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Dose-response simple isopleth for mold (DR SIM): A dynamic mold growth model for moisture risk assessment

Charles R. Boardman [a,*], Samuel V. Glass [a], Robert Lepage [b]

[a] USDA-FS Forest Products Laboratory, 1 Gifford Pinchot Dr, Madison, WI, 53726, USA

[b] Environment and Climate Change Canada, Canadian Centre for Climate Services, 200 Sacré-Coeur Blvd, Gatineau, QC, K1A 0H3, Canada

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ABSTRACT

A new mold growth model was developed to aid in moisture risk assessment of wood-based building assemblies. This proposed simple model relies on several features common to existing mold growth models but combines them in a new way with improved predictive power. Structurally the model is based on a dose-response relationship. Hygrothermal conditions conducive to mold growth are represented using a mold germination isopleth, i.e., a critical relative humidity curve as a function of temperature. The dose at a given time step depends on the difference between surface relative humidity and the critical relative humidity. Doses are accumulated over time and a sigmoidal function relates cumulative dose to predicted mold rating. During unfavorable conditions, the predicted mold rating does not decline; rather, it remains constant and again increases once favorable conditions resume, subject to a recovery period. The model parameters were optimized using a large database of laboratory growth results obtained from the literature. The model was shown to have improved predictive power compared to an earlier model, and to be consistent with available field data. A key model feature is the ability to capture numerically the stochastic nature of mold growth using a deterministic mathematical form. The Dose-Response Simple Isopleth for Mold (DR SIM) model thus provides a useful tool for detailed moisture risk assessment using hygrothermal simulation or field data inputs of temperature and relative humidity.

1. Introduction

Hygrothermal modeling of building assemblies is commonly used for forensic investigation of moisture related failure, to help design new durable and energy-efficient building envelopes, and to plan retrofit of existing buildings [1–4]. The evaluation of model outputs (such as relative humidity, temperature, and moisture content) to assess moisture related risk in building assemblies remains challenging. Conversion of these hygrothermal metrics to more relevant durability metrics (e.g. mold growth models) is a necessary step and first-pass guidance is provided by ASHRAE Standard 160–2021 [5] and professional judgment called for in EN Standard 15026 [6]. A variety of biological, chemical, and physical processes (mold growth, fungal decay, fastener corrosion, freeze/thaw, expansion/contraction, etc.) can damage building materials without proper moisture management [7,8]. A useful recent review of biodeterioration models can be found in Ref. [9]. A common proxy for full moisture risk assessment is to rely on a mold model, and mold modeling will be an important part in any full risk assessment [10–13]. This work develops a new mold growth model, Dose-Response Simple Isopleth for Mold (DR SIM), to improve the risk assessment tools used to evaluate the biodeterioration resistance

* Corresponding author.
E-mail address: charles.r.boardman@usda.gov (C.R. Boardman).

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of wood buildings.

There are a variety of mold models currently on offer. The VTT mold index model [14–17] is an influential and pioneering dynamic model still drawing interest for moisture risk assessment [18] and further model refinement [19]. The Mold Resistance Design (MRD) model [20] uses a dose-response relationship to describe the extent of mold growth as a function of local hygrothermal characteristics. Both VTT and MRD have been implemented as software post-processors [21] for evaluation of hygrothermal output created by WUFI [22,23], a commonly used hygrothermal simulation tool.

Despite the significant research on mold models, further improvements are still required. Vereecken and Roels [10] analyzed many existing mold growth models and showed they provide results inconsistent with each other due to various simplifications. Gradeci et al. [24] provided a review of mold models with suggestions for development using probabilistic-based approaches [25,26], and highlighting the many different factors that influence growth, which are handled inconsistently between models. Johansson et al. [27] report results of a round-robin study which evaluated use of six different models to predict mold growth in a field study. The variety of model input choices and model assumptions resulted in a wide variation in predicted mold growth. In field conditions with considerable variation in temperature and humidity the dynamic models underestimated mold growth, while one static model had reasonable predictive power. Static models are simpler in that they only predict a binary yes or no for mold growth based on crossing a boundary condition, usually referencing relative humidity (RH) or moisture content (MC). Dynamic models generally provide a time-varying output related to mold growth based on considering time-varying input conditions. In these dynamic models a binary answer can be provided by assuming that mold growth beyond a certain threshold value counts as too much mold growth.

As fungal growth is a stochastic process, models reflecting this reality have been previously attempted by Moon [28], Gobakken et al. [29], and Gradeci et al. [30]. However, these models have found limited application within practice due to their complexity and limitations of assumptions (e.g., field vs repeatable controlled laboratory experiments, material substrates). More recently, Lepage et al. [31] advanced a dynamic probabilistic mold model using a simplified logistic regression with a high degree of predictive power within a limit state framework. However, while probabilistic approaches provide relevant output to practitioners, significant

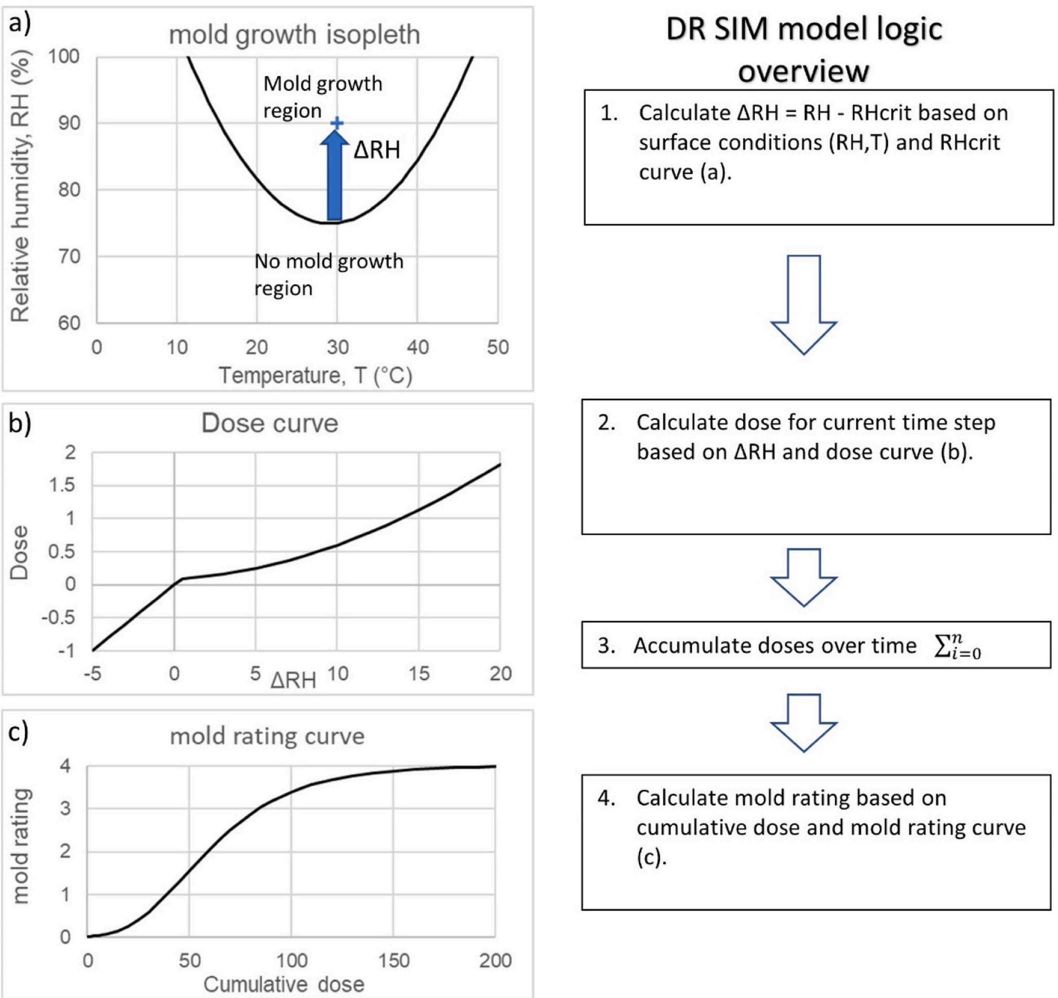

Fig. 1. Overview of DR SIM model logic.

challenges arise when attempting to compare accuracy against deterministic models. Reconciliation on a method to compare these two different classes of models (deterministic vs probabilistic) remain unresolved, and so both should be pursued independently in the interim.

The DR SIM model grew from work on the MRD model which was attractive because of its simplicity and well developed mold rating system [32–34]. Recent attempts to improve the MRD model were only modestly successful [35] suggesting a need for further model development. Like the MRD model the DR SIM model uses a dose calculation at each time step and accumulates doses over time to predict mold growth. DR SIM, and previous mold models like MRD and VTT, seek to predict mold growth so that they can be useful in assessment of moisture risk. Such mold growth predictions are typically based on laboratory experiments of exposed surfaces and are intended to apply also for cavities or material interfaces. There are numerous simplifying assumptions, the most important of which are that the surface relative humidity (RH) and temperature (T) are among the most critical model inputs. The effects of other potentially relevant influences like solar radiation or air speed on the surface can be captured in hygrothermal modeling and would have influence only through the RH and T. Clearly the surface material properties are also critical, and each model develops simple methods to account for a material's susceptibility to mold growth which varies by mold spore exposure, available food sources, and other surface characteristics which usually cannot be completely assessed prior to applying the model in the field.

The first objective of this work was to create a dynamic model with the simplicity and mold rating system of MRD but with improved predictive power. A dynamic model provides output values corresponding to the extent of mold growth over time, which allows a quantification of risk with more detail than the binary (yes, no) or stop light (red, yellow, green) risk outputs often used in evaluation of hygrothermal simulation outputs [36]. The second objective was to parameterize the model to capture stochastic features of mold growth in the built environment.

The key features in the DR SIM model are isopleths [37–39] combined with sigmoidal mapping functions. Briefly, in mold research, isopleth graphs typically provide two-dimensional (relative humidity and temperature) boundary curves describing constant mold growth rates. Such isopleths have been used to build mold growth models [39] and characterize mold growth on surfaces [34]. The sigmoidal mapping functions used in the DR SIM model are based on the Gompertz function commonly used to describe biological growth and are consistent with typical life-stages of fungi [40]. For a recent summary of a variety of growth functions see Ref. [41]. In the DR SIM model an isopleth and sigmoidal function are used to calculate the dose, while another sigmoidal function relates the accumulated dose to the mold growth rating. Fig. 1 outlines the logical flow of the DR SIM model from environmental inputs to mold rating.

2. Model development methodology

Development of the DR SIM model required a two-step process: 1) the compilation of a comprehensive mold growth database to expand and refine the DR SIM model, then 2) optimization of the fitting functions to ensure the DR SIM model provides accurate predictions.

2.1. Building a mold growth database from literature

Different models use different rating systems to characterize fungal growth. Unifying the various mold rating metrics is a necessary first step to translate and compare laboratory derived experimental data. Similar to the VTT and MRD models, the DR SIM model was developed based on laboratory measurements. Literature data were used to create a comprehensive results database. The database included mold growth ratings over time used to develop both the VTT and MRD models. The different studies used different mold inoculation techniques with different mixtures of fungal species which were intended to capture the most commonly encountered species of concern in wood-frame construction. Since the mixture of species cannot be known in advance for field studies mold growth predictions are not specific to a mixture of particular species. Mold growth ratings were extracted from figures in published papers

Table 1
Literature sources for laboratory mold growth ratings.

Shorthand Label	References	Materials[a,d,e]	Duration, weeks[b]	T Range	RH Range[c]	Fluctuating RH?
VTT	Viitanen and Ritschkoff 1991 [42] Viitanen and Bjurman 1995 [43] Viitanen and Ojanen 2007 [15]	Pine sw Spruce sw	12 | 4 | 24	5–40 °C	80–99%	Yes
Johansson	Johansson et al., 2012, 2013 [32,33]	Pine/spruce sw	12 | 6 | 32	5–22 °C	75–95%	Yes
Nielsen	Nielsen et al., 2004 [44]	Pine sw	17 | 17 | 30	5–25 °C	78–95%	No
Yang	Yang 2005 [45]	OSB, Plywood, Aspen sw/hw, Jack pine sw, White spruce sw	8 | 8 | 8	10–28 °C	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).
[d] Materials are abbreviated in subsequent Tables and Figures: VTTP, VTT Pine; VTTS, VTT Spruce; Joh, Johansson Pine/spruce; Niel, Nielsen Pine; OSB, Yang OSB; Ply, Yang Plywood; AspS, Yang Aspen sw; AspH, Yang Aspen hw; JPS, Yang Jack pine sw; SprS, Yang White spruce sw.
[e] VTT, Johansson, and Nielsen Pine is Scots pine (*Pinus sylvestris*), and Norway spruce (*Picea abies*), while the Yang wood species are Jack pine (*Pinus banksiana*), White spruce (*Picea glauca*) and Aspen (*Populus tremuloides*).

when not available in table form. The initial data sets were collected from five literature sources [15,32,33,42,43]. A rating represents the mean or median of multiple specimen observations at the same environmental conditions at a point in time. In order to explore low RH conditions in pine (Scots pine), data from Nielsen [44] were also included. These European datasets were supplemented with North American materials and mold ratings from Yang [45]. This Yang subset covered 6 materials, which included OSB and plywood. These datasets are summarized in Table 1. The details on all growth ratings, a summary of mold species grown, and the material substrate wood species used to create the DR SIM model are provided in Appendix A.

A significant difficulty in compiling a mold growth results database across multiple literature sources is the different ways researchers have characterized mold growth using their own mold growth rating systems. Vereecken et al. [11] provide some discussion and a suggested map between selected rating systems. For the DR SIM model, which uses the 0–4 rating scheme of Johansson [32,34], the mappings documented in Table 2 were used, which differ somewhat from those previously suggested by Vereecken. Specifically, the mapping consolidates all ratings with more than 50% area coverage in a mold rating above 3. This mapping reflects the Johansson rating scale emphasis on early mold growth. Fig. 2 provides an illustration of the scale with example mold growth on a surface.

The Johansson scale was developed primarily to document early mold growth, with the rating of 2 indicating problematic growth. Use of the scale for the DR SIM model extends to the heavy growth region where a rating of 4 lumps together ratings which would be distinguished in the VTT and Yang scales which go from 0 to 6. Further details on the different rating scales are provided in Appendix B.

2.2. Optimization of DR SIM using difference between measurement and prediction

Unlike the MRD model which can generate a mold growth prediction using input from only one experimental measurement on a particular substrate, the DR SIM model requires multiple experiments at different RH and T conditions. This is because the model parameters are calculated by minimizing the root-mean-squared error (RMSE) between model prediction and measured growth rating across a range of environmental conditions. This method allows a better characterization of the variability across substrates and across different T/RH combinations. The uncertainty inherent to a particular substrate is handled by providing a range of values for the relevant parameter. All mold growth data and model predictions were implemented in a spreadsheet and the Excel Solver (Microsoft Corp., Redmond, WA, USA) was used to minimize the total RMSE across all data sets. The final DR SIM model, presented in the next section, was the result of a dialectical process of adjusting model features and parameters to reduce the total RMSE. All the model components work together to yield the final mold growth rating prediction, and it is this final result which was compared with measured mold growth. Individual model features were not optimized separately and should not be interpreted as corresponding to particular physical processes. The justification for a particular model feature is that it reduces the total RMSE. Further discussion of such model features and how they contribute to reducing the RMSE will be briefly presented in the Results section following the model description.

3. DR SIM model description

The key objective of the DR SIM model is to provide accurate mold growth predictions while retaining simplicity and transparency in use. This section provides model details. First, the dose calculation method is explained in two steps, using an isopleth and sigmoidal function. Second, the rules for accumulating doses over time are provided. Third, the sigmoidal function which converts the accumulated dose to a mold rating is detailed. Finally, there is discussion of the parameter used to account for the stochastic features of mold growth and how that optimization works.

3.1. Isopleth used to characterize germination

The foundation of the DR SIM model is a plot of critical relative humidity, RH_{crit}, vs. surface temperature, T. This parabolic curve defines the surface relative humidity required for the onset of mold growth as a function of surface temperature; see Equation (1) and Fig. 3.

$$RH_{crit}(T) = \begin{cases} RH_{min} + \frac{c}{100}(T - T_{min})^2, 0\,^\circ C < T < 50\,^\circ C; RH_{crit}(T) \leq 105 \\ 105, T \leq 0\,^\circ C \text{ or } T \geq 50\,^\circ C \end{cases} \tag{1}$$

where RH is expressed in percentage, T is temperature (°C), the vertex of the parabola occurs at (T_{min}, RH_{min}), and the constant c defines the strength of the temperature effect and hence the shape of the parabola. A parabolic critical relative humidity curve has been

Table 2
Mold rating mapping used to convert all scales to Johansson.

Johansson	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

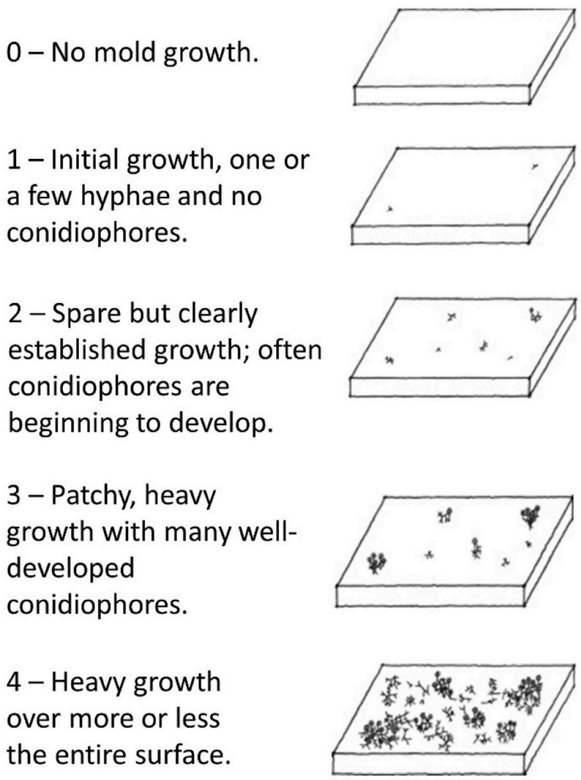

Fig. 2. Johansson mold rating scale - adapted from Ref. [32] with permission from Elsevier.

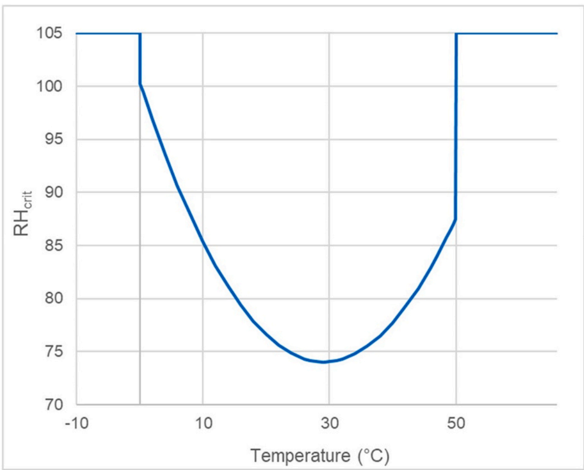

Fig. 3. RH_{crit} versus temperature for example material.

used in prior work [46,47].

In this work each material substrate in the database has its own RH_{crit} curve and thus unique RH_{min} and c values. T_{min} was set to 29.1 °C for all materials. The parabola is defined when T is between 0 and 50 °C. RH_{crit} has a maximum value of 105, which is also the value used when the temperature is outside the defined range. Fig. 3 plots an example RH_{crit} curve. Individual material RH_{crit} curves optimized across the full dataset outlined in Table 1 will be provided in the Results section.

3.2. *Dose calculation from RH and RH_{crit}*

The conduciveness of the conditions for mold growth at a given time step is defined by a dose curve, which is a sigmoidal function of ΔRH, the difference between the surface RH and RH_{crit} ($\Delta RH = RH - RH_{crit}$). The dose D_i is defined for both positive and negative ΔRH;

see Equation (2) for details and Fig. 4 for the example.

$$D_i = \begin{cases} a \exp\left[\quad \exp\left(b \quad \dfrac{d}{100} \Delta RH \right) \right], \Delta RH > 0.3 \\ m \Delta RH, \Delta RH \leq 0.3; \ D_i \geq \quad 1.05 \end{cases} \tag{2}$$

where a, b, and d are the parameters defining the sigmoidal curve (Fig. 4) and m is the slope of the linear segment, given by $m = \frac{a}{0.3} \exp\left[\quad \exp \ b \quad \frac{d}{100} \bullet 0.3) \right]$. Thus $D_i = 0$ at ΔRH $= 0$ and the linear segment matches the sigmoidal curve at the transition point (ΔRH $= 0.3$). The DR SIM model uses a 12-h time step, identical to that of the MRD model [20]. Hourly values of T and RH are processed into 12-h average values prior to running the DR SIM model. Negative doses (which can occur when ΔRH <0) are limited to 1.05 so that the Dose curve has a constant negative value when ΔRH has a large negative value.

3.3. Dose accumulation and delay after unfavorable periods

Doses for each 12-h time step are accumulated over time to produce a cumulative dose, D_{acc}, which is used to predict the mold growth rating at that time. When conditions are continuously favorable for mold growth (as defined by the RH_{crit} curve in Fig. 3), the doses for individual time steps are simply added to give a cumulative dose $D_{acc}(t)$. When conditions are unfavorable (RH < RH_{crit}) and a given dose is negative, the cumulative dose does not decrease. Instead, negative dose values delay the increase in the cumulative dose once favorable conditions return, similar to the concept of a recovery function [48]. Negative dose values are used in a 13-day lookback function (average across all the days) to define when mold can resume growth based on previous surface conditions.

$$L_i = \left(\sum_{i \ 26}^{i \ 1} D_i \right) \Big/ 26 \tag{3}$$

where L_i is the average dose over the previous 13 days (26 represents the number of 12-h time steps). If 13 days of prior conditions are unavailable, the average is taken across the days available. The dose is accumulated each time step (using a 12-hr time step) according to this simple rule: if the average dose over the previous 13 days is positive and the dose for the current time step is positive, it is added to the cumulative dose; otherwise, the cumulative dose is unchanged for the current time step.

$$D_{acc}(t_i) = \begin{cases} D_{acc}(t_{i \ 1}) + D_i, D_i > 0 \text{ and } L_i > 0 \\ D_{acc}(t_{i \ 1}), D_i \leq 0 \text{ or } L_i \leq 0 \end{cases} \tag{4}$$

where $D_{acc}(t_i)$ is the cumulative dose up to the current time step. This method of accumulation prevents the cumulative dose from decreasing as happens in other models. In adverse conditions, fungi may cease growth or go dormant, but the vegetative mycelium do not typically “reverse” unless hostile conditions occur. Even under extreme conditions, the formation of resting spores permits a rapid return upon resumption of adequate environments. Further optimization of the accumulation rules may be possible when longer running field studies become available.

3.4. Sigmoidal function for mold rating as function of cumulative dose

The cumulative dose is then transformed to a predicted mold rating using a sigmoidal function. Further, each material has a defined threshold value Z. The mold rating is zero until the cumulative dose $D_{acc}(t)$ has exceeded the threshold value. The predicted mold rating $R_m(t)$ at time t, on the 0–4 scale as defined above, is given by

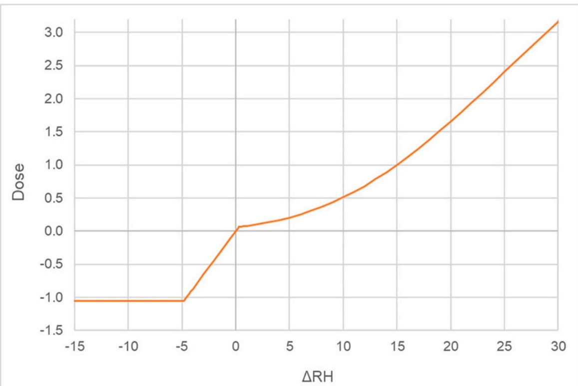

Fig. 4. Plot of Dose as function of ΔRH, which models the conduciveness of the conditions for mold growth in a given time step. The transition in shape occurs at ΔRH = 0.3 and the negative Dose limit is 1.05.

$$R_m(t) = \begin{cases} 0, D_{acc}(t) \leq Z \\ f\ \exp\left[\quad \exp\left(g \quad \frac{h}{100}\left[D_{acc}(t) \quad Z\right]\right)\right], D_{acc}(t) > Z \end{cases} \tag{5}$$

where *f*, *g*, and *h* are fitting parameters which define the shape of the sigmoidal function (Fig. 5). Here the value of $f = 4$, which defines the largest mold rating output from Eq. (5).

3.5. Threshold value, Z, used to characterize variability

The threshold value *Z* is set for each material and has a range of values which characterize the variability in mold growth results for that material. Like the c and RH_{min} values in Eq. (1), the Z value was initially optimized across all the data sets for a particular material. All other parameters for the DR SIM model were optimized across the full database including all materials. Recall that this optimization is a minimization of the total RMSE. But the Z value can also be optimized for each individual RH and T condition among the material substrate data set. Changing the value of Z shifts the sigmoidal curve shown in Fig. 5 left or right. These individual values of Z, optimized using the much smaller set of data points for one T and RH condition, were then used to create the range of possible values for Z, providing an indication of the variability in mold growth for that material. Specifically, the highest and lowest individual Z values for a material substrate define that range.

4. Results

4.1. General optimization results

Examples of the DR SIM model in use across a variety of materials and laboratory conditions are provided in Fig. 6.

These results reflect the optimization across the full database with parameter values detailed in Table 3 for fixed values and Table 4 for values which vary by material substrate.

4.2. Comparison of root-mean-squared error with MRD model

The primary objective was to create a simple mold growth model with improved predictive power. Fig. 7 documents the achievement of that goal by comparing the RMSE across the full results database for three different models: an MRD model optimized for each material substrate, an improved MRD model (labeled MRD*), and the optimized DR SIM model. MRD* was documented in Ref. [35] and includes three improvements: modifying the T and RH dose factors, adding the recovery function to the rules for accumulation of doses, and replacing the linear map from cumulative dose to mold rating with a sigmoidal function similar to that used in the DR SIM model. The improved MRD* model uses the original method to calculate the dose (product of T and RH dose factors), not the RH_{crit} isopleth used in the DR SIM model. Inspection of Fig. 7 suggests that while the sigmoidal mapping of cumulative dose to mold rating is useful, the core dose calculation in MRD needed improvement. The optimized DR SIM model has significant predictive power.

4.3. Optimization of specific model features

4.3.1. Isopleth results

T_{min} (from Equation (1)) was fixed at 29.1 °C for all materials for simplicity. Allowing T_{min} to vary by material substrate does not significantly improve the overall optimization (less than 0.15% improvement in RMSE). In contrast, the c and RH_{min} values vary significantly (see Table 4) and allow the DR SIM model to track different material substrates. Fig. 8 illustrates the isopleth curves for select materials. These material optimizations reduce the total RMSE by allowing variation in the c and RH_{min} values in each material individually.

The RH_{crit} maximum value of 105, also used in Equation (1), was chosen to improve the overall optimization through the dose

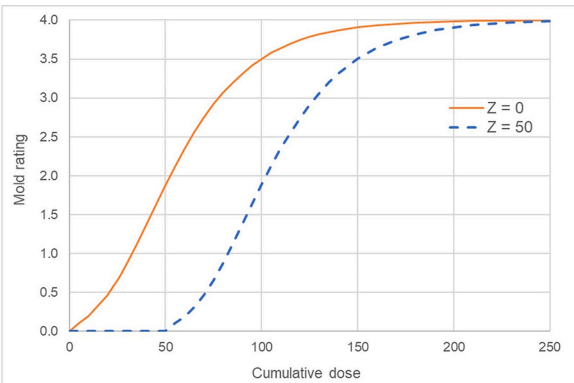

Fig. 5. Mold rating versus cumulative dose, allowing mold growth prediction based on changing environmental conditions which influence the mold growth at each time step. The fitting parameter f is set to 4, while g and h are shared by all materials; only threshold value Z is allowed to vary by material. Example threshold Z values are 0 and 50.

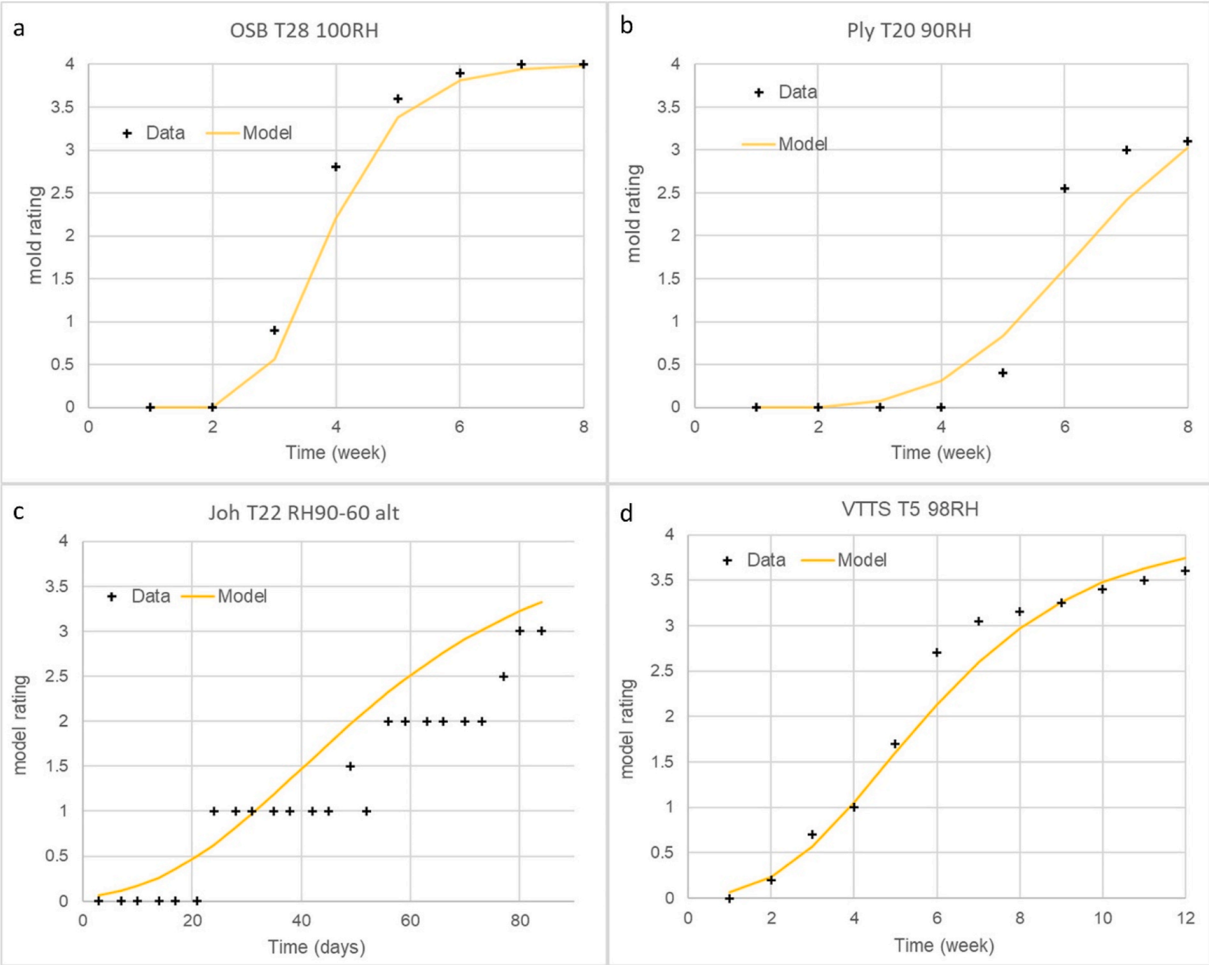

Fig. 6. Examples of DR SIM model in use: a) OSB at T = 28 °C 100% RH, b) Plywood at T = 20 °C 90% RH, c) Johansson pine at T = 22 °C alternating %RH between 90 and 60, d) VTT Spruce at T = 5 °C and 98% RH. See Table 1 or Appendix A for data references.

Table 3
DR SIM model parameters applicable to all materials in database.

Parameter	T_{min}	*a*	*b*	*d*	*m*	*f*	*g*	*h*
Equation	(1)	(2)	(2)	(2)	(2)	(5)	(5)	(5)
Value	29.1 °C	7.0249	1.5594	5.9503	0.21906	4	1.4587	3.4803

Table 4
Material specific DR SIM model parameters.

Material	*OSB*	*Ply*	*AspH*	*AspS*	*SprS*	*JPS*	*VTTS*	*VTTP*	*Niel*	*Joh*
RH_{min} (Eq. (1))	72.8	74.0	75.2	73.1	73.3	73.8	75.2	75.4	74.7	72.9
c (Eq. (1))	3.401	8.778	4.493	3.444	1.632	1.356	1.796	1.710	2.088	2.439
Z (Eq. (5))	45.8	16.9	23.2	19.4	45.7	28.9	9.2	9.2	12.6	1.7

calculation (Equation (2)). This higher than 100 RH_{crit} allows a larger negative dose for unfavorable conditions which improves prediction accuracy under fluctuating conditions.

4.3.2. Dose calculation shape

The sigmoidal dose curve transition point ($\Delta RH = 0.3$) was chosen to reduce the total RMSE at low RH conditions. This is similar to the behavior of the MRD dose model and reflects the more linear relationship between RH and dose when surface RH is near the critical condition for mold growth. The dataset includes a limited number of results at these conditions and the transition point may be

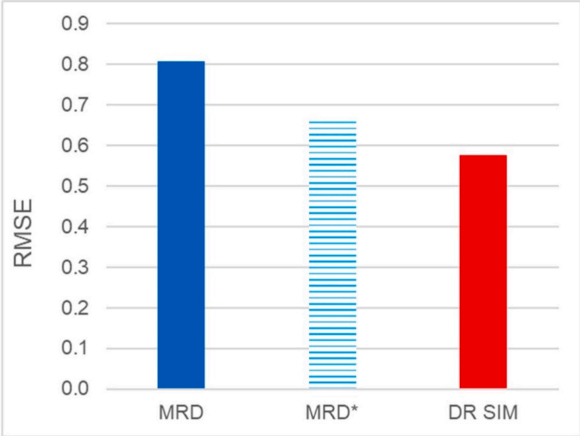

Fig. 7. Root-mean-squared error (RMSE) for different mold models optimized to the laboratory data summarized in Section 2; see text for description of models.

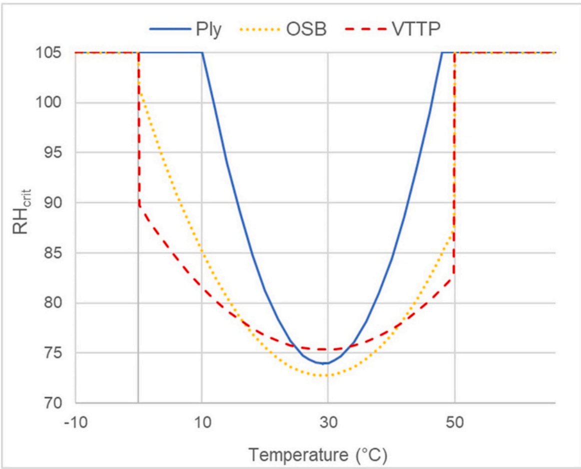

Fig. 8. RH_{crit} versus temperature for 3 materials: Yang Plywood (Ply), Yang OSB (OSB), VTT Pine (VTTP).

improved when additional experimental or field results become available.

4.3.3. Accumulation rules

The 13-day lookback period used in Equations (3) and (4) optimized the model predictions to the database which has limited information on fluctuating conditions. The details of this accumulation rule are likely to be improved when additional field results become available because field results will expand the set of fluctuating conditions and allow revisiting the lookback period and calculation methods.

4.4. DR SIM model predictive power and remaining variability

Fig. 9 plots the model predictions using the values in Tables 3 and 4 versus the measured mold ratings for a selection of results, to show both the model power and the extent of scatter. Inspection of Fig. 9a shows the data scatter, while 9b illustrates that many results are close to the line of perfect agreement. However, some results show greater deviation from that line, which will be explored next.

4.5. Using threshold parameter Z to capture variability

The threshold parameter Z allows the cumulative dose to mold rating curve (Fig. 5) to be shifted to the right (positive threshold) which reduces the predicted mold rating for any given cumulative dose. Thus, it is one of the measures of the susceptibility of the material to mold growth (in addition to c and RH_{min}) and was added to the DR SIM model to provide a quantitative method to capture the variability inherent to mold growth. In addition to the average value of Z reported in Table 4 there is the ability to define a maximum and minimum threshold value. Each set of RH/T conditions for a material was individually optimized to find the best Z value for that one condition by minimizing the RMSE. Fig. 10 displays that range of optimum values for the VTTS subset by placing Z values in bins to group them by range of Z value. Inspection of Fig. 10 shows the range is significant, with many results of Z above 20, while the global average is 9, although only one condition falls in the range between 5 and 10.

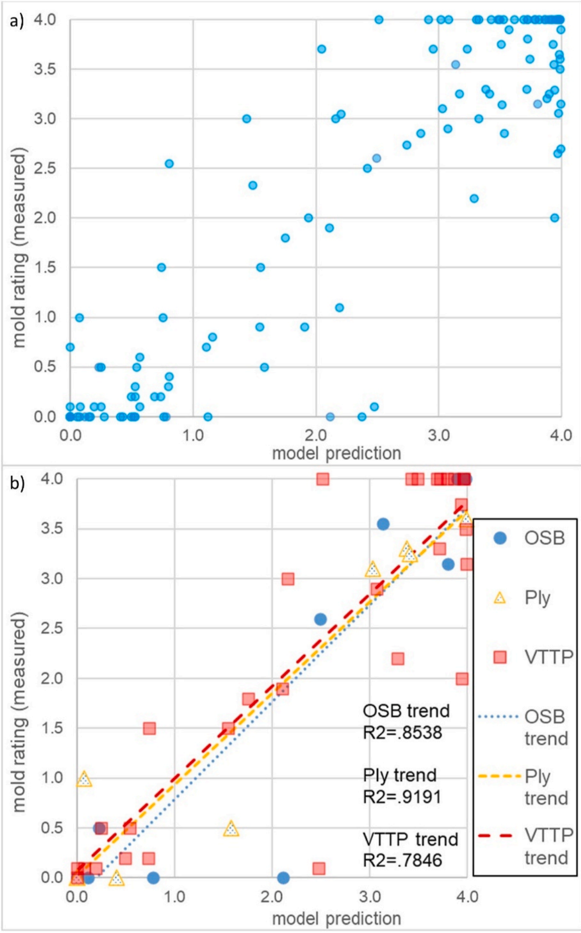

Fig. 9. Measured mold rating versus model predicted rating: a) illustrating data scatter including the highest cumulative dose across all subsets in full dataset, b) illustrating trendlines for 3 materials including the range in coefficient of determination (R^2).

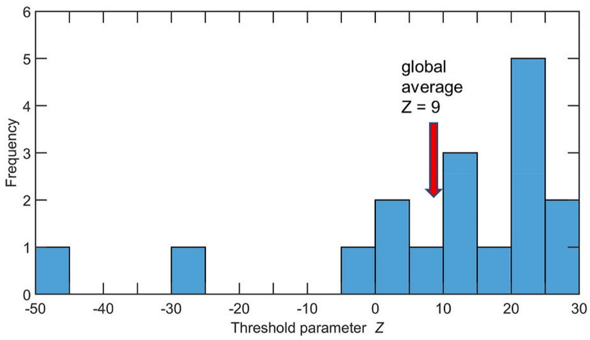

Fig. 10. Histogram of threshold Z values across the VTTS data subset.

Table 5
Variation in threshold values Z (high and low) for select materials.

Material	*OSB*	*AspS*	*SprS*	*Ply*	*VTTS*
High Z	101	55	64	33	26
Low Z	12	3	6	11	46
Overall best Z	46	19	46	17	9

Table 5 presents the result of finding maximum and minimum threshold values across all the data subsets for select materials. The high and low Z values are shown along with the overall value which is the same as in Table 4. This result documents the achievement of the secondary objective of using a range of values in Z to capture remaining mold growth variability. If sufficient data were available for a given material, the range of Z values could be represented by a statistical distribution, and Z could then be treated as a stochastic variable. This enhancement would enable a user of the DR SIM model to predict the probability of exceeding a particular mold rating under a given set of conditions.

5. Comparison of DR SIM model output with field studies

The ultimate goal is to have a simple and reliable model for mold growth prediction which is useful in actual buildings. Evidence that the DR SIM model is promising can be supplied by comparing its predictions against field studies. Two studies, both previously examined by Ref. [18] to test the VTT model, are explored first, then a more recent study. In the first example the DR SIM model was run on RH and T data from a field study in Devens, MA of a double-stud wall with 300 mm of dense-packed cellulose insulation, latex paint on gypsum board as interior vapor control, and exterior OSB sheathing. Full details of the field study can be found in Ref. [49]. Fig. 11 (right) plots the DR SIM and MRD model predictions for the duration of the study along with the RH and T data (left) for the North (top) and South (bottom) wall.

Inspection of Fig. 11 suggests the conditions were favorable for mold growth in the Spring when the wall was drying out from high RH and the weather was warm enough to support growth, starting around day 500 (late April 2013). However, no mold growth visible to the naked eye was observed at the end of the study when the walls were disassembled. The predicted mold growth is modest (1.7) in the South wall and would not have triggered a warning (a DR SIM rating above 2 is considered risky), but high (3.3) in the North wall. Complicating matters further the cellulose insulation had a borate additive which acts both as a fire retardant and a preservative, which may have helped protect the OSB. For comparison, as discussed further in Glass et al. [18] these walls do fail the ASHRAE (2009) Standard 160 30-day running average surface temperature and relative humidity criterion, but the walls have maximum mold index values less than 3 (threshold for visible mold growth) using the VTT model. The DR SIM model indicates that the North wall has significant risk. The risk can be better quantified by using the maximum and minimum values of the Z to indicate a range of possible results for this set of conditions. For example, in the South wall, the maximum threshold value ($Z = 101$) indicates no mold growth, while the minimum value ($Z = 12$) yields a DR SIM rating of 3.1 indicating the possibility of significant mold growth. There is some risk to this South wall. The DR SIM model quantifies this possibility and indicates that the North wall has higher risk than the South wall as one would expect since the RH was generally higher for the North wall. Further, the range of Z values is a useful feature of the DR SIM model allowing the addition of error bars to the mold prediction.

The second example is a case where considerable mold growth visible to the naked eye was found after disassembly. The data comes from Gatland et al. [50] who worked in the Natural Exposure Text Facility in Puyallup, WA. Test walls were identical, except for the interior vapor control layer, with stucco exteriors over OSB on nominal 2″ x 6" lumber framing filled with fiberglass batt insulation. The wall with visible mold had latex paint as the only interior vapor retarder, while other walls with no visible mold had polyethylene sheet or a smart vapor retarder. Fig. 12 (right) plots the DR SIM and MRD predictions for the duration of the study along with the RH and T data (left) for the wall with latex paint as interior vapor retarder. The DR SIM mold rating of 3.95 is only reduced to 3.64 when using the maximum threshold value ($Z = 101$), still indicating significant mold growth as would be expected given the long period of RH at 100%. The DR SIM rating of the walls with polyethylene and smart vapor retarder was zero, indicating no risk.

Finally, a more recent experimental study also found spotty mold growth visible to the naked eye in unvented roof assemblies in Westford, MA documented in Ref. [51]. That study included using the VTT model to predict mold risk on OSB sheathing covering the deep rafter cavities filled with fibrous insulation. Inspection after the second winter which had high interior RH found the spotty mold in north cavity 3 (fiberglass filled). The VTT model predicted no visible mold, with a maximum value of 1.5 (visible mold is predicted if the VTT rating is 3 or above). Fig. 13 plots the RH and T conditions (left) and various mold predictions (right) for the sheathing in this roof cavity.

The range of mold growth predicted during the warm Spring 2018 period (near day 500) while the OSB was still wet is consistent with the report of spotty mold growth observed after disassembly. A more granular rating of the mold growth in future field studies would be helpful.

6. Discussion

While the simulation results reported in section 5 show the DR SIM model has promise of predicting field results, there is still a need for further field evaluation and perhaps further model tuning. A strength of the DR SIM model is that most of the parameters are fixed, and there is no need to assign a material sensitivity class or mold decline parameter, which have been shown to vary considerably from user to user [27]. However, each material substrate would need laboratory mold testing at multiple T and RH conditions to establish the DR SIM model parameters which are material specific, including the RH_{crit} curve and the range of Z values. The need for material testing is especially acute in manufactured wood products like OSB and plywood. As a manufactured product OSB's mold growth potential will depend on the wood species used in fabrication and possibly other factors including adhesives and pressing conditions [52,53]. We know from previous experience handling OSB from diverse locations within North America [54] that the mold growth potential varies significantly by location. This is relevant for interpretation of results from field studies as it introduces even greater uncertainty in predicted outcome unless the specific materials used in the building under investigation are characterized.

An additional concern is that field studies have typically reported only the presence or absence of mold growth visible to the naked eye, if they report any inspection after disassembly. One recent study is an exception and provides an example for future studies [27].

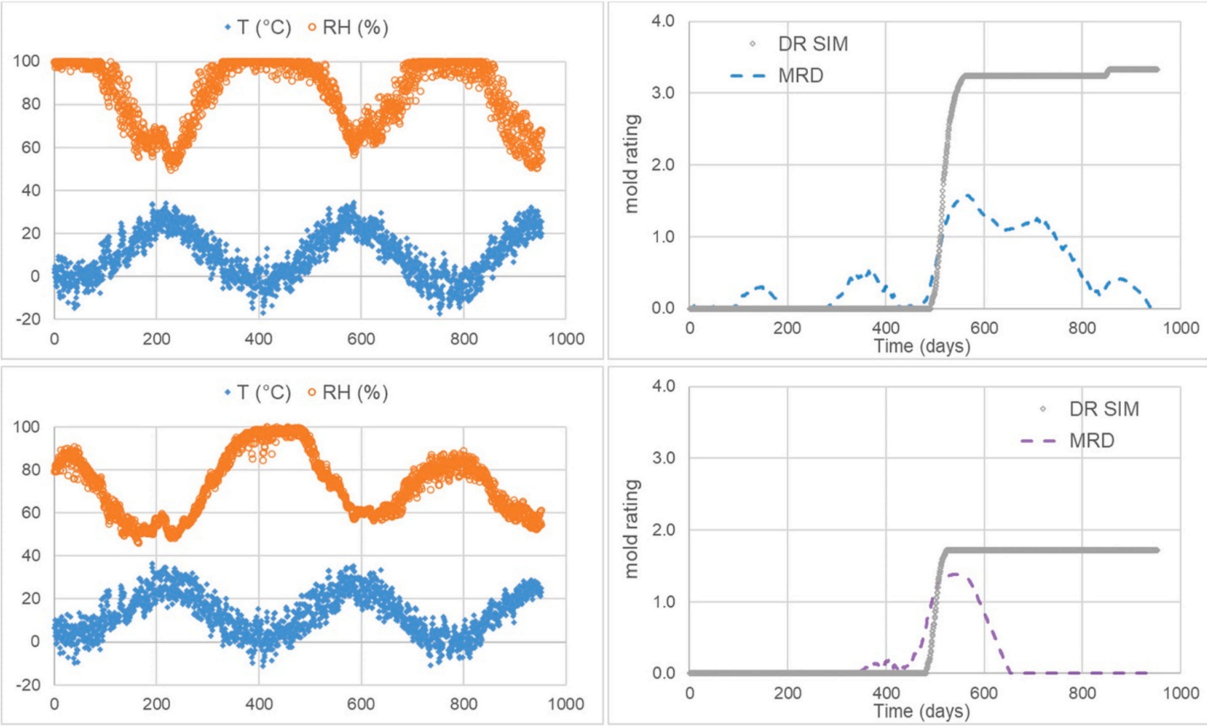

Fig. 11. Temperature and relative humidity data (left) for Devens MA field study, with mold rating predictions from DR SIM and MRD models (right). Top row North wall, bottom row South Wall. Day 1 was December 8, 2011.

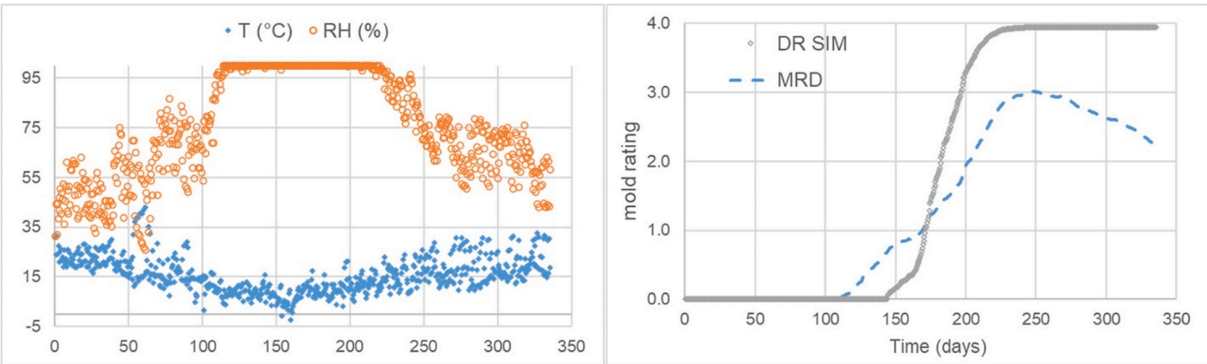

Fig. 12. Temperature and relative humidity data (left) for Puyallup WA field study, with mold rating predictions from DR SIM and MRD mold models (right). Day 1 was July 30, 2003.

To advance mold modeling a careful mold rating, ideally on the Johansson scale with 10 - 40× magnification, would be needed. Thus, new field investigations would need to plan for measurement of not only the typical wall environment parameters (surface RH and T, and possibly moisture content), but also inspection of material samples periodically throughout the lifetime of the study.

One further issue needs brief mention. The recovery function used in the DR SIM model is a good characterization of the biology of mold growth but could prove problematic if the DR SIM model is run for extended periods (say more than 5 years). Would it be reasonable to fail a wall assembly because multiple brief periods of high RH many years apart eventually cause the DR SIM rating to exceed 2? One way to handle this would be to use a mold rating higher than 2 as the trigger for concern in longer studies, or the DR SIM model runs could be broken up into chunks, effectively resetting the rating at the start of each new time period. This question remains open, which again suggests the need for longer running field studies.

The robustness of the DR SIM model is explored in Appendix C, which documents little change in model output if the time period for averaging environmental conditions is changed from 12 h to 1 h, or when given some uncertainty in the RH conditions measured during the laboratory mold growth experiments.

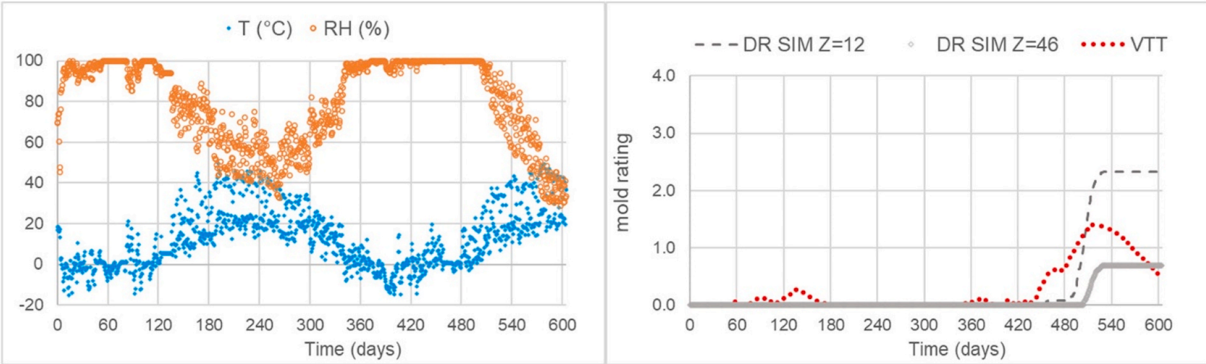

Fig. 13. Temperature and relative humidity data (left) for Westford, MA field study, with mold rating predictions from DR SIM model (right). The Z = 12 prediction uses the lowest Z value in the OSB range predicting the most growth during the warm period near day 500 (Spring 2018). Day 1 was December 13, 2016.

7. Conclusion

A new dynamic mold growth model (DR SIM) has been presented which yields improved predictions of mold growth compared to the MRD model across a large database of laboratory experimental results from the literature. Although more field data is needed to test the model under long-term fluctuating conditions, the DR SIM model also shows promise for providing predictions which better match results from the field. An additional feature of the model is that the threshold parameter Z captures the inherent variability of mold growth and can thus be used to calculate more or less conservative predictions within the range of values available for a tested material substrate. With sufficient data, Z can be represented by a statistical distribution and treated as a stochastic variable in probabilistic mold modeling.

CRediT authorship contribution statement

Charles R. Boardman: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization.

Samuel V. Glass: Conceptualization, Methodology, Validation, Investigation, Data Curation, Writing - Review & Editing, Visualization, Project administration.

Robert Lepage: Conceptualization, Methodology, Writing – Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jobe.2023.106092.

Appendix B. details on mold ratings

B.1 Overview of the mold rating systems

Transfer functions are used to convert various mold growth ratings (Yang, VTT, Nielsen) into the 0–4 rating scale (the Johansson scale) used in the MRD and DR SIM mold models. The Johansson scale was selected for the combined mold growth results database because it was in use in a popular mold rating system, and because the well-defined rating method has training available in use of the rating method. Ratings conversions are inherently difficult because the rating scales are based on different observations: some are of the visible surface (typically related to % area coverage), and some at microscopic magnification. Vereecken et al. Table 2 [11] attempts to supply a transfer map which includes Nielsen - percent coverage via microscope - [44], VTT (0–6 scale combining microscopic and visual assessment), and the Johansson scale (0–4 with 10 to 40× magnification). This is a helpful start, but a transfer from Yang's 0–6 scale [45] was also needed since the database includes North American materials. Yang uses a visible scale similar to VTT. The VTT scale was developed [16] to further define both visible and microscopic inputs after it was first introduced, such that VTT rating 3 is < 10% surface coverage visible, but up to 50% coverage by microscope, and VTT 4 is < 50% visible, but over 50% coverage by microscope. The fuller definition for the VTT mold index scale is show in Table B1.

Table B.1
VTT mold index (from Table 1 Ojanen et al., 2010 [16])

VTT	comment
0	none, spores not activated
1	small amounts on surface (microscope), initial stages of growth
2	several local mold growth colonies on surface, <10% coverage (microscope)
3	visible mold <10%, or <50% microscope
4	visible 10–50%, or >50% microscope
5	plenty of mold growth on surface >50% visual
6	heavy and tight growth, approx. 100% coverage

B.2 Modifying the Vereecken map – alternative paths to percent coverage

While the Vereecken et al. transfer map is helpful, parts of it need modification. Careful attention to the visual aid in Johansson Table 4 [32], which provides both words and a conceptual image of mold growth for the rating scale (see Fig. 2 in the main body of the paper) suggests a different mapping at the high ratings. The map of the Johansson scale to percent coverage at microscopic magnification (as used by both Nielsen and Johansson) is given in Table B2 below. This table starts with Johansson 1 = 5% microscopic coverage. Many, including Vereecken, are using the 5% figure as not yet visible, just getting started or initial growth. Next, based on the Johansson image for Johansson 2, 15% coverage was selected (while Vereecken has 10% and maps Johansson 2 = VTT 2). However, there are approximately 3× increases on the Johansson scale from 1 to 2 and again from 2 to 3, so that 1 = 5%, 2 = 15% (sparse), 3 = 45% coverage (patchy). This is a significant difference for what Johansson 3 means according to Vereecken's suggestion, which assigns Johansson 3 as > 70% coverage, and thus Johansson 3 = VTT 5. But the Johansson picture of Johansson 3 is not over 50% coverage. Further, this choice follows the logic that the Johansson rating scale (and the MRD model) was intended to support identification of early mold growth, with Johansson = 2 the trigger point for failure, i.e., there is clearly mold growth, but not much. Johansson has less interest in making the scale uniform, but a strong focus on early periods.

Table B.2
Estimated map between Nielsen microscopic coverage and Johansson rating scale

Nielsen	Johansson
0%	0
5%	1
15%	2
45%	3
80%	4

It remains to discuss Johansson rating 4, which is mapped to 80% coverage. It is clearly not 100% in Fig. 2. The language is "more or less" the entire surface, but the image has a fair amount of white space. Here is another significant difference from Vereecken Table 2 which has 100% coverage and maps Johansson 4 = VTT 6.

B.3 Mapping VTT mold index to Johansson rating scale

The Johansson maps to VTT for Johansson 1 = VTT 1 and Johansson 2 = VTT 2 as suggested by Vereecken were discussed and accepted above. It remains to summarize how to map Johansson 3 and 4 (45% and 80% coverage) to the VTT scale and show the resulting full map. If Johansson 3 is 45% area coverage, then it must map to near VTT 3, which is defined as < 50% coverage by microscope. Table B3 is the map of VTT scale at microscopic coverage, and the simplified VTT to Johansson map is detailed in Table B4 and plotted in Figure B1.

Table B.3
Estimated map between Nielsen microscopic coverage and VTT mold index

Nielsen	VTT	comment
0	0	
5%	1	

(*continued on next page*)

Table B.3 (*continued*)

Nielsen	VTT	comment
15%	2	
35%	3	Visible <10%, mag <50%
65%	4	Moderate visible 10–50%, mag >50%
95%	5	Plenty visible >50%
100%	6	Even more visible 100%

Table B.4
Estimated map between VTT mold index and Johansson rating scale

VTT	Johansson
0	0
1	1
2	2
3	3
4	3.5
5	4
6	4

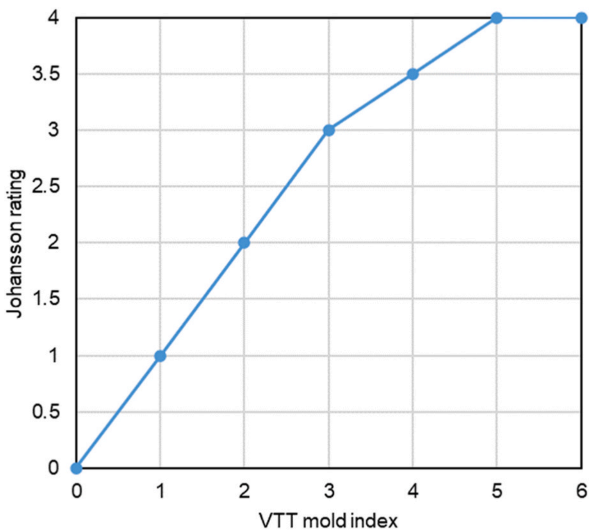

Fig. B.1. VTT to Johansson transfer function.

B.4 Adding in the Yang mold rating

So far, simple functions have been provided to map Nielsen and VTT to the Johansson scale. Still needed is the Yang to Johansson translation. Yang's scale runs from 0 to 6 based on visible mold growth as detailed in Table B5.

Table B.5
Yang mold growth scale

Yang	comment (visible)	Johansson	comment (40×)
0	none	0	none
1	no visible, trace at 25×	1	initial growth
2	visible <5% area	2.5	more than clearly established
3	5–25% area visible	3	patchy, heavy growth
4	25–50% area covered	3.5	
5	over 50% area covered	4	heavy growth
6	100% and very heavy mold	4	

Yang 1 = Johansson 1 as this expresses the initial growth, but Yang 2 maps to more than Johansson 2 because there is more than sparse microscopic growth. The patchy growth indicated at 40× magnification for Johansson 3 can translate to significant visible (>5% visible) growth on Yang 3 scale.

The resulting mapping function is plotted in Figure B2.

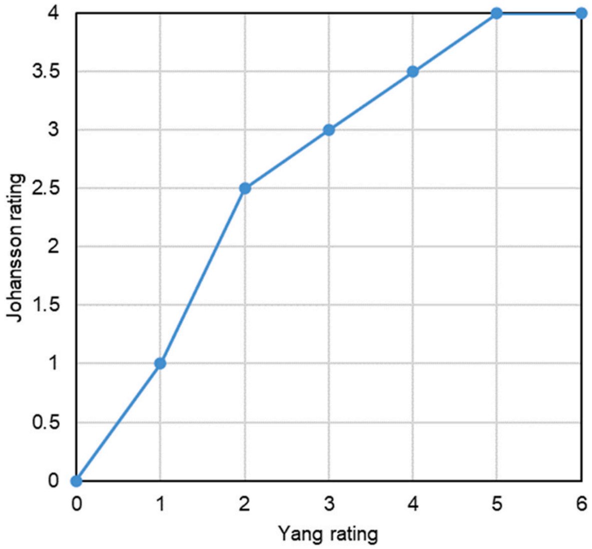

Fig. B.2. Yang to Johansson transfer function.

Above then (Tables B2, B4, B5) are the transfer functions used to map the various data sources to the Johansson 0–4 scale used in the DR SIM model and summarized in Table 1 of main body of the paper.

Appendix C. Robustness of Optimization

C.1 Brief exploration of averaging (12 h vs 1 h)

The DR SIM model inherits from MRD the 12-h average RH and T used for dose calculation, although hourly output is often used in hygrothermal modeling. This has the effect of cutting out extreme conditions and thus changing the growth predictions. To illustrate how this changes model output, the first two field studies reported in section 5 were rerun with hourly data rather than the 12-h averages (which used 8am to 8 p.m. for day, and 8 p.m. to 8 a.m. next morning for night, to create the two half-day averages). The hourly dose calculation was 1/12 the value from Eq. (2) and accumulated hourly. For the Devens, MA South wall the DR SIM value increased from 1.71 to 1.91. For the Puyallup, WA wall with paint as the vapor retarder the DR SIM values decreased from 3.95 to 3.89. There is an economy for model input and output with the data reduction to 12-h chunks which has little effect on the model prediction for these two field studies.

C.2 Brief exploration of effects of RH uncertainty

The DR SIM model relies on accurate RH readings in the laboratory studies used to create the mold growth database. These studies used a variety of RH measurement methods (saturated salt solutions, RH sensors) with different levels of accuracy. For purposes of exploring the robustness of the DR SIM model to RH uncertainty, the model static parameters were held constant as originally optimized, but the material specific parameters (Table 4) were allowed to vary to track systemic changes to the underlying database. First, all the RH values were raised by 2% (unless this took the value over 100%), then lowered by 2%, and the c, RH_{min}, and Z parameters reoptimized to track the new reported conditions in each case. The overall effect of these changes increased the RMSE less than 6% (from near 0.58 to near 0.61). To further assess the effect on model predictive power Table C1 compares the original parameter values to the new higher RH and lower RH values for the same selected cases as reported in Table 5.

Table C.1
Model parameters for select materials with RH systematically raised or lowered by 2%

		OSB	AspS	SprS	Ply	VTTS
DR SIM	RH_{min}	72.8	73.1	73.3	74.0	75.2
	c	3.401	3.444	1.632	8.778	1.796
	Z	45.8	19.4	45.7	16.9	9.2
RH+2%	RH_{min}	74.5	74.6	74.5	75.2	75.2
	c	3.034	2.966	1.332	8.203	1.804
	Z	47.7	24.1	51.6	25.8	23.9
RH-2%	RH_{min}	72.5	73.2	73.1	73.8	74.4
	c	3.518	3.366	1.646	7.821	1.828
	Z	29.8	7.3	28.9	2.2	0.0

Inspection of Table C1 shows that the RH_{min} and c values are only modestly changed given reasonable RH uncertainty, while the Z value sees the most significant change. Yet the change in threshold value is well within the maximum and minimum range reported in Table 5, indicating the variation in threshold value due to RH uncertainty is also modest compared to the variability which already exists across the T/RH conditions for a material.

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