Spatiotemporal distribution of the potential risk of frost damage in tea fields from 1981–2020: A modeling approach considering phenology and meteorology

Kensuke KIMURA^{a,†}, Ken KUDO^b and Atsushi MARUYAMA^a

(^aNational Agriculture and Food Research Organization (NARO), Institute for Agro-Environmental Sciences,
3-1-3 Kannondai, Tsukuba, 305-8604, Japan
^bSaitama Tea Research Institute, 244-2 Kamiyaganuki, Iruma, 358-0042, Japan)

Abstract

Climate change may induce severe frost damage to crops, and thus a reasonable assessment of frost risk, considering both crop phenology and meteorology, is required. Here, we introduced a new index of potential frost risk (F_{risk}) using thermal time (minimum air temperature below the threshold value) weighted by the percentage of budburst (P_{bud}). Moreover, we evaluated the spatiotemporal distributions of F_{risk} in tea fields within a 60 km × 60 km area in east Japan from 1981–2020, using 1 km²-gridded meteorological data and a newly developed model of P_{bud} . The P_{bud} model considered three phenological phases (endodormancy, ecodormancy, and progress of budburst) and successfully represented changes in the P_{bud} of the tea buds for 15 years, with root mean square errors of 8.5 percentage points. The spatiotemporal distributions of F_{risk} over the past 40 years showed that potential frost risk significantly increased at elevations ranging from 50 m to 300 m because the budburst advanced at a faster rate than the temperature warming. These elevations corresponded to areas where tea plants were mainly cultivated, which indicates that tea cultivation is becoming vulnerable to frost, and the risk of economic losses due to the frost is increasing. The proposed assessment of frost risk could contribute to predicting frost damage and developing more reliable strategies for the operation of frost protection under the effects of future climate change.

Key words: Budburst, *Camellia sinensis*, Cold stress, Mathematical model, Minimum temperature

1. Introduction

Frost often damages crops and induces huge economic losses in agriculture (Snyder *et al.*, 2005). In recent years, tremendous frost damage has been reported in fruit orchards in the United States (112 million USD in 2007; Gu *et al.*, 2008) and in tea fields in China (268 million USD in 2010; China Tea Marketing Association, 2010) and Japan (45 million USD in 2010; Matsuo *et al.*, 2010). Owing to recent climate warming, the risk of such frost damage may be expected to decrease in the future because of advances in the date of the last spring frost (Schwartz *et al.*, 2006). However, climate warming has also caused advances in phenological events such as budburst, leafout, and flowering in spring (Parmesan and Yohe, 2003), reducing the cold hardiness of plants. These advances in spring phenology and extreme temperature events, such as sudden cold spells in future climates, may increase the risk of frost damage (Augspurger, 2013; Ma *et al.*, 2019).

Many investigations into frost risk have been performed based on trends in observed minimum temperatures, which give the dates of freezing events and the resulting length of the growing season. By analyzing data of daily minimum temperatures observed at ~1,000 meteorological stations, Easterling (2002)

found that the number of frost days decreased in the United States from 1948–1999. Robeson (2002) used data from a longer observation of minimum temperature in Illinois from 1906–1997 and found trends of the earlier spring freezing events. Some investigations have considered plant phenology as well as minimum temperature trends. To quantify the potential frost risk, a false spring index (FSI; Marino *et al.*, 2011) is defined as the difference between the date of the last spring freeze and the date of phenological events such as budburst, leafout, and flowering, and positive values of FSI indicate risk situations.

Vitasse *et al.* (2018) evaluated the FSI of tree species in Switzerland and revealed that the frost risk increased at higher elevations and remained the same at lower elevations from 1975–2016. The use of FSI is a reasonable approach that accounts for both meteorological and phenological aspects. However, FSI depends on the date when a certain percentage of a population reaches the stage of budburst, leafout, and flowering, and thus ignores temporal changes in the percentage of phenological events in the population. As the percentage increases with time (i.e., the number of buds, leaves, and flowers that have lost cold hardiness increases), the potential frost risk and resulting agricultural losses probably increase. Thus, considering the changes in the percentage of phenological events can lead to a more reliable assessment of frost risk.

Phenological events are often estimated using an empirical model because of limited data on observed phenology, and many models have been developed to estimate phenological development in crops (e.g., Horie and Nakagawa, 1990, Nakagawa and Horie, 1995 and Yin *et al.*, 1997 in rice; Weir *et al.*, 1984, Maruyama *et al.*, 2010 and Kawakita *et al.*, 2020 in wheat; Williams *et al.*, 1985, Caffarra

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[†]Corresponding author: kimurak081@affrc.go.jp

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and Eccel, 2010 and Sugiura *et al.*, 2019 in grapes). Conventional phenological models of budburst, leafout, and flowering, which are required for the assessment of frost risk, are mainly divided into two types: one-phase models (e.g., Cannell and Smith, 1983; Chuine and Cour, 1999), considering the ecodormancy processes affected by forcing temperatures in spring, and two-phase models (e.g., Richardson *et al.*, 1974; Chuine, 2000), which consider endodormancy processes affected by chilling temperatures from autumn to winter as well as the ecodormancy processes. These models generally predict the dates of phenological events (not the percentages), and require some modification to evaluate the changes in the percentage of phenological events.

Tea plants (*Camellia sinensis* (L.) O. Kuntze), one of the most important economic crops around the world, have been seriously damaged by recent frost, leading to huge economic losses as mentioned above. Given the critical importance of assessing frost risk under current warming climate trends, some researchers have considered minimum temperatures in their investigation of the frost risk in tea fields (e.g., Li *et al.*, 2018), and a model to predict phenology of tea buds (cold acclimation and deacclimation) has been developed (Kimura *et al.*, 2021). However, frost risk in terms of both meteorology and phenology, remains unclear in tea plants. Tea plants are cultivated in a wide range of regions, from plains to mountains, and frost risks vary in space and time at different scales in different species (Bennie *et al.*, 2010; Vitasse *et al.*, 2018). Thus, the spatial variability of frost risk should be assessed in terms of reasonable strategies for the application of frost protection (e.g., frost protective fan, Kimura *et al.*, 2017; and sprinkler, Suzuki *et al.*, 1993) across a wide range of regions and for a long period under future warming climate.

The objectives of this study were 1) to develop a new index for the potential frost risk based on changes in the percentage of phenological events and in daily minimum temperature, 2) to model the changes in percentage of the phenological event (in this study, budburst in tea plants), and 3) to assess the spatiotemporal distribution of the potential frost risk in tea fields using the developed index and the model over the period 1981–2020 on a regional scale.

2. Materials and methods

2.1 Study area

A 60 km × 60 km area located in east Japan from 35.78° to 36.25° N latitude and 138.92° to 139.63° E longitude was selected (Fig. 1a, b) to assess the spatiotemporal distribution of the potential frost risk. In this area, elevation ranges from 0 to 1,300 m (Fig. 1b), and tea plants are widely cultivated from plains to mountains (Omata, 2008). Representative points (P1–P4 in Fig. 1b) near automated meteorological data acquisition systems (AMEDAS) were selected to compare long-term trends in the potential frost risk at different elevations. The study area is the northern limit of economical tea production in Japan and has a humid subtropical climate. According to averaged records of AMEDAS stations within the area (17 stations) from 1981–2019, an annual mean temperature of 14.2 °C and an annual mean precipitation of 1,427 mm have been recorded in the area.

2.2 Evaluating potential frost risk

We developed a new index for the potential frost risk during the growing season (F_{risk}) under the assumption that a higher percentage of a phenological event in a population results in a larger risk of frost damage under the same temperature. This assumption was based on the finding that cold hardiness tended to decrease gradually during bud development in tea plants (Yanase, 1972) and other tree species (Lenz *et al.*, 2013). Using this assumption, F_{risk} can be defined as the accumulation of frost risk at a given date t ($F_{risk,t}$), which is expressed by thermal time (the daily minimum air temperature [$T_{min,t}$] below the threshold value [T_{frost}]) weighted by the percentage of budburst ($P_{bud,t}$).

$$F_{risk} = \sum_{t=D_s}^{D_e} F_{risk,t} \quad (1)$$

$$F_{risk,t} = (T_{frost} - T_{min,t}) \times P_{bud,t} / 100 \quad (T_{min,t} < T_{frost}) \quad (2)$$

$$F_{risk,t} = 0 \quad (T_{min,t} \geq T_{frost})$$

Fig. 1. (a) Schematics of the geographic location of the study area (b) and map of the digital elevation model (DEM) of the study area. The representative points (P1 – P4) near the automatic weather stations and the observation point of budburst (Saitama Tea Research Institute) are indicated on the DEM map.

The $F_{risk,t}$ shows positive values (i.e., risk situations) only if $T_{min,t}$ is below T_{frost} and $P_{bud,t}$ is above 0% (i.e., budburst conditions). The calculation of Eq. (1) began when budburst definitely did not occur ($D_s = 1$ in day of year) within the study area and continued until T_{min} was definitely not below T_{frost} ($D_e = 150$ in day of year) within the study area. In this study, T_{frost} was set at 3 °C, where frost protection (e.g., frost protective fans) is conventionally required in tea fields (Araki *et al.*, 2010).

2.3 Modeling percentage of budburst

For modeling P_{bud} , the phenological cycle for tea budburst is divided into three phases: endodormancy from autumn to winter, ecodormancy from winter to spring, and initial budburst and subsequent increase of P_{bud} (Fig. 2).

Endodormancy, which coincides with the cold acclimation of buds, was assumed to be induced by decreasing temperature and released by fulfilling the chilling requirement or increasing the photoperiod (Charrier *et al.*, 2011; Laube *et al.*, 2014; Du *et al.*, 2019). Chilling requirement at a given date t (CR_t) was based on the cold acclimation model imitating cold stress memory in plants (Kimura *et al.*, 2021), which was expressed as accumulation of thermal time (daily average air temperature [T_{ave}] below the threshold value [T_{ac}] corresponding to the temperature when endodormancy starts in autumn) weighted by a forgetting curve:

$$CR_t = \sum_{n=endo}^t \left\{ (T_{ave,n} - T_{ac}) \times \frac{k}{\{\log(t-n+1)\}^c + k} \right\} \quad (3)$$

where k and c are the parameters of the forgetting curve, and *endo* is the date when endodormancy starts. The forgetting curve shows

values from 0 to 1, and the values are highest on the latest day, decreasing gradually as the number of days decreases (Fig. 2). Thus, Eq. (3) shows that the thermal time in the latter days (n close to t) strongly contributes to cold acclimation and that in the former days (n close to *endo*), it does not (Kimura *et al.*, 2021). The calculation of Eq. (3) began when T_{ave} first fell below T_{ac} in autumn within the study area. When CR_t reached the critical value (CR_{crit}), endodormancy was released and the ecodormancy phase started. If the chilling requirement did not reach CR_{crit} , the critical daylength (DL_{crit}) offset insufficient chilling, and the ecodormancy phase started (Kimura *et al.*, 2021).

Ecodormancy, which coincides with cold deacclimation of buds, was assumed to be driven by competition between chilling and forcing requirements (Chuine, 2000) at a given date t (CF_t) as modeled by (Kimura *et al.*, 2021):

$$CF_t = CR_t + FR_t \quad (4)$$

$$FR_t = \sum_{n=eco}^t (T_{ave,n} - T_{de}) \quad (5)$$

where FR_t is the forcing requirement at a given date t , which was calculated by the thermal time above the threshold temperature (T_{de}), and *eco* is the date when ecodormancy starts. The calculation of Eq. (5) began when the ecodormancy phase started. Ecodormancy was released when CF_t reached the critical value (CF_{crit}), and when the initial budburst occurred (i.e., P_{bud} was first above 0%).

After the initial budburst, P_{bud} increased in response to warm temperatures, so that the daily change in P_{bud} was modeled by:

Fig. 2. Modeling of the percentage of budburst (P_{bud}), divided into three phases: endodormancy, ecodormancy, and increase in P_{bud} . Details of equations and model parameters are described in section 2.3 and Table 1.

$$P_{\text{bud},t} = P_{\text{bud},t-1} + \frac{1}{1 + \exp\{a(T_{\text{ave},t} - T_{50})\}} \quad (6)$$

where a is the parameter of the temperature response curve for P_{bud} , and T_{50} is the temperature where P_{bud} increased by 50 percentage points (pp.) in a day. The calculation of Eq. (6) continued until P_{bud} reached 100% and P_{bud} remained constant at 100%.

2.4 Model parameterization and validation

For parameterization and validation of the model, P_{bud} was observed in a tea field located in Saitama, Japan (Saitama Tea Research Institute; 35°48'29"N, 139°20'52"E, 148 m a.m.s.l., Fig. 1b). The observation was conducted for the cultivar Yabukita, which is widely cultivated in Japan, from mid-April to late-May for 15 years (2006–2020), at intervals of ~5 d. Budburst was defined as when the length of the new bud enveloped by leaves was twice as long as these leaves (The annual scientific conference of tea, 1986), and P_{bud} was calculated as the ratio between the number of budbursts and the number of non-bursting buds ($n = \sim 100$ leaves).

The model parameters were assessed by minimization of the root mean square error (RMSE) between the estimated and observed values of P_{bud} for 15 years. For the parameterization, the differential evolution algorithm was applied using the 'DEoptim' R package (version 2.2-5), as proposed by Mullen *et al.* (2011). A two-fold cross validation was conducted. The dataset for 15 years was randomly partitioned into two sets (d_1 for 8 years and d_2 for 7 years), then the model was parameterized on d_1 and validated on d_2 , followed by parameterizing on d_2 and validating on d_1 .

To reduce model complexity, three parameters (T_{ac} , T_{de} , and c) were fixed at the values established by Kimura *et al.* (2021) from 10 years of observed cold-hardiness data from the same cultivar Yabukita. These fixed parameters were determined on the basis of the Akaike information criterion (AIC; Akaike, 1974), which can consider both model accuracy and complexity. Among various combinations of fixed and fitted parameters, the combination was chosen wherein AIC showed the smallest value (i.e., the combination in which T_{ac} , T_{de} , and c were fixed, and other parameters were fitted). The optimized parameters were determined using all data for 15 years (Table 1).

To calculate P_{bud} and F_{risk} , meteorological data of T_{min} and T_{ave} during 1981–2020 within the study area were obtained from the Agrometeorological Grid Square Data (AMGSD; Ohno *et al.*, 2016). The AMGSD provides 1 km²-gridded data of T_{min} and

T_{ave} using spatial interpolation among the observed values at AMEDAS located at intervals of ~20 km in Japan and corrects for the differences in temperature due to elevation. These data were used to study the effects of climate change on crops (e.g., Nakano *et al.*, 2017; Fukui *et al.*, 2019). Photoperiods were calculated using the day of the year, sun position, and latitude in each grid.

2.5 Spatiotemporal analysis of potential frost risk

The values of P_{bud} , ΣT_{min} (accumulated T_{min} below T_{frost} [3 °C] after initial budburst), and F_{risk} from 1981–2020 were assessed in each grid of AMGSD within the study area. The significance of trends in P_{bud} , ΣT_{min} , and F_{risk} from 1981–2020 were determined using non-parametric Mann-Kendall tests at 5% significance level (Kendall, 1975), and then Sen's slope (Sen, 1968), which represents the degree of trends, was assessed in the grids wherein significant trends were found. The grids wherein T_{min} was below −15 °C in winter were removed from the trend analysis because the maximum cold tolerance in Yabukita is around −15 °C in midwinter (Kimura *et al.*, 2021).

3. Results

3.1 Model validation

Seasonal changes in T_{ave} , which is the input variable of the model of P_{bud} , showed different patterns over 15 years (Fig. 3). In 2011–2012, T_{ave} represented the coldest winter and spring, and, in contrast, 2019–2020 represented the warmest winter and spring. In 2012–2013 and 2017–2018, the changes in T_{ave} showed an alternative pattern, that is, colder autumn–winter and warmer spring.

These different changes in T_{ave} resulted in different durations of endodormancy and ecodormancy (Fig. 3) and large variations of P_{bud} (Fig. 4) in the model simulation. Except for the initial budburst in 2007, the present model of P_{bud} successfully captured the observed variations of P_{bud} for 15 years (Fig. 4), even when tea buds were exposed to both colder and warmer climates. The error variance in the validation dataset was higher in the high P_{bud} region. Overall, the observed variation of P_{bud} explained 91% and 87% of the predicted variation of P_{bud} for the calibration and validation datasets, respectively, and the accuracy of the model was less than 10%. (root mean square error [RMSE] = 7.0 pp. in calibration and 8.5 pp. in validation) (Fig. 5).

3.2 Spatiotemporal distributions of budburst, minimum temperature, and potential frost risk

Trends in P_{bud} , ΣT_{min} , and F_{risk} were divided into two types of patterns (Fig. 6). In the plain (P1) and mountain (P3) areas,

Table 1. Parameters used to model the percentage of budburst.

Parameter	Description	Value	Unit	Source
T_{ac}	Threshold temperature effective to endodormancy (cold acclimation)	17.4	°C	Fixed (Kimura <i>et al.</i> , 2021)
k	Parameter of the forgetting curve	6.0	Dimensionless	Fitting (this study)
c	Parameter of the forgetting curve	3.4	Dimensionless	Fixed (Kimura <i>et al.</i> , 2021)
T_{de}	Threshold temperature effective to ecodormancy (deacclimation)	−4.0	°C	Fixed (Kimura <i>et al.</i> , 2021)
CR_{crit}	Critical chilling requirement that tea buds are ready for ecodormancy	−472.5	°C day	Fitting (this study)
DL_{crit}	Critical daylength in which ecodormancy starts	11.3	hour	Fitting (this study)
CF_{crit}	Critical thermal time that budburst starts	−46.0	°C day	Fitting (this study)
a	Parameter of temperature response curve for percentage of budburst	−0.15	Dimensionless	Fitting (this study)
T_{50}	Temperature where percentage of budburst increases by 50 pp. in a day	33.6	°C	Fitting (this study)

the date of budburst advanced over the course of 40 years (0.18 d y^{-1} in P1 and 0.30 d y^{-1} in P3, for the initial budburst), but $\Sigma T_{\min}$ did not increase. Consequently, F_{risk} did not increase in these areas. By contrast, in the hilly areas (P2), the date of budburst advanced (0.33 d y^{-1} for the initial budburst) and $\Sigma T_{\min}$ increased ($0.16 \text{ }^{\circ}\text{C y}^{-1}$), together leading to a significant increase in F_{risk} . An exceptional trend was found in P4 (Fig. 7). Significant advances in P_{bud} were not detected at P4, but $\Sigma T_{\min}$ significantly increased over the 40 years. This increase in $\Sigma T_{\min}$ resulted in a significant increase in F_{risk} .

The dates of the initial budburst significantly advanced across almost all study areas (Fig. 8), and the areas where significant advances were found decreased with the increase in P_{bud} . The advance rates were higher in the hilly and mountainous areas than in the plain areas and decreased with increasing P_{bud} across the study area (Fig. 8).

Significant increases in $\Sigma T_{\min}$ were concentrated in the hilly areas (Fig. 9). In almost all these areas, the increase in $\Sigma T_{\min}$ was attributed to the advance of budburst, but in the limited area near P4, $\Sigma T_{\min}$ increased even though the dates of budburst did not

Fig. 3. Seasonal changes in the moving average temperature calculated for the reference periods of the past 28 d (solid line) for 15 years. As a reference, the moving average temperatures are averaged over 15 years (dashed line). Data on the temperatures were obtained from the Agro-Meteorological Grid Square Data (see section 2.4), and the values at the grid, including the experimental tea field, where model calibration and validation were performed, were used. Vertical lines in each plot represent dates of the start of endodormancy corresponding to *endo* in Eq. (3) and Fig. 2 (left line), ecodormancy corresponding to *eco* in Eq. (5) and Fig. 2 (middle line), and budburst (right line), calculated from the model.

advance. The spatial distribution of the trend in F_{risk} approximated that of ΣT_{min} (Fig. 8), with slight differences because ΣT_{min} was biased by P_{bud} for evaluating F_{risk} . Overall, the significant increase in F_{risk} was concentrated at elevations ranging from 50 m to 300 m within the study area (Table 2). These elevations corresponded to hilly areas where tea plants were mainly cultivated.

4. Discussion

4.1 Evaluation of F_{risk} and P_{bud} model

To date, potential frost risk has often been evaluated by comparing dates between the last freeze and budburst (Marino *et al.*, 2011), as mentioned earlier. However, to assess frost risk, the period between initial budburst and full leafout (the period of vulnerability to frost) should be considered as well as the date of

budburst (Chamberlain *et al.*, 2019). Thus, F_{risk} was formulated in this study by introducing the thermal time (T_{min} below T_{frost}) weighted by P_{bud} . To our knowledge, this study is the first to consider the impact of the changes in budburst percentage on frost risk. The F_{risk} calculation assumed that higher P_{bud} in a population has a larger frost risk; this assumption could be suitable because cold hardiness tends to decrease gradually during bud development in tea plants (Yanase, 1972) and in the other tree species (Lenz *et al.*, 2013).

There have been many models for predicting the dates of phenological events (e.g., Chuine, 2000; Caffarra *et al.*, 2011); however, to our knowledge, there is no published model for predicting P_{bud} with consideration to endodormancy and ecodormancy phases. Conventional models of budburst have

Fig. 4. Time courses in the percentage of budburst (P_{bud}) over 15 years in the experimental tea field. Observed values are shown as black circles, and simulated values are shown as broken (calibration dataset) and solid (validation dataset) lines, which were derived from the cross validation described in section 2.4.

Fig. 5. Simulated versus observed percentage of budburst (P_{bud}) in the calibration and validation datasets. The root mean square error (RMSE) and R^2 values of the linear regressions are indicated. The simulated values were derived from the cross validation described in section 2.4.

predicted the date when P_{bud} exceeded 50% with a mean absolute error (MAE) of 4.88–6.65 d in *Betula pubescens* (Caffarra *et al.*, 2011) and 3.80–9.14 d and an RMSE of 5.04–10.9 d in *Vitis vinifera* L. (Camargo-alvarez *et al.*, 2020); the present model provided an MAE of 1.8 d and RMSE of 2.0 d. Thus, the accuracy of the present model compares favorably against conventional models, although MAE and RMSE could not be directly compared across the different datasets with different ranges of budburst dates. High accuracy of the model for P_{bud} was noted with the validation using 15 years of data, including unusually cold and warm weather, indicating that this model could predict the development of tea buds that experienced different temperature changes.

The fixed parameter T_{ac} had the value of 17.4 °C, indicating that endodormancy (cold acclimation) in tea plants started when the daily average temperature fell below 17.4 °C. At a similar temperature, an increase begins in tea plants of sugar levels and sugar-related gene expression, which play essential roles in driving cold acclimation (Yue *et al.*, 2015).

Eq. (6) in the P_{bud} model the function newly introduced to express the increase of the budburst percentage produced a logistic curve of increasing P_{bud} even in a high temperature

region, although plant growth is generally suppressed during particularly high temperatures (Warrington and Kanemasu, 1983). Moreover, Eq. (6) had the fitted parameter T_{50} of 33.6 °C. This value indicates that 33.6 °C in daily average temperature increases budburst by 50 pp. in a day, but validity of the fitted value was not investigated in the present study. The logistic function and the fitted parameter would be applicable within the study area, but a large variance across high- P_{bud} regions in the model validation may be attributed to the function and the parameter value. Thus, Eq. (6) should be validated in future studies by measuring P_{bud} in different locations with a wide range of temperature conditions.

4.2 Spatiotemporal distributions of frost risk in the tea fields

A few investigations of frost risk have been conducted in tea fields. Li *et al.* (2018) evaluated the risk of tea frost in Zhejiang in China from 1971 to 2017, using daily minimum temperature data, a digital elevation model, and slope data. They indicated that the risk was higher in hilly and mountainous areas than in plain areas, finding similar results to the present study. Lou *et al.* (2013) evaluated the risk of tea frost in Longjing in China from 1971 to 2010, as the difference between the beginning date of tea plucking and the date of last frost. They indicated that almost all the points (12 meteorological stations) had no significant trends in the risk, but this result cannot be directly compared to our results because data on the elevation was not provided in their study.

This study consistently highlighted the significant increase in frost risk in hilly areas (50 m < elevation < 300 m), where tea plants are mainly cultivated. This is because the budburst advanced at a faster rate than the temperature warming in the areas, and, consequently, the period of budburst further overlapped the period when T_{min} was below T_{frost} (3 °C) (see ΣT_{min} at P2 in Fig. 6). These results indicate that tea plants in the main cultivation areas are becoming vulnerable to frost, and the risk of economic losses is likely to increase. By contrast, a trend in the frost risk in the mountainous areas (elevation > 450 m) was not found because the date of the initial budburst rarely reached the period where T_{min} was below T_{frost} (3 °C) over the period of 1981–2020 (see ΣT_{min} at P3 in Fig. 6), despite the faster advancement of budburst in the mountainous areas than in the hilly areas. The higher rate of advancement of budburst at higher elevations was attributed to the amplification of the warming rate with elevation (Pepin *et al.*, 2015). This elevation-dependent warming (EDW) impacts changes in ecosystems and farming communities in mountainous environments (Pepin *et al.*, 2015). In this study, F_{risk} in the mountainous areas did not increase over 40 years, but if EDW continues, F_{risk} may increase rapidly in the near future. The increased risk of frost exposure at high elevations has been demonstrated in tree species in Switzerland from 1975–2016 (Vitasse *et al.*, 2018). In the plain areas (elevation < 20 m), no significant trend in frost risk was attributed to the brief vulnerability to frost, as is the case for the mountain areas.

4.3 Limitations of this study

One significant limitation of this study is that F_{risk} does not consider the relative contributions of T_{min} and P_{bud} contributed to the potential frost risk; this is because F_{risk} is formulated by

Fig. 6. Trends in day of year (DOY) in which percentage of budburst (P_{bud}) exceeded 0% (initial budburst) and 50% and reached 100%, accumulated daily minimum temperature below 3 °C after the initial budburst (ΣT_{min}), and potential frost risk (F_{risk}) from 1981–2020 at the representative points P1, P2, and P3. The locations of P1 – P3 are described in Fig. 1. Linear lines represent Sen's slopes with Mann-Kendall tests at 5% significance level, and data without lines show no trends at 5% significance level.

simple multiplication (Eq. 2). For a more reliable assessment of frost risk, the contribution of T_{min} and P_{bud} should be explicitly quantified by measuring the actual frost damage.

In tea fields, frost protective fans are usually operated to prevent frost damage (Kimura *et al.*, 2017). The frost protective fan mitigates temperature inversion on radiative frost nights and increases the surface temperature of tea plants, probably leading to some temperature difference between a meteorological station and an actual tea field. For more accurate evaluation of the spatiotemporal distributions of F_{risk} and P_{bud} , the temperatures in the actual tea field should be used. However, this is hampered by the necessity for sensor networks consisted of numerous accurately corrected thermometers.

The applicability of the bud model to different cultivars and other climate zones was unclear. Particularly, CR_{crit} and CF_{crit} , which are temperature requirements determining the transition of the phenological phases in the model, may vary with latitude even in the same species (McKown *et al.*, 2018), under the influence of such other factors as precipitation and the resultant changes in soil moisture. To develop a more robust model and apply the model to wider regions, a set of data on the P_{bud} observed for different cultivars and in other climate zones is required.

The exceptional trend near P4 indicates that the period of vulnerability to frost increased despite the absence of a significant advance of budburst; that is, the minimum temperature decreased over the past few decades. This may perhaps be caused by changes in the local geographical effects of urbanization; land use near P4 has tended to urbanize over the past 15 years, according to the National Land Numerical Information provided by the Japanese Ministry of Land, Infrastructure, Transport, and Tourism.

Finer spatial resolutions of temperature are needed to more

Fig. 7. Trends in day of year (DOY) in which percentage of budburst (P_{bud}) exceeded 0% (initial budburst) and 50% and reached 100%, accumulated daily minimum temperature below 3 °C after the initial budburst (ΣT_{min}), and potential frost risk (F_{risk}) from 1981–2020 at the representative point P4. The location of P4 is described in Fig. 1. Linear lines represent Sen's slopes with Mann-Kendall tests at 5% significance level, and data without lines show no trends at 5% significance level.

Fig. 8. Spatial distributions of Sen's slope (degree of trend) of the day of year (DOY) in which percentage of budburst (P_{bud}) exceeds 0% (initial budburst) and 50% and reaches 100% from 1981–2020. Blank areas show no trends at 5% significance level using Mann-Kendall tests. The representative points (P1 – P4) are indicated on the map.

meaningfully assess distributions of F_{risk} and P_{bud} . In the hilly and mountainous areas where the tea plants are usually cultivated, significant differences in temperature occur within a 1 km² grid section, mainly due to cold air drainage on radiative frost nights (Chung *et al.*, 2006), leading to a bias of P_{bud} within the grid. Chung *et al.* (2006) developed a minimum-temperature prediction model which considered cold air drainage and temperature inversion strength in complex terrain, using a digital elevation model. Moreover, Maclean *et al.* (2019) provided a method and an

Fig. 9. Spatial distributions of Sen's slope (degree of trend) of accumulated daily minimum temperature below 3 °C after the initial budburst (ΣT_{min}) and potential frost risk (F_{risk}), from 1981–2020. Blank areas show no trends at 5% significance level using Mann-Kendall tests. The representative points (P1 – P4) are indicated on the map.

Table 2. Sen's slope (degree of trend) of potential frost risk (F_{risk}) during the period 1981–2020 at different elevations (50 m intervals). Standard deviation, SD.

Elevation (m)	Sen's slope of F_{risk}	SD
0–49	1.6	0.68
50–99	2.5	1.38
100–149	2.4	1.48
150–199	3.0	1.10
200–249	3.1	0.70
250–299	2.3	0.57
300–349	1.4	0.51
350–399	0.6	0.24
400–449	0.2	0.10

R program to assess the spatially fine distribution of air temperature (resolution < 30 m), considering the local effects of cold air drainage and other microclimate conditions. These methods were

based on the calculation of airflow direction and accumulation within a study area, allowing the assessment of where cold air converges. The integration of these methods with the bud model could provide more meaningful assessments of frost risk.

Nevertheless, we believe that the new index of potential frost risk and the model of budburst percentage proposed in this study could improve the conventional assessment of frost risk and contribute to the development of reliable strategies for the application of frost protection under the effects of future climate change.

5. Concluding Remarks

A new index for potential frost risk, considering phenology and meteorology, was proposed using thermal time (minimum air temperature below the threshold value) weighted by the proportion of budburst. The proportion of budburst in tea plants was modeled, by formulating endodormancy, ecodormancy, and the subsequent increase of the number of budbursts. This model successfully predicted the proportion of budburst in tea plants over 15 years, with root mean square errors of 8.5 percentage points. Using the proposed index and the model, spatiotemporal distribution of frost risk in tea plants was evaluated in east Japan from 1981–2020. The distribution showed that frost risk increased over that period in hilly areas where tea plants are mainly cultivated. This result suggests an urgent need for improved frost protection in tea fields.

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