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Evaluating the Impact of Meteorological Data Sources on Moisture Prediction Accuracy of *Eucalyptus nitens* Log Pile Natural Drying Models

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Abstract

Drying forest biomass at roadside can reduce transport costs and greenhouse gas emissions by reducing its weight and increasing its net calorific value. Drying models are required for forest supply chain analysis to determine optimum storage times considering storage costs and returns. The study purpose was to evaluate the impact of the source of meteorological data on the goodness of fit and practical application of Eucalyptus nitens *log pile drying models. The study was conducted in Long Reach, NE Tasmania, Australia from the 6th of February to 6th of August 2020. Four data sources were compared: the nearest meteorological station, interpolated meteorological data, a portable weather station, and digital temperature/RH sensors. Predicted moisture content (*MC*) values from the only previously published* E. nitens *log pile drying model were also evaluated using the current study data sources as inputs.*

Log pile MC *changes were determined from weight changes measured by placing the study logs on a steel frame bolted to load cells at each corner. As the study was based on debarked logs, dry matter losses were assumed to be negligible. Initial* MC *of the logs was determined by extracting samples using an electric drill and drying them until constant weight was achieved.*

Initial log pile drying rates were high with several daily MC *losses >2%. Portable weather station data produced the best goodness of fit drying model. The second-best goodness of fit model was based on meteorological station data. From a user acceptability perspective (highest proportion of results within ±5% of measured values), the best model was based on temperature/RH sensor data. Goodness of fit measures for the temperature/RH sensor data model were poorer than for the other data sources, but still acceptable. The published* E. nitens *log drying model had the poorest results for goodness of fit and user acceptability.*

In conclusion, portable weather stations are best suited to research trials due to the expense of placing a weather station at each log pile. Drying models based on data from the nearest meteorological station or temperature/RH sensors are best suited for practical applications, such as forest supply chain analysis. Additional benefits could accrue from a forest estate-wide network of low cost temperature/RH sensors potentially supplying data to forest supply chain analysis as well as fire prediction and tree growth models.

Keywords: forest biomass, supply chain, sensor network, natural drying model, cost saving

1. Introduction

Cost efficiencies are critical to the success of forest biomass supply chains (Cambero and Sowlati 2014). Weight reduction and increased net calorific value following natural drying of stored log and forest biomass piles can substantially reduce secondary transport costs (Strandgard et al. 2021a), which can account for >40% of delivered costs (Rodriguez et al. 2011, Ghaffariyan et al. 2013) and reduce transport-related greenhouse gas emissions. Conversely, stored logs and forest biomass can incur dry matter losses from decay or physical losses (Jirjis 2005, Nilsson et al. 2015) and costs, through payment deferment during storage (Acuna et al. 2012), return of equipment to the site to load trucks or feed chippers (Lin et al. 2016) and delaying of site preparation and re-establishment (Richardson et al. 2002).

The complexities associated with designing forest biomass supply chains have resulted in the development of numerous supply chain models (Shabani et al. 2013, Cambero and Sowlati 2014, Acuna et al. 2019), few of which include consideration of natural drying (Strandgard et al. 2019). Predicted cost savings from natural drying can be substantial, for instance, Strandgard et al. (2021b) modelled delivered cost savings of up to 30% from roadside drying of *Eucalyptus globulus* logging residue and whole trees. Real-world savings are likely to be less than those predicted as supply chain models are a simplification of reality and typically assume perfect knowledge (Shabani et al. 2014). The lack of consideration of natural drying in supply chain models is partly explained by the lack, until recently, of tools and techniques to incorporate highly granular meteorological data to enhance moisture content prediction as well as the high cost and time-consumption involved in drying model development.

Prevailing weather conditions are the major driver of the rate of natural drying of logs and forest biomass (Erber et al. 2014). Other factors include: species, log size, debarking, pile size, and pile covering (Stokes et al. 1987, Pettersson and Nordfjell 2007, Röser et al. 2011, Lin and Pan 2013, Klepac et al. 2014, Visser et al. 2014). The majority of published log and biomass roadside drying models were developed for northern hemisphere species and conditions (Strandgard et al. 2019) with few published models for species grown extensively in the southern hemisphere, including *Pinus* and *Eucalyptus* spp., e.g. (Strandgard and Mitchell 2017, Strandgard et al. 2020). The species studied in the current paper, *E. nitens*, is a major southern hemisphere plantation species for which there is one published log drying model, based on a study in southern Chile (Bown and Lasserre 2015).

Most roadside log and forest biomass drying models have been derived from weather variables recorded using onsite weather stations, whereas operational application of the drying models typically relies on data from the nearest meteorological station which may be ≥10 km from the stored material, particularly in forested areas. Given that weather variables can vary considerably temporally and spatially (Erber et al. 2017, Grimmond et al. 2000, Ma et al. 2010), insufficient research has been conducted to evaluate the impact of different sources of meteorological data on the accuracy of *MC* prediction of log and forest biomass piles drying at roadside and the implications of each data source on practical implementation of the drying models.

The objectives of the paper were to compare the goodness of fit (model fit to observations) and fitness for purpose (degree at which user requirements were met) of natural drying models for a pile of drying *E. nitens* logs developed using meteorological data from a range of sources:

- ⇒ the nearest Bureau of Meteorology (BOM) weather station
- ⇒ interpolated BOM weather data (SILO)
- ⇒ data from a portable weather station adjacent to the pile
- ⇒ digital temperature and relative humidity sensors in the pile

and to test the predictive accuracy of the Bown and Lasserre (2015) log drying model *MC* estimates calculated using meteorological data collected in the current study. Consideration was also given to the operational implementation of the models based on each data source.

2. Materials and Methods

2.1 Experimental Design

The natural drying study took place at the Forico P/L Long Reach Mill in north-east Tasmania (41° 10′ 12″S,

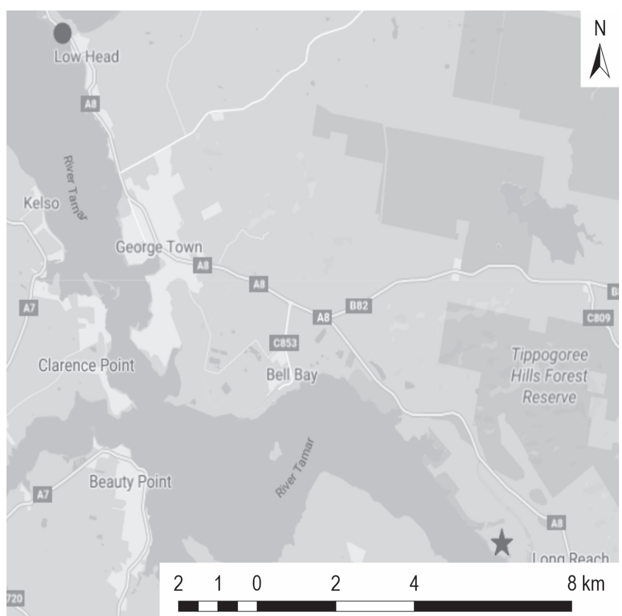

Fig. 1 Map showing approximate locations of study site (grey star near Long Reach) and nearest meteorological weather station (grey circle near Low Head)

146° 55′ 48″E) (Fig. 1) between the 6th of February and 6th of August 2020 (182 days) to examine drying from summer through to winter. The gravel-based site sloped slightly to the south (<5°) and was clear on all sides of the log pile for ≥15 metres. The closest vegetation was 5–6 metres high. Long term mean annual precipitation at the site was 675 mm and monthly mean maximum and minimum temperatures were between 12.8–21.1°C and 6.9–14.6°C, respectively.

The debarked *E. nitens* logs were harvested approximately seven hours prior to the trial (Table 1). The major cause of the delay in transporting the logs was the need to fit the small load of trial logs into the truck delivery schedule. Initial *MC* of the logs was determined from 30 wood samples obtained with a battery-operated drill from a range of locations along the logs and log sizes. Sample *MCs* were determined by drying samples at 103°C until constant weight was achieved. All *MC* values were expressed as a percentage on a wet basis.

Table 1 Parameters of the trial *E. nitens* logs

Parameter	Value
Number of logs	24
Mean length, m	11.9
Mean large end diameter, mm	265
Initial *MC*, %	52
Initial weight of logs, t	11.86

2.2 Log Pile Moisture Content

The initial weight of the logs (11.86 t) was measured by the Long Reach mill weighbridge. The logs were placed on an automated weighing platform which consisted of a metal frame (length: 6 m, height: 2 m, width: 3 m) (Strandgard et al. 2020). The frame was bolted to double ended shear beam load cells (Hanzhong Quan Yuan Electronic Co Ltd Load cell model QH-43B). Load cell voltage readings were converted to digital values (ADS1115 16-Bit ADC) and recorded every four hours on a Raspberry Pi 1 A+ (www.raspberrypi.org). At each time of measurement, the voltage was measured at one second intervals for one minute to reduce the chance of spurious readings. Data files were sent to a remote FTP server using the 3G mobile phone network and converted to weight values. Weight changes were assumed to only result from changes in the *MC* of the logs. As the logs were delimbed and debarked prior to delivery, physical losses were likely to be minimal.

2.3 Meteorological Data

Meteorological data for the study period were obtained from the nearest Australian Bureau of Meteorology (BOM) weather station, the SILO interpolated weather database (https://www.longpaddock.qld.gov.au/silo/), a portable weather station adjacent to the log pile and temperature and relative humidity (*RH*) sensors in the log pile. All models were based on daily meteorological data.

2.3.1 BOM Weather Station Data

The nearest BOM weather station to the study site was at Low Head (Latitude: –41.05, Longitude: 146.79) (approximately 15.8 km distant) (Fig. 1). Daily values of the following data were obtained for the Low Head site: evapotranspiration, rainfall (9 AM to 9 AM and midnight to midnight), maximum and minimum temperature and *RH*, average 10 m wind speed, solar radiation. The 9 AM to 9 AM rainfall data were recorded from 9 AM the previous day to 9 AM of the day the rainfall was reported. Midnight to midnight rainfall data were derived from half-hourly rainfall data for the day the rainfall was reported, which are available from the BOM for a fee.

The SILO weather database provides meteorological data at point locations within Australia interpolated from nearby BOM weather stations. Daily values for the following data were obtained for the study site: maximum and minimum temperature (°C), *RH* (%) at the maximum and minimum temperature, 9 AM to 9 AM rainfall (mm), evaporation (mm), solar radiation (MJ/m^2), vapour pressure (hPa) and evapotranspiration (mm).

2.3.2 Portable Weather Station

The portable weather station was installed three metres from the log stack. The weather station recorded mean wind speed (km/h) at 2 m height, wind direction, rainfall (mm), temperature (°C) and *RH* (%) at ten-minute intervals. Weather station components were a Davis 7911 anemometer, a SHT20 temperature and *RH* sensor in a Davis radiation shield and a Renke tipping bucket rain gauge (resolution 0.2 mm). Data were recorded using a Raspberry Pi 1 A+ and transmitted via the mobile phone network to a remote FTP site. Modelling was based on daily mean wind speed, maximum and minimum temperature and *RH* and daily rainfall.

The weather station data collection software was based on the Raspberry Pi Foundation's Weather Station (https://projects.raspberrypi.org/en/projects/build-your-own-weather-station).

2.3.3 Temperature and Relative Humidity Sensors

Four battery-powered sensors were used to measure the temperature (°C) and *RH* (%) in the log stack. The design was based on the »Cave Pearl Data Logger« (Beddows and Mallon 2018) and consisted of an Arduino Pro Mini clone (8 MHz, 3.3 v), a real-time clock module and a SHT20 temperature and *RH* sensor powered by a 18650 2600 mAh Lithium-ion battery. Temperature and *RH* readings were recorded on a mini SD card every ten minutes.

The temperature and *RH* sensors were placed amongst the logs at four positions along the log pile. To avoid false readings from the sun directly striking the temperature/RH sensor, each sensor was placed where it was shaded by logs.

Data were recorded for the complete study period by only one temperature/*RH* sensor as the battery power was exhausted within two to three months for the other three sensors. Future versions would recharge the battery using a small solar panel.

2.4 Statistical Analysis

Log drying models were developed from each set of meteorological data using linear regression analysis (Minitab v.19 (www.minitab.com)). The dependent variable was the daily change in log pile *MC* (Δ*MC*). For each meteorological dataset, independent variables were selected using the Minitab linear regression »Best sets« function. For the Low Head BOM meteorological dataset, the »Best sets« function was run with three variations of the rainfall data: the 9 AM to 9 AM rainfall data, the 9 AM to 9 AM rainfall moved back one day as 15 of the 24 hours covered occurred on the previous day, and the midnight-to-midnight rainfall. For the SILO meteorological dataset, the »Best sets« function was run with the 9 AM to 9 AM rainfall data and the 9 AM to 9 AM rainfall moved back one day.

The best fitting regression model for each meteorological dataset was selected on the basis of the model meeting the assumptions of linear regression and having the highest R^2_{adj} and lowest standard error of the regression (*S*) with the least number of variables. Minimising the number of variables reduces the chance of overfitting and simplifies application of the model. All variables were statistically significant ($p<0.05$) and had a Variance Inflation Factor (*VIF*) <5 (low multicollinearity). The best fitting drying models for each meteorological dataset were compared on the basis of their R^2_{adj}, *S* and mean absolute error (*MAE*) between measured and predicted *MC* values. Models were also assessed on their ability to meet user accuracy requirements, which were set to ±5% based on the requirements of forest energy businesses in Finland (Routa et al. 2015) as there has been no equivalent Australian analysis of forest energy businesses.

Log diameter has been found to be inversely related to log drying rate (Defo and Brunette 2007, Visser et al. 2014) though Bown and Lasserre (2015) found in their study that log diameter had little effect on drying rates for *E. nitens* logs. Based on this finding and the impracticality of measuring log diameters in roadside log piles, the authors decided to exclude log diameter based variables from models in the current study.

The Bown and Lasserre (2015) *E. nitens* log drying model uses mean daily temperature and *RH* values and the number of logs per square metre to predict daily change in the *MC* of a log pile. Meteorological data recorded during the current study were used as inputs into the model to predict Δ*MC*. Predicted *MC* values from this model were compared with the measured *MC* values.

2.5 Sensitivity Analysis

The strength of the relationship between each independent variable and the dependent variable (Δ*MC*) was determined by comparing their standardised regression coefficients (Siegel 2016). For each meteorological dataset, standardised regression coefficients were obtained by subtracting the mean from each observation and then dividing by the standard deviation and regressing the resulting dataset. The larger the standardised regression coefficient, the larger its impact on Δ*MC*.

2.6 Valid Range

The suggested valid range for each meteorological variable for predictive purposes was limited by the 5% and 95% quantiles (Table 2). The drying models can be used for piles of *E. nitens* logs with a mean diameter of approximately 265 mm. The model can be applied to log lengths >5 m as drying rates are little affected by changes in log length beyond 5 m (Defo and Brunette 2007).

Table 2 Valid range for each model variable (5% and 95% quantiles)

Variable, daily values	5%	95%
Maximum temperature, °C	11.5	24.2
Minimum *RH*, %	42.9	83
Average temperature, °C	6	18.7
Average *RH*, %	69.6	100
Rainfall, mm	0	17.4
Solar radiation, MJ/m^2	3.7	22.3

3. Results

3.1 Description

Daily mean minimum and maximum temperature and *RH*, daily mean wind speed and predominant direction and total rainfall for the study period are provided in Table 3.

Table 3 Daily mean temperature, *RH* and wind speed, predominant wind direction and total rainfall during study period

Variable	Value
Minimum/maximum temperature, °C	8.7/16.5
Minimum/maximum RH, %	64.3/94.7
Windspeed, km/h	2.7
Wind direction	NE and SW
Rainfall, mm	555

The study period commenced in late summer and ended in late winter, which was reflected in the downward trend in daily mean temperature and upward trend in daily mean *RH* (Fig. 2).

In the first week of the study, the logs dried rapidly in response to relatively high air temperatures and low *RH* with a number of daily *MC* losses of >2% and a cumulative *MC* loss of >11% (Fig. 3). The rate of *MC* decline reduced considerably after approximately two months of drying when the log pile *MC* dropped below 32% in early April. By mid-May, the *MC* had dropped to ~30% (±1%), where it remained for the rest of the study period. The lowest *MC* was 29.2% on the 3rd of August. Small increases in log pile *MC* (≤3%) occurred in response to rainfall events (Fig. 3).

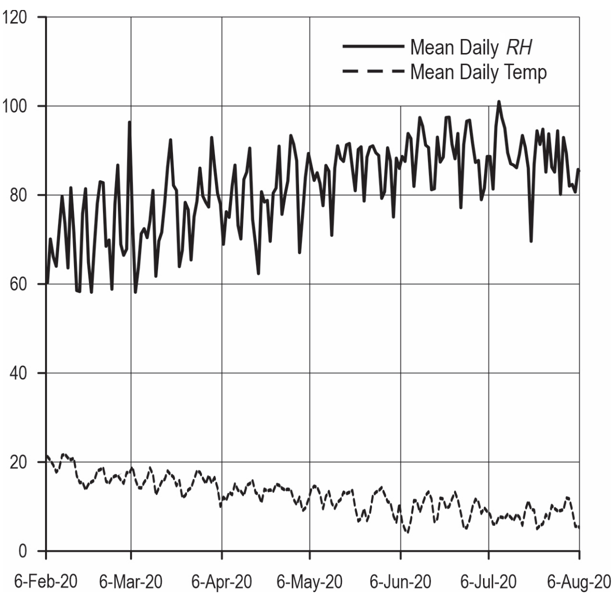

Fig. 2 Daily mean temperature and *RH* values for the study period

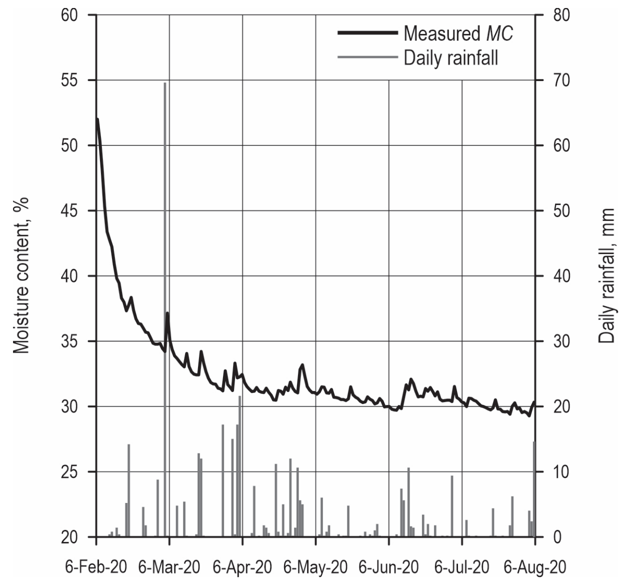

Fig. 3 Log pile *MC* (%) and daily rainfall (mm) during the study period

3.2 Drying Models

The best fit drying model developed using the Low Head BOM weather station data, used the midnight-to-midnight rainfall data (Eq. 1) (Table 4) (Fig. 4). The poorest fitting model used the 9 AM to 9 AM rainfall data on the day it was reported (R^2_{adj}=45%). Moving the 9 AM to 9 AM rainfall data back one day improved the fit (R^2_{adj}=53%).

The best fit drying model developed using the SILO meteorological data was developed using the 9 AM to 9 AM rainfall data moved back one day (Eq. 2) (Table 4) (Fig. 4).

The best fit drying model developed from the portable weather station meteorological data (Eq. 3) (Table 4) (Fig. 4) had the best fit to the measured *MC* values of all of the equations developed from the various meteorological datasets tested (69% R^2_{adj}).

The best fit drying model developed from the temperature and *RH* sensor meteorological data is shown in Eq. 4 (Table 4) (Fig. 4).

The fit of the Bown and Lasserre (2015) *E. nitens* log pile drying model was poor for all meteorological data sources tested. The best fit of the Bown and Lasserre (2015) drying model used the portable weather station data (Fig. 5). The *MAE* using this data source was 2.4%.

Table 4 Regression models for each source of meteorological data. The best fit model is shown where multiple models were developed from a dataset

Data source	Model	R^2_{adj}, %	Standard error	Mean absolute error, %	Equation
Low head weather station	$\Delta MC = 0.0238 - 0.092 \times InitMC + 0.0005 \times DayRn + 0.00046 \times MaxT - 0.00036 \times SolRd$	65	0.0038	0.7	Eq.1
SILO	$\Delta MC = 0.0274 - 0.106 \times InitMC + 0.00042 \times BkRn + 0.00038 \times VP$	57	0.0042	0.5	Eq. 2
Portable weather station	$\Delta MC = 0.0171 - 0.114 \times InitMC + 0.0005 \times MaxT + 0.00014 \times MinRH + 0.00035 \times DayRn$	69	0.0036	0.5	Eq. 3
Temperature and *RH* sensor	$\Delta MC = 0.0154 - 0.128 \times InitMC + 0.00072 \times AveT + 0.00018 \times AveRH$	39	0.005	0.7	Eq. 4

Where:
- *ΔMC* change in moisture content of the log pile, %/day
- *InitMC* log pile moisture content at the start of the day, %
- *DayRn* daily rainfall between midnight to midnight, mm
- *MaxT* daily maximum air temperature, °C
- *MinRH* daily minimum relative humidity, %RH
- *AveT* daily average air temperature, °C
- *AveRH* daily average relative humidity, %RH
- *SolRd* daily solar radiation, MJ/m2
- *BkRn* 9 am to 9 am rainfall moved back one day, mm
- *VP* Vapour Pressure at 9 AM, hPa.

3.3 Predicted Values Within ±5% of Measured Values

Of the models developed in the study, none met the user criterion of having all predicted values within ±5% of measured values. The best performing model was that developed from the temperature/*RH* sensor data, which had 96% of points within the ±5% range. The second-best models were the portable weather station data model and the SILO data with rainfall moved back one day, each of which had 93% of points within the ±5% range. The model developed by Bown and Lasserre (2015) had the lowest number of predicted values within ±5% of measured values (38%).

3.4 Sensitivity Analysis

The initial *MC* variable had the greatest impact on *ΔMC* for all the drying models. The next greatest impact was for the rainfall variables included in the BOM weather station, SILO data and portable weather station drying models and the temperature variable for the temperature and *RH* sensor drying model.

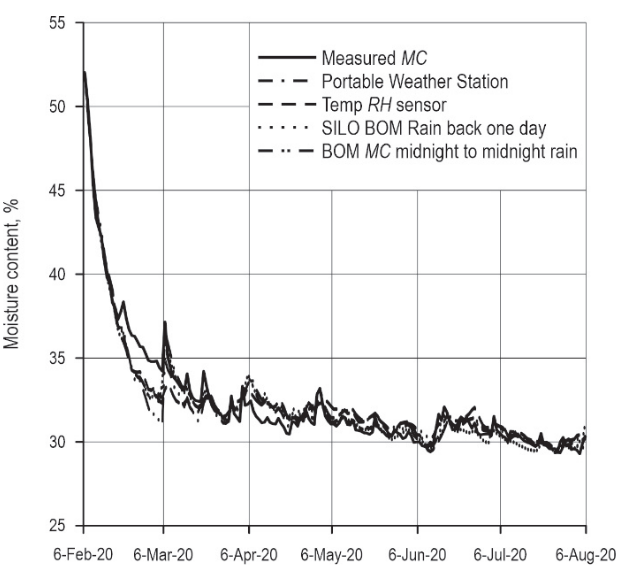

Fig. 4 Log pile *MC* (%) and *MC* predictions from each drying model during the study period

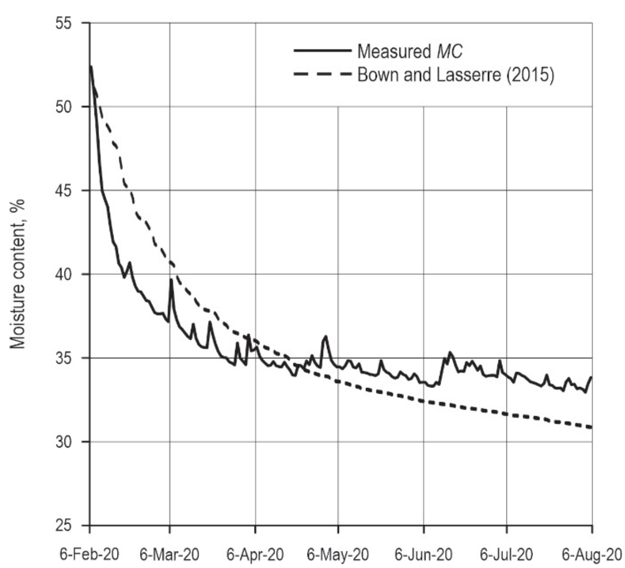

Fig. 5 Log pile *MC* (%) and *MC* predictions from Bown and Lasserre (2015) drying model during the study period

4. Discussion

The study compared the goodness of fit (model fit to observations) and fitness for purpose (degree at which user requirements were met) of modelled *MC* values for natural drying of an *E. nitens* log pile using models developed from meteorological data from the nearest Bureau of Meteorology (BOM) weather station, SILO interpolated weather data, a portable weather station adjacent to the log pile, and digital temperature/RH sensors in the pile.

The log pile drying pattern observed in the current study (high initial drying rate followed by an extended period of relatively stable *MC*) was similar to that observed for an *E. globulus* log pile in south-west Australia (Strandgard and Mitchell 2017). The *E. nitens* log piles in the Bown and Lasserre (2015) trial had a similar high initial drying rate to that of the current study log pile; however, the summer component of their study was too short to observe any *MC* stabilisation. General drying patterns and total moisture loss (~20%) for log piles of a number of species in Austria (Erber et al. 2012, Erber et al. 2016, Erber et al. 2017) were also similar to those for the log pile in the current study. Erber et al. (2012) noted that drying forest biomass to an *MC* of <35% may attract a premium sale price.

The general log pile drying pattern described above may reflect the nature of water within logs. Higher initial drying rates were likely to have resulted from rapid loss of unbound water from exposed surfaces, when conditions were conducive to drying (Defo and Brunette 2006). Slowing of drying rates would then have occurred as quantities of unbound water reduced and the distance increased between the remaining unbound water and the log surface. In the current study, the observed drying pattern explained why daily initial *MC* was a highly influential drying model variable as the reduction in the rate of *MC* change correlated with reducing values of daily initial *MC*. The other highly influential variable in three of the current study drying models, rainfall, caused minor (≤3%), short-term increases of the log pile *MC*, similar to those observed in other natural log drying studies (Erber et al. 2012, Erber et al. 2016).

Statistically, the best fit drying model was developed from the portable weather station meteorological data. The goodness of fit of the second-best drying model (BOM weather station data using midnight to midnight rainfall data) was only slightly poorer than that for the portable weather station data even though the BOM weather station was located over 15 km from the study site. From the perspective of potential users of the models, the best performing model was that developed from the temperature/RH sensor data as it had 96% of points within the user-defined acceptable range of within ±5% of the measured *MC* values.

The *E. nitens* log drying model developed by Bown and Lasserre (2015) had a poor fit to the measured *MC* data for all tested data sources. One reason for the poor fit was that the model form used was not able to model increases in *MC*, such as occurred in the current study in response to rainfall.

A limitation common to all forest biomass drying model development is that trials are conducted on relatively small log and logging residue piles due to the impracticality of monitoring *MC* changes for extended periods of commercial piles of logs or logging residue, which can be over three metres in height and hundreds of metres in length. Model developers make the assumption that the drying model developed from the smaller pile of logs or logging residue accurately represents the drying behaviour of a commercial log or logging residue pile. This assumption needs to be tested in further research trials. Further limitations are that the trial only studied a single log pile at one time of the year. Further trials are required to test the model applicability for different sites and seasons.

Where roadside drying of forest biomass is currently conducted in Australia, the typical approach is to store the material at roadside for one to two months with limited or no modelling of the biomass moisture content or supply chain cost/benefit trade-offs (Strandgard et al. 2021b). Strandgard et al. (2021b) found that optimising the forest biomass supply chain through the use of natural drying models reduced delivered forest biomass costs by 40% more than when biomass was stored at roadside for one to two months, due mainly to a substantial reduction in transport costs in the cost minimisation scenario.

Uses of the drying models developed in the current study include research purposes and operational management of *E. nitens* log piles stored at roadside. For research purposes, the model developed from the portable weather station data may be the most appropriate as it had the best statistical fit and deployment of portable weather stations to collect data for the model would be feasible for a research trial. However, forest managers are unlikely to be able to justify the cost to purchase, deploy and maintain portable weather stations across a commercial forest estate (Erber et al. 2017). Drying models developed from BOM meteorological data would be more appropriate in these cases as the data required by the model are readily available online. However, while the BOM meteorological data from the nearest weather station were well-correlated with the log drying in the current study, changes in meteorological and site conditions across a forest estate mean that this may not always be the case. For a diverse forest estate, the low cost and portability of the temperature/RH sensor tested in the study may be a more appropriate option. The temperature/RH sensor drying model had a lower R^2_{adj} than the other models but had acceptable *S* and *MAE* values and the best fit from a user perspective.

The relatively low cost of the temperature/*RH* sensors compared with a portable weather station suggests a sensor network could be established through a forest estate wirelessly connected to a centralised server via the 3G mobile phone network or LoRaWAN to capture near real time meteorological data across a broad area. In addition to its use in drying models, detailed forest estate level meteorological data could be used as inputs in forest fire models (Dowdy et al. 2009) to aid forest fire prediction and detection (Yu et al. 2005) and broad-scale tree growth models (Coops et al. 1998). Such a sensor network would form part of the Internet of Forest Things (IoFT) (Salam 2020), which is a critical component of the Forestry 4.0 concept (Gingras and Charette 2017).

5. Conclusion

Cost reductions are critical for the success of forest biomass supply chains. Transport costs, which are a major cost element in forest biomass supply chains, and transport-related greenhouse gas emissions can be considerably reduced through natural drying of biomass at roadside prior to transport. Determination of the appropriate time to store individual forest biomass piles requires predictive drying models to inform forest managers when sufficient drying has occurred. In the case of *E. nitens*, a major southern hemisphere plantation species, only one log drying model (developed in Chile) has been published and its performance under Australian conditions had not been tested. In the current study, a number of natural log drying models were developed from a range of meteorological data sources and compared on the basis of their goodness of fit (model fit to observations) and fitness for purpose (degree at which user requirements were met). The meteorological data collected in the study were also used to predict the *MC* of the studied *E. nitens* log pile using the Chilean drying model to examine the model's accuracy for the studied log pile.

Statistically, the best fitting model was developed from portable weather station data collected from adjacent to the log pile. The impracticality of establishing portable weather stations at each log pile over a large forest estate suggested this model would be best suited for further research studies rather than operational use. The drying model developed using meteorological data from the nearest weather station had a slightly poorer statistical fit than the portable weather station model but used data that were readily available online, enabling its use for operational management of roadside log piles. The drying model developed from the temperature/*RH* sensors had a poorer (but still acceptable) fit statistically but the best fit from a user perspective. This result combined with the potential for a forest estate-wide network of low-cost temperature/*RH* sensors feeding near real time data to a central server may make this a more attractive option for a forest manager, particularly if the data could support other forest activities, such as fire management and growth modelling.

The Chilean log drying model had poor accuracy predicting log pile *MC* using meteorological data collected in the current study compared with the drying models developed in the current study. A deficiency of the model form used in the Chilean drying model is that it cannot model *MC* increases which leads to inaccurate *MC* predictions when logs rewet following rainfall.

Priority areas for further study include checking the predictive accuracy of the models developed in the study for *E. nitens* log piles under different meteorological and site conditions against those in the study and checking how accurately the developed drying models predict drying in commercial scale piles of *E. nitens* logs.

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