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Full Length Article

Influence of Different Precipitation Periods on *Dendrolimus superans* Occurrence: A Biostatistical Analysis

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Abstract

Precipitation is one of the most important abiotic factors that affect *Dendrolimus superans* occurrence. In this study, a grey slope-correlation model was used, and a simplified grey slope-correlation model was constructed to uncover the most crucial periods of precipitation that pest occurrence. Results revealed that the two models were similar; however, the simplified grey slope-correlation model required less calculative steps and was easier to operate. The calculation results revealed that the most crucial period occurred during the first 10 days of July ($\gamma_{13} = 0.67$, $\gamma`_{13} = 0.69$). The other precipitation periods associated with pest occurrence included the first 10 days of August ($\gamma_{16} = 0.62$, $\gamma`_{16} = 0.61$), the third 10 days of May ($\gamma_{09} = 0.59$, $\gamma`_{09} = 0.62$), the sec 10 days of May ($\gamma_{08} = 0.58$, $\gamma`_{08} = 0.60$), and the third 10 days of August ($\gamma_{18} = 0.58$, $\gamma`_{18} = 0.60$). The less associated precipitation periods included the first 10 days of March ($\gamma_{01} = 0.54$, $\gamma`_{01} = 0.47$), the sec 10 days of March ($\gamma_{02} = 0.50$, $\gamma`_{02} = 0.49$), the third 10 days of April ($\gamma_{06} = 0.47$, $\gamma`_{06} = 0.48$), the sec 10 days of June ($\gamma_{11} = 0.51$, $\gamma`_{11} = 0.48$), and the third 10 days of June ($\gamma_{12} = 0.51$, $\gamma`_{12} = 0.51$). Precipitation in May ($\gamma_{07} + \gamma_{08} + \gamma_{09} = 1.74$, $\gamma`_{07} + \gamma`_{08} + \gamma`_{09} = 1.79$) and July ($\gamma_{13} + \gamma_{14} + \gamma_{15} = 1.74$, $\gamma`_{13} + \gamma`_{14} + \gamma`_{15} = 1.79$) was mostly associated with *D. superans* occurrence. The findings of this study provided a simple operative model for determining the most crucial precipitation periods of pest occurrence, and these analytical methods can serve as a theoretical reference for pest forecasting and early warning, which contributes to ecological protection.

Keywords: *Dendrolimus superans*; Grey slope correlation; Occurrence; Precipitation; Simplified model

Introduction

The occurrence of forest pests, which is known as "the no-smoke forest fire" are likely to cause tree die-out, ecological destruction, and subsequently reduce forest carbon sequestration (Xu 2015). *Dendrolimus superans* (Butler) is the main leaf-eating insect found in the northeastern forests of China, which turns tree branches bleak when its larvae gnaw the leaves (Dang *et al.* 2018). *D. superans* can also be found in other regions under similar latitude and climatic conditions (Kang 2005; Tomin *et al.* 2011; Myong *et al.* 2012). The pests can outbreak depending on the environment and climatic conditions, and the degree of damage, spreading direction, and duration of different stages can be forecast by studying the growth ratio of larvae (Natalia *et al.* 2009).

The occurrence of forest pests is a result of many factors, including biological characteristics, natural enemies, meteorological conditions, site conditions, and stand structure (Chen *et al.* 2017). The relationship between meteorological factors and the occurrence of forest pests is a system consisting of many mathematical inputs. These inputs have an interactive effect with one another, including evaporation capacity, precipitation, average temperature, and accumulated temperature (Tang and Niu 2010). However, it is difficult to formulate the relationship between a designated meteorological factor and the occurrence of forest pests (Feng *et al*. 2013). Most of the existing research has obtained an approximate relationship between these two factors through data integration, analysis, and exploration, and most of these results were non-linear (Zhang *et al*. 2012; Abdul *et al*. 2014).

Previous studies on the relationship between the occurrence of forest pests and meteorological factors in Northern China have revealed that temperature and precipitation during the spring and summer were the most critical factors influencing pest population (Tang and Niu 2010; Chen and Zhang 2011). This influence was greater at

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the larval stage, while the annual accumulated temperature (The sum, counted in degrees, by which the actual air temperature rises above or falls below a datum level over a year), annual precipitation, and dryness had the greatest Pearson correlation coefficients with pest area (Yang *et al*. 2014; Nie *et al*. 2017). A similar study concluded that extreme heat or cold had little effect on annual catches of *Ips typographus*, while growth rate had a linear relationship with temperatures between 15 and 25°C (Bakke 1992; Wermelinger and Seifert 1998). In a separate study, *Diprion hercyniae* outbreak was induced by the hot and dry climate and severe low moisture (Marchisio *et al.* 1994). Moreover, a stepwise regression analysis revealed that the daily average temperature during the winter and precipitation during the breeding season was a key factor influencing population fluctuations of *D. superans*, while the larval stage and breeding season were the most critical periods (Yu *et al*. 2016).

More and more novel algorithms are being used for pest control and forecasting by utilizing big data and information on climate globalization (Kumar *et al.* 2015). The artificial neural network, multilayer feedforward neural network (MLFN), generalized regression neural network (GRNN), support vector machine (SVM), and other algorithms have been used to forecast the occurrence of pest, and these machine learning measures have been more accurate than multiple linear regression predictions (Chon *et al*. 2000; Zhang *et al*. 2017; Rathee and Kashyap 2018). However, like other systemic analysis methods in machine learning measures, regression analyses require mass data and expect much of the data to take on a typical probability distribution (e.g., linear, exponential, logarithmic, and so on). Multiplication, division, and power operations are often involved in the computational process, but small errors can result in serious errors, which lead to discrepancies between the quantitative results and qualitative analysis. This may also lead to a relationship between systems that cannot be objectively expressed (Cao 2007; Liu and Xie 2013). Additionally, due to the complexity of computational models, they are not widely used by forest workers or researchers. Therefore, when the grey correlation analysis is used to study the relationship between meteorological variation and pest occurrence, the vector set was easy to divided and call for no more others variables, the model needs to possess less calculative complexity and easy to operate.

In this study, the selected meteorological index was easy to calculate and the system did not affect the simplicity or functioning of the model. Thus, this analytical method and the findings of this study can serve as a theoretical reference for pest forecasting and early warning. For example, this analytical method and the findings can be widely used for forest workers, when precipitation during the first 10 days of July (the Breeding season of *D. superans*) was less than others year, more attention should be paid the *D. superans* outbreak next year.

Materials and Methods

Location and status of the studied habitats

This study was conducted in the southeast of Xiaoxinganling Mountains located in Tieli of Yichun City, Heilongjiang Province, China. Regional vegetation mainly includes *Pinus koraiensis*, *Larix gmelinii*, and *Picea jezoensis*. As for the climate, the winters are long and the summer is short. The maximum air temperature may exceed 35°C, while the minimum air temperature can drop below -41°C. Meteorological data were collected from the Tieli weather station (128°01′E and 46°59′N). The altitude of the observation site was 210.5 m, and the altitude of the senor of the barometer was 213.4 m. The height of the wind speed sensor to the platform was 9.36 m, while the height of the observation platform to the ground was 11.76 m.

Statistics and data compilation

A grey correlation analysis was used to study the relationship between meteorological variation and pest occurrence. The selection of characteristic data is key for the foundation of this analysis. *D. superans* occurrence from 1997 to 2017 was used as the main time period response sequence: X_0 and $X_0 = x_0(k)$ ($k = 1, 2,\ldots n$), then $X_i = x_i(k)$ ($i = 1, 2,\ldots m$, $k = 1, 2,\ldots n$) ($n = 21$), where x_i was the ith influencing factor of the system and X_i ($i = 1, 2,\ldots n$) was the characteristic time response data sequence. The analysis in same sample plot did not consider the soil composition, stand structure, or human disturbance, which made *D. superans* occurrence of Tieli the main data sequence, while the temperature, precipitation, average wind speed, and other time node meteorological data were used as the characteristic data sequences. The grey correlation degree was acquired by the grey correlation analysis, and the degree revealed that precipitation during the spring and summer had the greatest effect on *D. superans*’ occurrence (Li *et al.* 2019).

The influence of different precipitation parameters on *D. superans* occurrence was investigated further. In this analysis, *D. superans* occurrence from 1997 to 2017 was the main time response sequence: X_0, and $X_i = x_i(k)$ ($i = 1, 2\ldots m$, $k = 1, 2,\ldots n$) ($m = 18$, $n = 21$), where X_i was the different precipitation periods from March to August. Each month was divided into 3 parts, x_1, x_2, and x_3, which represented the first, sec, and third 10 days of March, while x_4, x_5, and x_6 represented the first, sec, and third 10 days of April; this pattern spanned through August until x_{18} (Table 1). Then, the correlative relationship between precipitation and *D. superans* occurrence was investigated.

Data processing and analysis

The goal of the grey correlation analysis was to explore the similarity between data sequence trends, where higher similarity indicates a higher degree of correlation in the system. While comparing the similarity between these two data sequences, both the numerical values and the dimensions were considered. If the data sequence was incomparable, data transformation was conducted in order to eliminate dimensions.

Feature data processing

When $Xi = (x_i(1), x_i(2),\ldots, x_i(n))$ was the characteristic time response data sequence of the system, D_1 was the operator of the sequence, such that:

$$X_i D_1 = (x_i(1)d_1, x_i(2)d_1 \ldots, x_i(n)d_1) \quad \text{(Eq. 1)},$$

$$x_i(k)d_1 = \frac{x_i(k)}{\overline{X_i}}, \overline{X_i} = \frac{1}{n}\sum_{k=1}^{n} x_i(k), (k = 1,2,\ldots n) \quad \text{(Eq. 2)},$$

Where D_1 represents the average operator of the sequence and X_iD_1 represents the average image. Then, the characteristic average image sequence data table was acquired (Table 2).

Grey relational degree calculation

The calculation for the grey relational degree was conducted as follows: after data transformation, the characteristic average image sequence was obtained, then the grey degree was calculated. In addition to the general relation degree, the mathematical model according to the characteristics of this system was explored, including "B," "C," and "T" types of grey relation degrees, as well as the degree of grey slope-correlation (Liu and Xie 2013). The grey slope-correlation expresses the average change over time response sequence, system factors, and the main sequence (Wekan *et al*. 2011). If the change tended closer, then the grey slope-correlation was larger (Zhang *et al*. 2019). When investigating the influence of different precipitation periods on *D. superans* occurrence, these periods during different months exhibited a time response; this grey slope-correlation was selected for further analysis. When $\xi(k)$ was the correlation coefficient:

$$\xi(k) = \frac{1}{1 + \left| \frac{x_0(k+1) - x_0(k)}{x_0(k+1)} - \frac{x_i(k+1) - x_i(k)}{x_i(k+1)} \right|} \quad (i = 1, 2,\ldots m;\ k = 1, 2,\ldots n) \quad \text{(Eq. 3)}.$$

When calculating the last year, "k + 1"was empty. Therefore, it was decided to stop at the "k - 1" year. This did not affect the trend of data changes. In this calculation, i = 1, 2,… 18 and k = 1, 2,… 21. Then, the correlation coefficient sequence data was obtained (Table 3).

The grey slope-correlation relation degree of X_0 and X_i were donated as $\gamma(X_0, X_i)$, which was calculated as follows:

$$\gamma(X_0, X_i) = \frac{1}{n-1}\sum_{k=1}^{n-1}\xi(k) \quad (i = 1, 2,\ldots m;\ k = 1, 2,\ldots n) \quad \text{(Eq. 4)}.$$

Simplified grey slope-correlation model

The grey slope-correlation was used to compare the correlational degree of factors over time. However, the calculating process of Eq. 3 (ξ (k)) required many calculative steps. Therefore, the computational model was simplified as follows:

$$\xi`(k) = \frac{1}{1 + \left| \frac{x_0(k+1)}{x_0(k)} - \frac{x_i(k+1)}{x_i(k)} \right|} \quad (i = 1, 2,\ldots m, k = 1, 2,\ldots n) \quad \text{(Eq. 5)},$$

Where the simplified correlation coefficient, ξ (k), was affected by the denominator coefficient. When the numerical values of $\frac{x_0(k+1)}{x_0(k)}$ and $\frac{x_i(k+1)}{x_i(k)}$ were similar, the data sequence curves were parallel and the variation tendencies of X_0 and X_i were closer, thereby simplifying the calculation of the correlation coefficient data (Table 4).

Then, the simplified grey slope-correlation relation degree of X_0 and X_i were marked as $\gamma`(X_0, X_i)$, where

$$\gamma`(X_0, X_i) = \frac{1}{n}\sum_{k=1}^{n}\xi`(k) \quad (i = 1, 2,\ldots m;\ k = 1, 2,\ldots n) \quad \text{(Eq. 6)},$$

Results

The grey slope-correlation relation degree of X_0 and X_i

It could be derived from Eq. 4 that the results of the grey slope-correlation relation degree were γ_{01} = 0.54, γ_{02} = 0.50, γ_{03} = 0.63, γ_{04} = 0.50, γ_{05} = 0.54, γ_{06} = 0.47, γ_{07} = 0.57, γ_{08} = 0.58, γ_{09} = 0.59, γ_{010} = 0.53, γ_{011} = 0.51, γ_{012} = 0.51, γ_{013} = 0.67, γ_{014} = 0.59, γ_{015} = 0.48, γ_{016} = 0.62, γ_{017} = 0.53, and γ_{018} = 0.58, which represented the time responses of precipitation during different months and *D. superans* occurrence. The results revealed that precipitation during different seasons had different degrees of correlation with *D. superans* occurrence, when the value of γ (X_0, X_i) was higher, the correlation degree of X_0 and X_i was greater. Specifically, as it turns out, precipitation during the first 10 days of July had the largest correlation (γ_{013} = 0.67), and the third 10 days of March (γ_{03} = 0.63) and first 10 days of August (γ_{016} = 0.62) had better correlation with *D. superans* occurrence. Meanwhile, the precipitation during the third 10 days of April (γ_{06} = 0.47) and the third 10 days of July (γ_{015} = 0.48) correlated less with *D. superans* occurrence (Table 3).

The simplified grey slope-correlation relation degree of X_0 and X_i

From Eq. 6, the following results could be obtained: $\gamma`_{01}$ = 0.47, $\gamma`_{02}$ = 0.49, $\gamma`_{03}$ = 0.56, $\gamma`_{04}$ = 0.50, $\gamma`_{05}$ = 0.56, $\gamma`_{06}$ = 0.48, $\gamma`_{07}$ = 0.57, $\gamma`_{08}$ = 0.60, $\gamma`_{09}$ = 0.62, $\gamma`_{10}$ = 0.58, $\gamma`_{11}$ = 0.48, $\gamma`_{12}$ = 0.51, $\gamma`_{13}$ = 0.69, $\gamma`_{14}$ = 0.58, $\gamma`_{15}$ = 0.52, $\gamma`_{16}$ = 0.61, $\gamma`_{17}$ = 0.55, and $\gamma`_{18}$ = 0.60.

The simplified grey slope-correlation of X_0 and X_i revealed that the precipitation during the first 10 days of July had the best correlation ($\gamma`_{13}$ = 0.69), which reflected the results of the classical model. In the simplified model, the top 5 groups of precipitation that had better associations

Table 1: The characteristic sequence data table

Area and precipitation	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
X_0/×$10^5$$hm^2$)	4.07	7.73	5.05	3.25	3.07	2.75	4.13	2.87	1.67	1.24	1.31	0.95	0.9	0.98	0.8	0.75	0.35	0.35	0.28	0.34	0.48
X_1/(0.1mm)	5	0	6	25	73	0	28	0	32	99	21	147	62	0	18	41	7	37	122	40	63
X_2/(0.1mm)	22	204	51	68	36	0	1	67	51	30	4	63	44	193	75	3	0	30	127	10	38
X_3/(0.1mm)	67	61	88	16	79	0	120	46	64	113	144	220	94	85	0	91	95	0	73	0	0
X_4/(0.1mm)	0	51	71	31	89	164	0	50	99	11	125	89	3	163	7	0	9	4	122	115	20
X_5/(0.1mm)	76	38	85	48	11	305	216	123	103	1	85	0	161	91	2	77	33	18	11	53	71
X_6/(0.1mm)	77	90	150	225	64	175	92	58	306	84	1	281	5	79	30	252	3	110	32	10	40
X_7/(0.1mm)	13	75	37	127	145	71	0	385	144	32	124	393	54	459	302	72	249	266	247	368	201
X_8/(0.1mm)	183	263	1	183	195	286	175	189	163	0	329	129	9	354	56	67	206	391	467	364	205
X_9/(0.1mm)	436	365	134	161	26	139	444	212	111	34	520	309	133	151	367	244	156	545	146	228	166
X_{10}/(0.1mm)	616	571	51	91	50	504	215	3	600	284	222	336	180	156	536	1504	432	115	368	456	126
X_{11}/(0.1mm)	175	699	275	62	223	421	137	352	211	863	15	233	760	80	197	340	401	145	320	275	785
X_{12}/(0.1mm)	106	732	568	316	33	320	342	349	58	861	395	192	1278	126	15	115	391	1535	1313	826	398
X_{13}/(0.1mm)	447	1646	969	253	426	230	688	477	441	343	280	608	668	351	586	1388	970	943	923	1021	100
X_{14}/(0.1mm)	88	12	54	1217	347	351	565	75	342	371	222	170	447	561	346	297	209	749	32	67	960
X_{15}/(0.1mm)	961	97	505	992	514	39	521	180	1468	794	378	2	304	312	62	157	786	1518	892	670	88
X_{16}/(0.1mm)	1119	631	449	741	393	300	625	372	173	355	226	273	479	1066	790	528	1562	110	787	353	1669
X_{17}/(0.1mm)	194	550	193	327	533	218	494	33	137	161	148	58	804	245	528	110	393	1108	203	262	0
X_{18}/(0.1mm)	621	327	273	533	221	424	1206	443	41	121	669	591	289	812	110	790	292	188	187	238	247

Table 2: The characteristic average image sequence data table

Average image	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
X_0D_1	1.98	3.75	2.45	1.58	1.49	1.33	2	1.39	0.81	0.6	0.64	0.46	0.44	0.48	0.39	0.36	0.17	0.17	0.14	0.17	0.23
X_1D_1	0.13	0	0.15	0.64	1.86	0	0.71	0	0.81	2.52	0.53	3.74	1.58	0	0.46	1.04	0.18	0.94	3.1	1.02	1.6
X_2D_1	0.41	3.84	0.96	1.28	0.68	0	0.02	1.26	0.96	0.56	0.08	1.18	0.83	3.63	1.41	0.06	0	0.56	2.39	0.19	0.71
X_3D_1	0.97	0.88	1.27	0.23	1.14	0	1.73	0.66	0.92	1.63	2.08	3.17	1.36	1.23	0	1.31	1.37	0	1.05	0	0
X_4D_1	0	0.88	1.22	0.53	1.53	2.82	0	0.86	1.7	0.19	2.15	1.53	0.05	2.8	0.12	0	0.15	0.07	2.09	1.97	0.34
X_5D_1	0.99	0.5	1.11	0.63	0.14	3.98	2.82	1.61	1.35	0.01	1.11	0	2.1	1.19	0.03	1	0.43	0.24	0.14	0.69	0.93
X_6D_1	0.75	0.87	1.45	2.18	0.62	1.7	0.89	0.56	2.97	0.81	0	2.73	0.05	0.74	0.29	2.44	0.03	1.07	0.31	0.1	0.39
X_7D_1	0.07	0.42	0.21	0.71	0.81	0.4	0	2.15	0.8	0.18	0.69	2.2	0.3	2.56	1.69	0.4	1.39	1.49	1.38	2.06	1.12
X_8D_1	0.91	1.31	0	0.91	0.97	1.42	0.87	0.94	0.81	0	1.64	0.64	0.04	1.76	0.28	0.33	1.02	1.95	2.32	1.81	1.02
X_9D_1	1.82	1.53	0.56	0.67	0.11	0.58	1.86	0.89	0.46	0.14	2.18	1.29	0.56	0.63	1.54	1.02	0.65	2.28	0.61	0.95	0.69
$X_{10}D_1$	1.75	1.62	0.14	0.26	0.14	1.43	0.61	0	1.7	0.8	0.63	0.95	0.51	0.44	1.52	4.26	1.22	0.33	1.04	1.29	0.36
$X_{11}D_1$	0.53	2.11	0.83	0.19	0.67	1.27	0.41	1.06	0.64	2.6	0.05	0.7	2.29	0.24	0.59	1.02	1.21	0.44	0.96	0.83	2.36
$X_{12}D_1$	0.22	1.5	1.16	0.65	0.07	0.65	0.7	0.71	0.12	1.76	0.81	0.39	2.61	0.26	0.03	0.24	0.8	3.14	2.69	1.69	0.81
$X_{13}D_1$	0.68	2.51	1.48	0.39	0.65	0.35	1.05	0.73	0.67	0.52	4.23	0.93	1.02	0.54	0.89	2.12	1.48	1.44	1.41	1.56	0.15
$X_{14}D_1$	0.24	0.03	0.15	3.33	0.95	0.96	1.54	0.2	0.93	1.01	0.61	0.46	1.22	1.53	0.95	0.81	0.57	2.05	0.09	0.18	2.62
$X_{15}D_1$	1.8	0.18	0.94	1.85	0.96	0.07	0.97	0.34	2.74	1.48	0.71	0	0.57	0.58	0.12	0.29	1.47	2.84	1.67	1.25	0.16
$X_{16}D_1$	1.81	1.02	0.73	1.2	0.63	0.48	1	0.6	0.28	0.57	0.37	0.44	0.77	1.72	1.28	0.85	2.52	0.18	1.27	0.57	2.7
$X_{17}D_1$	0.61	1.72	0.61	1.03	1.67	0.68	1.55	0.1	0.43	0.5	0.46	0.18	2.52	0.77	1.66	0.34	1.23	3.47	0.64	0.82	0
$X_{18}D_1$	1.51	0.8	0.66	1.3	0.54	0.69	2.93	0.72	0.1	0.29	1.63	1.44	0.7	1.98	0.27	1.92	0.71	0.46	0.45	0.58	0.6

with *D. superans* occurrence included the precipitation during the first 10 days of July ($\gamma`_{13}$ = 0.69), the third 10 days of May ($\gamma`_{09}$ = 0.62), the first 10 days of August ($\gamma`_{16}$ = 0.61), the sec 10 days of May ($\gamma`_{08}$ = 0.60), and the third 10 days of August ($\gamma`_{18}$ = 0.60). However, according to the classical model, the top 5 group included the first 10 days of July (γ_{13} = 0.67), the third 10 days of March (γ_{03} = 0.63), the first 10 days of August (γ_{16} = 0.62), the sec 10 days of May (γ_{08} = 0.58), and the third 10 days of August (γ_{18} = 0.58). The results showed that, the top 5 groups of precipitation that had better associations with *D. superans* occurrence between the two models was very similar. In the simplified model, the 5 groups of precipitation that were less associated with *D. superans* occurrence included the precipitation during the first 10 days of March ($\gamma`_{01}$ = 0.47), the third 10 days of April ($\gamma`_{06}$ = 0.48), the sec 10 days of June ($\gamma`_{11}$ = 0.48), the sec 10 days of March ($\gamma`_{02}$ = 0.49), and the third 10 days of June ($\gamma`_{12}$ = 0.51). In the classical model, the 5 groups that were less associated with *D. superans* occurrence included the third 10 days of April (γ_{06} = 0.47), the third 10 days of July (γ_{15} = 0.48), the sec 10 days of March (γ_{02} = 0.50), the sec 10 days of June (γ_{11} = 0.51), and the third 10 days of June (γ_{12} = 0.51). The results also proved that the two models were very similar (concluded from Eq. 4 and Eq. 6).

Comparative and analysis

Considering that many complex computing models are not and cannot be widely used by forest workers or researchers, the simple grey slope-correlation model was developed to analyze the relationship between precipitation and *D. superans* occurrence. The grey slope-correlation model is able to express the average changes in many factors over a time response sequence.

Table 3: Correlation coefficient sequence data table

Correlation coefficient	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
ξ_{0k}	0.68	0.40	0.43	0.58	0.89	0.60	0.69	0.37	0.49	0.21	0.44	0.42	0.92	0.45	0.61	0.21	0.55	0.52	0.31	0.91
ξ_{1k}	0.70	0.29	0.56	0.55	0.89	0.60	0.41	0.71	0.73	0.14	0.43	0.70	0.59	0.43	0.04	0.47	0.50	0.51	0.08	0.68
ξ_{2k}	0.64	0.55	0.20	0.54	0.89	0.60	0.46	0.50	0.56	0.87	0.58	0.43	0.84	0.81	0.48	0.46	1.00	0.45	0.85	0.79
ξ_{3k}	0.65	0.56	0.57	0.58	0.63	0.75	0.41	0.45	0.12	0.54	0.98	0.03	0.53	0.04	0.93	0.32	0.47	0.46	0.81	0.17
ξ_{4k}	0.41	0.49	0.83	0.23	0.48	0.57	0.76	0.65	0.01	0.52	0.72	0.50	0.54	0.03	0.49	0.83	0.56	0.66	0.62	1.00
ξ_{5k}	0.75	0.53	0.53	0.29	0.57	0.45	0.87	0.40	0.30	0.94	0.42	0.02	0.54	0.43	0.51	0.01	0.51	0.31	0.31	0.67
ξ_{6k}	0.73	0.67	0.44	0.84	0.52	0.75	0.41	0.51	0.24	0.60	0.48	0.14	0.56	0.78	0.24	0.35	0.94	0.88	0.87	0.48
ξ_{7k}	0.86	0.67	0.39	0.89	0.70	0.51	0.66	0.64	0.74	0.52	0.46	0.06	0.53	0.17	0.81	0.36	0.68	0.73	0.69	0.49
ξ_{8k}	0.60	0.45	0.58	0.17	0.52	0.74	0.61	0.82	0.34	0.53	0.77	0.43	0.97	0.55	0.70	0.64	0.58	0.28	0.85	0.61
ξ_{9k}	0.65	0.09	0.50	0.56	0.49	0.37	0.69	0.37	0.56	0.75	0.58	0.54	0.81	0.52	0.58	0.42	0.27	0.53	0.98	0.26
ξ_{10k}	0.78	0.49	0.26	0.56	0.63	0.29	0.49	0.94	0.48	0.02	0.43	0.59	0.10	0.55	0.67	0.44	0.36	0.57	0.75	0.72
ξ_{11k}	0.72	0.83	0.81	0.11	0.50	0.79	0.69	0.19	0.44	0.45	0.59	0.54	0.10	0.12	0.51	0.35	0.57	0.96	0.57	0.43
ξ_{12k}	0.79	0.84	0.31	0.68	0.58	0.75	1.00	0.61	0.94	0.55	0.24	0.92	0.51	0.62	0.60	0.59	0.97	0.84	0.93	0.09
ξ_{13k}	0.12	0.43	0.40	0.29	0.88	0.96	0.14	0.40	0.70	0.58	0.94	0.62	0.89	0.72	0.92	0.59	0.58	0.04	0.76	0.60
ξ_{14k}	0.10	0.43	0.49	0.54	0.07	0.63	0.41	0.39	0.67	0.47	0.72	0.50	0.94	0.22	0.60	0.34	0.67	0.67	0.66	0.12
ξ_{15k}	0.45	0.91	0.52	0.54	0.84	0.84	0.82	0.70	0.54	0.62	0.65	0.70	0.68	0.90	0.70	0.36	0.07	0.48	0.42	0.65
ξ_{16k}	0.85	0.43	0.51	0.69	0.43	0.82	0.07	0.40	0.67	0.87	0.46	0.52	0.30	0.57	0.21	0.35	0.61	0.19	0.96	0.79
ξ_{17k}	0.42	0.78	0.49	0.43	0.75	0.70	0.28	0.15	0.50	0.57	0.79	0.49	0.64	0.14	0.52	0.63	0.65	0.84	0.95	0.81
ξ_{18k}	0.68	0.40	0.43	0.58	0.89	0.60	0.69	0.37	0.49	0.21	0.44	0.42	0.92	0.45	0.61	0.21	0.55	0.52	0.31	0.91

Table 4: The simplified correlation coefficient sequence data table

Simplified correlation coefficient	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
$\xi`_{1k}$	0.35	0.60	0.22	0.34	0.53	0.40	0.59	0.63	0.30	0.54	0.14	0.65	0.48	0.55	0.43	0.77	0.19	0.29	0.53	0.82
$\xi`_{2k}$	0.12	0.71	0.59	0.71	0.53	0.40	0.02	0.85	0.86	0.52	0.07	0.80	0.23	0.70	0.53	0.68	0.50	0.23	0.47	0.30
$\xi`_{3k}$	0.50	0.56	0.68	0.20	0.53	0.40	0.76	0.55	0.49	0.83	0.55	0.65	0.84	0.55	0.52	0.64	0.50	0.55	0.45	0.43
$\xi`_{4k}$	0.35	0.58	0.83	0.34	0.51	0.40	0.59	0.42	0.61	0.09	0.99	0.52	0.02	0.57	0.52	0.68	0.65	0.03	0.79	0.46
$\xi`_{5k}$	0.42	0.39	0.93	0.58	0.04	0.56	0.89	0.80	0.58	0.01	0.58	0.51	0.66	0.56	0.03	0.96	0.69	0.81	0.21	0.99
$\xi`_{6k}$	0.58	0.50	0.54	0.60	0.35	0.50	0.94	0.17	0.68	0.48	0.58	0.52	0.07	0.70	0.12	0.68	0.03	0.65	0.53	0.28
$\xi`_{7k}$	0.20	0.87	0.27	0.83	0.71	0.40	0.59	0.83	0.66	0.27	0.29	0.55	0.12	0.87	0.59	0.25	0.93	0.91	0.78	0.55
$\xi`_{8k}$	0.69	0.60	0.61	0.89	0.64	0.53	0.72	0.78	0.57	0.48	0.75	0.53	0.02	0.60	0.80	0.28	0.52	0.73	0.70	0.56
$\xi`_{9k}$	0.49	0.78	0.64	0.56	0.19	0.37	0.82	0.94	0.70	0.06	0.89	0.66	0.97	0.38	0.79	0.86	0.29	0.64	0.74	0.61
$\xi`_{10k}$	0.51	0.64	0.45	0.71	0.10	0.48	0.59	0.63	0.79	0.78	0.56	0.70	0.81	0.27	0.35	0.84	0.58	0.30	0.97	0.48
$\xi`_{11k}$	0.32	0.79	0.71	0.28	0.50	0.46	0.35	0.98	0.23	0.49	0.07	0.30	0.50	0.38	0.55	0.58	0.61	0.42	0.74	0.40
$\xi`_{12k}$	0.17	0.89	0.92	0.54	0.11	0.70	0.76	0.71	0.07	0.62	0.81	0.15	0.50	0.59	0.12	0.26	0.25	0.97	0.63	0.53
$\xi`_{13k}$	0.36	0.94	0.72	0.58	0.74	0.40	1.00	0.75	0.97	0.12	0.67	0.88	0.64	0.54	0.41	0.82	0.97	0.87	0.90	0.44
$\xi`_{14k}$	0.36	0.19	0.04	0.60	0.89	0.91	0.64	0.20	0.74	0.68	0.97	0.37	0.86	0.84	0.93	0.81	0.28	0.56	0.56	0.07
$\xi`_{15k}$	0.36	0.18	0.43	0.70	0.55	0.07	0.74	0.12	0.83	0.63	0.58	0.51	0.93	0.62	0.40	0.18	0.52	0.81	0.68	0.45
$\xi`_{16k}$	0.43	0.94	0.50	0.71	0.88	0.63	0.91	0.90	0.44	0.71	0.68	0.56	0.47	0.94	0.79	0.29	0.52	0.14	0.57	0.23
$\xi`_{17k}$	0.52	0.77	0.49	0.60	0.67	0.56	0.61	0.21	0.70	0.87	0.75	0.07	0.56	0.43	0.58	0.24	0.35	0.61	0.94	0.43
$\xi`_{18k}$	0.42	0.85	0.43	0.65	0.72	0.27	0.69	0.69	0.32	0.18	0.86	0.68	0.37	0.60	0.14	0.91	0.74	0.87	0.93	0.76

Table 5: The correlation coefficient accumulation table

Correlation coefficient accumulation	March	April	May	June	July	August
classical	$\gamma_{01}+\gamma_{02}+\gamma_{03}$ 1.67	$\gamma_{04}+\gamma_{05}+\gamma_{06}$ 1.51	$\gamma_{07}+\gamma_{08}+\gamma_{09}$ 1.74	$\gamma_{10}+\gamma_{11}+\gamma_{12}$ 1.55	$\gamma_{13}+\gamma_{14}+\gamma_{15}$ 1.74	$\gamma_{16}+\gamma_{17}+\gamma_{18}$ 1.73
simplified	$\gamma`_{01}+\gamma`_{02}+\gamma`_{03}$ 1.52	$\gamma`_{04}+\gamma`_{05}+\gamma`_{06}$ 1.54	$\gamma`_{07}+\gamma`_{08}+\gamma`_{09}$ 1.79	$\gamma`_{10}+\gamma`_{11}+\gamma`_{12}$ 1.57	$\gamma`_{13}+\gamma`_{14}+\gamma`_{15}$ 1.79	$\gamma`_{16}+\gamma`_{17}+\gamma`_{18}$ 1.76

In this study, the grey slope-correlation model of precipitation and *D. superans* occurrence in the Xiaoxinganling Mountain Tieli forest region was constructed and the grey slope-correlation relation degree was calculated. According to the calculations and analysis of the grey slope-correlation classical model, the simplified grey slope-correlation model required fewer steps and was easier to operate. After incorporating the correlation coefficient of each month in the classical and simplified models, the correlation coefficient accumulation was obtained (Table 5).

The correlation coefficient accumulation during May and July had good measure in both models (Table 5). This indicated that the precipitation during May and July were the greatest contributing precipitation factors on *D. superans* occurrence compared to other periods. Although both models exhibited different correlation coefficient accumulations, both models indicated that the precipitation period that contributed the least was during the spring. Moreover, the results of the models were similar, where the precipitation during May and July had the greatest associations with *D. superans* occurrence, but the simplified model required fewer calculative steps.

Discussion

According to the results, precipitation during May ($\gamma_{07} + \gamma_{08} + \gamma_{09} = 1.74$, $\gamma`_{07} + \gamma`_{08} + \gamma`_{09} = 1.79$) and July ($\gamma_{13} + \gamma_{14} + \gamma_{15} = 1.74$, $\gamma`_{13} + \gamma`_{14} + \gamma`_{15} = 1.79$) had the greatest associations with *D. superans* occurrence. In previous studies, the larval stage and breeding season were found to be the critical periods for *D. superans* (Yang *et al.* 2014; Yu *et al.* 2016). The life cycle of *D. superans* can be divided into the larval, larger larval, pupa, eclosion, adult, and spawning stages. *D. superans* produces 1 generation a year and overwinters as larvae in the Tieli forest region. The larval stage lasts for 3 seasons in Northeast China. Larvae hatch in autumn, stay in the litter layer during the winter, and finally climb up the trees during the spring of the next year. Precipitation has a great effect on *D. superans* occurrence. Aside from precipitation, temperature is also a critical factor that affects the larvae's ability to climb trees, while warm and dry climatic conditions benefit larval growth (Liu 1994; Tiit *et al.* 2010). Precipitation during the third 10 days of March ($\gamma_{03} = 0.63$, $\gamma`_{03} = 0.56$) was found to be the most important time period affecting *D. superans* occurrence compared to the other periods in March (Li *et al*. 2019). Because more precipitation tends to increase humidity, the additional humidity disturbs the water balance in insects, leading to epidemics of pathogenic microorganisms. Precipitation during the late spring promotes tree growth and provides food for larvae. When larvae experience high humidity for long periods of time, the body water loss balance can cause developmental delays or abnormalities (Chen and Zhang 2011; Abdul *et al*. 2014).

In the *D. superans* breeding season (July, August), precipitation during the first 10 days of July ($\gamma_{13} = 0.67$, $\gamma`_{13} = 0.69$) was found to be the most important factor affecting *D. superans* occurrence (Chen and Zhang 2011). This finding was similar to the results of a previous study on climate change and the occurrence of crop insects, where occurrence and precipitation exhibited a positive correlation (Zhang *et al*. 2012). When the average annual precipitation and heavy rainfall increased by 1 mm, pest occurrence rates increased by 0.004 and 0.008 and pest occurrence increased by 59.5×10^4 and 11.89×10^4 hm^2, respectively. Thus, precipitation clearly facilitated migratory pest decent and increased the base number of insects (Zhang *et al*. 2012). Moreover, precipitation influences pest food sources (i.e., trees and others plant), their natural enemies (e.g., *Trichogramma*), and other biotic factors (Vladimir *et al*. 2016)

The application of grey system theory requires less data input than the multiple linear regression analysis method, and the calculations are simple and easy to operate (Abdul *et al.* 2019; Zhang *et al*. 2019). Specifically, the selected meteorological index was easy to calculate and the system had no force requirement due to its simple capacity and regularity (Cao *et al.* 2007). Moreover, grey slope-correlation can reveal the correlational degree of factors over time (Wekan *et al*. 2011). The simplified correlation coefficient was affected by the denominator coefficient, while the simplified model was easy to calculate, required fewer steps, and the results was very similar with the classical model (concluded from Eq. 4, 6 and Table 5). These findings provide a theoretical reference for pest forecasting and early warning. This simple method was used to uncover the most critical periods of precipitation affecting pest occurrence, which was found to be the first 10 days of July. Thus, the grey system theory can be widely used by forest workers and researchers. Monitoring precipitation during the first 10 days in July should be a focus, and when the precipitation of the first 10 days in July increases while other factors are consistent, precautions should be implemented the next spring.

Different precipitation periods from March to August were measured by the weather service department. While *D. superans* was prone to sprawling, occurrence was the main time response sequence data that was difficult to calculate. In this study, occurrence data was obtained from actual measurements and empirical prediction, but its scientific foundation and precision needs to be improved. The period of precipitation with the greatest effect on pest occurrence was the first 10 days of July, which corresponds with the breeding season of *D. superans.* However, the life stages of this pest overlap in time and determining the specific pest stage (i.e., feathering, spawning, or hatching periods) was affected by which precipitation period was difficult to discern. Therefore, refinement of this scientific model requires further investigation.

Conclusion

Both grey slope-correlation and simplified models revealed that precipitation during the first 10 days of July had the greatest correlation ($\gamma_{13} = 0.67$, $\gamma`_{13} = 0.69$) with *D. superans* occurrence, while the first 10 days of August ($\gamma_{16} = 0.62$, $\gamma`_{16} = 0.61$), the sec 10 days of May ($\gamma_{08} = 0.58$, $\gamma`_{08} = 0.60$), and the third 10 days of August ($\gamma_{18}$=0.58, $\gamma`_{18}$=0.60) also had large correlations with *D. superans* occurrence. However, the least-correlated time periods of precipitation affecting *D. superans* occurrence were quite different between the two models. The classical model showed that third 10 days of April ($\gamma_{06} = 0.47$) were the least correlated, while the simplified model showed that the first 10 days of March ($\gamma`_{01} = 0.47$) were the least correlated with *D. superans* occurrence. When adding the correlation coefficients of each month in the classical and simplified models, the correlation coefficient in May and July had good measures in both models. Thus, precipitation during May and July was clearly the most important precipitation factor affecting *D. superans*' occurrence, while precipitation during the spring was the least important precipitation factor.

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Author Contributions

Zhiru Li and Zhenkun Miao conceived and designed the models; Xiaofeng Wu, Beihang Zhang and Quangang Li performed the experiments; Lizhi Han and Jun Wang contributed the insect data of forestry, and Zhiru Li wrote the paper.

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