quite different depending on the wood property of interest (e.g., wood density vs. longitudinal shrinkage) [90,94].

Besides intrinsic (cambial age and tree age) variables, climatic and site/soil variables can modify different wood properties. For example, in Douglas-fir growing in New Zealand, Beets et al. [71] found that outer-wood density was positively related to mean annual air temperature. Lundqvist et al. [68] accounted for intrinsic variables (cambial age and tree age) and extrinsic variables such as growing degree days and precipitation in four quarters of the vegetation period to simulate ring width, tracheid numbers and dimensions in *Picea abies* in Sweden. Distinct differences were found depending on whether cambial age or tree age were used as predictors in young trees. An area of opportunity for future research is around how to best include environmental and site variables in projection-type models.

It is also important to be able to incorporate silvicultural interventions in these models to adjust the relationship between environment, growth rate and wood properties [12,95]. Incorporation of responses to silviculture in models is necessary to reﬁne silvicultural practices for achieving maximum value [7]. Studies have shown that ring width alone cannot act as proxy for the effects of environmental conditions on wood properties and additional terms must be included to allow silvicultural treatments to contribute independently and significantly to predicted wood property variation [73,74,95]. Models predicting wood property variation as a function of silviculture, however, are still relatively rare[12] and research in this direction will therefore be an important contribution to modelling research in general.

### Models for predicting secondary changes

Apart from models focussing on properties in healthy wood that are the result of growth processes, a small number of models have also been developed to simulate secondary changes to wood. Examples are models of resin pockets that are induced defence investments of the tree and affect WQ. Seifert et al. [96] modelled resin pocket probability as a stochastic process based on height in the tree, crown length ring width, precipitation and wind speed with Generalised Linear Mixed Models (GLMMs). Work to model the environmental drivers of resin pockets in New Zealand *Pinus radiata*, and their within-tree variation, was partially successful, with occurrence predominantly in the transition zone from juvenile to mature wood [97]. Other models have been developed for predicting aspects like fungal stem decay in concert with spatially explicit growth simulation [98,99]. However, recent research in this area appears to be lacking, and there is need for more work on wood degradation and other secondary changes in standing trees.

## Hybrid and process-based models

Process-based models are mathematical representations of biological processes in systems of fundamental interest. In forestry, several process-based growth models exist which vary widely in complexity and scale [100], although the majority are at tree or stand level. Models of this kind which deal specifically with wood formation and wood quality are, by contrast, far less common.

### Branching models

Seifert [101] developed a spatially explicit branching/knot model AMOK for *Picea abies* as an integrated part of the individual tree-based distance-dependent growth simulator SILVA [102]. The model was developed with the aim to simulate any mode of growing space. The 3D branching model simulated whorl distances based on SILVA tree height growth and projects branch growth dynamically as a stochastic process from whorl age and branch individual competition for light in different directions of the tree (Figure 2a). Also using a mechanistic approach, Fernández et al. [103] proposed a functional-structural model of branch development in *Pinus radiata* that realistically reproduced patterns seen in sampled trees (Figure 2d, e).

### Cambial/xylogenesis models

The first, albeit conceptual, model of wood formation initiated a fascinating discussion about formal definitions of cell types and zones in the developing wood [104] which led to ongoing interaction within the scientific community (which at the time consisted of, for example, well respected wood scientists Brayton F. Wilson, Alan Wardrop, and Irving W. Bailey). They discussed the necessity of a clear definition of the cambium, cambial initials, and mother cells for scientific purposes as well as for teaching. Four years later, the first process-based model of wood formation was published by Wilson and Howard [105], using clear terms such as cambial, enlarging, thickening, and mature cells. This framework of wood formation still forms the building blocks of the xylogenesis concept in the newest models [106–109].

A recent review by Eckes-Shephard et al. [110] gives a comprehensive overview of 17 xylogenesis models from different disciplines (e.g., forestry, dendroclimatology and fundamental research). Of these, we summarise here models produced in the last twenty years which have potential application for wood quality predictions (Table 2). Other models, e.g., the models of Cabon et al [111] or Schiestl-Aalto et al. [112] (not listed in Table 2), provide useful predictions of tracheid production rate, but not tracheid properties as such.

Process-based wood formation models typically include sub-modules at the cell- or tissue-scale. Cell types (cambial, enlarging and thickening cells) are generally modelled explicitly and in sequence. This means that intra-annual environmental conditions can influence simulated final cell anatomy in complex ways. Many models also resolve these processes beyond the differentiating xylem itself (e.g., across the newly forming ring), which enables them to explicitly resolve the radial diffusion of water, and compounds such as sugars or hormones. This modelling structure is inherently useful to deal with the scale issues mentioned previously.

Table 2: Summary of inputs and wood-quality related outputs from a range of xylem development models (adapted from Eckes-Shepard et al [110]). TWT = tracheid wall thickness, TRD = tracheid radial diameter, WD = wood density, MFA = microfibril angle, VD = vessel diameter, FRD = fibre radial diameter, FWT = fibre wall thickness.

| Authors | Species | Predicted variables | Input variables |
| --- | --- | --- | --- |
| Carteni et al. [113] | *Larix decidua, Pinus cembra, Picea abies, Picea mariana* | TWT, TRD | Carbohydrates |
| Drew and Downes [114] | *Pinus radiata* | TWT, TRD WD, MFA | Xylem water potential, carbohydrates, temperature |
| Drew et al. [115] | *Eucalyptus* spp*.* | FWT, FRD, VD WD, MFA | Xylem water potential, carbohydrates, temperature |
| Friend [116]  | *Conifers* | WD, TRD | Temperature, carbohydrates |
| Hartmann et al. [117] | *Abies alba* | WD, TRD | Two signalling compounds |
| Hartmann et al. [118] | *NA* | TRD | Signalling compound concentration |
| Hölttä et al. [119] | *Pinus sylvestris* | TWT, TRD | Xylem water potential, carbohydrates, temperature |
| Vaganov et al. [120] | *Conifers* | TRD | Soil water content, temperature, daylength |
| Wilkinson et al. [121] | *Pinus pinaster* | WD, TRD, TWT | Temperature, soil water content, carbohydrates |

Modelling a complete radial cell file at the end of the growing season is equivalent to a tree ring cross section that is derived of a single line of cells. From this model output, many features relevant to WQ can be derived. Cell anatomical features such as cell diameter and wall thickness can be used to compute a density profile across the ring. From there, other possible variables are the proportion and density of Earlywood, Latewood and Transition wood (where applicable). These models rely heavily on being able to capture the key dynamics of cell production, expansion and wall thickening rates and durations, the important interplay between which was shown by Cuny et al. [122].

A problem that remains a major limitation and challenge for mechanistic wood quality modelling is, however, how to properly predict the causes and drivers of the variability in xylem developmental rates and durations. Perhaps for this reason, models that operate at this scale are not easily implemented, require data and parameter estimates that are very expensive or difficult to obtain and that are not immediately useful for predicting WQ. There are disagreements between modelers as to the mechanism and most important environmental or internal driver for each process [110,123,124], which makes the choice of wood formation model for forestry applications in widely varying locations difficult. Most models, however, show good correspondence to data in the areas and environmental conditions for which they were developed in the first place [114,115,120,121].

Despite gains in this fundamental area of WQ research our understanding of cambial and xylogenesis biology remains limited [124,125]. Although in the short-term basic xylogenesis research may seem to lack clear commercial outcomes, progress with modelling at this scale will require more fundamental research foci [109,126].

### Using model ensembles

Ensemble simulations could be used to mitigate against structural uncertainty in models and to reduce run-time and computational demands. For practical reasons, a hierarchical approach is sometimes used in xylogenesis modelling. In such an approach, WQ models build on the outputs of growth models, even stand-level models, which can potentially be an efficient and powerful way to subsequently model wood formation at varying levels of complexity.

Stand-level process-based or hybrid forest growth models like 3-PG [127] or CABALA [128] are generally very good at simulating stand- or ecosystem-level light interception, gross primary production (GPP), respiration, and evapotranspiration [129]. Models that use this approach can be expected to be acceptably accurate for long simulation periods (> 4 years from planting) and for “green field” scenario testing, as well as dealing with mixed species forests and changes in resource availability, climatic conditions, disturbances, management effects and other changes [130,131]. Taking advantage of these aspects, Ikonen et al [132] in *Pinus sylvestris*, Drew et al. [115] in *Eucalyptus* spp. and Drew et al. [114] in *Pinus radiata* used process-based growth models for primary predictions of forest development, and wood properties were simulated subsequently. Ongoing work in Australian *Pinus radiata* has led to the development of revised modelling approaches which build on a modified version of the 3-PG model (Figure 3). This approach works “backwards”, first predicting what kind of properties are likely to arise under a set of environmental/silvicultural circumstances. Subsequently, the number of cells with that particular property which can be “built” with the allocated amount of carbohydrate is calculated by the model.

# Making decisions: When WQ models meet forest management systems

In many regions the financial incentive for forest growers is to maximise the merchantable volume over a rotation, resulting in harvestable volume at younger ages. Unfortunately, this frequently results in a higher proportion of juvenile core, with its generally undesirable wood properties (low density and stiffness and greater tendency for distortion) [133,134]. The complexity of factors interacting to maximise the value of plantations needs to be understood to make the best commercial decisions. Some of these factors can be managed by the forest grower (site selection, genotype, stocking, thinning regimes, harvest age) whereas others cannot (rainfall patterns, market demands, financial markets) (Figure 4). It is important to understand wood quality variation in a forest landscape for management and planning [135] so that ultimately, by better understanding and quantifying wood quality, financial incentives can shift towards maximising overall value rather than just volume. Modelling wood properties as a function of climate, soils and physiological responses would be well directed at a holistic commercial outcome. WQ models should allow for decisions on options like thinning, species mixtures, rotation length that permit interaction between end-users, model developers, and different scientific disciplines [136] to get the best overall returns.

The within-tree, ring-level wood density modelling approach taken in New Zealand is a good example of an approach in which independent wood density model/s are linked back to models incorporated in systems such as the Forecaster platform [137,138] providing unambiguous decision support. Another is from Canada, where Li et al [139] extended forest inventory by developing a modelling system that includes wood fibre attributes and wood density (and other variables) to explore landscape scenarios by assessing forest value. This is particularly useful when a forest is used for varied purposes. The models of Newton [66] were developed to be incorporated in appropriate stand density management models, to assist in silvicultural decision-making. In Australian *Pinus caribaea* a software based system was developed to support silvicultural decision support by predicting links between wood quality, stand density and rotation length [140]. Xue et al. [141] looked at approaches that optimized thinning regimes and rotation length using the PipeQual process-based model (which takes the PIPE model as a basis for wood QUALity predictions). They found that implementing the differential evolution (DE) algorithm (that iteratively finds a candidate solution relative to a measure of quality) for stand management optimization was the most reliable.

## Taking the models to the managers

In the authors’ experience, for any prediction tool to be accepted and utilised commercially, it must have (1) the trust of users (they must believe the predictions, often through multiple stages of validation), (2) a simple user interface and (3) easily attainable and not too many input data requirements. While various systems with these attributes exist as decision support for forest management, clear communication is still needed between wood quality modellers and the developers of growth and yield simulators to implement WQ aspects into decision support tools [135]. It is still rare to find a system that allows exploration of the effect of management scenarios on wood quality.

One example of an interface, designed with these issues in mind, is in ongoing development with the Australian softwood industry to allow access to a simulation system for WQ variation. A demonstration version is presently available for testing at <https://forestquality.shinyapps.io/rCambium/>. The tool pulls data from the SILO interpolated weather surface [142] and from the ASRIS interpolated soils database [143], both available for the whole of Australia. It gives users the opportunity to run simulations without having to find these data for themselves. All that is needed is a location and information about the species and basic forest management. The simulation system provides visual representations of expected board grades that is easily interpreted (Figure 5). Hopefully, ongoing research in this area with an incentive to produce better quality WQ models, will lead to improvements in the simulation algorithms and the quality of the readily available input datasets.

It is also frequently of value to be able to understand wood quality predictions in terms of economic returns. Using the growth and board-strength simulation model of Poschenrieder et al. [144], Rais et al. [145] quantified the financial trade-off between growth and timber quality in young stands depending on variable silviculture. This kind of value-based output from forest growth and wood quality modelling is increasingly important and should not be neglected in applied research.

### Model applications for forecasting future WQ

A number of studies have been undertaken using forest growth models, particularly process-based models, to predict forest growth, yield and mortality under various future climate scenarios [e.g. 146–149]. Similar work exploring the potential impacts of changing climate on WQ is rarer. Drew et al. [150] considered the possible impacts of increasing temperature and variable rainfall on wood density in Australian plantations using a cambial model in conjunction with the CABALA process-based model [128]. The simulation predicted different outcomes for different regions, but generally forecast a decrease in wood density with increasing rainfall, and variable responses to temperature. Stoehr [151] modelled future wood density in south western British Columbia (Canada) and found that wood density reductions can be expected in the present range of coastal Douglas-fir. Given the uncertainty in future global climate, including WQ modelling into forest management forecasting systems is of great relevance to foresters, for better-informed decision making.

# Conclusions

A considerable amount of research has been focussed in the last several decades on producing forest growth models, but with far less work done in developing wood quality models. Ease and expense of data acquisition is likely a major factor in this, but the increasing availability of high-resolution wood quality data from standing trees can be expected to support an increase in wood quality modelling research. Wood density is the most common wood quality variable measured and modelled, with a number of studies also modelling anatomical characteristics (e.g., tracheid diameter) and MFA and derived variables like wood stiffness. Scale becomes an important question when making these predictions, and users need to be careful to select a modelling approach that does not unacceptably propagate error, on one hand, or inadequately capture resolution, on the other. Both process-based and fully empirical methods have been successfully used in wood quality models. In the former case, modelling within-tree variability and, specifically, how that variability arose over time, is always necessary. This is not the case with empirical approaches which may not give predictions of WQ variability at the tree or even stand level. Models which include time as a variable provide, however, a useful means of linking environmental conditions to wood properties.

There is still great scope for research explaining wood property variation as a function of environmental conditions and relatively few models explicitly include environmental variables as predictors. Much impetus in WQ modelling derives from the importance of being able to understand full potential product value from a managed forest resource. To this end, wood quality models are, and should increasingly be, part of decision support systems that aid forest managers to consider multiple objectives. The increasing availability of WQ data from routine forest inventories will accelerate this evolution and, in this context, ongoing development of good quality input data is perhaps the major requirement for future advances in WQ modelling. In parallel, a great need exists to better understand cambial biology and the processes of xylogenesis, to fundamentally advance our understanding of the phenomena that drive wood quality variability in the first place.

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The authors do not have existing conflict of Interest.

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Figures

Fig. 1 A basic classification proposed for grouping and describing wood quality models

Fig.2 Example of the dynamic branch model for Norway spruce AMOK: stand edge situations and different degrees of symmetric and asymmetric spacing are plausibly simulated (red dead branches, blue green branches) - missing trees have been taken out in previous thinning (a) [101], three-dimensional representations of predicted branches in *P. radiata* using the TreeBLOSSIM model (b) and predicted branching from TreeBLOSSIM included in a sawmilling simulation (red is the lowest board grade and blue is the highest) (c) [136]. Simulated five-year-old *P. radiata* branches and form in a modelled tree (d) and converted to knots in a simulated board (e) [103]

Fig. 3 Logic of the rCambium simulation tool developed for testing in *Pinus radiata* plantations. The steps within the red block are stand-level calculations of forest growth, within the green block are “average tree” level calculations and the purple block are wood quality simulation calculations performed at a position in the stem

Fig. 4 A simplified schematic representation of the concepts encapsulated in forest growth and wood properties models providing insight into the ramifications of growth and management impacts on timber processing through the value chain. Models must be able to capture the effects of decisions at establishment, environmental variability during the life of the trees and silvicultural management to predict effects that will be seen in the mill

Fig. 5 Screenshot of the prototype FWPA rCambium simulation tool graphical user interface showing simulated pith-to-bark variation in MOE, along with a representation of the simulated log end with boards of different stiffness grades and a summary of predicted product out-turn

1. Analysis undertaken on 9th March 2022: <https://www.webofscience.com/wos/woscc/basic-search> [↑](#footnote-ref-1)
2. https://www.webofscience.com [↑](#footnote-ref-2)
3. https://www.hyleccontrols.com.au/product/pilodyn-wood-density-meter/ [↑](#footnote-ref-3)
4. https://new.abb.com/products/7TCA083160R0059/st300 [↑](#footnote-ref-4)
5. https://www.scionresearch.com/about-us/about-scion/corporate-publications/scion-connections/past-issues-list/issue-17,-september-2015/meet-discbot,-our-new-quality-detective [↑](#footnote-ref-5)