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Complete List of Authors:	Zhang, Xiongqing; Research Institute of Forestry, Chinese Academy of Forestry, Cao, Quang; Louisiana State University duan, aiguo; research institute of forest, chinese academy of forestry Zhang, Jian-guo; Chinese Academy of Forestry
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Modeling tree mortality in relation to climate, initial planting
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logistic multilevel method

Xiongqing Zhang^{1,2}, Quang V. Cao³, Aiguo Duan^{1,2}, Jianguo Zhang^{1,2,*}

¹ State Key Laboratory of Tree Genetics and Breeding, Key Laboratory of Tree
Breeding and Cultivation of the State Forestry Administration, Research Institute of
Forestry, Chinese Academy of Forestry, Beijing 100091, P. R. China. Email:
xqzhang85@yahoo.com.

² Collaborative Innovation Center of Sustainable Forestry in Southern China, Nanjing
Forestry University

³ School of Renewable Natural Resources, Louisiana State University, Agricultural
Center, Baton Rouge, LA 70803, USA.

*Corresponding author: Jianguo Zhang
Email: zhangjg@caf.ac.cn. Tel: 0086-10-62889601. Fax: 86-10-62872015.

Abstract

Tree mortality models are important tools for simulating forest dynamic processes, and logistic regression is widely used for modeling tree mortality. However, most of the mortality models that have been developed generally ignore the hierarchical structure. In this study, Bayesian logistic multilevel mortality models were developed with the independent variables of initial the planting density, competition, site index and climate factors in Chinese fir plantations in southern China. The results showed that a Bayesian three-level model was best for describing tree mortality data with multiple sources of unobserved heterogeneity compared to fixed-effects and two-level models. The variance partition coefficient of tree mortality due to the tree level was much larger than that due to the plot level. The initial planting density and site index were positively correlated with mortality, and symmetric competition was negatively correlated. For climate variables, the mortality probability decreased with the increasing mean annual temperature and previous summer mean temperature. By contrast, the mortality probability increased with the increasing previous winter mean minimum temperature and annual heat-moisture index. Identifying different sources of variation in tree mortality will help further our understanding of the factors that drive tree mortality during climate change.

Key words: Bayesian logistic multilevel model; climate; initial planting density and competition; tree mortality; variance partition coefficient

46 **1. Introduction**

47 Tree mortality, one of the main components of forest succession, is important for
48 the maintenance of biological and structural diversity in forest ecosystems (Bigler and
49 Bugmann 2003; Zhang et al. 2011). A complex of endogenous and exogenous factors
50 acting as induction agents lead to tree death during forest succession (van Mantgem et
51 al. 2009). Among endogenous factors, perhaps the best-known cause of increasing
52 tree mortality probabilities is increasing competition for water, nutrients, and light
53 within a stand, resulting from increasing stand density and stand basal area (Franklin
54 et al. 2002). By manipulating the stand basal area and density, initial planting density
55 has a significant effect on inter-tree competition, thereby affecting tree mortality. Lutz
56 and Halpern (2006) reported that the initial planting density correlates strongly with
57 suppression-induced mortality.

58 In addition to endogenous factors, the effect of climate on tree mortality was
59 identified as an important exogenous factor (Breshears et al. 2005; Adams et al. 2009).
60 Tree mortality studies were performed primarily in established boreal or temperate
61 areas, where temperature is often a limiting factor. Additionally, temperature
62 conditions associated with water availability are an important determining factor
63 affecting tree mortality in these areas (Mueller et al. 2005; van Mantgem et al. 2009;
64 Peng et al. 2011; Zhang et al. 2014). Phillips et al. (2009, 2010) reported that tropical
65 forests also suffer increasing tree mortality probabilities in response to moisture stress.
66 Allen et al. (2010) reviewed the research of drought induced tree mortality and
67 revealed emerging climate change risks for forests worldwide.

68 The accurate prediction of tree mortality is an essential feature in any individual
69 tree forest growth and yield system. Hamilton (1974) introduced logistic regression to
70 modeling tree mortality and found that logistic regression is a good choice for
71 modeling tree mortality. Since then, logistic regression has been used to model tree
72 mortality for a variety of tree species (e.g., Avila and Burkhardt 1992; Yang et al. 2003;
73 Boeck et al. 2014), due to the ease of parameter interpretation (Rose Jr. et al. 2006).
74 Although logistic regression is the most widely used for modeling tree mortality, other
75 statistical methods have been used for describing and modeling tree mortality, such as
76 the exponential function (Moser 1972), Weibull function (Somers et al. 1980),
77 Richard's function (Buford and Hafley 1985), gamma function (Kobe and Coates
78 1997), the log-normal distribution (Preisler and Slaughter 1997), and hazards model
79 (Woodall et al. 2005). Vanclay (1995) recommended that logistic regression for tree
80 mortality in tropical forests is appropriate because of its biologically meaningful
81 interpretation, mathematic flexibility and ease of use.

82 However, most of the tree mortality models developed generally ignore the
83 heterogeneity that may occur due to repeated measurements nested within a tree and
84 trees nesting within a plot. Multiple sources of heterogeneity occur naturally for most
85 permanent plots used in forestry experiments. Recently, Bayesian multilevel models
86 have been widely used in forestry to account for multiple sources of heterogeneity and
87 to consider prior knowledge of the parameters (e.g., Dietze et al., 2008; Vieilledent et
88 al., 2010; Zhang et al. 2015; Chen et al., 2016).

89 Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook.), a fast-growing evergreen

coniferous tree, is one of the most important tree species for timber production in southern China. As a native species, Chinese fir has been widely planted for over 1000 years (Zhang et al. 2015). The objectives of this study were listed as follows: (1) develop an individual-tree mortality model using a Bayesian logistic multilevel method considering the full multiple sources of variability of data; (2) examine the effects of climate, initial planting density, and competition on tree mortality; and (3) calculate the variance partition coefficient (VPC) for reporting the variation associated with multiple levels in tree mortality models.

2. Materials and Methods

2.1 Data

The Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook.) stands were established in 1981 using bare-root seedlings in Fenyi County (27°30' N, 114°33' E), Jiangxi Province, in southern China, which has a middle-subtropical climate. A total of 15 plots were planted in a random block arrangement with the following tree spacing: 2 m × 3 m (1667 trees/ha), 2 m × 1.5 m (3333 trees/ha), 2 m × 1 m (5000 trees/ha), 1 m × 1.5 m (6667 trees/ha) and 1 m × 1 m (10,000 trees/ha). Each spacing level was replicated three times. Each plot comprised an area of 20 m × 30 m, and a buffer zone (two lines) consisting of similarly treated trees surrounded each plot. Tree diameter measurements in all plots were conducted after the tree height reached 1.3 m. More than 50 trees, including dominant trees in each plot, were tagged and measured for total height. Measurements were performed each winter from 1983 to 1989 and then every other year from 1989 to 1999. Summary statistics are shown in Table 1.

112 2.2 Methods

113 2.2.1 Candidate variables

114 *Endogenous variables*

115 The selection of appropriate independent variables should not only be based on
116 T-test statistics but also on a basic understanding of how forest ecosystems function
117 and how factors contributing to death are expressed (Pedersen 2007; Adame et al.
118 2010). Hamilton (1986) classified the endogenous factors contributing to mortality in
119 three groups: (i) measures of individual tree size, such as diameter at breast height (d)
120 or tree height; (ii) measures of tree competition, such as stand basal area (Ba), stand
121 density (N), the ratio of the diameter of the subject tree to the stand quadratic mean
122 diameter (d/Dg), and the ratio of the height of the subject tree to the stand dominant
123 height; however, the height of each tree in a plot was not recorded for the present data,
124 nor was it possible to appropriately calculate this value; and (iii) other growth-related
125 variables at the stand level, such as site fertility. For most tree species, the mortality
126 probability for the smallest tree in a plot is quite high and declines rapidly as small
127 trees survive to larger diameter classes (Adame et al. 2010), which can be captured
128 with a hyperbolic d^{-1} transformation of the diameter (Monserud and Sterba 1999). In
129 addition, Yao et al. (2001) reported that tree size is also used as a proxy of tree age (A).
130 Earlier studies found that trees exhibited different mortalities at different site quality
131 levels (Eid and Tihus 2001; Yao et al. 2001). In the present study we examined initial
132 planting density (IPD) effects, etc. Moreover, we normalized the initial planting
133 densities (1667 trees/ha, 3333 trees/ha, 5000 trees/ha, 6667 trees/ha, 10000 trees/ha)

134 before modeling. In summary, the following endogenous variables were tested for
135 inclusion in the mortality model: *IPD*, tree size index (A, d^{-1}), tree competition (d/Dg ,
136 Ba), and site quality (dominant height, $\log(Hd)$).

137 *Climate variables*

138 ClimateAP (Wang et al. 2014) was used to generate climate data across the study
139 region. ClimateAP is a climate data downscaling tool, which produces directly
140 calculated seasonal and annual climate variables and derives climate variables for
141 specific locations (scale-free) based on longitude, latitude, and elevation. The climatic
142 variables tested in this study are shown in Table 2 and are widely used in tree
143 mortality modeling (van Mantgem et al. 2007, 2009; Peng et al. 2011; Zhang et al.
144 2014). In addition, the annual heat-moisture index (*AHM*) (Wang et al. 2006) was
145 used to indicate the annual climatic water deficit because it integrates the mean annual
146 temperature (*MAT*) and annual precipitation (*MAP*) into a single parameter:
147 $AHM = (MAT + 10)/(MAP/1000)$, which better reflects evapotranspiration and soil
148 moisture content than precipitation and temperature alone (Zhang et al. 2014). Large
149 values of *AHM* indicate dry conditions due to high evaporative demand relative to the
150 available moisture, whereas low values of *AHM* represent relatively wet conditions.

151 Independent variables included in the function were selected as variables through
152 forward stepwise regressions. The set of variables is a combination of different groups
153 (tree size, initial planting density, competition, site quality, and climate), avoiding
154 correlations between the groups.

155 **2.2.2 Bayesian logistic multilevel models**

For a given single tree, survival or death can be represented as a binary that has a value of 1 if the tree survives or 0 if it dies over a given time interval. The most widely used link function for binary data is the logit link function, also named the logistic regression model (Vanclay 1995; Zhang et al., 2014). The traditional logistic mortality model is given by:

$$\ln\left(\frac{p}{1-p}\right) = \alpha_1 + \boldsymbol{\beta} \mathbf{x} \quad (1)$$

where $\mathbf{x}$ is a vector of explanatory variables, including non-climatic candidate variables, initial planting density (*IPD*) and climatic variables. α_1 is the intercept, and $\boldsymbol{\beta}$ is a vector of parameters including intercept.

Two-level models

In this study, we developed two two-level models: measurement occasions (level 1) and trees (level 2) called two-level1; measurement occasions (level 1) and plots (level 2) called two-level2. Let i ($i=1, \dots, N$) denotes the level-2 units (trees or plots) and j ($j=1, \dots, m_i$) denotes the level-1 units (measurement occasions); therefore, a two-level random intercept logistic model is expressed as

$$\ln\left(\frac{p}{1-p}\right) = \alpha_1 + \boldsymbol{\beta} \mathbf{x}_{ij} + \mu_i$$

$$\mu_i \sim N(0, \sigma^2) \quad (2)$$

where μ_i is a level-2 random effect assumed to have a normal distribution with mean 0 and variance σ^2 .

Three-level model

The simple two-level model (eq. 2) may be adequate for analyzing data from the permanent plots because the trees that are measured repeatedly are also nested within plots. Therefore, a three-level random intercept logistic model is needed:

$$\ln\left(\frac{p}{1-p}\right) = \alpha_1 + \beta \mathbf{x}_{ijk} + \mu_i + \nu_k$$

$$\mu_i \sim N(0, \sigma_\mu^2), \nu_k \sim N(0, \sigma_\nu^2) \quad (3)$$

where μ_i and ν_k represent the random effects of the i th tree and k th plot, respectively.

In the Bayesian models, we used “non-informative” priors for all parameters, i.e., a normal distribution with zero mean and a large variance (10^4). Such priors typically arise in the form of a parametric distribution with large or infinite variance. Notably, the word “non-informative” prior used here is the classical expression but does not necessarily mean that the prior is truly non-informative (Li et al. 2011). The random effect in the intercept is assumed to follow a normal distribution with a mean 0, and the variance of the random effects is given a prior distribution by the inverse gamma (0.001, 0.001). The Bayesian method is performed through Markov chain Monte Carlo (MCMC) simulation using the SAS procedure PROC MCMC (SAS Institute Inc. 2011), which uses a random walk Metropolis algorithm to obtain posterior samples (Lindsey 2011). The total number of iterations for tree mortality models was 250000 with a burn-in of 30000. Additionally, the thinning parameters were all set to 50 to reduce autocorrelation.

Bayesian model evaluation

The Bayesian three-level model was compared with Bayesian fixed-effects (nonhierarchical), two-level1 and two-level2 models using deviance information

199 criterion (DIC). This is very useful in Bayesian model selection (Spiegelhalter et al.
200 2002), which is given by:

$$201 \quad \text{DIC} = \text{Dbar} + \text{pD} \quad (4)$$

202 where Dbar refers to the posterior mean of the deviance and pD is the effective
203 number of parameters in the model. The posterior mean of the deviance
204 is $\text{Dbar} = E_{\theta}(-2\log(p(y|\theta)))$ and $\text{pD} = \text{Dbar} - \text{Dhat}$. Dhat is a point estimate of
205 deviance given by $\text{Dhat} = -2\log(p(y|\bar{\theta}))$. The advantage of DIC over other criteria in
206 Bayesian model selection is that DIC is easily calculated from samples generated by a
207 MCMC simulation. Models with lower DIC values indicate a better fit to the data, in
208 which differences ≥ 5 are regarded as substantial evidence, and differences ≥ 10 are
209 regarded as very strong evidence in favor of the model with the lowest DIC (Hurst et
210 al. 2011).

211 The value of the area under the receiver operating curve (AUC) is widely used
212 for evaluating tree mortality models (Saveland and Neuenschwander 1990, Zhang et
213 al. 2011) and was also used in this study. The larger the value of the AUC, the better
214 the model performs (Fielding and Bell 1997). A rough guideline for the AUC follows
215 the traditional academic point system as follows: 0.9-1 = excellent (A), 0.8-0.9 = good
216 (B), 0.7-0.8 = fair (C), 0.6-0.7 = poor (D), and 0.5-0.6 = fail (F) (Zhang et al. 2011).

217 **2.2.3 Variance partition coefficient in multilevel logistic model**

218 Multilevel models, also known as hierarchical models, assume multiple sources
219 of unobserved heterogeneity and recognize units at one level as grouped (nested) in
220 the next higher level. In multilevel models, the residual variance is split up into

221 components that are attributed to the various levels in data (Goldstein 1995).
222 Partitioning the variance in binary models is complex because the level-1 variance
223 (Bernoulli) is measured on a different scale compared to the level-2 variance.
224 Rodríguez and Goldman (2001) said that if the relationship between the dependent
225 and independent variables is nonlinear (e.g., logit link function), then ignoring
226 grouping (nested) structures can result in large biases in estimating parameters.
227 Additionally, note that for the logistic multilevel model, the level-1 variance is not
228 identifiable from the likelihood. The classically reported fixed variance pertains to the
229 latent continuous scale and is the variance of $\pi^2/3$ (3.29), a standard logistic density
230 for logit (Goldstein et al. 2002, Rodríguez and Eio, 2003). Goldstein et al. (2002)
231 defined the variance partition coefficient (VPC) as the percentage of the variation due
232 to higher levels of the model and also showed the method to calculate the VPC at each
233 level. A large VPC value (close to 1) indicates maximally segregated clusters, and a
234 low VPC value (close to zero) suggests homogeneous risk of tree mortality among
235 clusters. Here, we adopt the nomenclature in which the random error term is
236 recognized as the lowest level. Therefore, we have measurement occasions nested
237 within trees (level 1), trees nested within plots (level 2), and plots (level 3). VPC due
238 to tree level and plot level are given by:

239
$$VPC_{tree} = \frac{Var(level2)}{Var(level2) + Var(level3) + Var(level1)} \quad (5)$$

240
$$VPC_{plot} = \frac{Var(level2)}{Var(level2) + Var(level3) + Var(level1)} \quad (6)$$

241 where $Var(level1)$ is $\pi^2/3 \approx 3.29$.

242 3. Results

243 3.1 Tree mortality models and VPC

244 According to the stepwise analysis, the endogenous variables of *IPD*, *d/Dg*, and
245 $\log(Hd)$ were reserved. Additionally, the climate variables of *MAT*, *AHM*, *WMMT*,
246 and *SMT* are reserved in basic models and used for modeling tree mortality with
247 Bayesian methods.

248 Parameter estimates, associated standard deviation, DIC and AUC for Bayesian
249 fixed-effects (nonhierarchical), two-level, and three-level models are presented in
250 Table 3. The fixed-effect parameter estimates in multilevel models were larger for
251 most than in the fixed-effects model; therefore, ignoring random effects
252 underestimated most of the fixed-effect parameters. DIC and AUC value outputs from
253 both Bayesian two-level models and three-level models were much smaller than the
254 fixed-effects model, which indicates that multilevel models are superior to
255 fixed-effects model (Table 3). For the Bayesian multilevel models, the DIC from the
256 three-level model was approximately 24 less than the two-level1 and nearly 67 of the
257 two-level2 (Table 3). These DIC values provide a measure of model fit and allow the
258 researcher to compare how different models perform in their ability to model the
259 mortality data satisfactorily. The lower DIC value indicates which model fits the data
260 best. The AUC value was 0.9736 for Bayesian three-level model, versus 0.9668 and
261 0.9554 for two-level models, and 0.9543 for the fixed-effects model (Table 3). All
262 four models were considered excellent. The AUC test has advantages in assessing
263 model performance in a threshold-independent fashion and comparing several

different models (e.g., Jan et al. 2007; Zhang et al. 2011). Thus, the Bayesian three-level model was the best model for fitting the tree mortality of Chinese fir plantations.

The VPC due to tree level was calculated as 0.1463, which indicates that 14.63% of the variation in mortality is attributed to tree variability, and the VPC due to the plot level was 0.0838. These results suggest significantly more variation in mortality data at the tree level than at the plot level.

3.2 Effects of initial planting density and competition on tree mortality

In the Bayesian multilevel mortality model, the *IPD* was significantly positive with tree mortality (Table 3). Because the mortality probability of a tree is influenced by its relative position (competitive status) within the stand, we calculated the competition index using the ratio of d to Dg . For a given Dg , a tree with a larger diameter has lower mortality probability (Table 3). The positive estimated coefficient for dominant height in the mortality model indicates that mortality is higher on better sites.

3.3 Climate effects on tree mortality

A summary of the parameter estimates obtained in the climate sensitive mortality models is provided in Table 3. Four climatic variables, including *MAT*, *AHM*, *WMMT*, and *SMT*, are significantly correlated with tree mortality. In the mortality models, the mean annual temperature *MAT* had a negative effect on the mortality of Chinese fir. A negative significant correlation to *SMT* was also found. By contrast, the tree mortality probability had a positive significant correlation to *WMMT*. Additionally, *AHM* was

significantly positively correlated with mortality probabilities (Table 3), which suggests that climate change induced drought increases tree mortality. Although the climate effects, including *MAT*, *AHM*, *WMMT*, and *SMT*, on mortality were significant (Table 3), the effects were relatively small (Fig. 1).

4. Discussion

4.1 Bayesian multilevel methods in tree mortality

A Bayesian multilevel model is an alternative method that accounts for variation at multiple clustering levels of data, such as the tree or plot level in the tree mortality analysis. An advantage of Bayesian methods over classical methods when fitting models is that independent, prior information, if available, can be incorporated into the model through prior distributions of unknown parameters (Masuda and Stone 2015). In this paper, we do not intend to argue that the Bayesian multilevel model is superior to the classical mixed-effects model. We believe both classical and Bayesian methods have their own features. In particular, when the Bayesian prior is uninformative, the results would be very close to those obtained with classical mixed-effect models (Pinheiro and Bates 2000, McCarthy 2007).

Bayesian logistic models with fixed effects only and with multilevel random effects added to the intercept were fitted, including both endogenous and exogenous variables. One two-level model (two-level1) was fitted to account for the correlation in measurement occasions (level 1) from a tree (level 2). The other two-level model (two-level2) was also fitted to account for the correlation in measurement occasions (level 1) of a tree in a plot (level 2), as well as the three-level logistic model

accounting for the correlation in repeated measurements (level 1) from trees (level 2) nested in a plot (level 3). The multilevel models were much better than the fixed-effects only model according to DIC, and the three-level model also performed best compared to the two-level models (Table 3). Ma et al. (2013) reported that the multilevel logistic model incorporating both the plot and measurement random effects performed the best compared to standard logistic and marginal logistic models based on the generalized estimating equations. Thapa (2014) modeled loblolly pine (*Pinus taeda* L.) mortality using multilevel mixed-effects logistic regression and found that the model accounting for measurement, tree and plot three levels compared to the two levels of measurement and plot, was consistent with our study. Groom et al. (2012) observed that inclusion of a random intercept in multilevel tree mortality models for Douglas fir stands significantly reduced model bias compared to the fixed-effects model.

The VPC attributed to tree level was 74.58% larger than that due to plot level. This may be because a large part of the variance is due to the direct environment of the tree, which cannot be fully described with the symmetric competition index. Some researches reported that the variation of seeds used for seedlings also resulted in different mortality probabilities(Bonfil 1998; Leishman et al. 2000; Khan and Shankar 2001; Westoby et al. 2002).

4.2 Endogenous factors affecting tree mortality

A major mortality agent is inter-tree competition, which can be either symmetric or asymmetric (Yang et al. 2003; Adame et al. 2010). In symmetric competition, larger

330 trees in a plot have competitive advantages over smaller trees and neighbors do not
331 affect the growth (Cannel et al. 1984). Hamilton (1986) reported that the variable
332 d/Dg was a good symmetric competition index (Avila and Burkhart 1992; Zhang et al.
333 1997). A positive effect of d/Dg on tree survival is shown in Table 3, indicating that
334 tree death tended to occur in strong symmetric competition stands, which was
335 consistent with the result obtained by Laarmann et al. (2009). For long-term
336 competition, if a given tree size was small compared with a mean tree size, the tree
337 must have strong competition in the stand. In an undisturbed stand, intense
338 competition for nutrients, water and light particularly affect small trees and induce a
339 higher mortality probability (Coomes and Allen 2007). In asymmetric competition, all
340 trees in a plot impose some competition on their neighbor trees, regardless of their
341 size (Cannel et al. 1984), and this can be described by stand density and basal area.
342 Young et al. (2003) found that the stand basal area is a good measure of stand
343 crowding and could adequately capture asymmetric competition because it combines
344 both tree size and density. However, here the two variables were excluded in the
345 mortality model according to the stepwise analysis.

346 Stand density management, using different initial planting densities, was a key
347 factor driving the mortality process. For a given age and site index,
348 competition-induced mortality was higher at higher planting density (Williams, 1994;
349 Zhao et al. 2007), which was consistent with the result of this case (Table 3). The
350 increase in crown ratio and crown length led to a reduction in the relative risk of death
351 among the surviving trees (Thapa 2014). The live crown length and crown ratio

352 decreased with increasing planting density due to competition from neighbors
353 (McClain et al. 1994; Akers et al. 2013).

354 Site index has frequently been introduced into mortality models. For a given age
355 and initial planting density, the mortality probability of Chinese fir increased with the
356 site index (Table 3). Our finding is consistent with the conclusion of Eid and Tuhus
357 (2001), Yao et al. (2001) and Zhang et al. (2015) that higher mortality was related to
358 better productivity. Empirical evidence suggests that density dependent mortality in
359 plantations becomes apparent earlier in better sites and increases with site productivity
360 (Diéguez-Aranda et al. 2005). However, opposite results were obtained in some
361 studies. Woolons (1998) reported that mortality decreased with increasing site index.
362 Jutras et al. (2003) found that site index had a significant effect on mortality, with a
363 higher mortality probability for Scots pine but lower mortality probability for
364 pubescent birch. Zhao et al. (2007) also found that site productivity affects mortality
365 in an opposite way in the Piedmont/Upper Coastal Plain (PUCP) and Lower Coastal
366 Plain (LCP) of the southern United States as follows: mortality increases with
367 increasing productivity in the PUCP, but in the LCP, higher mortality is related to
368 lower productivity. The different effects of site index on mortality may be related to
369 the availability of certain key nutrients (Jutras et al. 2003).

370 **4.3 Climate variables affecting tree mortality**

371 In addition to endogenous variables, climate variables were also directly related
372 to tree mortality and may be helpful for exploring the effects of climate change on
373 forest dynamics under future climate scenarios. However, the effects of these four

climate variables were relatively small (Fig. 1). This may be because the forest stand structure and age mediated the climate effects on tree mortality (Ruiz-Benito et al. 2013, Bell et al. 2014). In general, an increasing mean annual temperature decreases tree mortality probabilities physiologically, when water availability is not limiting. Temperature exerts effects on tree growth and mortality by altering rates of photosynthesis, respiration, cell division and elongation, chlorophyll synthesis, enzymatic activity, water uptake, and transpiration (Ricker et al. 2007). Additionally, an increasing mean annual temperature prolongs the non-frost growing season during the entire year and increases the CO₂ sequestration rate (Bergh et al. 2003). The tree mortality of Chinese fir decreased with increasing *MAT* (Table 3, Fig. 1). However, our finding was different from other studies showing that temperature was positively related to tree mortality (Van Mantgem et al. 2009; Ruiz-Benito et al. 2013; Zhang et al. 2014). Chinese fir is a shade intolerant tree species, the growth of which tends to increase with high temperature, thus decreasing the mortality probability (Wu, 1984). In addition, a warm late summer can extend the growing season, increasing radial growth and consequently affecting tree mortality in the following year, which is supported by the negative relationship between the late summer mean temperature and tree mortality probabilities observed in this study.

For the *AHM*, higher mortality was related to a higher *AHM* (Table 3). This result confirmed findings by Breshears et al. (2009), Peng et al. (2011), Zhou et al. (2013), and Zhang et al. (2014), who showed that climate change induced drought stress increased tree mortality. Zhang et al. (2014) reported that drought-induced mortality

396 may be primarily caused by three factors: (i) carbon starvation, which halts most
397 photosynthesis, thus failing to support metabolism and carbon balance; (ii) hydraulic
398 failure, which increases water deficits and drought stress on trees; or (iii) outbreaks of
399 biotic agents, such as the growth and reproduction of insects and pathogens that attack
400 trees (Van Mantgem et al. 2009). Generally, climate change induced drought was an
401 inciting tree mortality factor (Bigler et al. 2006; Allen et al. 2010).

402 **5. Conclusions**

403 This study investigated tree mortality models with the inclusion of initial
404 planting density, competition and climate variables in Chinese fir plantations in
405 southern China using Bayesian logistic multilevel methods. The Bayesian three-level
406 model was the best to describe tree mortality data with multiple sources of unobserved
407 heterogeneity. The VPC attributed to the tree level was much larger than that due to
408 the plot level.

409 The endogenous factors of IPD , d/Dg , and $\log(Hd)$ were significantly related to
410 mortality. Tree mortality increased with increasing IPD and Hd and with a decreasing
411 symmetric competition index d/Dg . Four climate variables were also related to tree
412 mortality. In the mortality model, MAT and SMT had negative effects on the mortality
413 of Chinese fir. By contrast, the tree mortality probability was positively significantly
414 correlated to $WMMT$ and AHM .

415 The effect of the initial planting density has implications for forest management
416 because high planting density results in high mortality. Inclusion of climate variables
417 in mortality models can facilitate the projection of tree mortality under future climate

change conditions. The Bayesian multilevel model accounting for the uncertainty in parameter estimates showed by the posterior distribution and the heterogeneity that may occur due to the measurement occasions nesting within a tree (i.e., repeated measurements) and trees nesting within a plot was a good method for modeling the tree mortality of Chinese fir plantations.

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Figure legends

Fig. 1. Effects of Climate variables on the predicted probabilities of mortality in Chinese fir plantations.

Draft

Table 1. Summary statistics of stand and tree variables of Chinese fir plantations.

Density	<i>Dg</i>		<i>N</i>		<i>Ba</i>		<i>Hd</i>		<i>d</i>		Number of death	
	Mean	SD.	Mean	SD.	Mean	SD.	Mean	SD.	Mean	SD.	Min	max
1	13.12	3.48	1663	8.07	24.00	11.47	10.65	3.16	12.93	4.07	0	1
2	10.55	2.62	3316	33.90	30.62	13.67	10.29	3.17	10.27	3.47	0	5
3	8.88	2.22	4893	170.16	31.76	13.72	9.81	2.76	8.55	3.08	1	18
4	7.78	1.97	6483	287.88	32.17	13.94	8.71	2.41	7.42	2.85	0	44
5	7.41	1.84	9225	989.16	40.34	14.95	9.37	2.67	6.96	2.69	9	55

Note: SD. is standard deviation. *Dg* is stand quadratic mean of diameter (cm); *N* is live num of tree per ha; *Ba* stand basal area (m²/ha); *Hd* is stand dominant height (m), *d* is diameter at breast (cm).

Table 2. Summary statistics of climate variables.

Climate variables	Descriptions	Mean	Min.	Max.
MAT (°C)	mean annual temperature	18.18	17.3	19.2
MAP (mm)	mean annual precipitation	1697.29	1334	1975
MCMT (°C)	mean coldest month temperature	6.96	4.1	9.1
AHM	annual heat-moisture index (Wang et al., 2006)	16.82	14.4	21.1
DD_0	degree-days below 0 °C, chilling degree-days	3	2	9
NFFD	the number of frost-free days	349	334	355
SMMT (°C)	summer mean maximum temperature	32.02	30.7	33.3
WMMT (°C)	winter mean minimum temperature	4.28	2.3	6
SMT (°C)	summer (Jun. - Aug.) mean temperature	27.27	26.4	28

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Table 3. Parameter estimates (standard deviation) of tree survival models from fixed-effects (nonhierarchical), two-level and three-level random-effects models using Bayesian method.

Parameters	Fixed-effects	Two-level1	Two-level2	Three-level
x_1 : (Intercept)	-106.9(10.2526)*	-119.6(12.2375)*	-105.9(10.6529)*	-114.2(12.2388)*
x_2 : d/Dg	8.9948(0.2374)*	9.6711(0.3080)*	9.2175(0.2478)*	9.7465(0.2846)*
x_3 : IPD	-5.1925(0.2519)*	-5.7857(0.3070)*	-6.7770(0.8996)*	-7.0934(0.9994)*
x_4 : $\log(Hd)$	-6.8546(0.3522)*	-7.4654(0.4070)*	-7.8437(0.4385)*	-7.1610(0.4773)*
x_5 : MAT	5.7495(0.5022)*	6.3514(0.5983)*	5.9990(0.5320)*	6.3809(0.6018)*
x_6 : AHM	-0.3482(0.0378)*	-0.3845(0.0455)*	-0.3826(0.0405)*	-0.4038(0.0456)*
x_7 : $WMMT$	-1.3833(0.1515)*	-1.4721(0.1745)*	-1.3162(0.1562)*	-1.3802(0.1728)*
x_8 : SMT	1.1672(0.1150)*	1.3346(0.1360)*	1.0929(0.1175)*	1.2009(0.1377)*
Variance components				
tree level				
		0.9659(0.1495)*		0.6253(0.2267)*
plot level				
			0.3380(0.1782)*	0.3581(0.1961)*
measurement level				
		3.29	3.29	3.29
DIC	4700.3890	4560.6140	4603.9500	4536.8260
AUC	0.9543	0.9668	0.9554	0.9736

*p-value<0.05.

Fig. 1