Optimization of the Mold Resistance Design Model for North American Materials

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ABSTRACT

A wide variety of mathematical models exist which attempt to assess the risk of mold growth in building envelopes. Model predictions often fail to adequately represent observations from field experiments. We examine ways in which one model, the mold resistance design (MRD) model, can be improved to better align with empirical data. A database of laboratory mold growth results was assembled from the literature, which included not only the European spruce and pine on which pioneering models were based, but also materials commonly used in North America, such as oriented strand board (OSB) and plywood. Next, this database was used to test modifications to the core temperature (T) and relative humidity (RH) dose factors in the MRD model. These dose factors together create a total dose based on average T and RH in a 12-hour period. The accumulation of these doses over time yields a prediction of mold growth and the original model uses a linear mapping to relate cumulative dose to mold rating. Improvement to the dose-response correlation was achieved by implementing a sigmoidal map of cumulative dose to mold rating to increase model predictive power. In addition, improvements were made for unfavorable conditions for mold growth to better align with known biological processes. Instead of a decline in the predicted mold rating, a recovery function was devised such that the predicted mold rating remains constant during unfavorable conditions and increases only upon resumption of favorable conditions contingent on a delaying period. Each modification is shown to improve predictions for the database materials, with promise for improvement in field studies. However, even these improvements still exhibit significant variation in predictive accuracy across our large database of mold growth measurements.

INTRODUCTION

Mathematical modeling of biodeterioration is a useful tool for moisture management in buildings. Lepage et al. (2019) provided a critical review of many common biodeterioration models. This work focuses on mold modeling (Vereecken et al. 2015; Gradeci et al. 2017), as it is often used to evaluate building assembly designs using the relative humidity (RH) and temperature (T) output from hygrothermal models. For example, ASHRAE Standard 160-2021 ("Criteria for Moisture-Control Design Analysis in Buildings" 2021) supplies performance criteria for evaluation of model outputs. Early revisions to Standard 160-2009 which incorporate the VTT mold index model (Ojanen et al. 2010) were evaluated by Glass et al. (2017). Despite the large number of mold models and significant modeling efforts there is still work needed to improve model predictive power. For example, Johansson et al. (2021) coordinated a round-robin study of six different mold models and found that most underestimated the potential for mold growth in one long-term field study. Clearly, more field studies are needed to provide a robust test bed for model evaluation.

However, existing mold models are based on laboratory experiments. This work continues to rely on laboratory data

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because further fundamental development is required. Vereecken et al. (2015) provided a helpful summary of challenges. Most significant are the differences in how mold growth is reported, as different research groups used different methods and rating scales to report their experimental results. In addition, there are a variety of other factors, such as different inoculation techniques, different substrates, and different incubation procedures, all of which hinder accurate comparisons of generic mold growth with simple models. Our goal was to explore a simple model and improve it based on aggregate experimental datasets and identify improvements to modelling predictive capacity. Further, the model is extended so that it includes materials commonly used in North American construction, namely oriented strand board (OSB) and plywood. The laboratory data for pioneering models was based on European spruce and pine (Viitanen and Ritschkoff 1991; Viitanen and Bjurman 1995; Viitanen and Ojanen 2007), used for example in development of both the VTT model and the mold resistance design model (MRD) which is our focus (Thelandersson and Isaksson 2013). We choose the MRD model because of its simplicity, ability to handle different materials using the critical dose parameter, and well documented mold growth rating scale (P. Johansson et al. 2012; P. Johansson 2014; P. Johansson et al. 2013). We report results from extending the MRD model to North American woods and wood-based materials, along with improvements to the MRD model structure which increase its predictive power.

METHODS

Assembly of the mold growth database from literature

The database used to extend and improve the MRD model included mold growth ratings and environmental conditions over time from four main literature sources, as summarized in Table 1. This database includes 463 mold ratings in European pine varying from 7 to 30 T-RH permutations across multiple datasets (Viitanen and Ritschkoff 1991; Viitanen and Bjurman 1995; Viitanen and Ojanen 2007; P. Johansson et al. 2012; P. Johansson et al. 2013; Nielsen et al. 2004). An additional 213 ratings in European spruce were identified from the VTT datasets. An additional 529 ratings from North American materials (Yang 2005) were included. In cases where the raw data were not tabulated, values were extracted from published figures.

Together these data sets cover a relative humidity range from 75 to near 100%. The Yang data included samples exposed to 10, 20, and 28 °C (50, 68, 82 °F). The larger set ranges from 5 to 40 °C (41 to 104 °F) because the VTT data includes this broader temperature range. Most of the experiments were conducted under nearly constant conditions, but a few, including selections from Yang, VTT, and Johansson, included some cases of modest fluctuation in relative humidity, alternating between a high and low (below 75%) RH condition held for different time periods from 12 hours to 2 weeks.

Table 1. Literature Sources for Laboratory Mold Growth Ratings

Shorthand Label	References	Materials[a]	Duration, weeks[b]	No. of T/RH Conditions	T Range	RH Range[c]	Fluctuating RH?
VTT	Viitanen and Ritschkoff 1991 Viitanen and Bjurman 1995 Viitanen and Ojanen 2007	Pine sw Spruce sw	12 | 4 | 24	30 20	5–40 °C (41–104 °F)	80–99%	Yes
Johansson	Johansson et al. 2012, 2013	Pine/spruce sw	12 | 6 | 32	12	5–22 °C (41–72 °F)	75–95%	Yes
Nielsen	Nielsen et al. 2004	Pine sw	17 | 17 | 30	7	5–25 °C (41–77 °F)	78–95%	No
Yang	Yang 2005	OSB, Plywood, Aspen sw/hw, Jack pine sw, Spruce sw	8 | 8 | 8	10	10–28 °C (50–82 °F)	85–100%	Yes

[a] sw, sapwood; hw, heartwood
[b] Duration given as [typical value | minimum | maximum]; minimum duration applies to conditions in which mold grew rapidly and ratings were stopped; maximum duration applies to conditions in which mold growth was barely detectable
[c] RH range for constant conditions (not including fluctuating conditions)

The largest challenge in assembly of the database was reconciliation of the different mold growth rating scales, some of which were based on visible mold and others which relied on microscopic investigation. Most were loosely based on a percentage area coverage at various levels of magnification. We created mappings from Yang (0-6 visible and 25x magnification), VTT (0-6 visible and microscopic), and Nielsen (0-100% area coverage microscopic) to the MRD 0-4 scale (40x magnification) first proposed by Johansson (P. Johansson et al. 2012) and used in the MRD model. Table 2 provides a summary of those mappings, which differ somewhat from the proposal of Vereecken et al. (2015).

Table 2. Mapping various mold grow rating scales to the MRD scale used in the results database

MRD	Nielsen	VTT	Yang
0	0%	0	0
1	5%	1	1
2	15%	2	
2.5			2
3	45%	3	3
3.5		4	4
4	80%	5	5
4		6	6

Key elements of the MRD model

At the heart of the MRD model are two dose factors based on RH and T averaged over a 12-h period. Within a limited range of conditions that are considered favorable for growth, these dose factors are represented by exponential functions:

$$D_\varphi(\varphi_i) = 0.5\exp\left[A\ln\left(\frac{\varphi_i}{90}\right)\right] \text{ for } 75 < \varphi_i \leq 100 \tag{1}$$

$$D_T(T_i) = \exp\left[B\ln\left(\frac{T_i}{20}\right)\right] \text{ for } 0.1 < T_i \leq 30 \tag{2}$$

where D_φ is the RH dose factor, D_T is the temperature dose factor, φ_i is 12-h average RH (%), T_i is 12-h average temperature (°C), and A and B are fitting parameters (15.5 and 2.0, respectively, in the original model). The shapes of these dose factors are illustrated in Figure 1. Note that because D_T was only defined up to 30 °C (86 °F), two ad hoc additions were made to the model to handle the VTT data at 35 and 40 °C (95, 104 °F), indicated by red circles in Figure 1. The exponential function for D_T is not appropriate above 30 °C (86 °F) and the two D_T values needed were optimized individually for the small number of VTT data points at those specific temperatures. The high temperature data was quite limited and should not be used to create a general extension of MRD. For each 12-h period, these dose factors are multiplied to produce a dose D_i, which represents the relative favorability of the conditions for mold growth.

$$D_i = D_\varphi(\varphi_i) \cdot D_T(T_i) \tag{3}$$

The cumulative dose $D_{cu}(t)$ is calculated as the sum of the 12-h doses from the beginning up to time t. When RH ≤ 75% or T ≤ 0.1 °C, other equations apply such that D_i is negative, and the cumulative dose is thus reduced; further details can be found in the original paper (Thelandersson and Isaksson 2013).

The relationship between mold growth rating and cumulative dose is established by a reference condition of 20 °C (68 °F) and 90% RH. For a particular material, the critical dose D_{crit} is the time in days for observed mold growth to reach a rating of 2 (significant growth) in a laboratory test at the reference condition based on the 0-4 mold rating scale. Mold growth under varying T and RH conditions is assumed to vary linearly with the cumulative dose, normalized by the critical dose. The predicted mold rating $R(t)$ as a function of time t is given by

$$R(t) = 2\frac{D_{\mathrm{cu}}(t)}{D_{\mathrm{crit}}} \quad (4)$$

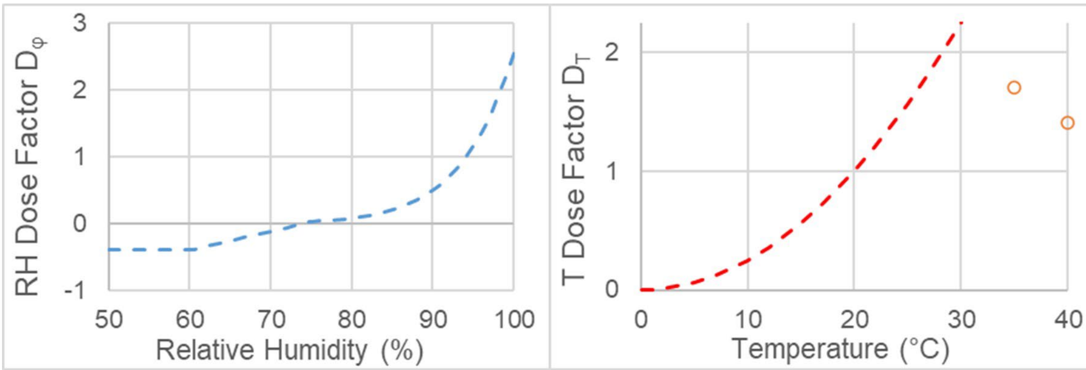

Figure 1 Basic RH (Eq. 1, A=15.5) and T (Eq. 2, B=2) dose factors for MRD model used to calculate mold growth.

D_{crit} optimization

The first model optimizations were performed by selecting D_{crit} values which reduced the difference between the observed mold growth rating and the model prediction. All measured ratings were weighted equally and the root-mean-squared error (RMSE), calculated using the sum of the squared differences for all 1205 data points in the database, was minimized. We note that this optimization procedure is already a modification to the original MRD model intention, which was to predict the onset of mold growth up to a rating of 2. Our extension tracks mold growth across the full rating scale, from 0 to 4. Our method was first applied to generate D_{crit} values for each material without any additional model revisions. Again, this is in contrast to the original MRD model for which the D_{crit} represents only one test measurement (at 20 °C and 90% RH), while our value minimized the RMSE across a wide range of conditions.

Optimization through model structural modification

Exponential dose function optimization. Next, we allowed the A and B values in Eq. 1 and 2 to vary, changing the shape of the RH dose and T dose exponential curves, to further reduce the RMSE.

Adding a recovery function. In addition, the model logic concerning use of the negative dose was modified. In the standard MRD model the cumulative dose rises with positive 12-hour dose values and falls with negative 12-hour doses. As a result, the mold rating can go back to zero given an extended period of conditions unfavorable to mold growth (for example RH < 75% or T <0 °C). While mathematically simple, this is a poor representation of mold growth, which goes dormant during unfavorable periods (Zabel and Morrell 2020; Adan and Samson 2011). The logic was altered so the cumulative dose never decreases. Instead, negative dose values were used to delay the increase in cumulative dose once favorable conditions return, similar to the recovery function of (S. Johansson et al. 2010). Specifically, the cumulative dose was allowed to increase if the current 12-hour dose calculation is positive, and the average of the previous 13-day dose calculations is also positive. The 13-day lookback period optimized our database but a dataset with more RH fluctuation across longer periods is still needed. This modification better aligns MRD with other dose-response models which are not reversible.

Dose-response optimization. We made an additional structural modification to the model, replacing the linear D_{crit} map from cumulative dose to mold rating (Eq. 4) with a sigmoidal function with three fitting parameters F, G, and H:

$$R(t) = F\exp\{-\exp[G - H \cdot D_{\mathrm{cu}}(t)]\} \quad (5)$$

The fitting parameters were chosen to reduce RMSE across the whole database. This allows a period of low predicted mold ratings at low cumulative dose values and then a sharp increase once the exponential growth phase commences (i.e., once the cumulative dose has reached a large enough value). This is an implementation of the Gompertz function commonly used in modeling biological growth and aligns with the Buchanan Life Phases theory of microbiotic organisms (Buchanan 1918). Sigmoidal growth curves in dose-response functions were also implemented by (Brischke and Rapp 2008).

RESULTS

D_{crit} values from optimization

The key to practical use of the MRD model is knowing the D_{crit} value, which indicates the material's sensitivity to mold growth by indicating how long it takes to reach significant growth at a reference condition. Table 3 provides values optimized for our material database. We report the overall RMSE of 0.807 between the model predictions and the measured mold ratings.

Table 3 Critical dose values (higher value indicates more resistance to mold growth)

Material	Original Dose Functions	New Dose Functions
OSB	97	95
Plywood	117	121
Spruce sapwood	90	80
Aspen sapwood	64	67
Aspen heartwood	111	121
Jack pine sapwood	60	58
VTT Spruce	52	55
VTT Pine	55	54
Johansson Pine	28	31
Nielsen Pine	39	46

Results from model structural modifications

Exponential dose function optimization. The MRD model was improved by modifications to the dose functions, specifically the A and B values in Eq. 1 and 2, which alters the shape and hence rate of the rise in the exponential term. The most significant alteration occurs in the temperature function as shown in Figure 2. These improvements require only modest changes to D_{crit} (see Table 3, right column) to reoptimize the model for the new dose functions and reduce the RMSE by 7% from its original value. The A coefficient changed from 15.5 to 15, while the B coefficient changed from 2 to 1.1.

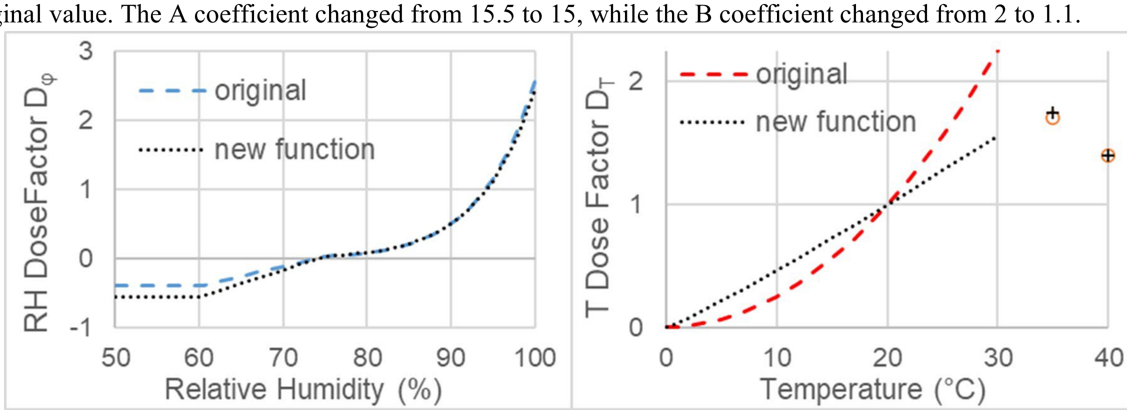

Figure 2 Improved RH and T dose functions for modified MRD model used to calculate mold growth.

Effects of the recovery function. Another modest improvement to the MRD model was achieved by implementation of the logic modification which prevents the cumulative dose from going down when the calculated dose is negative. As mentioned in the Methods section, the cumulative dose is allowed to increase if the current 12-hour dose calculation is positive, and the average of the previous 13-day dose calculations is also positive; overwise it stays the same. This alteration reduces the RMSE by 11% from its original value. This modification also holds promise of improved performance in field studies where fluctuating conditions are normal, unlike laboratory experimental data which frequently consists of steady state RH and T conditions. Figure 3 illustrates this modification for a European pine example alternating between 90 and 60% RH at 12 hr and also at 1-week intervals.

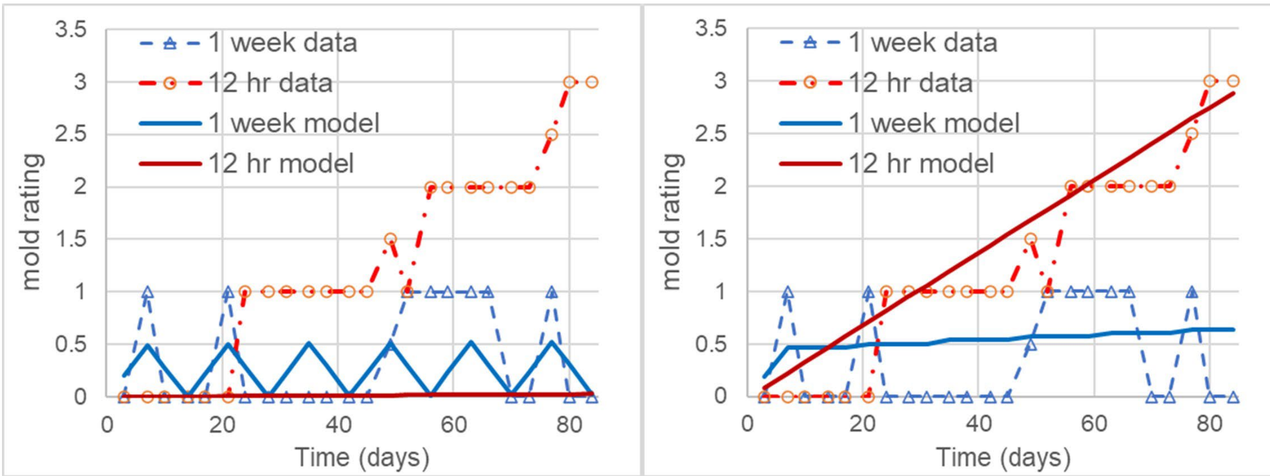

Figure 3 Mold growth data from pine under alternating RH conditions (hold for 12 hr - red, hold for 1 week - blue), with model predictions: Left - without recovery function; Right - with recovery function. Data from Johansson et al. (2013) and optimized model predictions.

Dose-response optimization. The final improvement explored in this paper modified the linear function which maps cumulative dose to the final mold rating. Thus, we replaced D_{crit} with three parameters which define a sigmoidal shape for this mapping, as described in Eq. 5, and here illustrated for the OSB data in Figure 4. This alteration reduces the RMSE by 17% from its original value.

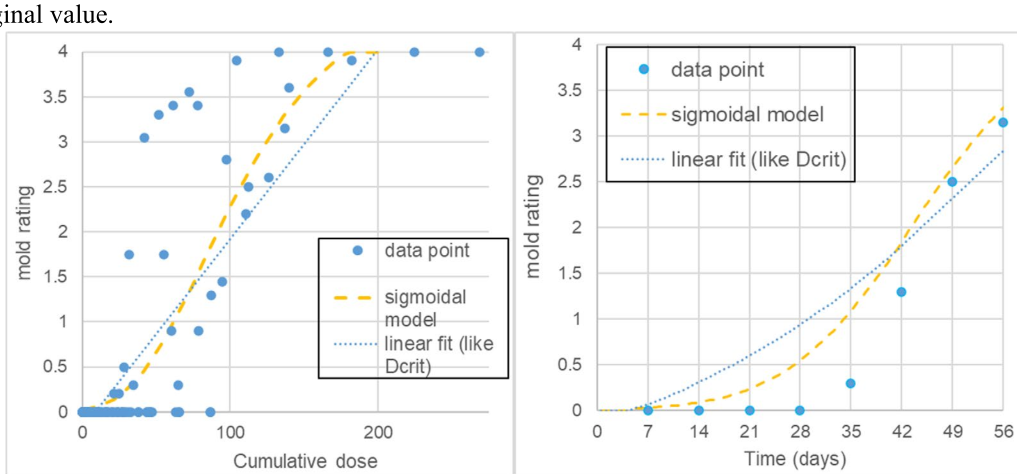

Figure 4 Alternative models for mapping the cumulative dose to the mold growth ratings: Left- all OSB data points with cumulative dose at maximum time, Right- Time series for OSB at 20 °C (68 °F) and 90 % RH. Data from Yang (2005) and model predictions.

Two caveats: On manufactured wood products and mold growth variability

Two further topics are worth brief discussion. First, the D_{crit} values shown are of course dependent on the materials tested. Specifically, the OSB value is characteristic of the specimens Yang had available, purchased in the British Columbia province of Canada nearly 20 years ago. OSB is a manufactured product category, and its mold growth potential will depend on the wood species used in fabrication and possibly other factors including adhesives and pressing conditions (Wang et al. 2010; Ye et al. 2006). We know from previous experience handling OSB from diverse locations within North America (Boardman et al. 2017) that the mold growth potential varies significantly by location. This is likely true of plywood as well. Second, we want to highlight the need for future models to specify a range for parameter values, rather than just using one number, to better characterize the wide scatter in mold growth results, seen for example in Figure 6 below. Gradeci et al. (2018; Gradeci and Berardi 2019) have started in this direction.

SUMMARY AND EVALUATION

Each small modification to the MRD model has improved the predictive power, so with all three improvements the overall RMSE was reduced by 17% from its original value. These improvements are further illustrated for select T/RH conditions in both OSB (top row) and plywood (bottom row), plotting the original MRD model (left) and fully improved model (right) in Figure 5.

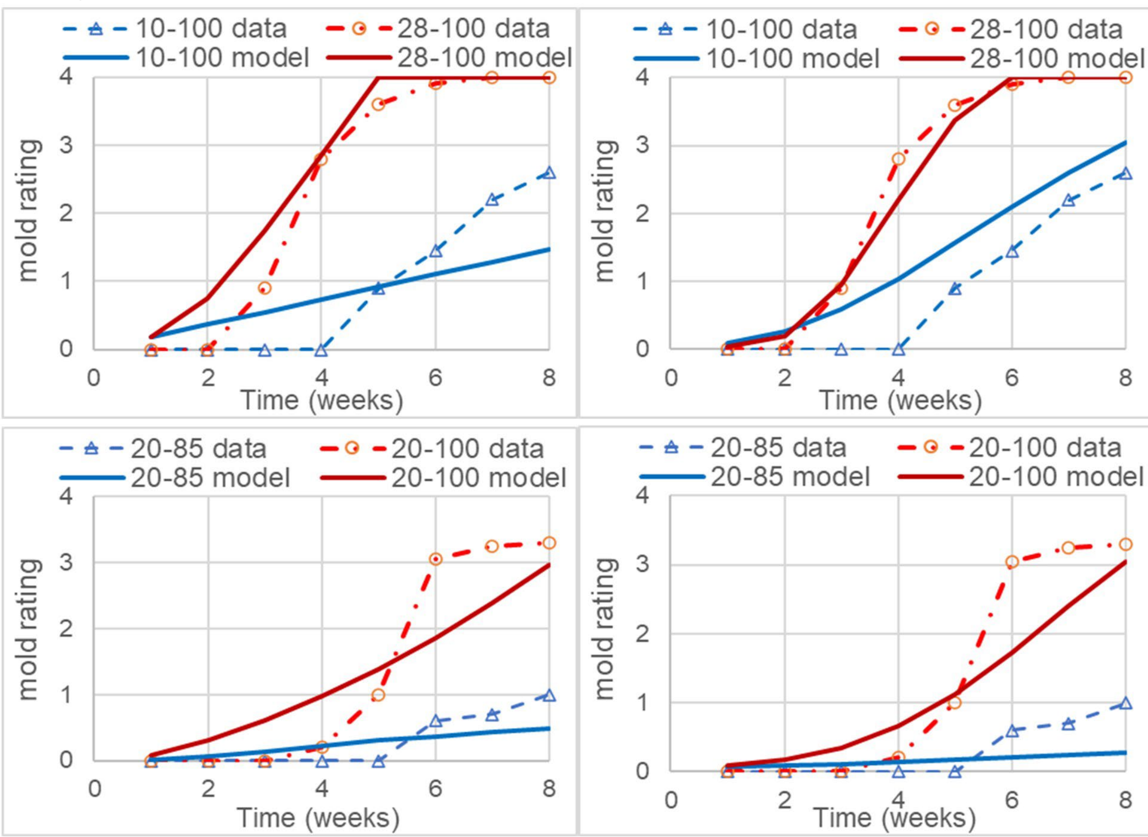

Figure 5 Time series of mold growth in OSB (top at 10 and 28° C and 100% RH) and plywood (bottom at 20 °C and 85 and 100 % RH) with original MRD model (left) and fully improved MRD model (right). Data from Yang (2005) and optimized model predictions.

Another way to understand how well the model performs is to plot the measured growth rating versus predicted mold growth rating, showing only the points with the largest cumulative dose (most time in any one experiment). Figure 6 provides two such plots side by side, one for the base MRD model and one with all improvements, along with the coefficient of determination (R^2).

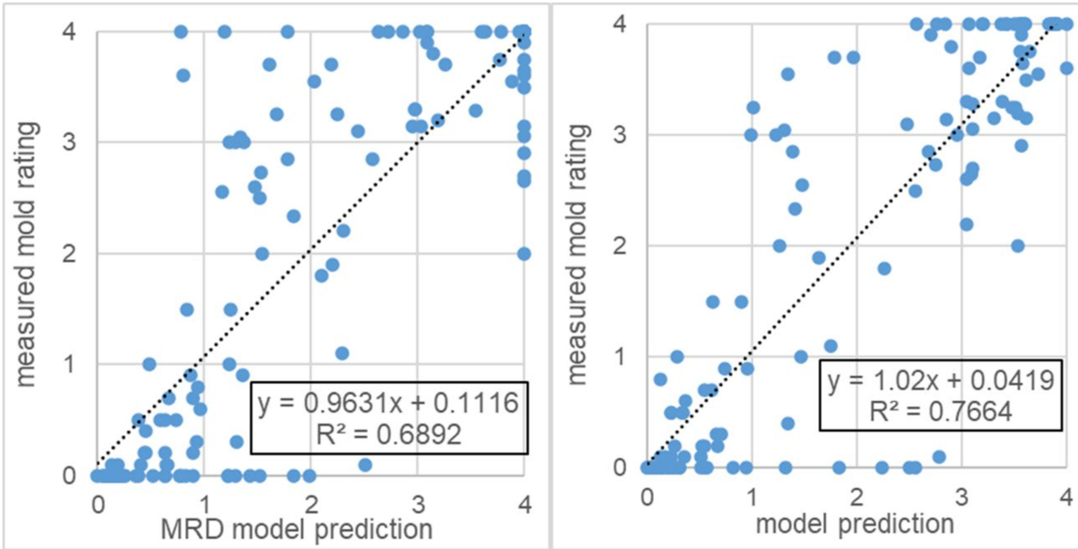

Figure 6 Measured mold growth data versus model predictions for original MRD model (left) and improved model (right). Data from all sources in Table 1 (VTT, Johansson, Nielsen, Yang) and model predictions.

Inspection of Figure 6 shows the fully improved MRD model has less scatter and a better correlation, but there are still instances of measured data far from the model prediction, both above and below the fit line. More field studies to help evaluate mold models are still needed, but this laboratory data is enough to indicate that further work on mold models is needed. Work currently underway at the Forest Products Laboratory aims to increase predictive power with a new mold model.

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