

DANIEL WINTER HECK

**FACTORS AFFECTING THE SPATIO-TEMPORAL DYNAMICS OF  
FUSARIUM WILT OF BANANAS IN BRAZIL**

Tese apresentada à Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Fitopatologia, para obtenção do título de *Doctor Scientiae*.

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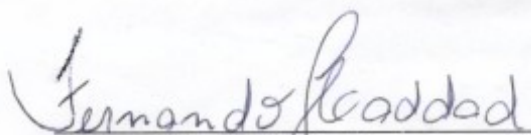
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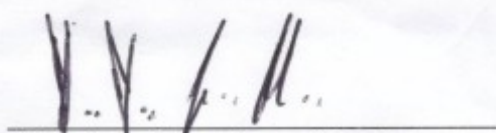
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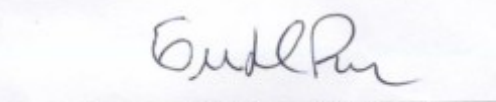
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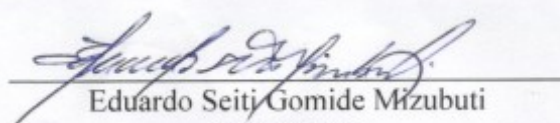
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\_\_\_\_\_  
Fernando Haddad

  
\_\_\_\_\_  
Francisco Ferraz Laranjeira Barbosa

  
\_\_\_\_\_  
Miguel Angel Dita Rodriguez  
(Coorientador)

  
\_\_\_\_\_  
Emerson Medeiros Del Ponte  
(Coorientador)

  
\_\_\_\_\_  
Eduardo Seiti Gomide Mizubuti  
(Orientador)

## SUMMARY

<b>ABSTRACT.....</b>	<b>iii</b>
<b>RESUMO.....</b>	<b>iv</b>
<b>GENERAL INTRODUCTION.....</b>	<b>1</b>
<b>REFERENCES.....</b>	<b>4</b>
<b>CHAPTER 1.....</b>	<b>7</b>
<b>Spatial pattern and factors driving the epidemics of Fusarium wilt of banana..</b>	<b>.8</b>
INTRODUCTION.....	9
MATERIAL AND METHODS.....	11
RESULTS.....	18
DISCUSSION.....	29
REFERENCES.....	36
<b>CHAPTER 2.....</b>	<b>43</b>
<b>Spatial and temporal dynamics of Fusarium wilt of bananas and aerial dispersal of Fusarium oxysporum f. sp. cubense under field conditions.....</b>	<b>44</b>
INTRODUCTION.....	45
MATERIAL AND METHODS.....	47
RESULTS.....	54
DISCUSSION.....	67
REFERENCES.....	74
SUPPLEMENTARY MATERIAL.....	83
<b>CHAPTER 3.....</b>	<b>84</b>
<b>Weevil borers and the spatio-temporal dynamics of Fusarium wilt of banana..</b>	<b>.85</b>
INTRODUCTION.....	86
MATERIAL AND METHODS.....	88
RESULTS.....	94
DISCUSSION.....	99
REFERENCES.....	103
<b>GENERAL CONCLUSIONS.....</b>	<b>109</b>

## ABSTRACT

HECK, Daniel Winter, D.Sc., Universidade Federal de Viçosa, March, 2019. **Factors affecting the spatio-temporal dynamics of Fusarium wilt of bananas in Brazil.** Adviser: Eduardo Seiti Gomide Mizubuti. Co-advisers: Emerson Medeiros Del Ponte and Miguel Angel Dita Rodríguez.

Fusarium wilt (FW), caused by *Fusarium oxysporum* f. sp. *cubense* (*Foc*), is one of the most destructive diseases of bananas. Great yield losses have been recorded for decades. Nevertheless, information about FW epidemiology is scarce. There is no basic information about the disease intensity, spatio-temporal pattern, spread mode and potential factors involved in these processes. This study aims to answer some of the epidemiology gaps to support the design of efficient management strategies. Initially, a survey was carried out in 30 banana fields in the main producing regions of Brazil. In total, 95 ha and more than 100 thousand plants were evaluated. Aggregation of FW was detected by all analytical methods in 43% of the fields. FW was more aggregated in high-input fields. The incidence of FW in banana fields in Brazil is high and is affected predominantly by cultivar, soil physical factors, and field management. The spatio-temporal patterns of FW epidemics were studied in eight plots, totaling 5 ha. All plants were evaluated bimonthly to FW symptoms and spatio-temporal analyses were conducted. The monomolecular model best fit incidence data over time. Aggregated patterns of diseased plants were frequently observed by quadrat-based methods, and the level of aggregation was higher when FW incidence was also high. The clusters of diseased plants were randomly distributed in most plots. The possible aerial dispersal of *Foc* under field conditions was investigated and spores of the pathogen were caught in Burkard spore trap. To investigate whether weevil borer (*Cosmopolites sordidus*; WB) was an effective vector of FW a comparative epidemiology study under field conditions and an association study between *Foc* and WB were performed. Incidence of FW was lower in the field where the population of WB was managed with *Beauveria bassiana* and higher degree of disease aggregation was observed. A great number of *Fusarium* spp. isolates were associated with WB but none was *Foc*. The design of efficient management strategies to mitigate the damage of *Foc* race 1 and the risk of introduction of *Foc* tropical race 4 require solid knowledge of FW epidemiology.

## RESUMO

HECK, Daniel Winter, D.Sc., Universidade Federal de Viçosa, março de 2019. **Fatores que afetam a dinâmica espaço-temporal da Murcha de Fusarium da bananeira no Brasil.** Orientador: Eduardo Seiti Gomide Mizubuti. Coorientadores: Emerson Medeiros Del Ponte e Miguel Angel Dita Rodríguez.

A murcha de Fusarium (MF), causada por *Fusarium oxysporum* f. sp. *cubense* (*Foc*), é uma das doenças mais destrutivas da banana. Grandes perdas de produtividade foram registradas por décadas. Mesmo assim, informações sobre a epidemiologia da MF é escassa. Não há informações básicas sobre a intensidade da doença, padrão espaço-temporal, modo de disseminação e os potenciais fatores envolvidos nestes processos. Este estudo tem por objetivo responder algumas das lacunas da epidemiologia para suportar o desenvolvimento de estratégias de manejo eficientes. Inicialmente, um levantamento foi realizado em 30 campos de banana nas principais regiões produtoras do Brasil. No total, 95 ha e mais de 100 mil plantas foram avaliadas. O padrão agregado da MF foi detectado por todos os métodos analíticos em 43% dos campos. A MF foi mais agregada em campos com alta tecnologia. A incidência da MF nos campos de banana no Brasil foi alta e é afetada predominantemente pela cultivar, fatores físicos do solo e manejo da cultura. O padrão espaço-temporal das epidemias da MF foram estudadas em oito parcelas, totalizando 5 ha. Todas as plantas foram avaliadas bimensalmente para sintomas da MF e análises espaço-temporais foram realizadas. O modelo monomolecular apresentou o melhor ajuste aos dados de incidência. Padrões agregados de plantas doentes foram frequentemente observados pelos métodos baseados em *quadrat* e o nível de agregação foi maior em maiores incidências. Os agrupamentos de plantas doentes estavam aleatoriamente distribuídos na maioria das parcelas. A possível dispersão aérea de *Foc* sob condições de campo foi investigada e esporos do patógeno foram capturados em armadilhas tipo Burkard. Para investigar se o moleque-da-bananeira (*Cosmopolites sordidus*, CS) foi um vetor efetivo da MF, estudos de epidemiologia comparativa em campo e de associação entre *Foc* e CS foram realizados. A incidência da MF foi menor no campo onde a população de CS foi manejada com *Beauveria bassiana* e maior grau de agregação foi observado. Um grande número de isolados de *Fusarium* spp. estava associado com CS, mas nenhum isolado de *Foc* foi confirmado. Sólidos conhecimentos epidemiológicos da MF são

necessários para o desenvolvimento de estratégias de manejo eficientes para mitigar os danos causados pela raça 1 de *Foc* e reduzir o risco de introdução da raça 4 tropical.

## GENERAL INTRODUCTION

Paradoxically, the success of a control practice can compromise the motivation and continuity of the studies of a plant disease and may even challenge the sustainability of a crop in the future. This conundrum is exemplified by what happened to the banana crop in the past half-century. Banana is the world's most important fruit (Faostat 2018) and is affected by one of the most destructive plant pathogens, *Fusarium oxysporum* f. sp. *ubense* (*Foc*) (E. F. Smith), a fungus that causes Fusarium wilt (FW) (Snyder and Hansen 1940; Stover and Simmonds 1987). In the mid-20th Century, large areas cultivated with bananas were devastated by FW. The substitution of 'Gros Michel', the most planted export cultivar at that time, by varieties of the subgroup 'Cavendish' resulted in immediate control of FW. Consequently, after this accomplishment, initiatives to keep investigating and generating basic information about FW lost impetus in most countries. As it commonly happens with human and animal diseases, old threats can re-emerge and cause severe losses (Ploetz 2005; Morens et al. 2004; Sailleau et al. 2017; Couto-Lima et al. 2017). The appearance of Tropical Race 4 (TR4) of *Foc*, which can overcome resistance of the 'Cavendish' bananas is raising high concerns that include the availability of the fruit in the future. Now, that new strategies to manage need to be devised, researchers face the lack of basic epidemiological knowledge of FW.

The intensity of FW in Brazil, its spatial pattern in the field, the temporal dynamics and the potential factors associated with disease increase in time and space remain largely unknown. To date, there are no accurate quantitative data on the intensity of FW in the different banana producing regions in Brazil. It is generally assumed that FW can reach up to 100% incidence in areas cultivated with highly

susceptible cultivars and favorable environmental conditions. These areas are normally abandoned, converted into pasture or cultivated with other crops. In Indonesia, one of the bigger banana producers, FW incidence was an average of 24%, but can reach 100% (Hermanto et al. 2011). In Africa, some fields showed 77% incidence in Ethiopia and, in East and Central Africa 54% of the fields assessed had more than 40% of FW incidence, with the highest values recorded in Tanzania (64%) (Mengesha et al. 2018; Karangwa et al. 2016). These assessments are important to describe the potential damages and impact of FW. Only two studies were conducted to address the spatial pattern of FW under field conditions (Meldrum et al. 2013; Liu et al. 2015). Temporal dynamics studies are even more scarce. Spatial arrangement is an important ecological process associated with plant disease epidemics (Madden et al. 2007) and can be used to devise hypothesis about pathogen dispersal or suggest mechanisms that give rise to them. Initial inoculum may have a direct relationship with the spatial pattern (Ristaino and Gumpertz 2000). Likewise, studies of disease increase in space and time can help us understand how the epidemic develops and how they can be affected by factors related to the: environment (soil, temperature, etc.); host (cultivars, susceptibility, etc.); pathogen (virulence, dispersal, etc.); and anthropogenic actions. The dynamics of FW epidemics can be strongly affected by the way *Foc* is dispersed in the field and this is one of the main gaps in the epidemiology of FW.

The role of wind and insects as dispersal agents remains elusive despite the impact the proper understanding of the role played by these agents may have to the management of FW epidemics. Members of *Fusarium* spp. and *F. oxysporum* were identified in air samples (Schweigkofler et al. 2004; Palmero et al. 2011; Katan et al. 1997; Lin et al. 2013). In some crops, as basil and tomato, *F. oxysporum* f. sp.

*radicis-lycopersici* and *F. oxysporum* f. sp. *basilici*, were able to infect aerial tissues of the hosts (Rekah et al. 2000). *F. oxysporum* f. sp. *cucumerinum* was also detected in air samples in greenhouse condition, but it was not able to establish in wounds (Scarlett et al. 2015). Regarding the contribution of weevil borer (*Cosmopolites sordidus*) as vector of FW much needs to be clarified. *C. sordidus* is one of the main insect pests of banana. *Foc* propagules were identified in the exoskeleton of the insects (Meldrum et al. 2013). Its role as pest and potentially as disease-vector is an important epidemiological issue. The involvement of wind dispersal of *Foc* propagules can also affect the dynamics of FW epidemics and no conclusive study has been conducted so far to test this hypothesis. Wind dispersal of *Foc* can increase the risk of introduction of more virulent variants, such as the Tropical Race 4, in other areas and preventive measures needs to be developed.

The objectives of the present study are translated in the following research questions: (i) What is the intensity of FW in Brazil? (ii) What is the spatial and temporal dynamics of FW in Brazil? (iii) Can *Foc* propagules be dispersed by the wind? Are weevil borers effective vectors of FW? To address these questions, epidemiological studies were conducted and provided valuable information to help develop better strategies for FW management.

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## **CHAPTER 1**

**Spatial pattern and factors driving the epidemics of Fusarium wilt of banana.**

## 1     **Spatial pattern and factors driving the epidemics of Fusarium wilt of banana.**

2     **Abstract:** Management of Fusarium wilt (FW) of bananas depends on the knowledge  
3     of the dynamics of the disease in time and space. The objectives of this work were to  
4     estimate disease intensity, investigate the spatial pattern of FW in banana fields and  
5     to measure the association of physical and chemical variables of the soil factors with  
6     FW intensity and spatial pattern. Fields planted with Silk (N = 10), Pome (N = 17) or  
7     Cavendish (N = 3) banana subgroups distributed in six regions in Brazil, totaling 95  
8     ha, were evaluated. In each field, all plants were inspected and the symptomatic ones  
9     were georeferenced. Information about the cultural practices was collected as well as  
10    soil and foliar samples from healthy and diseased plants. Incidence maps were  
11    constructed and quadrat-based and distance-based methods were used to investigate  
12    the spatial pattern of the disease. FW incidence varied from 0.09 to 41.4%. The  
13    incidence of FW was higher in Silk fields (median 14.3%). Aggregation of FW was  
14    detected by all analytical methods in 43% of the fields (1 of Cavendish, 11 of Pome  
15    and 1 of Silk). In the other 17 fields a total of 85 tests were conducted: 62 revealed  
16    aggregation and 23 randomness. Overall, aggregation was detected in 85% of the  
17    tests. Soil density was associated with higher disease intensity. FW was more  
18    aggregated in high-input fields. The incidence of FW in bananas fields in Brazil is  
19    high and affected predominantly by cultivar, soil physical factors, and field  
20    management.

21    **Keywords:** *Fusarium oxysporum* f. sp. *cubense*; Panama disease; disease incidence;  
22    cultural practices; management.

## 23 INTRODUCTION

24 Wilted banana plants, probably by a fungal pathogen, were first observed in  
25 Australia in 1874 (Bancroft 1876). In 1890, the banana wilt was reported in Cuba,  
26 Central America, and was associated to *Fusarium oxysporum* by E. F. Smith (Stover  
27 1962). Currently, Fusarium wilt of banana or Panama disease (FW) is caused by  
28 *Fusarium oxysporum* f. sp. *cubense* (*Foc*) (E. F. Smith) W. C. Snyder and H. N.  
29 Hansen (Snyder and Hansen 1940), a soil-borne pathogen (Stover 1962). The  
30 movement of infected planting material was responsible for the fast spread of the  
31 disease worldwide (Ploetz 2015). This practice is still common among banana  
32 farmers, mainly, but not only in systems of subsistence agriculture (Karangwa et al.  
33 2016). Despite the long history of epidemics damaging banana crops worldwide,  
34 there are important gaps of knowledge about basic epidemiological features of FW.  
35 One such gap is related to the spatial pattern of FW epidemics.

36 Spatial arrangement is an important ecological process associated with plant  
37 disease epidemics (Madden et al. 2007). Spatial pattern is primarily affected by  
38 biological and ecological characteristics of the pathogen and of the disease  
39 (Campbell and Benson 1994). A direct relationship between the initial inoculum and  
40 the spatial pattern can be seen in some cases (Ristaino and Gumpertz 2000). Spatial  
41 pattern analysis can be used to construct a hypothesis about pathogen dispersal or to  
42 suggest mechanisms that have originated the observed pattern (Gigot et al. 2017;  
43 Macedo et al. 2018). Quantitative information on population dynamics of pathogens  
44 (Madden 1989; Macedo et al. 2018), design of experiments in epidemiological  
45 research (Madden and Hughes 1995), sampling programs for disease or pathogen  
46 monitoring (Madden et al. 1996; Liu et al. 2015), assessment of crop losses in  
47 relation to disease intensity (Hughes 1988), and development of management

48 strategies are some of the goals in studies of spatial pattern analysis of plant diseases  
49 (Ristaino and Gumpertz 2000).

50 Studies of the spatial pattern of FW on bananas could help understand the  
51 processes involved in the dispersal of *Foc* and to set mitigation actions in case of  
52 introduction of new variants of the pathogen into an area. To date, only two studies  
53 were conducted to analyze the spatial pattern of FW (Liu et al. 2015; Meldrum et al.  
54 2013). An aggregated pattern of FW was found in six fields (1334 m<sup>2</sup> each)  
55 cultivated with Cavendish banana plants in China (Liu et al. 2015). There was a  
56 direct relationship between aggregation and FW incidence, i.e., the higher the disease  
57 intensity, the higher the aggregation (Liu et al. 2015). FW was also reported to have  
58 an aggregated pattern in banana fields in Australia, but scattered diseased plants  
59 could also be found in some fields (Meldrum et al. 2013). The authors suggested that  
60 weevil borers could have spread FW and contributed to infect plants far from the foci  
61 (Meldrum et al. 2013). Another important biological fact to support for the potential  
62 aerial dispersal of the pathogen was the presence of sporodochia and hyphal growth  
63 in external surface of senescing leaves (Warman and Aitken 2018). If spores could  
64 be dispersed by winds and if inoculation can be successful, diseased plants scattered  
65 in the field may constitute in a reasonable outcome in addition to the random  
66 distribution of inoculum in the soil. Other forms of spore dispersal cannot be ruled  
67 out, such as transport by animals, water, soils, substrates and anthropogenic factors  
68 (Dita et al. 2018). However, cultural practices are effective to spread FW inside and  
69 outside the field. Some practices, such as sharing contaminated planting material and  
70 tools with neighbors or when performing cultural practices in asymptomatic, but  
71 infected plants, are common practices in banana plantations and may have been

72 responsible for the introduction of *Foc* tropical race 4 (TR4) from Southeast Asia to  
73 Africa or Middle East (Ploetz et al. 2015).

74         The lack of essential information about the epidemics of FW in bananas, such  
75 as the incidence and the spatial pattern of the disease in different conditions, was one  
76 of the major constraints to develop more precise management strategies. The  
77 objectives of this study can be summarized by the research questions it attempts to  
78 address: (i) what is the intensity of FW in Brazil? (ii) what is the predominant spatial  
79 pattern of FW epidemics? (iii) which factors are driving the intensity and spatial  
80 pattern of the disease?

## 81 **MATERIAL AND METHODS**

### 82 **Fields**

83         Thirty banana fields with records of naturally occurring epidemics of FW  
84 were evaluated in Brazil from March 2016 to April 2017. The fields were classified  
85 in six groups based on the level of technology adopted and in their geographic  
86 region: The Litoral Sul Paulista (LSP; n = 4 fields), São José do Rio Preto and  
87 Araçatuba (SJA; n = 8), located in São Paulo state; Vale do Paraíba Paulista and  
88 Zona da Mata (VPM; n = 6), located in São Paulo and Minas Gerais states,  
89 respectively; Norte de Minas and Vale do São Francisco da Bahia (NMB; n = 5),  
90 located in Minas Gerais and Bahia states, respectively; Norte Catarinense (NCA; n =  
91 5), located in Santa Catarina state; and Norte Pioneiro Paranaense (NPP; n = 2),  
92 located in Paraná state (Fig 1a). The fields were distributed from latitude 13°14'S to  
93 26°28'S, from longitude 43°21'W to 50°50'W and from altitude 45 to 1150 masl.  
94 These states account for 43% of the planted area and 53% of the Brazilian banana  
95 production in 2017 (IBGE, 2018). Field size varied from 0.85 to 6.67 ha and were

96 planted with Silk (10 fields; total of 34.7 ha), Pome (17 fields; 51.4 ha) or Cavendish  
97 (3 fields; 8.5 ha) banana subgroups.

## 98 **Assessments**

99 In each field, all banana plants were visually assessed for external symptoms.  
100 When external symptoms were observed, such as wilt and yellowing of older leaves,  
101 collapse of leaves at the base of petiole, fallen and dried leaves around the  
102 pseudostem, wrinkling and distortion of leaf blades or splitting at the base of  
103 pseudostem in a plant of the mat, a small cut was made in the pseudostem to observe  
104 internal symptoms. Banana plants affected by FW present yellow, reddish brown or  
105 black discolorations in vascular tissues. If external and internal symptoms were  
106 present in at least one plant of the mat, the whole mat was considered diseased and  
107 was georeferenced using a handheld GPS device (GPSMAP® 64, Garmin).  
108 Fragments (5 cm of length x 5 cm of width) of pseudostems taken from 5 to 10  
109 symptomatic plants from each field were collected to isolate the pathogen and to  
110 confirm the presence of *Foc* by morphological (Leslie and Summerell 2008) and  
111 molecular methods (Heck et al. *in development*).

112 Two data sets were constructed with the geographic coordinate data: one  
113 containing the polygon and the other containing information about diseased plants of  
114 each field. These data sets were converted to a text file and imported into R, version  
115 3.5.1 (R Core Team 2018). For each field, the two data sets were used for spatial  
116 analyses.

117 Information about cultural practices performed by the farmer, such as  
118 cultivar, planting density (spacing), age, chemical and organic products used, soil  
119 preparation, and the action performed when a diseased plant showing FW symptoms

120 was identified were acquired for the 30 fields. Data of annual mean temperature and  
121 precipitation for each field were obtained from the closest climate station and  
122 provided by Instituto Nacional de Meteorologia (INMET) of Ministério da  
123 Agricultura, Pecuária e Abastecimento (MAPA).

124 In 21 of the 30 fields subsamples of soil ( $n = 10$ ) were collected at 0.5 m of  
125 symptomatic and asymptomatic banana plants. Approximately 0.2 Kg of soil was  
126 taken at 20 cm-deep. The subsamples were pooled to compose one sample per field  
127 and analyzed for chemical properties (Raij et al. 2001). Organic matter (OM), pH in  
128  $\text{CaCl}_2$ , phosphorous (P), calcium (Ca), magnesium (Mg), potassium (K), base  
129 saturation (V%), copper (Cu), iron (Fe), zinc (Zn), and boron (B) were analyzed.

130 Sand, silt, clay, bulk density, and porosity were the physical variables  
131 analyzed (Camargo et al. 2009). Eight samples, 4 from symptomatic and 4 from  
132 asymptomatic, per field, in 15 fields were analyzed. In the same 15 fields, the  
133 nutritional status of the plants was analyzed collecting two composite samples per  
134 field. A sample was made of 10 subsamples of banana leaves. A subsample was a  
135 fragment of 10 x 10 cm from the central portion of the leaf blade. The concentration  
136 of macro (N, P, K, Ca and Mg) and micronutrients (B, Cu, Fe, Mn and Zn) was  
137 determined (Bataglia et al. 1983).

### 138 **Disease intensity**

139 The number of diseased plants ( $y_i$ ) in each field was recorded and the  
140 incidence ( $\bar{y}$ ) calculated as  $\bar{y} = y_i / n_i$ , where  $n$  is the estimated number of plants in the  
141  $i^{\text{th}}$  field. The total number of plants in each field ( $n$ ) was estimated using the area of  
142 the polygon and plant spacing (plant distance within and between rows).

### 143 **Spatial analysis**

144 Two types of spatial analyses were conducted: a quadrat-based and a  
145 distance-based. The polygons and diseased plants data sets were used to produce  
146 maps with the spatial distribution of diseased plants.

#### 147 *Quadrat-based*

148 The diseased plant data set was used for quadrat-based analyses, the maps  
149 were *quadratized* using the QUADRATCOUNT function of the SPATSTAT  
150 package (Baddeley and Turner 2005). The exact number of plants in each quadrat  
151 could not be computed because in most fields the rows were not regularly spaced or  
152 straight, but it was assumed that the maximum number of plants inside each quadrat  
153 was 4 in 2 x 2 to 36 in 6 x 6 quadrat-sizes. The area (m<sup>2</sup>) of the sampling units varied  
154 among fields because different spacing between plants were observed, but the  
155 relation between the distance within and between rows was the same. The number of  
156 diseased plants in each quadrat was determined and used to perform the spatial  
157 analysis.

158 *Spatial hierarchy.* Initially, four hierarchical levels, 2 x 2 (lowest), 3 x 3, 4 x  
159 4 and 6 x 6 (highest) estimated plants per quadrat were used to characterize the  
160 sampling units. The probability that an element is diseased or contains at least one  
161 diseased individual was denominated as  $p_{low}$  and  $p_{high}$ , respectively (Madden et al.,  
162 2007). The subscript ‘low’ refers to within-sampling-unit and ‘high’ the sampling  
163 unit scale. The relationship between  $p_{low}$  and  $p_{high}$  was described as:  $p_{high} = 1 - (1 -$   
164  $p_{low})^v$  (Hughes and Gottwald, 1999). The equation can be rewritten as the  
165 complementary log-log transformation (CLL) where  $v$  is a parameter that can be  
166 estimated by the data and is also interpreted as an effective sample size (Madden and

167 Hughes, 1999; Madden et al., 2007). Values of  $v$  less than the number of individuals  
168 at the lower hierarchical level per sampling unit (highest level), characterize  $\beta$ -  
169 binomial curves that fall below the binomial curve and suggest aggregation within-  
170 sampling-unit. The spatial hierarchy analysis was performed using SPATIAL\_HIER  
171 from EPIPHY package.

172 *Dispersion index.* The index of dispersion for binomial data,  $D$ , was  
173 calculated for each field as the ratio of the observed and the estimated variances  
174 (Madden and Hughes, 1995).  $D < 1$  indicates underdispersed data (regular pattern);  
175  $D = 1$  indicates a random pattern and  $D > 1$  indicates overdispersed data (aggregated  
176 pattern). To test the null hypothesis for dispersion index ( $D = 1$ ) a  $\chi^2$  test was  
177 performed. The analysis was conducted using the AGG\_INDEX function from the  
178 EPIPHY package (Gigot 2018).

179 *Distributions.* The binomial and  $\beta$ -binomial distributions were fitted to the  
180 disease incidence data for each individual field evaluated using the 3 x 3 quadrat-  
181 size. The binomial model suggest a random pattern for binary data, such as incidence  
182 data. On the other hand, the  $\beta$ -binomial distribution is suitable for overdispersion of  
183 these data type. The  $\beta$ -binomial and binomial parameters were estimated for all fields  
184 studied by maximum likelihood (Sparks et al. 2008). The  $\chi^2$  goodness-of-fit test for  
185 both distributions and a log-likelihood ratio test (LRS) were used to determine  
186 whether the  $\beta$ -binomial better fits the observed frequency than the binomial  
187 distribution. This analysis was performed using the FIT\_TWO\_DISTR function from  
188 the EPIPHY package.

189 *Spatial Analysis by Distance IndicEs (SADIE).* This method uses the location  
190 of the sampling units (i.e. quadrats) and the number of diseased individuals (i.e. mat)  
191 inside the unit to analyze the spatial arrangement of the diseased individuals by the

192 distance to regularity ( $D_r$ ). The  $I_a$  statistic given by *SADIE* is an overall index of  
193 aggregation obtained by the ratio between the distance moved to achieve a regular  
194 pattern for the observed data and a theoretical mean to regularity based on random  
195 permutations of the individuals among the sampling units (Perry et al. 1999). *SADIE*  
196 was performed using an intermediate quadrat-size (3 x 3). The index developed by Li  
197 et al. (2012) was computed by the *SADIE* function from EPIPHY package.

### 198 *Distance-based*

199 *Point process.* The distance-based statistic (Madden, Hughes and Bosch,  
200 2007) was used to complement the quadrat-based methods. In this analysis patterns  
201 of points were described based on intervals in space among events. The observed  
202 distribution,  $T$  (coordinates x and y of diseased plants), was compared with a predict  
203 distribution (expected) of  $T$  function assuming CSR by Kolmogorov-Smirnov test  
204 (Baddeley and Turner 2005). The goodness-of-fit of the point process model was  
205 performed using a CDF.TEST function from SPATSTAT package.

### 206 *Concordance analysis*

207 Concordance analysis was conducted to check for the agreement of the results  
208 from the different methods used to study the spatial pattern of FW. The results of the  
209 statistical methods were transformed to a categorical data (aggregated or random)  
210 and tested by Cohen's kappa for paired agreement among the methods, and the Fleiss  
211 's kappa for an overall agreement for all methods used. The analysis was performed  
212 using the KAPPA2 and KAPPAM.FLEISS functions from the IRR package for R  
213 (Gamer et al. 2012).

214 *Binary power law*

215           The binary power law was used to evaluate the relationship between the  
216 observed variance and the corresponding variance on the assumption of a binomial  
217 distribution of FW incidence. The classic equation for binary form of Taylor's power  
218 law,  $\log_{10}(s^2_y) = \log_{10}(A) + b \log_{10}(s^2_{\text{bin}})$ , where  $s^2_y$  is the observed variance and  $s^2_{\text{bin}}$  the  
219 corresponding variance under binomial distribution,  $A$  and  $b$  are the linear regression  
220 parameters to be estimated. The analysis was performed using an intermediate  
221 quadrat-size (3 x 3). A t-test was performed to test the null hypothesis for a binomial  
222 distribution:  $A = b = 1$ .

223           Categorical values referred to different factors, such as cultivars (Cavendish,  
224 Pome or Silk), management levels (high, moderate or low) based on cultural  
225 practices (herbicide, insecticide, fungicide or lime applications, soil analysis, organic  
226 and chemical amendment, defoliation, irrigation and type of seedlings); density of  
227 plants (high or low, with < 10 or > 10 m<sup>2</sup> per plant, respectively), planting age (< 5 or  
228 > 5 years old), and annual mean temperature (low or high temperature, with < 22 or  
229 > 22 °C, respectively) were included in each data set and the parameter estimates of  
230 the models were compared by t-test against the null hypothesis and between them.

### 231 **Factors driving disease intensity and spatial pattern**

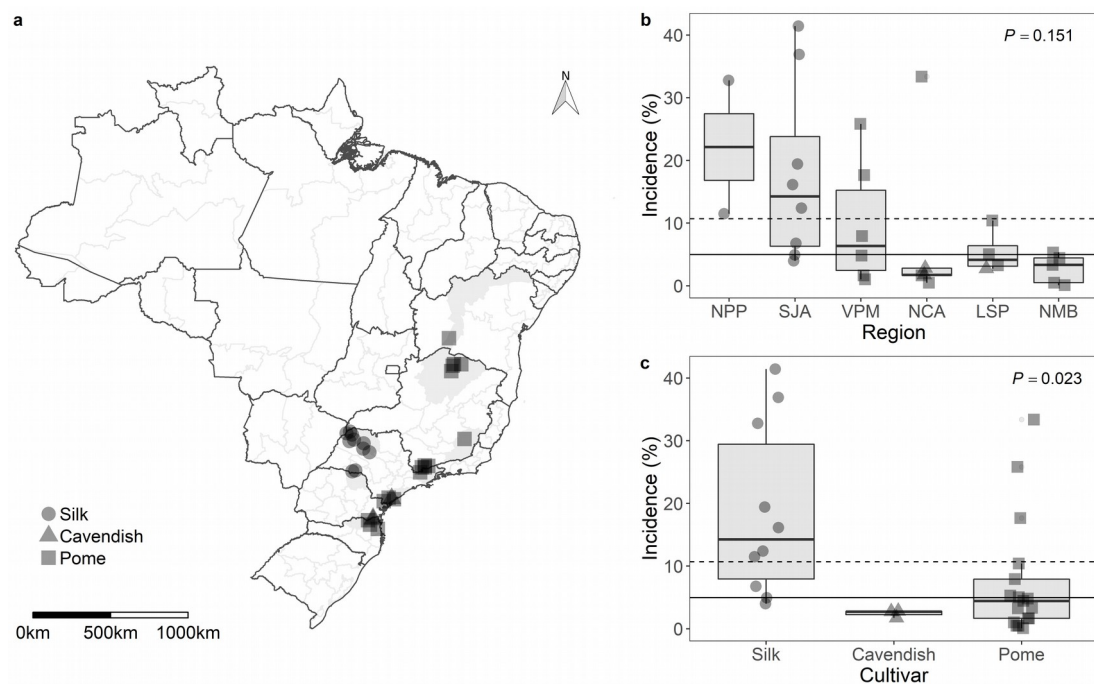
232           To understand the main factors related with disease intensity, the annual  
233 average temperature, precipitation, soil chemical and physical properties, the macro  
234 and micronutrients in leaves, frequency of herbicide, insecticide or fungicide  
235 applications were used in a principal component analysis (PCA) using the  
236 FACTOMINER package version 1.41 (Husson et al. 2018). To assess the influence

237 of management practices in the spatial pattern and intensity of FW, a multiple  
238 correspondence analysis (MCA) was performed using the MCA function of package  
239 FACTOMINER.

## 240 RESULTS

### 241 Disease intensity

242 Fusarium wilt incidence ranged from 0.1 to 41.4% across the fields with  
243 mean and median values of 10.7% and 5%, respectively (Fig 1b, Table 1). The  
244 incidence did not differ ( $P = 0.151$ ) among the regions. Nevertheless, the highest  
245 values were observed in fields located in NPP with median incidence of 22.1%,  
246 followed by SJA with a median of 14.3%. In other regions the median incidence  
247 values were less than 7.9% (Fig 1b).



248 Fig 1. Location of 30 fields in five states of Brazil (a). Mesoregions were shaded by  
249 gray and exact location of fields were identified by geometrical shapes that  
250 correspond to banana cultivars. Close fields got superimposed and shapes are darker.

251 Boxplots for incidence of Fusarium wilt on banana fields in different regions from  
 252 Brazil (b) and for different cultivars (c). The overall mean and median values are  
 253 represented by dashed and solid lines, respectively.

254 Table 1. Median value (Med.) for incidence ( $\bar{y}$ ) of Fusarium wilt of bananas and  
 255 proportions of fields classified as aggregated pattern (Agg.) by the aggregation index  
 256 ( $D$ ),  $\beta$ -binomial parameter ( $\theta$ ), log-likelihood ratio statistic (LRS), index of  
 257 aggregation of the Spatial Analysis by Distance IndicEs (*SADIE*) procedure ( $I_a$ ) and  
 258 distance-based point process (K-S statistic) relative to different regions <sup>a</sup>.

Region <sup>b</sup>	$\bar{y}$		$D^c$		$\theta^c$		LRS <sup>c</sup>		$I_a^c$		K-S statistic <sup>d</sup>	
	Med. <sup>ns</sup>	Med. <sup>ns</sup>	Agg.	Med. <sup>ns</sup>	Agg.	Agg.	Med. <sup>ns</sup>	Agg.	Med.	Agg.		
LSP	4.1	2.0	4/4	0.149	4/4	4/4	1.75	4/4	0.212 ab	4/4		
NCA	1.8	1.5	5/5	0.076	5/5	5/5	2.15	4/5	0.126 b	2/5		
NMB	3.3	1.5	4/5	0.121	4/5	4/5	1.52	4/5	0.189 ab	4/5		
NPP	22.1	3.1	2/2	0.357	2/2	2/2	2.22	1/2	0.212 ab	2/2		
SJA	14.3	2.2	8/8	0.209	6/8	8/8	1.30	3/8	0.104 b	4/8		
VPM	6.4	3.5	6/6	0.455	6/6	6/6	1.83	4/6	0.337 a	6/6		
Overall	5.0	2.3	29/30	0.199	27/30	29/30	1.73	20/30	0.187	22/30		

259 <sup>a</sup> Spatial statistics were analyzed in 30 fields evaluated in different regions in Brazil. Aggregated pattern was  
 260 inferred when the null hypothesis of randomness was rejected ( $P < 0.05$ ). To infer about the  $\beta$ -binomial parameter  
 261 ( $\theta$ ), the null hypothesis is aggregation ( $P > 0.05$ ).

262 <sup>b</sup> Litoral Sul Paulista (LSP); Norte Catarinense (NCA); Norte de Minas and Vale do São Francisco da Bahia  
 263 (NMB); Norte Pioneiro Paranaense (NPP); São José do Rio Preto and Araçatuba (SJA); Vale do Paraíba Paulista  
 264 and Zona da Mata (VPM).

265 <sup>c</sup> Quadrat-based statistics with quadrat-size of 3 x 3 plants.

266 <sup>d</sup> Distance-based statistic.

267 Differences were observed for incidence among cultivars ( $P = 0.023$ ). The  
 268 highest values of median incidence were observed for fields planted with Silk (N =  
 269 10), 14.3%, a minimum of 4% and maximum of 41.4%. Pome (N = 17) had  
 270 intermediate median values, 4.4%, and varied from 0.1% to 33.4%. Fields planted

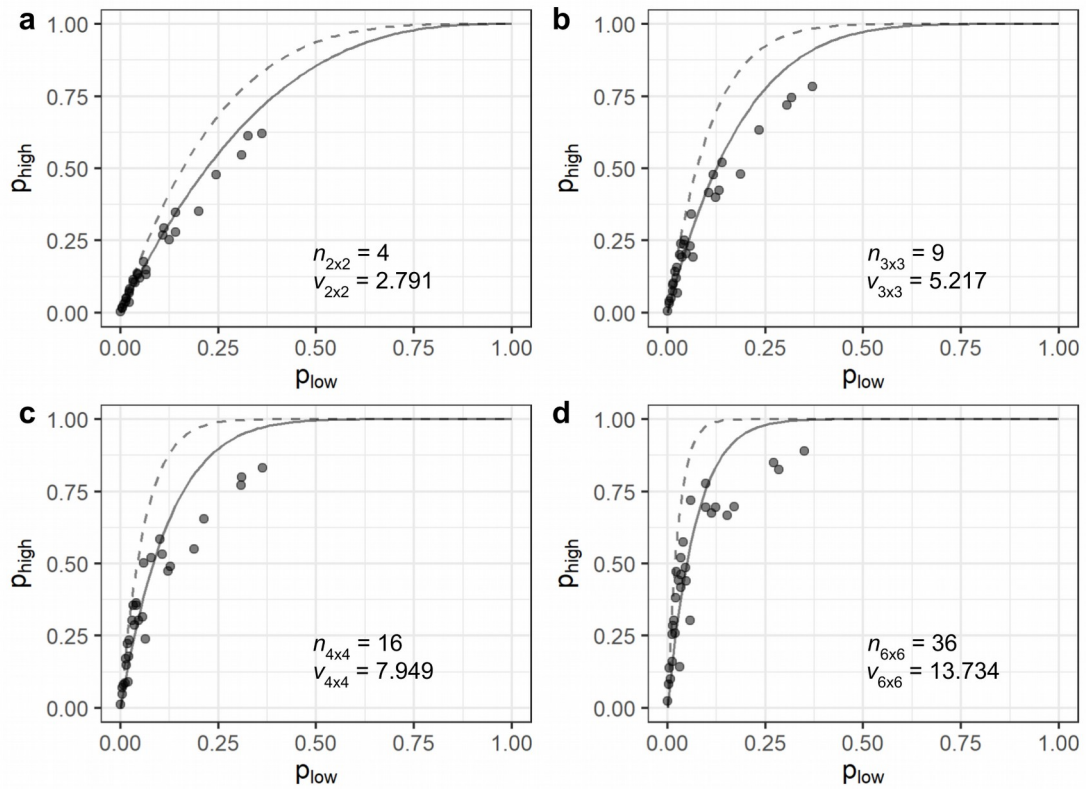
271 with Cavendish ( $N = 3$ ) resulted in lowest disease intensity with median of 2.7% and  
272 varied from 1.8% to 2.8% (Fig 1c). Incidence on Silk was greater than in Pome ( $P =$   
273 0.039) and in Cavendish ( $P = 0.005$ ). Pome also differed from Cavendish ( $P =$   
274 0.046).

## 275 **Spatial analysis**

### 276 *Quadrat-based*

277 Analyses at the four hierarchical levels resulted in  $\beta$ -binomial curves that fall  
278 under the binomial curves (Fig 2). Values of  $v$ , interpreted as effective sample size,  
279 were lower than the real number of individuals ( $n$ ) for all hierarchical levels ( $P <$   
280 0.001). Effective sample sizes were estimated at  $v_{2 \times 2} = 2.79 (\pm 0.12)$  for the  $2 \times 2$   
281 quadrat-size containing 4 individuals,  $v_{3 \times 3} = 5.22 (\pm 0.32)$  for the quadrat containing  
282 9 individuals,  $v_{4 \times 4} = 7.95 (\pm 0.67)$  for the quadrat with 16 individuals, and  $v_{6 \times 6} = 13.73$   
283 ( $\pm 1.48$ ) for the  $6 \times 6$  quadrat-size containing 36 individuals at the highest level (Fig  
284 2). These values of  $v$  correspond to 69.8, 57.9, 49.7 and 38.2% of the  $n$  in the four  
285 hierarchical levels, respectively. Despite that, only an intermediate quadrat-size ( $3 \times$   
286 3) was used in further quadrat-based analyses.

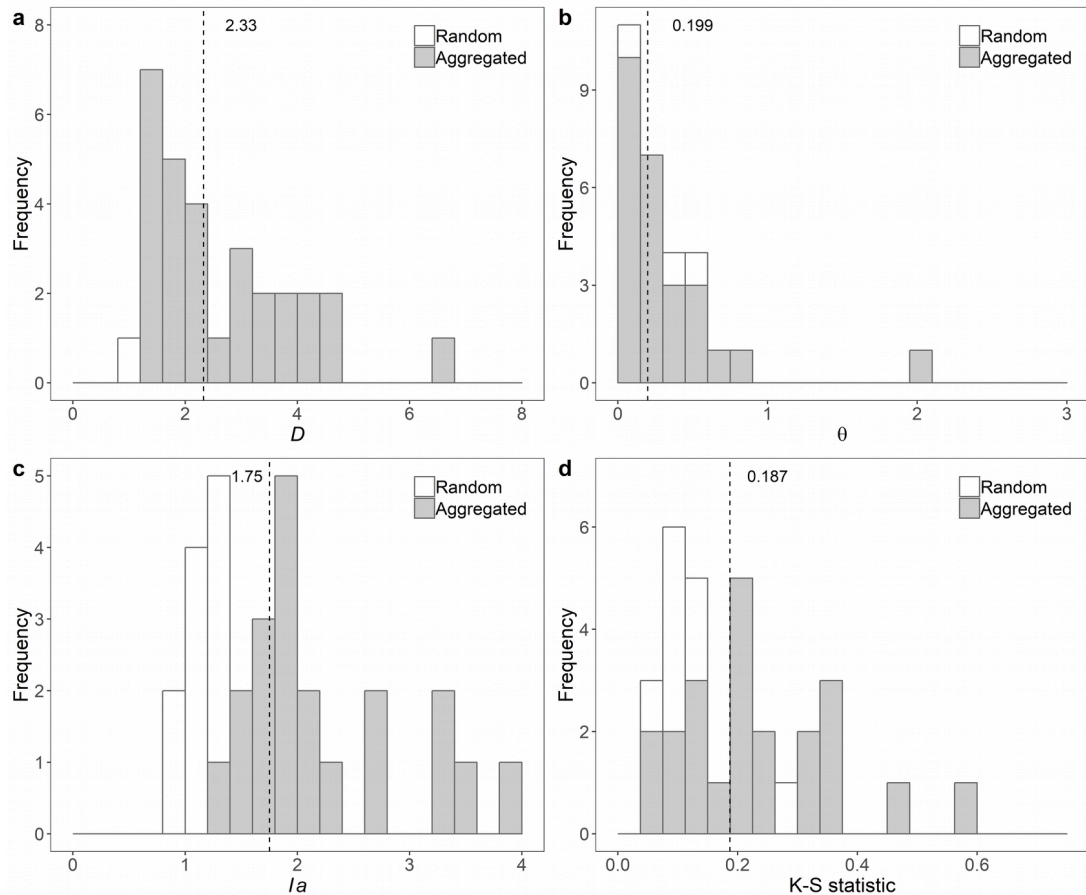
287 Dispersion index was successfully calculated for the 30 fields using the  $3 \times 3$   
288 quadrat-size. Values of  $D$  ranged from 1 to 6.5 with median of 2.3 (Fig 3a). Only one  
289 out of 30 fields had a random pattern (Table 1). There were no differences among  
290 regions regarding the values of  $D$  ( $P = 0.119$ ) (Table 1).



291 Fig 2. Relationships between the incidences of Fusarium wilt at the 2 x 2 (a); 3 x 3  
 292 (b); 4 x 4 (c); and 6 x 6 (d) quadrat dimensions collected in 30 banana fields. The  
 293 sampling unit was the highest and the number of individuals per quadrat at the lowest  
 294 hierarchical level. Binomial (dashed-lines) and  $\beta$ -binomial (solid-lines) distributions  
 295 were fit to the data. The number of individuals ( $n$ ) and effective sample size ( $v$ )  
 296 estimated in each level are presented in the graphs.

297 The frequency of diseased plants in quadrats was well described for 90% of  
 298 the fields by the  $\beta$ -binomial distribution ( $P > 0.05$ ) (Table 1). For one field (3.3%)  
 299 the frequency was better described by the binomial distribution (data not shown).  
 300 The  $\theta$  parameter for the  $\beta$ -binomial distribution ranged from 0.02 to 2.01 (median =  
 301 0.20) (Fig 3b). There were no differences among regions for the  $\theta$  parameter ( $P =$   
 302 0.26; Table 1). The  $\beta$ -binomial better described the distribution of diseased plants in

303 the data sets than binomial in 96.7% of the cases ( $P < 0.05$ ) (Table 1). The only case  
 304 where the LRS was not significant, i.e. the binomial and  $\beta$ -binomial models could  
 305 both describe the distribution of diseased plants, was in a field where the FW  
 306 incidence was very low (0.5%).



307 Fig 3. Histograms of the index of dispersion ( $D$ ; a),  $\beta$ -binomial parameter ( $\theta$ ) from  
 308 distribution fitting (b), aggregation index ( $I_a$ ) from Spatial Analysis by Distance  
 309 IndicEs (SADIE; c) and the Kolmogorov-Smirnov test (K-S statistic) of a point  
 310 process (d). The frequencies were based on 30 fields assessed for incidence of  
 311 Fusarium wilt of bananas in different regions. Dashed lines and values represent the  
 312 median of the statistics. On the spatial statistics graphs the final classification of  
 313 fields were presented in different colors as random (white) or aggregated (gray).

314 The distance to regularity ( $D_r$ ) computed by SADIE was calculated for all  
315 studied fields. The median of the aggregation index ( $I_a$ ) was 1.75 for all fields, but  
316 ranged from 0.93 to 3.86 (Fig 3c). Differences among regions were not observed for  
317  $I_a$  ( $P = 0.114$ ; Table 1). Considering the 30 fields in six regions, the random pattern  
318 of FW was inferred for 10 (33.3%) fields (Table 1). Five of them were located at  
319 SJA, all planted with Silk.

### 320 *Distance-based*

321 The maximum difference ( $D_{K-S}$ ) between the observed and expected  
322 distributions ranged from 0.064 to 0.566 (median = 0.187) (Fig 3d). The hypothesis  
323 of randomness for K-S statistic was rejected for 73.3% of the fields assessed (Table  
324 1). Differences among the regions were observed for  $D_{K-S}$  ( $P = 0.018$ ). The smallest  
325 values of  $D_{K-S}$  were observed in SJA and NCA (mean of 0.130) regions where almost  
326 all fields inferred as having a random pattern were located. In these regions, there  
327 was no evidence to reject the null hypothesis in 50% and 60% of the fields,  
328 respectively. Only one field inferred as having a random pattern was located in  
329 another region, in NMB. This NMB field had an intermediate value for  $D_{K-S}$  (0.214)  
330 and the lowest FW incidence (0.09%).

### 331 *Concordance analysis*

332 The FW epidemics were inferred to present random or aggregated patterns.  
333 Cohen's Kappa paired agreement was weak or null for most of the spatial statistics  
334 used (Table 2). There was weak agreement between the aggregation index and  $\beta$ -  
335 binomial distribution, despite 90% (26/30) of the fields being classified in the same

336 category (aggregated). The  $D$  index and LRS agreed ( $P < 0.001$ ) with the highest  
 337 proportion of fields classified as the same pattern (100%). The  $SADIE$  index ( $I_a$ ) also  
 338 shows a weak agreement with K-S statistic ( $P = 0.04$ ), despite 22 of 30 fields  
 339 presented the same classification, 17 fields as aggregated and 5 as random. For the  
 340 Fleiss's Kappa overall agreement among the classification of the spatial analyses the  
 341 null hypothesis for a random classification was rejected ( $P = 0.001$ ). Agreement  
 342 could be detected by the test, on which 43.3% (13/30) of the fields presented the  
 343 aggregated pattern for all spatial statistics (Table 2).

344 Table 2. Cohen's and Fleiss's Kappa agreement and proportions of fields with the  
 345 same classification for index of aggregation ( $D$ ),  $\beta$ -binomial distribution, log-  
 346 likelihood ratio statistic for distributions (LRS), Spatial Analysis by Distance IndicEs  
 347 ( $I_a$ ) and Kolmogorov-Smirnov (K-S) statistic for 30 fields assessed to Fusarium wilt  
 348 incidence in Brazil <sup>a</sup>.

Spatial statistic <sup>b</sup>	$\theta$	LRS	$I_a$	K-S statistic
$D$	-0.01 (26/30)	<b>0.03</b> (30/30)	-0.06 (19/30)	-0.06 (21/30)
$\theta$		<b>-0.05</b> (26/30)	-0.03 (17/30)	-0.03 (19/30)
LRS			-0.01 (19/30)	-0.01 (21/30)
$I_a$				<b>0.37</b> (22/30)
Overall <sup>c</sup>		-0.147 ( $P = 0.001$ ) (13/30)		

349 <sup>a</sup> The fields were classified as aggregated or random pattern according the  $P$ -values ( $P < 0.05$ ; or  $P >$   
 350  $0.05$  for  $\beta$ -binomial distribution) of the spatial statistic computed. Kappa values in bold differed  
 351 significantly from 0 (random classification) by  $z$  statistic ( $P < 0.05$ ). The proportion of fields  
 352 classified as the same pattern were in parentheses.

353 <sup>b</sup> Cohen's Kappa paired agreement between tests.

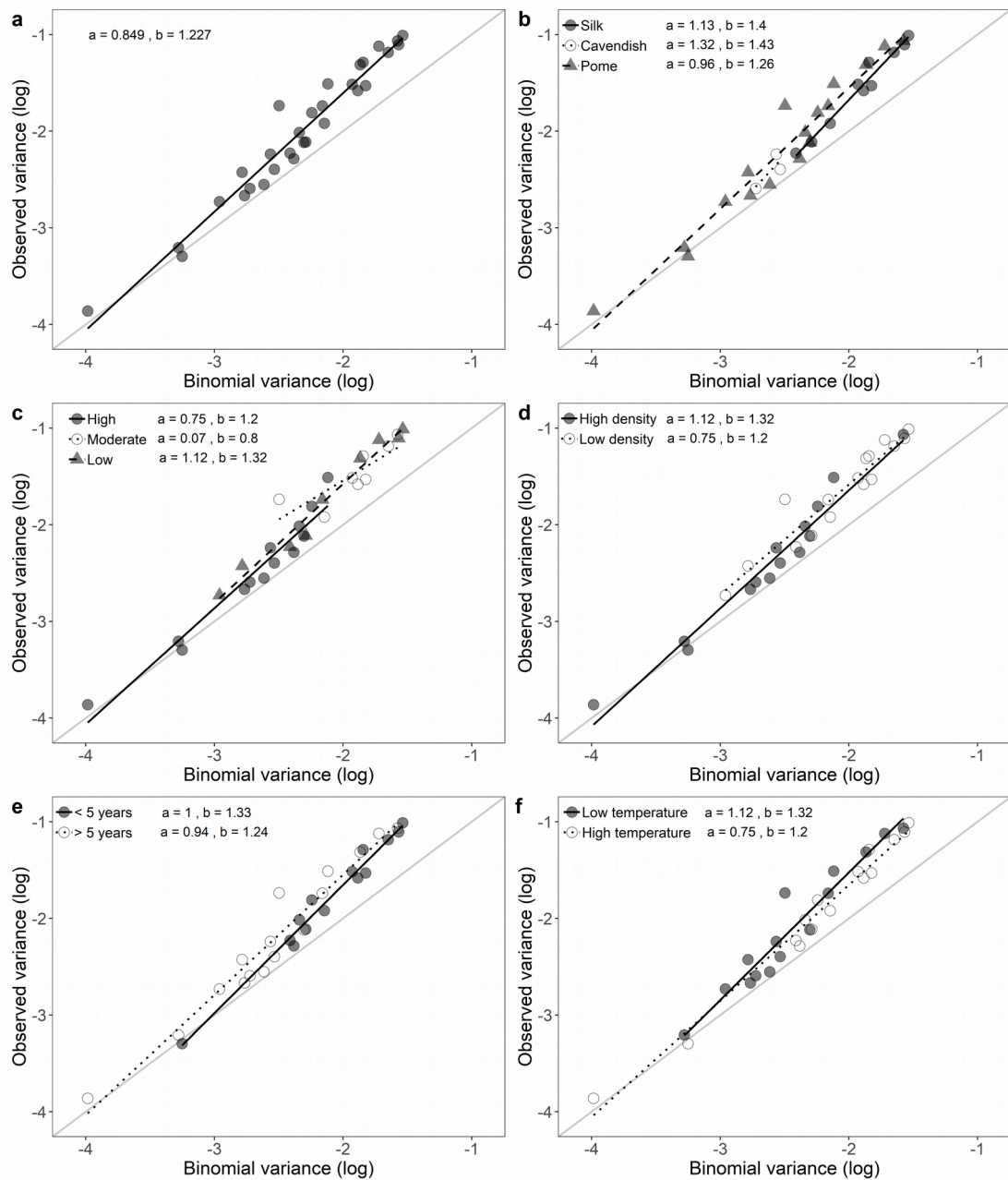
354 <sup>c</sup> Fleiss's Kappa overall agreement among the tests.

355 *Binary power law*

356           The relationship between the logarithm of the observed and theoretical  
357 variances for binomial data from 30 fields in Brazil was well described by the binary  
358 power law ( $R^2 = 0.955$ ) (Fig 4a). Estimates of both parameters of the binary power  
359 law,  $\log_{10}(A)$  ( $0.849 \pm 0.031$ ) and  $b$  ( $1.227 \pm 0.013$ ), were significantly ( $P < 0.001$ )  
360 different from 0 and 1, respectively. As  $\log_{10}(A)$  was higher than 0 and  $b$  higher than  
361 1, in general the disease has an aggregated pattern. Aggregation was directly  
362 associated with incidence.

363           The spatial pattern of FW varied according to the cultivar. FW had an  
364 aggregated pattern in Silk and Pome fields ( $P < 0.001$ ) (Fig 4b). The estimated  
365 parameters from the binary power law differed for Silk and Pome ( $P < 0.05$ ). In  
366 general, the level of aggregation was higher and more influenced by incidence in Silk  
367 ( $\log_{10}(A) = 1.13 \pm 0.17$ ) than in Pome fields ( $\log_{10}(A) = 0.96 \pm 0.19$ ;  $b = 1.25 \pm 0.07$ ).  
368 Cavendish did not differ from Silk and Pome for both parameters ( $A$  and  $b$ ).

369           The null hypothesis of random pattern was rejected in fields that used high or  
370 low levels of management practices ( $P < 0.001$ ) (Fig 4c). In addition, there were no  
371 clear differences among management levels regarding the spatial pattern in fields  
372 (Fig 4c). High ( $\log_{10}(A) = 0.74 \pm 0.23$ ;  $b = 1.20 \pm 0.08$ ) and low ( $\log_{10}(A) = 0.89 \pm$   
373  $0.18$ ;  $b = 1.23 \pm 0.08$ ) levels did not differ ( $P > 0.05$ ) between each other for both  
374 parameters ( $A$  and  $b$ ). However, parameters estimates for the high and low levels of  
375 management, both differed for fields classified as of moderate level ( $P < 0.003$ ).  
376 There was higher aggregation and lower influence of mean in fields with moderate  
377 ( $\log_{10}(A) = 0.07 \pm 0.44$ ;  $b = 0.80 \pm 0.23$ ) than in the high or low levels of  
378 management.



379 Fig 4. Relationship between the logarithm of the observed variance ( $\log_{10}(s^2)$ ) and the  
 380 logarithm of theoretical variance ( $\log_{10}(s^2_{bin})$ ) for incidence data of Fusarium wilt of  
 381 bananas on 30 fields in Brazil. Linear regression for all of the 30 fields assessed for  
 382 disease incidence (solid dark line) (a); for Silk ( $n = 10$  fields), Cavendish ( $n = 3$ ) or  
 383 Prata ( $n = 17$ ) cultivars (b); for high ( $n = 13$ ), intermediate ( $n = 8$ ) or low ( $n = 9$ )  
 384 levels of management (c); for fields with high density of plants ( $< 10 \text{ m}^2$  plant;  $n =$

385 14) or low density ( $> 10 \text{ m}^2$  per plant;  $n = 16$ ) (d); for new plantings ( $< 5$  years old;  $n$   
386  $= 14$ ) or old plantings ( $> 5$  years old;  $n = 16$ ) (e); and fields with low temperature  
387 (annual average  $< 22 \text{ }^\circ\text{C}$ ) or high temperature (annual average  $> 22 \text{ }^\circ\text{C}$ ) (f). Binary  
388 power law parameters ( $A$  and  $b$ ) were presented in figure.

389 Fields with low or high densities of plants differed ( $P < 0.001$ ) from random  
390 pattern for both parameters and were considered as aggregated by binary power law.  
391 The two plant density classes differed from each other for the  $b$  parameter ( $P = 0.01$ ).  
392 Fields with high density of plants ( $b = 1.22 \pm 0.06$ ) were more affected by incidence  
393 than fields with low plant density ( $b = 1.14 \pm 0.09$ ) (Fig 4d).

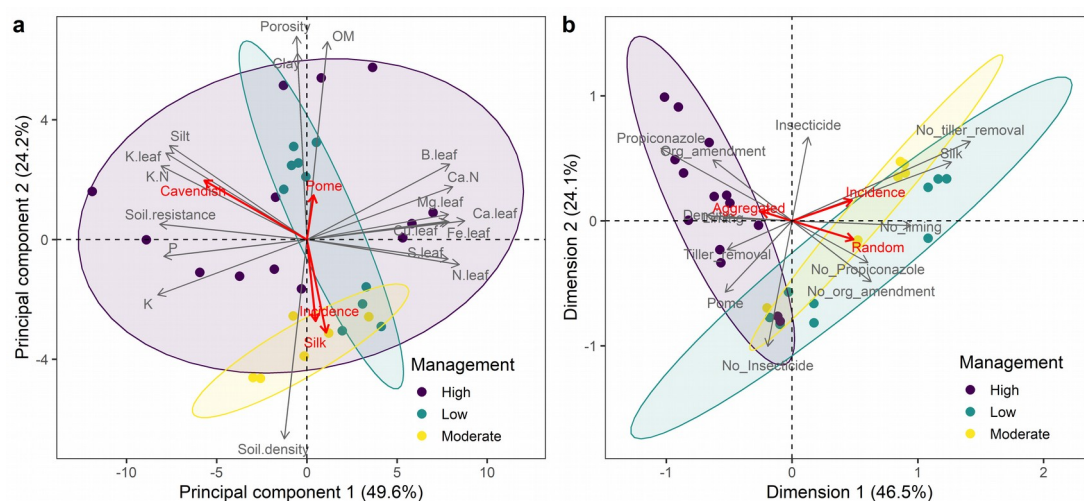
394 When fields were stratified according to age, both, new ( $< 5$  years) and old ( $>$   
395  $5$  years) plantings, differed from the random pattern for  $A$  and  $b$  parameters ( $P <$   
396  $0.001$ ). Older plantations ( $b = 1.24 \pm 0.08$ ) were less ( $P = 0.002$ ) affected by the  
397 incidence than new ones ( $b = 1.32 \pm 0.06$ ) (Fig 4e).

398 Aggregation of FW was also detected in fields located in regions with either  
399 high or low temperatures ( $P < 0.001$ ) by binary power law (Fig 4f). Parameters  
400 estimates also differed for fields classified between the two classes of temperature ( $P$   
401  $< 0.001$ ). Fields located in regions with low temperature ( $\log_{10}(A) = 1.12 \pm 0.27$ ;  $b =$   
402  $1.32 \pm 0.10$ ) had higher degree of aggregation and were more influenced by  
403 incidence than plantations in higher temperature regions ( $\log_{10}(A) = 0.74 \pm 0.11$ ;  $b =$   
404  $1.20 \pm 0.05$ ).

#### 405 **Factors driving disease intensity and spatial pattern**

406 The PCA for edaphic variables, management levels and intensity of FW in  
407 banana fields explained 73.8% of the total variance (Fig 5a). The first component

408 explained 49.6% of the total variance, the significant factors with higher contribution  
 409 were macro (N, K, Ca, Mg, S, K:N and Ca:N) and micronutrients in leaves (B, Cu  
 410 and Fe), and the soil chemical (P and K) and physical (silt and soil resistance)  
 411 properties. The second component explained 24.2% of the variability and was related  
 412 to factors with higher correlation with FW incidence. Organic matter (OM), total  
 413 porosity and clay content were negatively correlated with incidence, while soil  
 414 density had the highest positive correlation coefficient. When cultivars were  
 415 investigated, FW incidence was correlated with plantations of Silk only. There was  
 416 no clear relationship between levels of management and the soil or leaves variables  
 417 significantly related with principal components 1 and 2 (Fig 5a).



418 Fig 5. Principal Component Analysis (a) and Multiple Correspondence Analysis (b)  
 419 from quantitative and qualitative data, respectively, from 30 fields assessed for  
 420 incidence of Fusarium wilt of banana in Brazil. The coordinates of field datasets  
 421 were identified by individual points and grouped according to management levels.  
 422 Only significant factors ( $P < 0.001$ ) were presented by arrows (gray). Cultivars and  
 423 incidence (a); and pattern obtained by Spatial Analysis by Distances IndicEs  
 424 (*SADIE*) and incidence were presented as supplementary information (red arrows).  
 425 Ellipses represent the multivariate t-distribution with confidence interval of 90% for

426 each management level. The corresponding variance in each direction were presented  
427 in x and y axis.

428 Multiple correspondence analysis for categorical data of cultural practices  
429 used by farmers explained 70.6% of the total variability which was represented by  
430 eight out of 44 factors studied. The clusters formed by levels of management were  
431 well defined. In one region of the dimension 1, that explained 46.5% of the  
432 variability, fields with high levels of management were grouped together (circles)  
433 (Fig 5b). Fields with high levels of management were negatively correlated with no  
434 sucker removal, no liming, no propiconazole applications and no organic  
435 amendment, Silk cultivar and with higher FW incidences. Fields with high  
436 management levels were positively correlated with the classification of aggregation  
437 from *SADIE* while fields with moderate (squares) or low (triangles) management  
438 levels were more likely to present a random pattern of FW (Fig 5b).

## 439 **DISCUSSION**

440 The gap of knowledge related to the spatial pattern of FW of banana has been  
441 recently raised in a review of the epidemiology of the disease (Dita et al. 2018). The  
442 present study is the most comprehensive conducted so far to estimate the intensity of  
443 the disease and its spatial pattern. In total, 95 ha, 109,280 plants were visually  
444 assessed and 7,941 diseased plants with symptoms of FW were georeferenced.  
445 Cultivar, cultural practices, density of plants, age and climate data were also  
446 collected to understand the disease intensity and spatial pattern. Additionally, soil  
447 physical and chemical properties, and foliar analysis were assessed to study the  
448 factors driving the intensity of FW. The goals of most spatial analyses are to detect  
449 spatial patterns that cannot be clearly perceived by visual inspection (Szmyt 2014). It

450 is also of interest to study the factors that affect the spatial arrangement of diseased  
451 plants (Turechek and McRoberts 2013; Horne and Schneider 1995). Our study  
452 employed two approaches, a spatial analysis at different scales and an investigation  
453 of the processes that can affect FW epidemics.

454         The incidence of FW in Brazil was moderate (mean = 10.7%). In a study  
455 conducted in two districts in Southwest Ethiopia FW incidence achieved a maximum  
456 of 77% in a 100 m<sup>2</sup> field, with a mean ranging from 14.7% to 22.4% in a total of 180  
457 fields (Mengesha et al. 2018). In East and Central Africa, disease incidence was  
458 greater than 40% in more than 50% of the fields (Karangwa et al. 2016). The  
459 moderate incidence of FW in Brazil can have socio-economic impacts because most  
460 affected fields are subsistence farms. In Brazil the highest FW incidence was  
461 observed in NPP and SJA regions where there is a higher proportion of susceptible  
462 cultivar, Silk, planted. Cultivar resistance is effective to reduce the incidence of FW.  
463 Pome and Cavendish fields were significantly less affected by the disease.

464         The aggregated pattern of FW was detected in 43% of the fields by all spatial  
465 statistics and the random pattern was detected in 57% of the data sets by one or more  
466 analytical methods. The quadrat-based statistics (*D* and distribution fitting) classified  
467 higher number of fields in an aggregated pattern than the distance-based methods  
468 (*SADIE* and point process) (Table 3). The quadrat-based statistics has a limited  
469 capacity to describe the spatial pattern in the entire field and they only infer the  
470 heterogeneity at scales below that the threshold at which the data were collected.  
471 Quadrat-based methods do not use the spatial information of the sampling units  
472 (Perry et al. 1999). Its use was important to detect the degree of heterogeneity within  
473 disease clusters when few clusters were present. When quadrat-based method is used  
474 in association with distance-based methods the entire process of disease spread could

475 be better studied. However, a clear relationship between quadrat and distance-based  
476 methods was not expected because of the intrinsic features adjusted for the different  
477 physical scales set to study spatial heterogeneity.

478 FW in bananas occurs in an aggregated pattern as demonstrated by the  
479 quadrat-based methods, but clusters of diseased plants (foci) can be randomly  
480 distributed in the field. Thus, at the beginning, the random localization of the  
481 inoculum determines the occurrence of a diseased banana mat. From a focus,  
482 neighboring plants are more likely to become infected originating the aggregated  
483 pattern. Consequently, aggregation is likely to be detected at lower intensity at the  
484 beginning of the epidemics and a random pattern may stand when a larger area is  
485 inspected. This was demonstrated by binary power law: fields with low incidences  
486 had weaker aggregation parameters than fields with higher incidence (Fig 4a). Soil-  
487 borne diseases caused by pathogens that can be dispersed plant-to-plant usually  
488 present this pattern (Musoli et al. 2008; Rekah et al. 1999). For coffee wilt, a disease  
489 caused by the soil-borne pathogen, *Fusarium xylarioides*, an infected plant can  
490 contaminate up to three healthy neighboring trees, in an aggregated pattern (Musoli  
491 et al. 2008). *Fusarium* crown and root rot of tomato caused by *F. oxysporum* f. sp.  
492 *lycopersici* (*Fol*), had an aggregated pattern, and the pathogen can spread from one  
493 plant to the closest four plants in a row by infected roots (Rekah et al. 1999). The  
494 spatial pattern of FW of banana was studied in Australia and aggregation was  
495 detected by the joint-count statistic, and isolated *Foc* TR4-infected plants were also  
496 found (Meldrum et al. 2013).

497 The random pattern of FW epidemics may warn about other processes  
498 affecting the dispersal of *Foc* to sites far from the main foci. In addition to plant to  
499 plant spread, weevil borer, other animals, cultural practices, wind, runoff or irrigation

500 water may contribute to disease dissemination (Dita et al. 2018). Aerial dispersal of  
501 *Fol* and *F. oxysporum* f. sp. *cucumerinum* has been reported (Katan et al. 1997;  
502 Scarlett et al. 2015). External sporulation was also observed for *Foc* and can act as  
503 inoculum if rain and/or wind can remove and carry the propagules to infection sites  
504 (Warman and Aitken 2018). It can be hypothesized that weevil borer (Meldrum et al.  
505 2013), feral pigs (Biosecurity of Queensland 2016); and anthropogenic factors  
506 (Ploetz et al. 2015) could be involved in the dispersal of *Foc*.

507 Many biological and ecological processes can directly affect the spatial  
508 pattern of plant diseases (Campbell and Benson 1994). The study of the effect of  
509 cultivars, levels of management, plant density, age and temperature in the  
510 distribution of FW indicated that the disease has an aggregated pattern and was  
511 affected by incidence (Fig 4). The power law parameter,  $A$ , was significantly  
512 different between Silk and Pome cultivars. Silk is more susceptible than Pome, thus a  
513 clearer aggregated pattern was more often observed in fields planted to the latter.  
514 Based on this pattern, it is possible to infer that *Foc* can be dispersed to more distant  
515 plants and infect when epidemics occurs in highly susceptible cultivars. FW may be  
516 more restricted to neighbor plants when a less susceptible cultivar is affected. Plants  
517 with intermediate resistance levels are less affected by FW up to certain densities of  
518 inoculum (Dita et al. 2018). But, when located in areas with high densities of  
519 inoculum, such as close to diseased plants, even these plants can be infected.

520 Management can also affect FW epidemic (Dita et al. 2018). However, in this  
521 study regardless of management levels FW had an aggregated pattern. The high  
522 incidence of FW in fields that used intermediate levels of management did not  
523 influence the degree of aggregation. The high intensity of the disease prevented  
524 differences in aggregation levels. Many cultural practices, such as defoliation or

525 sucker removal, were not used by the farmers in fields with low management or in  
526 fields with high levels of management the cultural practices were conducted with  
527 more accurate technical knowledge. The practices conducted in both levels of  
528 management probably contribute to reduce the spread and heterogeneity of FW in  
529 fields.

530         Fields planted with high-density, old plants or in areas with low annual mean  
531 temperature had higher aggregation than fields with low-density, new plantings or  
532 planted in regions with high-temperature. As shown for *Fol* in tomato, it is expected  
533 that *Foc* propagules do not move significant distances in soil without the presence of  
534 a susceptible host (Rekah et al. 1999). High density of plants and old plantings  
535 increase the probability of contact among the roots of asymptomatic and diseased  
536 plants. Most likely, the younger the plantation, the greater the influence of the initial  
537 inoculum on the spatial pattern. The initial inoculum can be present in the field or  
538 come from outside by factors such as planting material, insects, animals, wind or  
539 anthropogenic factors. Many of these can give rise to random spatial patterns. After  
540 the infection by the initial inoculum, the same or many other factors can act  
541 dispersing *Foc* inside the field giving rise to the observed patterns. The optimum  
542 limits of temperature for the development of FW is between 22 and 31 °C (Robinson  
543 and Saúco 2011). The reduced development of FW symptoms in fields located in  
544 regions with low annual mean temperature (< 22 °C) is expected. The restrained  
545 development of *Foc* reduce the inoculum production that was restricted to the  
546 diseased or to immediate neighbor plants giving rise to a higher degree of  
547 aggregation.

548         When all factors were analyzed using a multivariate approach, soil physical  
549 properties and cultivars were the most influential factors on FW intensity. Porosity,

550 clay and organic matter were negatively correlated with FW incidence as previously  
551 reported (Amir and Alabouvette 1993; Deltour et al. 2017; Domínguez et al. 2001).  
552 Low incidence of FW was associated with soils with low bulk density. The more  
553 conducive soils were associated with higher sand and silt content (Deltour et al.  
554 2017). Similarly, in Canary Islands, soils that had high clay content were more  
555 suppressive to FW on bananas (Domínguez et al. 2001). Soils with high clay content  
556 have lower bulk densities than soil with low clay and high sand contents (Jones  
557 1983). On the other hand, no clear relationship could be observed about the variables  
558 of components 1 and 2 with the levels of management adopted by farmers. This  
559 happened probably because the cultural practices used to classify in high, moderate  
560 or low management level were not directly associated with chemical or physical soil  
561 properties.

562 To understand the cultural practices related to the spatial pattern of FW  
563 observed in fields, a MCA was performed. High-input fields clustered together.  
564 Although the aggregated pattern was weakly correlated with dimensions 1 and 2 of  
565 MCA, it was related with fields with high level of management practices. Removal  
566 of suckers and defoliation are some of the main practices performed in high levels of  
567 management and these practices were related with the aggregated pattern.  
568 Aggregation was also correlated with fungicide application, organic amendment, and  
569 with the Pome cultivar. On the other hand fields classified as moderate or that  
570 employed low levels of management were related with no sucker removal, no liming,  
571 Silk cultivar and with higher FW intensity and a random spatial pattern. FW intensity  
572 in a moderately susceptible cultivar was 58% lower in plots conducted with high-  
573 input management when compared with low-input techniques (Haddad et al., 2018).  
574 It was not possible to attribute any direct effect of cultural practices on the spatial

575 pattern. Long-term experiments to assess the management practices need to be  
576 performed. Nevertheless, the present study supports the relation between the level of  
577 technology employed and the spatial pattern of FW. In general, fields that have an  
578 aggregated pattern for FW are easier to manage than those presenting a random  
579 pattern of the disease.

580         There were no differences regarding the chemical properties of soils  
581 associated with FW incidence. In other studies, pH (Rishbeth 1957; Deltour et al.  
582 2017), electrical conductivity (EC) (Deltour et al. 2017; Domínguez et al. 2001), Ca  
583 (Alvarez et al. 1981) and Zn (Jerez et al. 1983) content were negatively correlated  
584 with the intensity of FW. Other chemical properties of the soil, such as organic  
585 matter (OM), nitrate ( $\text{NO}_3^-$ ), Si, K, P and B concentration were also negatively  
586 correlated with FW under manipulated environments (Orr and Nelson 2018). The  
587 weak association between chemical properties of soils associated with FW intensity  
588 could be due to the widespread usage of lime and fertilizers. Under this situation, the  
589 differences is expected to be slight. The potential association of soil physical factors  
590 detected in this study may be useful to design more specific experiments to  
591 investigate the effects further.

592         The intensity and spatial pattern of FW are influenced by cultivar, cultural  
593 practices, soil physical properties, density and age of plantings, and annual mean  
594 temperature.. These insights about the epidemiology of FW can help banana farmers  
595 improve their decisions to manage the disease and reduce crop losses. Assuming the  
596 general pattern of non-TR4 populations of *Foc* could be used as proxy, this large-  
597 scale study is also useful to policy makers in charge of formulation of actions to  
598 mitigate the consequences of the introduction of *Foc* TR4 in a region.

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## **CHAPTER 2**

**Spatial and temporal dynamics of Fusarium wilt of bananas and aerial dispersal  
of *Fusarium oxysporum* f. sp. *cubense* under field conditions**

1 **Spatial and temporal dynamics of Fusarium wilt of bananas and aerial dispersal**  
2 **of *Fusarium oxysporum* f. sp. *cubense* under field conditions**

3 **Abstract:** There is very limited information about the spatial and temporal  
4 dynamics of Fusarium wilt (FW) of bananas. The objectives of this work were to  
5 study the spatio-temporal dynamics of FW and to investigate the possibility of aerial  
6 dispersal of *Fusarium oxysporum* f. sp. *cubense* (*Foc*). Two banana fields, one  
7 planted with Prata type (Pome subgroup) and the other with Maçã (Silk subgroup)  
8 were regularly monitored for FW incidence over 24 and 12 months, respectively. In  
9 total, 3,263 banana mats were visually inspected at every two months. Symptomatic  
10 plants were georeferenced and the coordinates were used to produce distribution  
11 maps. Incidence data were used to study disease progress. Additionally, air samplers  
12 were set in the field to collect airborne propagules and to quantify the presence of  
13 *Foc* by qPCR. Incidence was low in the first (max 8.2%) but reached 63.7% at the  
14 last assessment date. The monomolecular model best fit the incidence data.  
15 Dispersion index (*D*) indicated aggregation for all plots in almost all assessments. *D*  
16 changed over time indicating higher degree of aggregation at higher incidences.  
17 Spatial Analysis by Distance Indices (*SADIE*), otherwise, indicated aggregation for  
18 37.5% of the plots and randomness was inferred for 62.5% of the plots. Spatio-  
19 temporal association was detected for 6 of 8 plots by binary power law and  
20 significant association between successive assessments by Pearson correlation for the  
21 clustering indices. Evidence of aerial dispersal of *Foc* was confirmed and the copy  
22 number of the target gene of *Foc* was high. Precipitation and atmospheric pressure  
23 were the most consistent environmental variables associated with the weekly  
24 quantification of airborne propagules. The general pattern of the epidemics of FW

25 resembled that of monocyclic diseases. Aggregation was observed and the clusters of  
26 symptomatic plants were randomly distributed in most plots. The aerial dispersion of  
27 *Foc* was confirmed.

28 **Keywords:** Panama disease; epidemiology; aerobiology; airborne inoculum; spatial  
29 distribution.

### 30 INTRODUCTION

31 Fusarium wilt (FW) of banana, caused by *Fusarium oxysporum* f. sp. *cubense*  
32 (*Foc*) (E. F. Smith) W. C. Snyder and H. N. Hansen, is one of the most destructive  
33 plant diseases (Stover and Simmonds 1987) that affects banana, the world's most  
34 important fruit (Stover 1962, Faostat 2018). The causal agent of FW is a soil-borne  
35 fungus that can infect the host through the roots. *Foc* colonizes the xylem and the  
36 rhizome, releases toxins, induces wilt and kills the plant (Stover 1962). The  
37 pseudostems of dead plants and infected roots return large quantities of *Foc*  
38 propagules to the soil. These propagules, in turn, may give rise to new infections.  
39 Epidemics of FW have been reported for decades. Lately, the banana production is at  
40 risk because of a variant of the pathogen, Tropical Race 4 (TR4), which have been  
41 dispersed from Southeast Asia to Africa and to the Middle East (García-Bastidas et  
42 al. 2014; Ordoñez et al. 2015) and now to South America (ICA, 2019). The  
43 epidemics caused by TR4 severely reduced yield in countries to where it has  
44 established (Damodaran et al. 2019; Molina et al. 2009).

45 In general diseases caused by soil-borne pathogens are considered to be  
46 monocyclic (Vanderplank 1963). Monocyclic diseases usually develop from small  
47 aggregates of inoculum and only one cycle of infection occurs during the crop season  
48 (Vanderplank 1963). Ploetz (2015) suggested that FW of banana is a “polycyclic”

49 disease because multiple cycles of infection can occur in banana plantations. The  
50 main biological characteristics of this pathosystem that support the polycyclic nature  
51 of FW are: the long crop cycle and the possibility of transmission by different ways,  
52 such as root-to-root, vectors, wind, and strong influence of cultural practices. The  
53 semi-perennial nature of the banana crops means that once established in a field it  
54 can be productive for many years (Price 1995) and, in the same way, once infected  
55 by *Foc* it could be an inoculum source for many cycles. Soil-borne pathogens such as  
56 *Phytophthora capsici* (Bowers et al. 1990), *Rhizoctonia solani* (Firman and Allen  
57 1995), and *F. oxysporum* f. sp. *radicis-lycopersici* (Forl) in tomato (Rekah et al.  
58 1999), produce multiple infections in one cycle of the host by root-to-root contact  
59 (Rekah et al. 1999). *F. oxysporum* members were also reported to be potentially  
60 dispersed by aerial processes (Rekah et al. 2000; Katan et al. 1997; Scarlett et al.  
61 2015), but no study relating this dispersal mechanism to disease dynamics in the field  
62 was conducted. Other natural or anthropogenic ways of pathogen dispersal can affect  
63 the temporal dynamics too, and an appropriate approach to investigate this question  
64 is by comparative epidemiology analysis.

65         The spatial and temporal analyses of epidemics are important to understand  
66 how the disease distribution changes over time and space. It may allow us to infer  
67 about important processes affecting the pathogen dispersal in the field and the role  
68 played by different factors on the disease increase over time. A direct relationship  
69 between the initial inoculum and the spatial pattern can be seen in some cases  
70 (Ristaino and Gumpertz 2000). Anthropogenic factors have been reported as  
71 responsible for the long distance dispersal of *Foc*, mainly by informal exchange of  
72 asymptomatic seedlings, *Foc*-infested tools, infested soil adhered to shoes or tires  
73 and movement of fruit containers carrying infected parts of banana plants such as

74 leaf petioles (Ploetz 2015; Dita et al. 2018). In addition, *Foc*-contaminated surface  
75 water used for irrigation was responsible for the spread of FW in China, Malaysia,  
76 and the Philippines (Ploetz et al. 2015). Meldrum (2013) suggested that weevil  
77 borers (*Cosmopolites sordidus*) could be involved in the appearance of isolated  
78 banana mats with FW symptoms. Warman and Aitken (2018) observed sporodochia  
79 and hyphal growth externally on the surface of senescing leaf sheaths of infected  
80 banana plants and the aerial dispersal may be suggested. Conidia of *F. oxysporum* f.  
81 sp. *cucumerinum*, *F. oxysporum* f. sp. *basilici* (*Fob*) and *Forl* were detected in air  
82 samples and the inoculum of the last two were able to infect basil and tomato,  
83 respectively, after foliage inoculation (Scarlett et al. 2015; Rekah et al. 2000).

84 A proper understanding the dynamics of FW epidemics is required to plan  
85 more efficient management strategies. The lack or limited information about the  
86 spatio-temporal dynamics of FW prevents the development of more efficient  
87 strategies to manage epidemics in banana fields worldwide. The objectives of this  
88 study are to: (i) investigate the temporal dynamics of epidemics of FW in a low-input  
89 management field; (ii) understand the dynamics of the spatial pattern of FW over  
90 time; and (iii) study the aerial dispersal of *Foc*.

## 91 MATERIAL AND METHODS

### 92 Fields and data acquisition

93 One Prata (Pome subgroup) banana field with 4.4 ha established in 2012 in  
94 Teixeiras, Minas Gerais state, Brazil (42° 50' 1.835'' O; 20° 38' 18.366'' S and 749  
95 masl) with a historical occurrence of FW was selected to study the dynamics of the  
96 disease in space in time. The field was cultivated under a low-input system, such as  
97 no sucker removal, defoliation, fertilization, or other cultural practices. Bunches

98 were harvested regularly during the study. Seven plots ranging from 0.3 to 1.0 ha  
99 were set in the field. The plots were delimited by the dirty roads in the area. The  
100 number of plants per plot ranged from 171 to 649. Plants were spaced approximately  
101 3 m x 5 m, within and between rows, respectively. The plots were assessed from  
102 April 2017 to February 2019 at every two months, resulting in 12 assessments.

103 In addition to the plots set in the low- input system, a new field was  
104 established in an area that was not cultivated with banana. The field has 0.6 ha and  
105 was established in November 2017 with 398 plants of Maçã cultivar (Silk subgroup).  
106 The Maçã field was in the same region (42° 49' 35.371'' O; 20° 37' 50.246'' S and  
107 687 masl) but it was located 1150 m from the Prata field. The entire Maçã field was  
108 considered as one plot. It was assessed from December 2017 to February 2019 at the  
109 same dates as previously described, resulting in eight assessments.

110 The incidence of FW was quantified in all banana plants of both fields at each  
111 assessment date. The plants were visually assessed for external and internal  
112 symptoms of FW. When external symptoms were observed in a plant of the mat, a  
113 small cut was made in the pseudostem to observe vascular discolorations. If external  
114 and internal symptoms were present, the mat was considered symptomatic. Zebra  
115 ribbon was used to identify the symptomatic mat which was georeferenced using a  
116 handheld GPS device (GPSMAP® 64, Garmin). When symptomatic plants were  
117 identified, fragments (5 cm of length x 5 cm of width) of pseudostems taken from 10  
118 symptomatic plants from fields were collected to isolate the pathogen and confirm  
119 the presence of *F. oxysporum* by morphological (Leslie and Summerell 2008) and  
120 molecular methods (Lin et al. 2009; Heck et al., *in development*).

121 Hourly records of temperature, relative humidity and dew point were  
122 automatically taken using a HOBO data logger (Onset, Bourne, MA, USA).

123 Atmospheric pressure, wind velocity, radiation and precipitation data was obtained  
124 hourly from the closest climate station located at 14.4 Km from the fields and was  
125 provided by Instituto Nacional de Meteorologia (INMET) of Ministério da  
126 Agricultura, Pecuária e Abastecimento (MAPA).

## 127 **Temporal analysis**

128 Two data sets were constructed with the geographic coordinates: one  
129 containing the polygon and the other containing information about the location of  
130 symptomatic plants in each plot. These data sets were converted to a text file and  
131 imported into R, version 3.5.1 (R Core Team 2018). For each plot, the two data sets  
132 were used for the analyses. Polygons and diseased plants data sets were used to  
133 produce maps with the spatial distribution of symptomatic plants in each assessment.

134 The polygon data set was used to estimate the area, centroid and the number  
135 of plants ( $n$ ) in each plot ( $i$ ). The total number of plants in each plot was estimated  
136 using the area of the polygon and plant spacing (distance within and between rows).  
137 The diseased plant data set was used to estimate the total number and location of  
138 symptomatic plants ( $x$ ) in plots at each assessment. The average incidence ( $\bar{y}$ ) was  
139 calculated as  $\bar{y} = x_i / n_i$ , where  $x$  was the number of symptomatic plants and  $n$  the  
140 estimated number of total plants (including symptomatic and asymptomatic) in the  $i^{\text{th}}$   
141 plot. The incidence was calculated at each assessment time. The Monomolecular,  
142 Logistic and Gompertz models were fit to the disease incidence plotted over time by  
143 nonlinear regressions using the nlsLM function from MINPACK.LM package  
144 (Elzhov et al. 2016). The choice of the best model was performed by linear mixed-  
145 effects model (Laird and Ware 1982) using the LME function from NLME package  
146 (Pinheiro et al. 2018).

147 **Spatial analysis**

148 Two types of spatial analyses were conducted: a quadrat-based analysis, to  
149 study the heterogeneity of the data at or below the physical size of the sampling unit;  
150 and a distance-based analysis, to study the degree of heterogeneity between sampling  
151 units in a scale above the sampling unit (Madden et al., 2007).

152 The data sets were used for quadrat-based analyses, the maps were  
153 *quadratized* using the QUADRATCOUNT function of the SPATSTAT package  
154 (Baddeley and Turner 2005). The quadrat size used was 2 x 2, i.e. the area occupied  
155 by two plants within and two plants between rows, respectively. The number of  
156 symptomatic plants in each quadrat was determined and used to perform the spatial  
157 analysis. The exact number of plants inside each quadrat could not be computed  
158 because the direction of rows was irregular.

159 *Dispersion index.* The index of dispersion for incidence data,  $D$ , sometimes  
160 referred to as a relation between two variances (ratio of the observed variance and  
161 theoretical variance) was used as quadrat-based method.  $D < 1$  indicates a  
162 underdispersed data (regular pattern);  $D = 1$  indicates a random pattern and  $D > 1$   
163 indicates a overdispersed data (aggregated pattern). To test the null hypothesis for  
164 dispersion index ( $D = 1$ ) a  $\chi^2$  test was performed. The analysis was performed using  
165 the AGG\_INDEX function from the EPIPHY package (Gigot 2018).

166 *Spatial Analysis by Distance IndicEs (SADIE).* This method was used to  
167 study the spatial heterogeneity in a large-scale pattern. It uses the location of the  
168 sampling units (i.e. quadrats) and the number of individuals (i.e. symptomatic plants)  
169 inside the unit to analyze the spatial arrangement of the diseased individuals by the  
170 distance to regularity ( $D_r$ ). In *SADIE*, the  $D_r$  is achieved when all the sampling units

171 of a given data set (plot) have the same number of diseased individuals. The  $I_a$   
172 statistic given by *SADIE* is an overall index of aggregation obtained by the ratio  
173 between the distance moved to achieve a regular pattern for the observed data and a  
174 theoretical mean to regularity based on random permutations of the individuals  
175 among the sampling units. When  $I_a < 1$ , a regular pattern is inferred; if  $I_a = 1$  or if  $I_a$   
176  $> 1$ , a random or an aggregated pattern is inferred, respectively. The local clustering  
177 indices  $v_i$  and  $v_j$ , given by *SADIE*, estimate the contribution of a given unit to a patch  
178 or a gap, respectively. The index developed by Li et al. (2012) was computed by the  
179 *SADIE* function from *EPIPHY* package.

## 180 **Spatio-temporal analysis**

181 The relationship between the observed variance and mean of FW incidence  
182 per sampling unit across the fields and assessments was evaluated. The equation for  
183 the binary power law,  $\log_{10}(s^2) = \log_{10}(A) + b \log_{10}(s_{bin}^2)$ , where  $s^2$  is the observed  
184 variance and  $s_{bin}^2$  the theoretical variance,  $A$  ( $\log_{10}(A)$ ) and  $b$  are the parameters to be  
185 estimated. The null hypothesis of binary power law assumes that a random pattern  
186 for incidence data is well described by the binomial distribution. Estimates of  $A = b =$   
187 1 suggest a random distribution. If  $A > 1$  ( $\log_{10}(A) > 0$ ) and  $b = 1$  then an aggregated  
188 fixed pattern across all data sets analyzed can be inferred. If  $b > 1$ , then the degree of  
189 overdispersion varies with  $y$  and is not fixed. This value suggests higher aggregation  
190 levels with greater disease incidence values (Madden and Hughes 1995, Madden and  
191 Hughes, 1999). A t-test was performed to test the null hypothesis for a binomial  
192 distribution ( $\log(A) = 0$  and  $b = 1$ ) for individual fields and all fields.

193 For each plot, a temporal association analysis of the spatial pattern of FW was  
194 performed. First the measurement of the degree of local clustering ( $\chi_p$ ) in sampling

195 units (quadrats) was used to calculate the similarity in the cluster indices of two  
196 sequential assessments. Local clustering obtained in *SADIE* analysis by the method  
197 of Li et al. (2012), is a measure of the contribution for a patch or gap at that location  
198 based on the original data and  $D_r$ . The overall association ( $\chi$ ) was obtained by the  
199 correlation coefficient of the local clustering between pairs of assessments. The t-test  
200 corrected for spatial association was used to test the significance of  $\chi$  (Clifford et al.  
201 1989; Dutilleul et al. 1993). The analysis was performed using the *SADIE* and  
202 *MODIFIED.TTEST* functions from *EPIPHY* and *SPATIALPACK* (Osorio and  
203 Vallejos 2018) packages, respectively.

#### 204 **Aerial dispersal of *Fusarium oxysporum* f. sp. *cubense***

205 *Air sample collection.* Airborne propagules were sampled using a Hirst-type  
206 seven day spore trap (Burkard Scientific Ltd., Uxbridge, United Kingdom) with  
207 rotating collection surface to determine the presence of *Foc* propagules in the Prata  
208 and Maçã fields. The spore traps were placed in plots 5 and 8, respectively. Hirst-  
209 type air sampler operates at a fixed rate of 10 L<sup>-1</sup> of air per minute and particles are  
210 impacted on a polyester film (Melinex tape, Burkard Scientific Ltd.). The tapes were  
211 manually impregnated with a thin film of liquid vaseline (Dyne, Quimibrás, RJ,  
212 Brazil). The tape was 33.6 cm long by 2 cm wide, totaling an area of 67.2 cm<sup>2</sup>.  
213 Airborne particles were aspirated towards the surface of the tapes. The sampler was  
214 placed in the middle of the plot and at a fixed height of 75 cm above the ground,  
215 where air samples were taken continuously for seven days. After this period, the  
216 Melinex tape was collected and changed by a new tape. Melinex tape was divided in  
217 seven portions, each one corresponding to the 24-hour period of spore collection.  
218 The pieces of the tape had 2 cm wide and 4.8 cm long, totaling an area of 9.6 cm<sup>2</sup>.

219 Immediately, these individual segments were divided into smaller fragments of  
220 approximately 0.5 cm<sup>2</sup> and packed into 2 ml microtubes properly identified. Samples  
221 were stored at -20 °C to maintain the integrity and viability of the spores collected.  
222 The sampling was done weekly for 12 months, from March 2018 to March 2019 in  
223 plot 8 and for 10 weeks in plot 5, from March 2018 to June 2018.

224         *DNA purification.* Total DNA was extracted from the 385 air samples using  
225 the Wizard Genomic DNA Purification Kit (Promega, Madison, WI, United States of  
226 America) following the manufacturer's instructions with the following modification:  
227 Prior to DNA extraction, 0.2 g pre-sterilized glass beads (500 µm diameter) and 220  
228 µL of 0.5% Triton X-100 were transferred into 2 mL microtubes containing the  
229 fragments kept frozen and the tissues were disrupted for 2 min using the TissueLyser  
230 II (Qiagen, Valencia, CA, USA). After the centrifugation using the "Protein  
231 Precipitation Solution" the supernatant was transferred to a clean microcentrifuge  
232 tube containing 300 µL of 2% mixed alkyl trimethyl ammonium bromide (MATAB)  
233 and 300 µL of chloroform-isoamyl alcohol (24:1 v/v) and vortexed at high speed for  
234 20 s. Tubes were centrifuged at 14,000 rpm for 10 min and the supernatant was  
235 collected. The remainder of the DNA extraction was performed according to the  
236 manufacturer's instructions. DNA integrity was analyzed using electrophoresis on a  
237 0.8% agarose gel in TBE (0.089M Tris base, 0.089M Boric acid, 0.002M EDTA pH  
238 8.0) and bromophenol blue dye and the GelRED® intercalating agent were added to  
239 each well. DNA quality and quantity were determined using NanoDrop 2000  
240 Spectrophotometer (Thermo Fisher Scientific, Waltham, MA, USA).

241         *Airborne propagules quantification.* Foc-UFV primers (forward and reverse)  
242 were developed to amplify a conserved region of the genome of *Fusarium*  
243 *oxysporum* f. sp. *cubense*. The amplified fragment had 122 bp, a suitable size for a

244 sensitive qPCR assay (confidential data, *in development*). The primer pair was used  
245 to carry out qPCR assay, conducted in triplicate, using a Rotor Gene-Q (Qiagen).  
246 PCR reactions were performed in a volume of 10  $\mu$ L, which consisted of 1  $\mu$ L  
247 template DNA, 1  $\mu$ L of the forward and reverse primers each (50 nM), and 5  $\mu$ L of  
248 2x QuantiFast SYBR Green PCR Master mix (Qiagen). The lightcycler conditions  
249 used were as follows: 95 °C for 5 min, followed by 35 cycles of PCR amplification  
250 at 95 °C for 10 s, and 60 °C for 30 s. Melting curves were obtained at an increasing  
251 temperature from 65 °C to 99 °C with a rise of 1 °C at every 5 s.

252 *Data analysis.* To monitor the airborne inoculum of *Foc* over the year the  
253 extracted DNA corresponding to seven days was mixed. The mixed DNA was  
254 analyzed by the qPCR assay described above. Copy number was expressed as  $\log_n$   
255 and presented as number of copies per  $m^3$  of air. These data were related with the  
256 environmental conditions by Pearson correlation performed by COR.TEST function.

257 To analyze the seasonality of airborne inoculum, four seven-day periods each  
258 in the middle of each of the seasons of the year were chosen. In total, 28 days were  
259 analyzed by the qPCR assay. The daily quantification of copy number was related  
260 with the environmental conditions of the day and compared among the climatic  
261 seasons by analysis of variance and multiple comparisons test by CRD function from  
262 EXPDES package (Ferreira et al. 2018). Environmental variables were also analyzed  
263 for differences among the seasons. Data that violated normality by Shapiro-Wilk test  
264 were analyzed with the non-parametric test of Kruskal-Wallis.

## 265 **RESULTS**

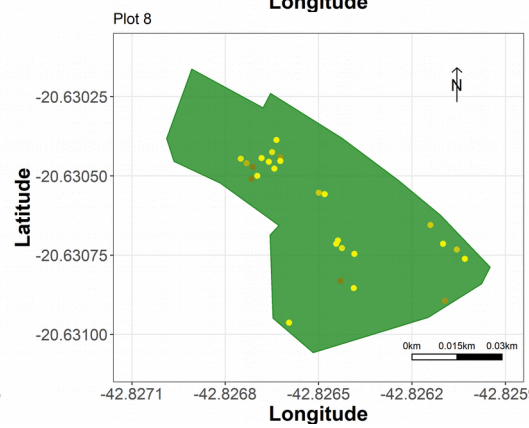
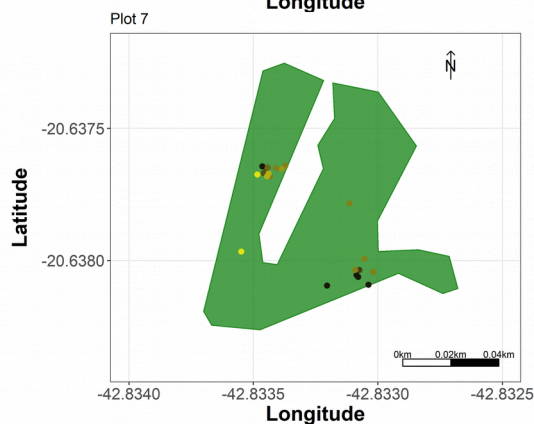
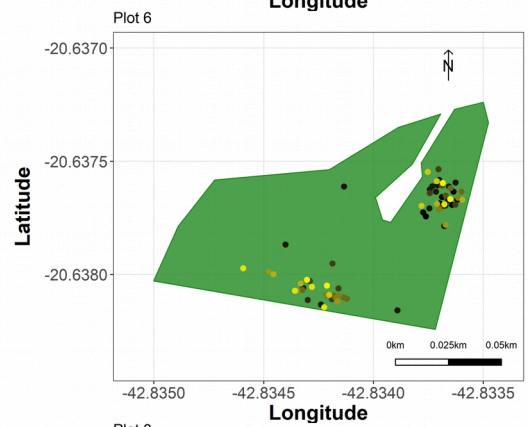
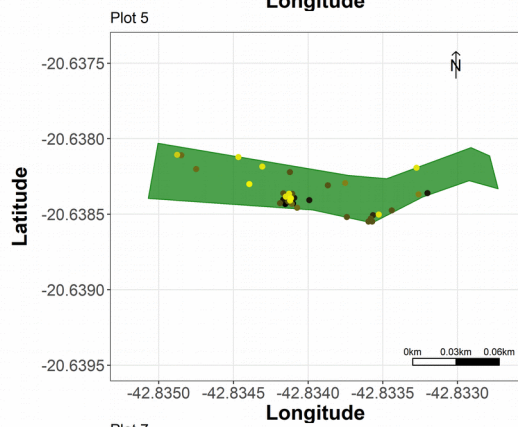
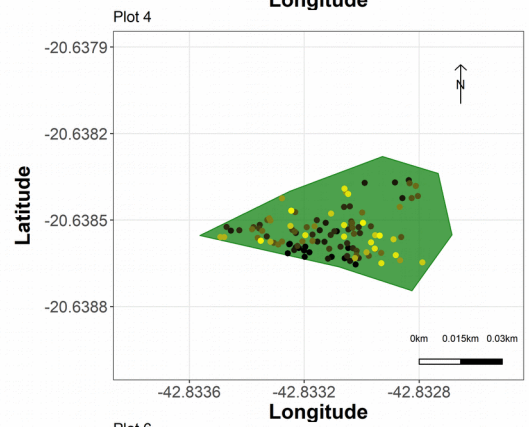
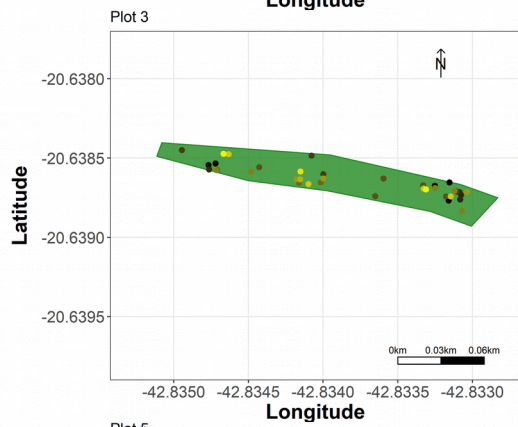
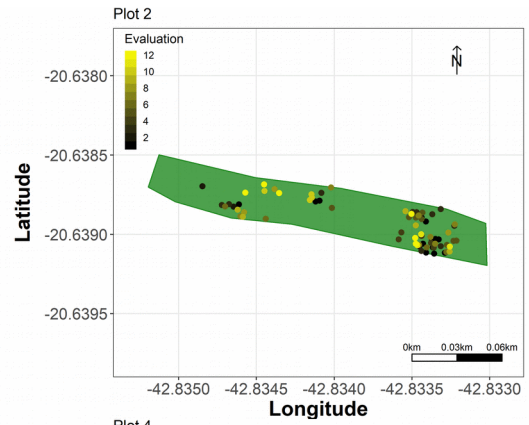
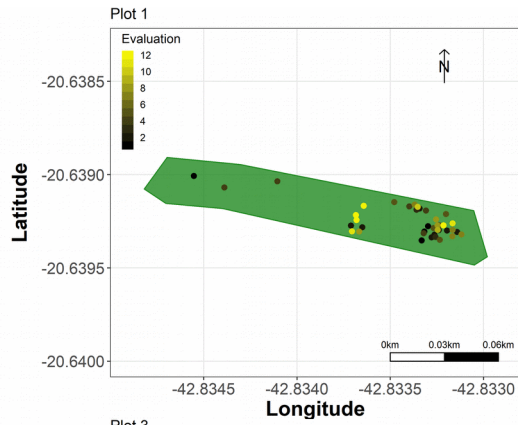
266 Maps of disease intensity were constructed for all eight plots (7 in the Prata  
267 field and 1 in the Maçã field) (Fig. 1). The symptomatic FW plants were identified as

268 points with different colors, from black to red, according to the assessment time.  
269 Clusters and sparsely diseased plants could be observed and no spatial pattern or  
270 temporal dynamics could be inferred by visual observations.

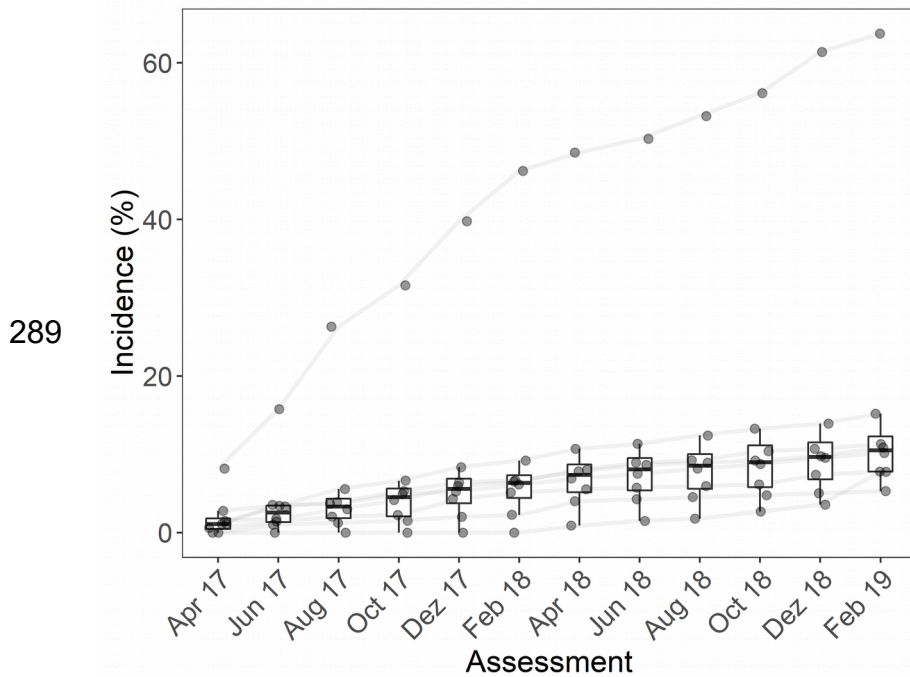
### 271 **Temporal analysis**

272 The incidence of FW in the first assessment date ranged from 0 to 8.19% with  
273 a mean of 1.9% and median of 1.1% (Fig. 2). Six of eight plots already had  
274 symptomatic FW plants before the beginning of the evaluations. In the Maçã field  
275 (plot 8) the first diseased plant was observed in April 2018, 150 days after planting.  
276 After six evaluations the incidence in all plots ranged from 0.9 to 48.5% with a  
277 median of 7.4% and in the last assessment the FW incidence ranged from 3.9 to  
278 63.7% with a median of 10.5% (Fig. 2).

279 Disease progress curves were best fitted by the monomolecular model in all  
280 plots studied (Table 1; Fig. 3). The initial incidence ( $y_0$ ) ranged from 0.001 to 0.106  
281 with a median of 0.018 and the progress rate ( $r$ ) ranged from 0.003 to 0.043, with a  
282 mean and median of 0.009 and 0.004, respectively. For plot 6 the estimated  $r$  value  
283 was considered as an outlier, this field had the highest final incidence (63.7%) while  
284 the much lower values of final incidence (< 15.2%) were recorded in other fields.



286 Fig 1. Maps for eight banana plots assessed for incidence of Fusarium wilt from  
 287 April 2017 to February 2019, in Teixeiras, MG, Brazil. Plots 1 to 7 were located in  
 288 the Prata field, and plot 8 was in the Maçã field.

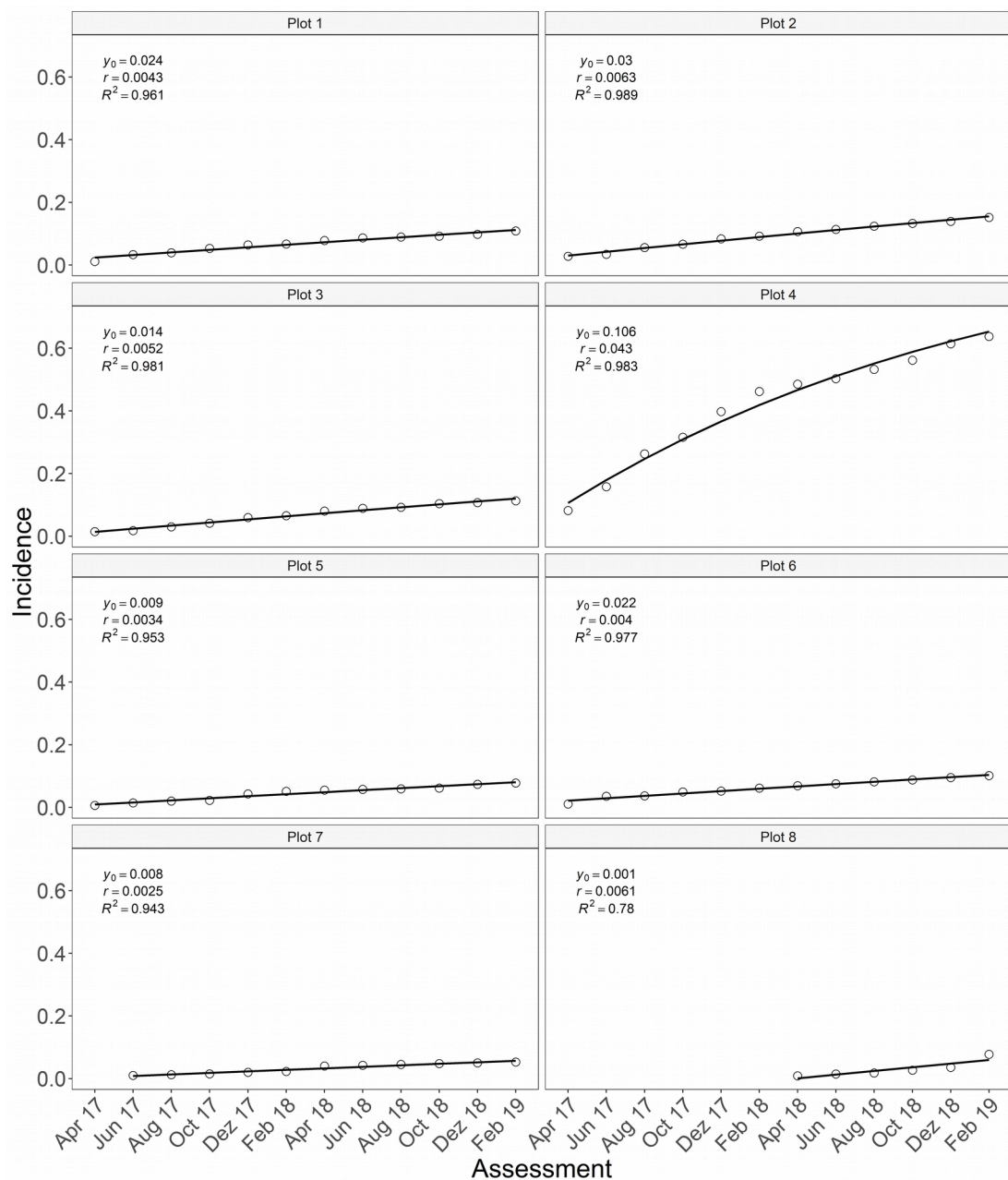


290 Fig 2. Incidence of Fusarium wilt in eight banana plots assessed from April 2017 to  
 291 February 2018. Incidence of each plot was represented by dots and lines, median and  
 292 quartiles in boxplot. The curve on top of the series of boxplots refers to Fusarium  
 293 wilt progress in plot 4, where FW incidence was highest.

294 Table 1. Summary of statistics used to study the progress of Fusarium wilt on eight  
 295 banana plots located in Teixeiras, Minas Gerais state, Brazil, from April 2017 to  
 296 February 2019.

Model	AIC	BIC	logLikelihood	Best adjust / <i>n</i>
Monomolecular	-376.84	-335.61	206.42	8 / 8
Logistic	-280.35	-239.12	158.18	0 / 8
Gompertz	-290.10	-248.87	163.05	0 / 8

297 AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.



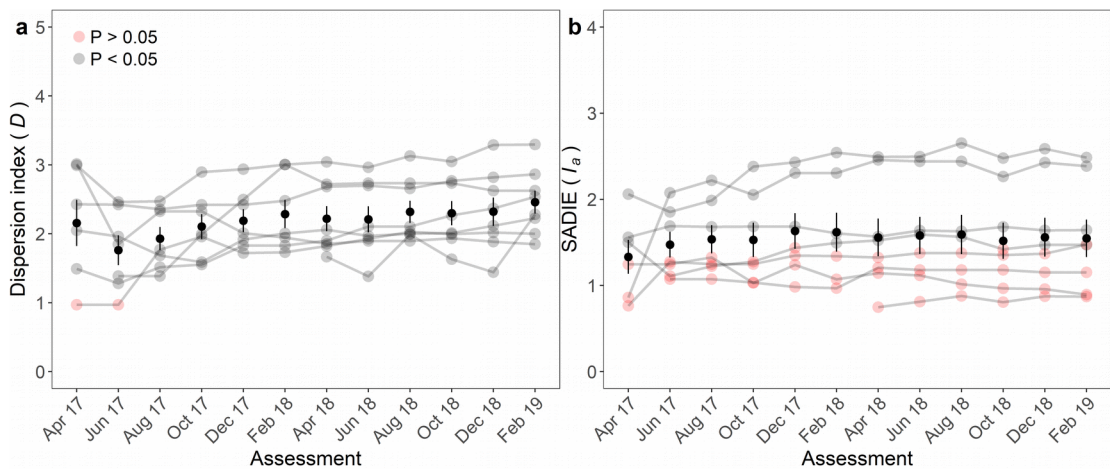
298 Fig 3. Monomolecular model adjusted to incidence data of Fusarium wilt of banana  
 299 from April 2017 to February 2019 in eight banana plots located in Teixeiras, Minas  
 300 Gerais state, Brazil. Points referred to observed incidence and integer line the  
 301 predicted incidence based in monomolecular model. Estimated initial incidence ( $y_0$ ),  
 302 progress rate ( $r$ ) of epidemics and the measure of the adjustment of predicted and

303 observed values ( $R^2$ ) were presented. Plots 1 to 7 were located in the Prata field, and  
304 plot 8 was in the Maçã field.

### 305 **Spatial analysis**

306 Dispersion index ( $D$ ) was the chosen to study the pattern of FW on banana by  
307 quadrat-based methods. In 10 of 12 assessments, banana plants with symptoms of  
308 FW were aggregated in all eight plots (Fig. 4a). In the first assessment performed in  
309 April 2017,  $D$  ranged from 0.97 to 3.01 with a mean of 2.16 and in the last, February  
310 2019,  $D$  varied from 1.85 and 3.30 with a mean of 2.46.  $D$  index for the eight fields  
311 increased with the FW progress. A random pattern of FW ( $P = 0.61$ ) was observed  
312 only in plot 4 in the first two assessments ( $D = 0.97$ ) when incidence was low ( $y_{max} =$   
313 1.8%). The highest  $D$  values was observed for plots 6 and 7 which had two defined  
314 clusters and a few sparsely diseased plants.

315 Aggregation of banana plants was confirmed by *SADIE* ( $P < 0.05$ ), a  
316 distance-based method, in plots 1, 2 and 6, which correspond to 37.5% of the plots  
317 analyzed. Plots 3, 5, 7 and 8 had a random pattern ( $P < 0.05$ ) in all assessments. Plots  
318 4 had an inconsistent pattern along the study period, varying between random and  
319 aggregated. In the first assessment, April 2017,  $I_a$  ranged from 0.76 to 2.06 with a  
320 mean of 1.33 and in the last, February 2019,  $I_a$  varied from 0.87 to 2.48 with a mean  
321 of 1.55. These results revealed that the index of aggregation of *SADIE* remained  
322 relatively stable over time (Fig 4b).



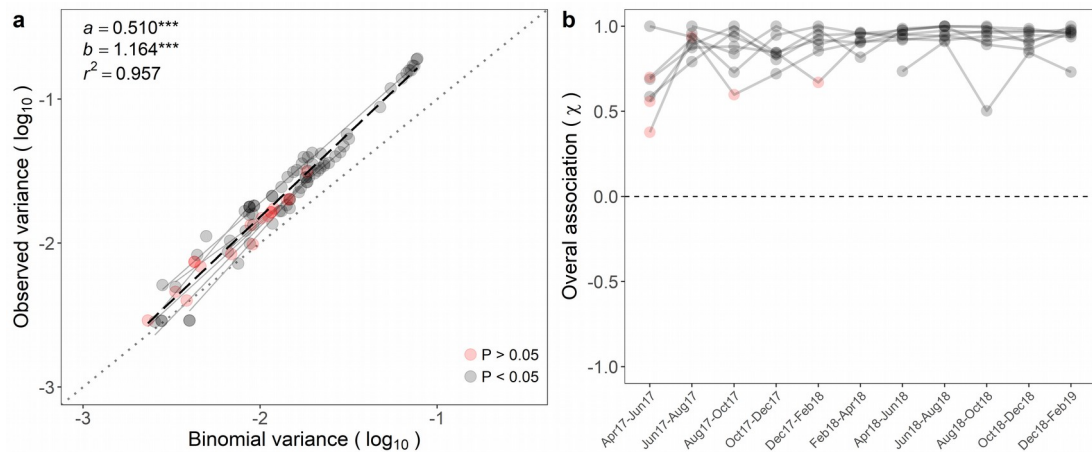
323 Fig 4. Dispersion index ( $D$ ) (a) and aggregation index from Spatial Analysis by  
 324 Distance IndicEs ( $SADIE; I_a$ ) (b) for incidence of Fusarium wilt of banana from April  
 325 2017 to February 2019 in 8 plots located in Teixeiras, Minas Gerais, Brazil. Red and  
 326 gray points were presented when the null hypothesis of randomness was not rejected  
 327 ( $P > 0.05$ ) or rejected ( $P < 0.05$ ), respectively. Error bars represent standard error and  
 328 black point the means.

### 329 Spatio-temporal analysis

330 The relationship between the logarithm of the observed variance and the  
 331 logarithm of the mean for the eight plots in 12 bimonthly assessments was well  
 332 described by the binary power law ( $R^2 = 0.96$ ) (Fig 5a). Parameters from power law,  
 333  $\log_{10}(A)$  ( $0.510 \pm 0.051$ ) and  $b$  ( $1.164 \pm 0.026$ ), were significantly ( $P < 0.001$ )  
 334 different from 0 and 1, respectively, when all plots were jointly analyzed. As  $\log_{10}(A)$   
 335 was higher than 0 and  $b$  was higher than 1, in general FW exhibited an aggregated  
 336 pattern and the degree of aggregation increased with disease incidence. When the

337 plots were analyzed individually over time, the correlation coefficient of  
338 determination ( $R^2$ ) ranged from 0.957 to 0.992,  $\log_{10}(A)$  was between -0.03 to 1.25  
339 and  $b$  varied between 0.90 to 1.45. Six of eight plots (75%) exhibited an aggregated  
340 pattern with  $\log_{10}(A)$  and  $b$  significantly higher than 0 and 1, respectively (Fig. 5a).  
341 The null hypothesis of randomness was not rejected by the binary power law in plot  
342 5 ( $\log_{10}(A) = -0.031 \pm 0.09$ ;  $b = 0.903 \pm 0.04$ ;  $P = 0.418$ ) and plot 8 ( $\log_{10}(A) = 0.382$   
343  $\pm 0.260$ ;  $b = 1.124 \pm 0.120$ ;  $P = 0.096$ ).

344 Spatial associations were detected between the pairs of successive  
345 assessments in local clustering ( $P < 0.05$ ) (Fig. 5b). In the beginning of FW  
346 epidemics, there was no association between the first (April 2017) and second (June  
347 2017) observations in three (plots 1, 5 and 6) of five plots ( $P = 0.334$ ; 0.189 and  
348 0.741, respectively). No association was observed for plot 3 between June and  
349 August ( $P = 0.058$ ) and between August and October 2017 ( $P = 0.186$ ), and for plot  
350 5 between December 2017 and February 2018 ( $P = 0.077$ ; Fig. 5b). After the fifth  
351 comparison, December 2017 and February 2018, all comparisons of the local  
352 clustering were significantly associated for all plots.



353 Fig 5. Binary power law (a) and overall association (b) of successive  
 354 (pairs) of clustering indices for incidence of Fusarium wilt of banana from April  
 355 2017 to February 2019 in 8 plots located in Teixeira, Minas Gerais, Brazil. Red and  
 356 gray points were presented when the null hypothesis of randomness was not rejected  
 357 ( $P > 0.05$ ) or rejected ( $P < 0.05$ ), respectively.

358 To study the spatial associations between observations more spread further  
 359 apart in time, comparisons between the first and middle or latest observations of the  
 360 epidemic, and between the middle and last assessments were performed (Table 2).  
 361 Plots 4 and 7 were positively associated ( $R > 0.543$ ;  $P < 0.046$ ) for the three  
 362 assessment times. Plot 2 exhibited significant association between the first and the  
 363 middle ( $P = 0.03$ ) and between the middle and the last ( $P < 0.001$ ) assessments of the  
 364 epidemic. No spatial association was observed for the other plots between the first  
 365 and middle assessments (Table 2). Plots 1, 3, 5, 6 and 8 were spatially associated  
 366 when comparing between the middle and latest observations (Table 2).

367 Table 2. Overall association of the spatial pattern of Fusarium wilt of banana  
 368 epidemics between three assessment times (first, middle and last assessment) for  
 369 eight fields.

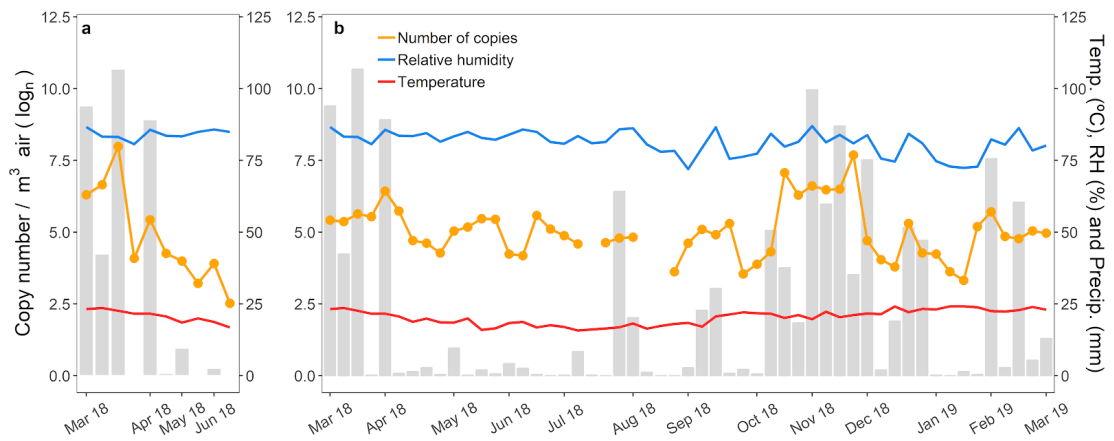
Plot	Assessment 1	Assessment 2	Overall association ( <i>P</i> -value) <sup>a</sup>
1	April 2017	February 2018	0.367 (0.264)
	February 2018	February 2019	<b>0.864 (0.004)</b>
	April 2017	February 2019	0.253 (0.423)
2	April 2017	February 2018	<b>0.611 (0.030)</b>
	February 2018	February 2019	<b>0.781 (&lt;0.001)</b>
	April 2017	February 2019	0.573 (0.019)
3	April 2017	February 2018	0.441 (0.106)
	February 2018	February 2019	<b>0.735 (&lt;0.001)</b>
	April 2017	February 2019	0.303 (0.227)
4	June 2017	February 2018	<b>0.563 (0.046)</b>
	February 2018	February 2019	<b>0.937 (&lt;0.001)</b>
	June 2017	February 2019	<b>0.543 (0.045)</b>
5	April 2017	February 2018	0.499 (0.237)
	February 2018	February 2019	<b>0.853 (&lt;0.001)</b>
	April 2017	February 2019	0.433 (0.253)
6	April 2017	February 2018	0.577 (0.106)
	February 2018	February 2019	<b>0.814 (&lt;0.001)</b>
	April 2017	February 2019	0.463 (0.113)
7	June 2017	February 2018	<b>0.880 (&lt;0.01)</b>
	February 2018	December 2018	<b>0.754 (0.001)</b>
	June 2017	December 2018	<b>0.663 (0.004)</b>
8	April 2018	October 2018	0.206 (0.262)
	October 2018	February 2019	<b>0.698 (&lt;0.001)</b>
	April 2018	February 2019	0.202 (0.243)

370 <sup>a</sup> Overall association based on Pearson correlation was calculated using the clustering index  
 371 from Spatial Analysis by Distances IndicEs (*SADIE*). *P*-value was obtained from a modified  
 372 t-test based on Clifford et al. (1989) and Dutilleul (1993). Significant correlations are shown  
 373 in bold (*P* < 0.05).

374 **Aerial dispersal of *Fusarium oxysporum* f. sp. *cubense***

375 Air sampling collection was successfully performed for 10 weeks in Prata  
376 field, from March to June 2018, and 50 weeks in Maçã field, from March 2018 to  
377 March 2019. The copy number detected by qPCR varied over the weeks (Fig 6). In  
378 Prata field the copy number ranged from 12.5 to 2944.4 per m<sup>3</sup> of air, with a median  
379 of 65.3 over 10 weeks. In Maçã field copy number ranged from 27.8 to 2177.8, with  
380 a median of 139.6 per m<sup>3</sup> of air over 50 weeks. No significant difference could be  
381 detected between the copy number ( $\log_{10}$ ) of both fields considering the same period.

382 Relationship between environmental conditions and density of copies in air  
383 samples was verified using Pearson correlation analysis. Temperature ( $R = 0.843$ ,  $P$   
384  $= 0.002$ ) and dew point ( $R = 0.841$ ,  $P = 0.002$ ) were significantly correlated with  
385 copy number in Prata field. Relative humidity (RH) was significantly correlated ( $R =$   
386  $0.391$ ,  $P = 0.005$ ) with copy number in Maçã field. Atmospheric pressure (hPa) ( $R =$   
387  $-0.820$  and  $-0.283$ ) and precipitation ( $R = 0.86$  and  $0.472$ ) were correlated ( $P <$   
388  $0.002$ ) with the copy number in both fields. There were no significant correlations  
389 between wind velocity and solar radiation with the copy number in any of the  
390 evaluated fields.



391 Fig 6. Average copy number ( $\log_n$ ) per  $\text{m}^3$  of air (orange line) of *Fusarium*  
 392 *oxysporum* f. sp. *cubense* at weekly mixed samples from March 2018 to March 2019  
 393 in Prata (a) and Maçã (b) fields. Average of temperature (Temp.) and relative  
 394 humidity (RH) were presented as red and blue lines, respectively, and cumulative  
 395 precipitation (Precip.) as gray bars.

396 Daily quantification of copy number ( $\log_n$ ) did not differ significantly among  
 397 the seasons (Table 3). Temperature, dew point and atmospheric pressure were the  
 398 climatic factors that differed among seasons ( $P < 0.001$ ). Temperature and dew point  
 399 were higher in summer and spring than in winter and autumn; while atmospheric  
 400 pressure was higher in autumn and winter than in summer and spring (Table 3).  
 401 Relative humidity, wind velocity, radiation and precipitation did not differ among  
 402 seasons (Table 3). No correlation among the environmental data from the different  
 403 seasons and copy numbers was detected (data not shown).

404 Table 3. Seasonality of copy number of *Fusarium oxysporum* f. sp. *cubense* airborne propagules and climatic conditions.

Season <sup>a</sup>	Copy number (log <sub>n</sub> ) <sup>ns</sup>	Temperature (°C)	Relative humidity (%) <sup>ns</sup>	Dew point (° C)	Atmospheric pressure (hPa)	Wind velocity (m.s <sup>-1</sup> ) <sup>ns</sup>	Radiation (kJ.m <sup>-2</sup> ) <sup>ns</sup>	Precipitation (mm.day <sup>-1</sup> ) <sup>ns</sup>
Summer	5.35	23.2 a	88.2	20.3 a	934.3 b	0.66	617.3	10.8
Autumn	5.74	16.0 b	82.9	12.6 c	939.3 a	0.50	498.1	0.3
Winter	4.89	17.0 b	92.6	15.3 b	938.9 a	0.52	392.0	9.2
Spring	5.49	21.5 a	92.4	19.5 a	935.1 b	0.94	696.6	2.6
CV (%)	21.6	8.6	7.7	9.5	0.26	52.7	42.7	127.3

405 <sup>a</sup> Data were obtained from daily quantification of seven days on each season.

406 **DISCUSSION**

407           One of the biggest constraints to develop efficient management strategies to  
408 FW on banana is the lack of information about the basic epidemiological processes  
409 of the disease: the spatial and the temporal dynamics. Studies involving the spatial  
410 and temporal dynamics of FW on banana fields are absent and gaps in epidemiology  
411 are constantly emphasized in reviews (Dita et al. 2018; Ghag et al. 2015; Ploetz  
412 2015). To fill some of these gaps bimonthly assessments of FW incidence with  
413 georeferenced data were conducted during two years.

414           Visual maps of diseased plants did not allow to conclude about the dynamics  
415 of FW over time and space. Plots 1 to 7 were cultivated with ‘Prata’ type banana  
416 since 2012, and had a historical occurrence of FW while plot 8 was a new field  
417 cultivated with ‘Maçã’, a highly susceptible cultivar. Overall the FW incidence was  
418 low in almost all plots (median = 10.5%); much lower than values reported in  
419 Indonesia and Africa (Hermanto et al. 2011; Karangwa et al. 2016; Mengesha et al.  
420 2018). Plot 5 was the exception where the epidemic developed fast and reached up  
421 63.7% of incidence on February 2019. Similar values of incidence were reported in  
422 Ethiopia (77%) (Mengesha et al. 2018) and Tanzania (63.6%) (Karangwa et al. 2016)  
423 in plantations at final production cycles.

424           In general diseases caused by soil-borne pathogens are considered  
425 monocyclic (Vanderplank 1963). Ploetz (2015) suggested that FW of banana is a  
426 “polycyclic” disease because multiple cycles of infection can occur in banana

427 plantations affected by *Foc*. However, the results showed that the monomolecular  
428 was the best fitted model to the data over two years of assessments in a low-input  
429 farm. Many characteristics of the pathosystem suggest otherwise. The semi-perennial  
430 nature of the banana plant means that once infected by *Foc* it could be a inoculum  
431 source for many years to neighboring plants. The need of intensive management to  
432 achieve high productivity and other mechanisms of dispersal could affect the  
433 dynamics of FW, as reported for other diseases caused by *F. oxysporum* (Rekah et al.  
434 1999; Scarlett et al. 2014, 2015). Similar argument was suggested for *Foc* (Meldrum  
435 et al. 2013). In the current study, there were limited cultural practices conducted in  
436 the field. Thus, *Foc* dispersal could be related to undocumented factors, such as  
437 natural occurrence of *Foc* in the soil, asymptomatic seedlings, root-to-root, vectors,  
438 floods or wind.

439         Spatial pattern analysis can shed light on the mechanisms involved in the  
440 spread of FW and on pathogen dispersal. Based on the dispersion index, there was  
441 evidence for an aggregated pattern of FW epidemics. Regardless of the location of  
442 the sampling unit, there was higher heterogeneity in the number of symptomatic  
443 plants inside the sampling units compared with FW incidence. In addition, the degree  
444 of aggregation changed over time, lowest  $D$  values were observed at the beginning of  
445 FW epidemics and increased as incidence increased. After the initial foci were  
446 formed the asymptomatic plants located near symptomatic ones were the first to be  
447 affected by FW. Similar results were reported with the use of quadrat-based methods

448 for epidemics caused by soil-borne pathogens (Musoli et al. 2008; Rekah et al.  
449 1999).

450 Distance-based methods detected a different pattern and divergences were  
451 observed between  $D$  and  $I_a$ . Aggregation was consistently observed in 37.5% (3/8) of  
452 the plots, while randomness could be detected in 62.5% (5/8) by *SADIE*. The method  
453 quantified the degree of contribution of each sampling unit towards the overall  
454 degree of clustering achieved by  $D_r$  (Perry et al. 1999). On the process to reach  
455 regularity ( $D_r$ ), one cluster of diseased plants (donors) was considered one patch and  
456 regions without diseased plant as gaps (receptors) (Perry et al. 1999). If the clusters  
457 were sparsely dispersed, the number of clusters or the degree of aggregation in  
458 clusters were low, what could be seen in plots 3, 5, 7 and 8, the probability of not  
459 rejecting the null hypothesis of randomness was high. From the first to last  
460 assessments a small variation in the degree of aggregation by *SADIE* was observed.  
461 Probably, in this case, the initial inoculum reached the plots by unobserved  
462 mechanisms, as symptomatic seedlings, vectors and wind, which gave rise to a  
463 random pattern. Once established in the field, plant-to-plant transmission may have  
464 contributed to the increase of the degree of aggregation of FW.

465 Strong evidence of aggregation was indicated by the binary power law over  
466 time. Power law was used as a spatio-temporal analysis and considered all  
467 assessments for each plot. The degree of aggregation was affected by the level of  
468 incidence itself and its rate of increase over time. In only two plots (5 and 8) the null

469 hypothesis of randomness was not rejected. This result did not agree with  $D$   
470 statistics, that is also a ratio between variances, but  $D$  considers only one assessment  
471 at a time to test for spatial pattern while binary power law considers all assessments  
472 through time (Laranjeira et al. 2000). Plot 8 resulted in the lowest values for  $D$  and  
473 for binary power law. Temporal associations of the clustering indices suggest  
474 correlations between the successive pairs of assessments. Only in the beginning of  
475 the epidemic, when the incidence was low, there were some fields with no spatial  
476 association (Fig. 5b, Table 2). This fact was expected because the new infections in  
477 different sampling units contribute to the lack of association over time. However,  
478 association between the clustering indices of middle and last assessment of the  
479 epidemic was observed. Turechek and Madden (1999) reported that spatial  
480 association was only detected when the clusters of disease expanded beyond the  
481 borders of the sampling units. As demonstrated by  $D$  and power law, aggregation  
482 was higher when incidence achieved higher values until the maximum observed  
483 (63%).

484         The initial inoculum seems to drive the epidemics of monocyclic diseases  
485 (Jeger 1987). Understanding how the inoculum arrives in the field and the  
486 mechanisms involved in *Foc* dispersal are key to propose efficient management  
487 strategies to avoid FW epidemics or, at least, reduce crop losses. As *SADIE* detected  
488 a consistent random pattern in some plots it is an indicative that the inoculum could  
489 have arrived from outside or have been dispersed not by root-to-root contact or

490 neighboring plants. Asymptomatic seedlings, muddy boots, *Foc*-infested tools, soil  
491 with *Foc* propagules adhered to machinery tires, mammals, insects, and wind are  
492 some of the factors suggested that can introduce *Foc* in new areas (Biosecurity of  
493 Queensland 2016; Dita et al. 2018; Meldrum et al. 2013; Ploetz et al. 2015).

494 In the present study *Foc* propagules were detected over one year of air  
495 sampling. Monitoring was made weekly and spores were detected on 100% of the  
496 samples analyzed at relatively high rates (median of 65 to 140 copies per m<sup>3</sup> of air).  
497 The copy number did not reflect the exact number of propagules because macro- and  
498 microconidia of *Fusarium* species had different number of cells. *F. oxysporum* f. sp.  
499 *cucumerinum* was detected in air samples of a greenhouse at rates that ranged from 1  
500 to 140 copies per m<sup>3</sup> of air (Scarlett et al. 2015). Both macro- and microconidia were  
501 detected in air samples but failed to establish infection on stem wounds of cucumber  
502 (Scarlett et al. 2015). These high rates observed in the air samples could be addressed  
503 by the proximity to a source of inoculum in the field. In Prata field the closest  
504 diseased mat was located approximately 5 m from the air sampler in Northwest  
505 direction. At longer distances diseased mats were present in all directions. In Maçã  
506 field no symptomatic plants were present inside the plot at the beginning of the  
507 monitoring. Diseased mats were only observed at the potential source of inoculum,  
508 an abandoned banana plantation, located approximately 80 m from the sampler in the  
509 South direction. No significant correlation could be detected between density of  
510 propagules in the air and the incidence of FW in fields.

511 Evidence for aerial dispersal of *Foc* propagules has accumulated over the  
512 years, but its epidemiological role remains elusive. *Fol* was observed sporulating on  
513 stems of cherry tomatoes growing in greenhouses and airborne propagules were  
514 trapped on selective medium (Katan et al. 1997). *Forl* and *Fob* were also detected  
515 sporulating in stems of tomato and basil, respectively, and airborne propagules were  
516 trapped by selective medium (Rekah et al. 2000). *Foc* SR4 was also able to grown in  
517 outer surface of pseudostem of banana infected plant on pathogenicity tests in  
518 greenhouse (Fig S1). Morphological (Leslie and Summerell 2008) and molecular  
519 (Lin et al. 2009) methods confirmed the presence of *Foc* externally. However, in the  
520 field, external sporulation was not observed during the monitoring study. Warman  
521 and Aitken (2018) observed an isolate of *Foc* SR4 genetically transformed with  
522 green fluorescent protein (GFP) in the outer surface of asymptomatic plants and  
523 sporodochia and hyphal growth on the outer surface of senescing leaf sheaths.  
524 Propagules produced in hyphae and sporodochia grown in the outer surface of plants  
525 can be released and carried long-distance by winds. However, to date, the capacity of  
526 aerially-dispersed propagules to infect banana plants has not been demonstrated.

527 Environmental conditions may influence the production, release, survival and  
528 deposition of these spores loaded by wind. On weeks with higher cumulative rainfall  
529 higher number of propagules were detected in air samples. Weeks with lower  
530 atmospheric pressure had higher number of airborne propagules. Average  
531 temperature, relative humidity and dew point were also related with the density of

532 propagules, but the effects were not consistent between the two fields analyzed.  
533 Changes in relative humidity could have some relation with changes in airborne  
534 propagules of *F. oxysporum* f. sp. *cucumerinum*, but no conclusion was reached  
535 (Scarlett et al. 2015). High humidity was also suggested as having some relation with  
536 *Fol* sporulation in external surface of tomato stems (Katan et al. 1997). The highest  
537 spore number of *Fusarium circinatum* in air samples was counted in autumn,  
538 suggesting a seasonal fluctuation (Schweigkofler et al. 2004). Airborne propagules of  
539 *Foc* did not show a seasonal fluctuation and only temperature, dew point and  
540 atmospheric pressure differed among the seasons.

541         The dynamics of FW of banana was partially clarified in the present study.  
542 However, it is important to point out that temporal, spatial and spatio-temporal  
543 characteristics of FW epidemics on a banana subsistence farm may not be the same  
544 as FW epidemics in other fields. The management system, cultivars, type of soil and  
545 climatic conditions are key factors to the development of FW epidemics and can vary  
546 from field to field (Dita et al. 2018). In addition to plant-to-plant, transmission of FW  
547 can involve other processes. Evidences of aerial dispersion of *Foc* propagules was  
548 highlighted here. The airborne propagules identified in this study are probably of  
549 *Foc* SR4 or race 1 (data not shown). Using this as a proxy, *Foc* TR4 may also be  
550 dispersed by aerial mechanisms, therefore, it can put in alert the banana production  
551 system worldwide. Additionally, this could explain the fast spread of the FW  
552 epidemics in Asia and Middle East caused by *Foc* TR4 and the transcontinental jump

553 in recent years (Chittarath et al. 2018; Damodaran et al. 2019; Dita et al. 2018;  
554 García-Bastidas et al. 2014; Hung et al. 2018; ICA, 2019; Maymon et al. 2018;  
555 Ordoñez et al. 2015; Ploetz et al. 2015; Zheng et al. 2018). This work can be used to  
556 direct similar dynamic studies in other regions to advance the understanding of FW  
557 epidemics and direct aerobiology studies of *Foc* to give rise on efficient management  
558 strategies in future years.

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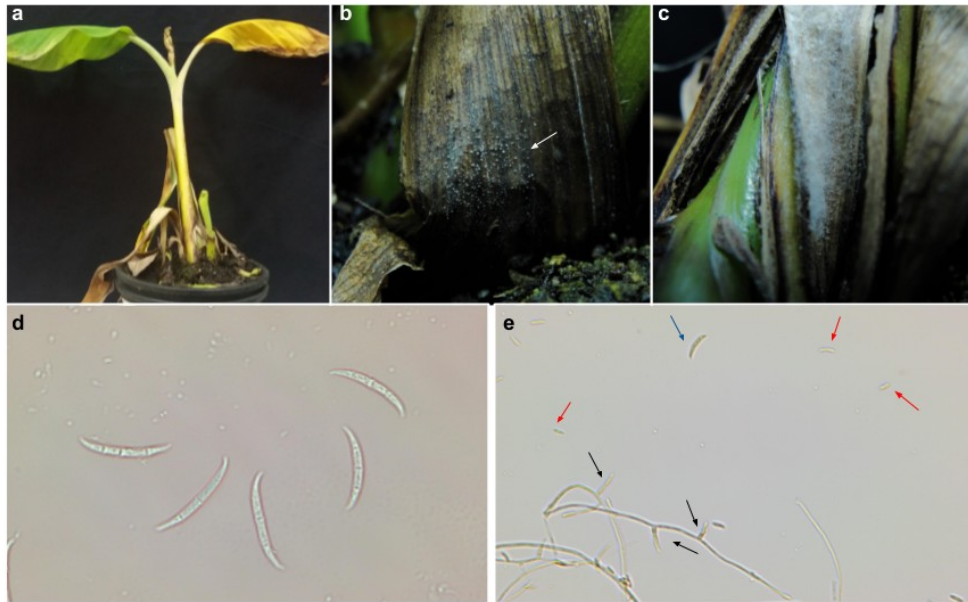
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704 SUPPLEMENTARY MATERIAL



705 Fig S1. Banana cv. Maçã with symptoms of *Fusarium* wilt grown in 1 L pots under  
706 greenhouse conditions (a). Roots were artificially inoculated with a *Fusarium*  
707 *oxysporum* f. sp. *cubense* isolate (*Foc*UFV-580) by root dipping. Sporodochia (white  
708 punctuations) in the outer surface of banana pseudostem (b). Hyphal growing in  
709 outer surface of disrupted pseudostem (c). Macroconidia recovered from sporodochia  
710 (white arrow) produced externally (d). Macro- (black arrow), microconidia (red  
711 arrow) and phialides (black arrow) recovered from hyphal growing externally in the  
712 pseudostem (e).

## **CHAPTER 3**

### **Weevil borers and the spatio-temporal dynamics of Fusarium wilt of banana**

## 1 Weevil borers and the spatio-temporal dynamics of Fusarium wilt of banana

2 **Abstract:** Dispersal of propagules of a pathogen has remarkable effects on the  
3 development of epidemics. Previous studies have suggested the role of banana insect  
4 pests on the development of Fusarium wilt (FW) epidemics. Here we provide  
5 complementary evidence for the involvement of two insect pests of banana,  
6 *Cosmopolites sordidus* L. (WB) and *Metamasius hemipterus* L. (FWB), in the  
7 dispersal of *Fusarium oxysporum* f. sp. *cubense* (*Foc*) using two approaches: a  
8 comparative epidemiology study under field conditions and an association analysis  
9 between pests and *Foc*. Two banana fields with historical records of FW epidemics  
10 were used, one managed with *Beauveria bassiana* to reduce the population of WB,  
11 and the other was left without management. The number of WB and FWB was  
12 monitored during two years and the FW incidence was also quantified. The  
13 population of WB and FW incidence (6.7%) in the field managed with *B. bassiana*  
14 were lower than in the field left unmanaged (13.0%). The monomolecular model best  
15 fit the FW incidence data and, as expected, the average estimated disease progress  
16 rate was lower in the field managed with the entomopathogenic fungus ( $r = 0.0024$ )  
17 compared to the unmanaged field ( $r = 0.0056$ ). Aggregation of FW was higher in  
18 field with WB management. The association analysis revealed a greater number  
19 (7,933) of colony forming units (CFU) of *Fusarium* spp. associated with WB ( $n =$   
20 115 insects) than with FWB (1,414 CFU;  $n = 102$  insects). WB affects the spatial and  
21 temporal dynamics of FW epidemics under field conditions. *Fusarium* spp. was  
22 associated with both pests but *Foc* was not detected.

23 **Keywords:** *Fusarium oxysporum* f. sp. *cubense*, Panama disease, spatio-temporal,  
24 banana weevil, West Indian sugarcane weevil

## 25 INTRODUCTION

26           Understanding the ways a pathogen is dispersed is one of the most important  
27 tasks in epidemiology of plant diseases. Without pathogen dispersal no epidemics  
28 occurs. For Fusarium wilt (FW) of bananas, caused by *Fusarium oxysporum* f. sp.  
29 *cubense* (*Foc*) (E. F. Smith) Snyder and Hansen, there is limited information about  
30 the mechanism of pathogen dispersal available. It is suggested that *Foc* can be  
31 dispersed mainly by human influence, such as exchange of asymptomatic  
32 propagation material, cultural practices performed with infested tools, and soil  
33 particles adhered to boots, machinery and tires of vehicles (Dita et al. 2018; Ploetz et  
34 al. 2015). Good management practices, sterilization of materials and appropriate  
35 training of plantation workers can greatly reduce dispersal and the likelihood of  
36 introduction of the pathogen in clean areas.

37           The influence of natural dispersal agents such as wind, rivers, animals,  
38 including mammals and insects are more difficult to detect and to control, but they  
39 certainly influence the development of epidemics. Some reviews highlighted the  
40 potential of these dispersal processes of *Foc* at short or long distances (Dita et al.  
41 2018; Ghag et al. 2015; Ploetz 2015; Ploetz et al. 2015). Surface water and rivers  
42 infested with *Foc* propagules were putatively associated with the rapid expansion of  
43 FW epidemics in China, Malaysia and the Philippines (Ploetz et al. 2015; Xu et al.  
44 2003). *F. oxysporum* species does not seem to move long distances in soil.  
45 Inoculation normally occurs when root growth contacts the inoculum distributed in  
46 the soil or by root-to-root contact (Rekah et al. 1999). The presence of sporodochia  
47 and hyphal growth externally in plant tissues suggests that aerial dispersal of *Foc* is  
48 possible (Warman and Aitken 2018). The free circulation of animals such as feral

49 pigs in banana fields was cited as a potential mechanism of dispersal of *Foc*  
50 (Biosecurity of Queensland 2016). Smaller animals such as insects, banana weevil  
51 borer (*Cosmopolites sordidus* L., Coleoptera: Curculionidae), referred here as weevil  
52 borer (WB), in particular, probably play a role in the inoculation of isolated banana  
53 plants in the field (Meldrum et al. 2013). The WB can occur in large numbers in  
54 banana fields and can contribute to spread the disease, but no conclusive results have  
55 been reached so far.

56 Any animal or material that can carry soil particles in banana fields is a  
57 potential dispersal agent of *Foc*. Weevil borer, is a main pest in banana fields (Gold  
58 et al. 2001). West Indian sugarcane weevil (*Metamasius hemipterus* L., Coleoptera:  
59 Curculionidae), referred as false weevil borer (FWB), is an important pest in  
60 sugarcane, but can also cause damage in banana under high populations and is  
61 commonly observed in many banana fields (Fancelli et al. 2012). Curculionidae  
62 members acting as vectors of plant diseases are commonly reported in some crops.  
63 *M. hemipterus* and *Rhynchophorus palmarum* (Coleoptera: Curculionidae) were  
64 suspected to be vectors of the nematode *Bursaphelenchus cocophilus*  
65 (= *Rhadinaphelenchus cocophilus*), causal agent of red ring disease in oil palm (Mora  
66 et al. 1994; Hagley 1963). *R. palmarum* was also reported as dispersal agent of bud  
67 rot disease (*Phytophthora palmivora*) in oil palm (Plata-Rueda et al. 2016) and stem  
68 bleeding (*Thielaviopsis paradoxa*) in coconut palm (Carvalho et al. 2011). However,  
69 since the study carried out by Meldrum et al. (2013) the potential of banana weevil to  
70 disperse *Foc* remains unanswered. Nevertheless, these answers may be useful to the  
71 development of preventive measures against quarantine pathogens, as *Foc* Tropical  
72 Race 4 (*Foc* TR4), and effective management strategies to control the expansion of  
73 FW foci within the field. The objective of this study was to understand the

74 relationship of two potential vectors of *Foc*, *C. sordidus* and *M. hemipterus*, using  
75 two approaches: (i) a comparative epidemiology study under field conditions and (ii)  
76 an association study between the potential vectors and *Foc*.

## 77 MATERIAL AND METHODS

### 78 Comparative epidemiology

#### 79 *Field experiment*

80 Two banana plots with history of epidemics of FW were evaluated in  
81 Teixeiras, Minas Gerais state, Brazil, from March 2016 to April 2017. These plots  
82 were cultivated with a Prata type banana (Pome subgroup) and managed in a low-  
83 input technology system. In one plot (20° 38' 21.444" S; 42° 50' 1.752" W and 772  
84 masl) of 1.03 ha WB was managed while the second plot (20° 38' 19.5" S; 42° 50'  
85 2.544" W and 759 masl) of 1.2 ha remained without any control practice for WB.  
86 The management of WB was conducted at every three months. Carbofuran (Furadan  
87 50 G<sup>®</sup>, FMC Corporation) was applied manually at 3 g of commercial product per  
88 trap once at the beginning of the experiment. Additionally, five grams of Ballvéria  
89 WP<sup>®</sup> (10<sup>9</sup> CFU of *Beauveria bassiana* per gram of commercial product) was applied  
90 in each trap. Applications of *B. bassiana* were made at every 3 months in 30 to 40  
91 pseudostem traps in the plot with control of WB. Traps were constructed by cross-  
92 cutting pseudostems of harvested plants at approximately 40 cm from the soil line.  
93 The biological insecticide was applied on the flat, cut surface, of one half of the trap,  
94 and the other half was placed back on top of the treated half.

95 *Weevil borer monitoring*

96           A second type of pseudostems traps were used to monitor the WB population.  
97 Pseudostems of harvested plants were cross cut in sections of 30 cm and  
98 subsequently lengthwise in half such as to produce two hemi-cylindrical traps. The  
99 sections were disposed with cut side down (in contact with soil). Fifteen pseudostem  
100 traps per plot were made and placed approximately 15 cm apart from the banana mat.  
101 The traps were randomly distributed in the plots and maintained in the same place  
102 throughout the experiment. Monitoring was performed from May 2017 to February  
103 2019. Traps were evaluated by counting the number of WB and FWB at every 14  
104 days and replaced by new ones.

105 *Fusarium wilt assessments*

106           Banana plants were visually assessed for external and internal symptoms of  
107 FW. When external symptoms were observed, a small cut was made in the  
108 pseudostem to inspect for internal symptoms. If external and internal symptoms were  
109 present, the mat was considered symptomatic and was georeferenced using a  
110 handheld GPS device (GPSMAP® 64, Garmin). The FW symptomatic banana mat  
111 was identified with a zebra ribbon to avoid double mark in future assessments. GPS  
112 files with geographic location of symptomatic plants and polygons were extracted  
113 and converted to text files and imported in R Statistical Software version 3.5.1 (R  
114 Core Team 2018). Fragments (5 cm of length x 5 cm of width) of pseudostems taken  
115 from symptomatic plants from each field were collected to isolate the pathogen and  
116 to confirm the presence of *Foc* by morphological (Leslie and Summerell 2006) and  
117 molecular methods (Heck et al. *in development*).

118 *Data analysis*

119 *Insect population.* The paired t-test was used to analyze differences between  
120 the average number of WB and FWB in each assessment date. T-test was also used  
121 to analyze differences in the average number of WB and FWB assessed between the  
122 managed and unmanaged plots.

123 *Temporal analysis.* The area, centroid and the total number of plants in each  
124 plot were estimated using the polygon data set and the plant spacing information  
125 (distance within and between rows). The symptomatic plant data set was used to  
126 estimate the total number and location of symptomatic plants ( $y$ ) in plots. The  
127 incidence ( $\bar{y}$ ) was calculated as  $\bar{y} = y_i / n_i$ , where  $y$  was the number of diseased plants  
128 and  $n$  the estimated number of total plants (asymptomatic and symptomatic) in the  $i^{\text{th}}$   
129 plot. The incidence was calculated at each assessment date. The Monomolecular,  
130 Logistic and Gompertz models were fit to the disease incidence data and fitted over  
131 time by nonlinear regressions using the nlsLM function from MINPACK.LM  
132 package (Elzhov et al. 2016). The choice of the best model was performed by linear  
133 mixed-effects model (Laird and Ware 1982) using the LME function from NLME  
134 package (Pinheiro et al. 2018).

135 *Spatial analysis.* Spatial analyses were performed using quadrat- and distance  
136 based methods. The symptomatic plant data set was used for quadrat-based analyses,  
137 in which the plot maps were *quadratized* using the QUADRATCOUNT function of  
138 the SPATSTAT package (Baddeley and Turner 2005). The quadrat size used was 2 x  
139 2, i.e. the area occupied by two plants within and between rows, respectively. The  
140 number of symptomatic plants in each quadrat was determined and used to perform  
141 the spatial analysis. The exact number of plants inside each quadrat could not be

142 computed because the direction of rows and spacing between plants was irregular.  
143 The estimated precision of the GPS device varied between 3 and 7 m during the  
144 assessments depending on the environmental conditions.

145 Dispersion index for binomial data,  $D$ , referred sometimes as the ratio  
146 between variances was used for a quadrat-based method. To test the null hypothesis  
147 for dispersion index ( $D = 1$ ) a  $\chi^2$  test was performed. The analysis was conducted  
148 using the AGG\_INDEX function from the EIPHY package (Gigot 2018). Spatial  
149 Analysis by Distance IndicEs (*SADIE*) was the method chosen in the distance-based  
150 approach. *SADIE* uses the location of the sampling units (i.e. quadrats) and the  
151 number of individuals (i.e. symptomatic plants) inside the unit to analyze the spatial  
152 arrangement by the distance to regularity ( $D_r$ ) criterion.  $D_r$  is achieved when all the  
153 sampling units have the same number of diseased individuals. *SADIE* returns an  
154 overall aggregation index ( $I_a$ ) which reflects the ratio between the distance moved to  
155 achieve a regular pattern for the observed data and a theoretical mean to regularity  
156 based on random permutations. The index developed by Li et al. (2012) was  
157 computed by the *SADIE* function from EIPHY package. On these two methods ( $D$   
158 and *SADIE*) a regular pattern was inferred when the indices were equal to 1, an  
159 aggregated pattern when they were higher than 1, and regular when less than 1.

160 *Spatio-temporal analysis.* The relationship between the observed and  
161 theoretical variances of FW incidence per sampling unit was evaluated. The equation  
162 for binary power law,  $\log_{10}(s^2) = \log_{10}(A) + b \log_{10}(s_{bin}^2)$ , where  $s^2$  its the observed  
163 variance,  $s_{bin}^2$  the theoretical variance assuming a binomial distribution, and  $A$   
164 ( $\log_{10}(A)$ ) and  $b$  are the parameters to be estimated. Estimates of  $\log_{10}(A) = 0$  and  $b =$   
165 1 suggest a random distribution, if  $\log_{10}(A) > 0$  and  $b = 1$  suggest an aggregated  
166 pattern with fixed value independently of the incidence level; and if both parameters,

167  $\log_{10}(A)$  and  $b$ , are higher than 0 and 1, respectively, the higher the incidence the  
168 greater the values of the aggregation index (Madden and Hughes 1995). A t-test was  
169 performed to test the null hypothesis for individual plots, and to test if the parameters  
170 differed between the plots.

#### 171 **Association between *Fusarium oxysporum* f. sp. *cubense* and weevil borer**

172 *Insect collection.* WB and FWB were collected in the same plots and in the  
173 same pseudostem traps used to monitoring. Collections were performed 14 days after  
174 setting the traps in the plot. Insects were collected four times in one year period, one  
175 in each climatic season, from June 2017 to June 2018. At each time, WB and FWB,  
176 were quantified and placed individually in microtubes properly identified.

177 *Fusarium spp. collection.* Microtubes containing the insects were filled with  
178 300  $\mu$ L of water containing streptomycin (1 g/L). The insects were washed following  
179 the procedures described by Meldrum et al. (2013) and the suspension was spread in  
180 plates containing Komada medium (Komada 1975) with 0.5% of lactic acid. Plates  
181 were maintained in growth chamber at 25 °C, in dark conditions for seven days.  
182 Fungal colonies were quantified and a maximum of 5 per plate were selected and  
183 subcultured into potato-dextrose-agar (PDA). *Fusarium* spp. colonies were analyzed  
184 for morphological aspects under an optical microscope (400X; Olympus CX31)  
185 (Leslie and Summerell 2006). Isolates were transferred to SNA, maintained at 25 °C  
186 for ten days, mycelial disks were transferred to microtubes and stored at 10 °C and  
187 add to the *Ins*-UFV collection.

188 *DNA purification.* Total DNA was extracted from 370 isolates using the  
189 Wizard Genomic DNA Purification Kit (Promega, Madison, WI, United States of  
190 America) following the manufacturer's instructions with some modifications. Briefly,

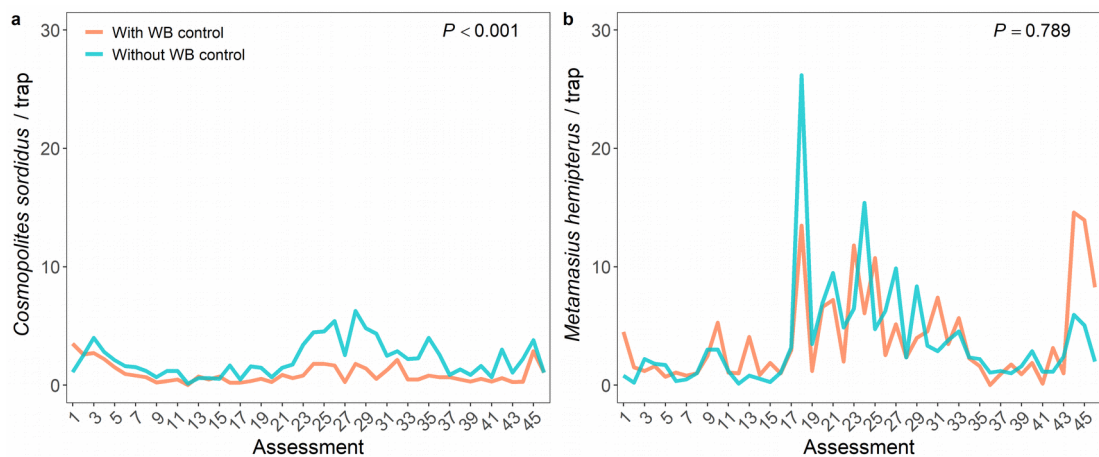
191 dried mycelium was disrupted for 2 min using TissueLyzer II (Qiagen, Valencia, CA,  
192 USA). After the nuclei lysis and protein precipitation steps the supernatant was  
193 transferred to a clean microtube containing 300  $\mu$ L of 2% mixed alkyl trimethyl  
194 ammonium bromide (MATAB) and 300  $\mu$ L of chloroform-isoamyl alcohol (24:1  
195 v/v) and vortexed at high speed for 20 s. Tubes were centrifuged at 14,000 rpm for  
196 10 min and the supernatant was collected. The remainder of the DNA extraction was  
197 performed according to the manufacturer's instructions. DNA integrity was analyzed  
198 using electrophoresis on a 0.8% agarose gel in TBE (0.089M Tris base, 0.089M  
199 Boric acid, 0.002M EDTA pH 8.0). DNA quality and quantity were determined  
200 using NanoDrop 2000 Spectrophotometer (Thermo Fisher Scientific, Waltham, MA,  
201 USA).

202         *Pathogen detection.* Foc-UFV primers (forward and reverse) were developed  
203 to amplify a conserved region of 122 bp of the genome of *Foc* (confidential data, *in*  
204 *development*). PCR reactions were performed in a volume of 12.5  $\mu$ L, which  
205 consisted of 2.5  $\mu$ L of 5x GoTaq<sup>®</sup> Reaction Buffer (Promega), 0.25  $\mu$ L of PCR  
206 nucleotide (10 mM), 0.2  $\mu$ L of the forward and reverse primers each (1  $\mu$ M), 0.05  $\mu$ L  
207 GoTaq<sup>®</sup> DNA Polymerase (5u/ $\mu$ L), 1  $\mu$ L template DNA (~ 10 ng/ $\mu$ L), and nuclease-  
208 free water to 12.5  $\mu$ L. The thermal cycler conditions used were as follows: initial  
209 denaturation at 95 °C for 5 min, followed by 35 cycles of PCR amplification at 95 °C  
210 for 30 s for denaturation, annealing at 63 °C for 30 s, extension at 72 °C for 45 s,  
211 with a final extension at 72 °C for 5 min. Positive control consisted of substituting 1  
212  $\mu$ L of DNA from the insects isolates for the *Foc*-UFV581, isolated from a FW  
213 symptomatic plant in the field. Negative control was used substituting the DNA for  
214 nuclease-free water. PCR products were analyzed on a 1.7% agarose gel in TBE.

215 **RESULTS**

216 **Comparative epidemiology**

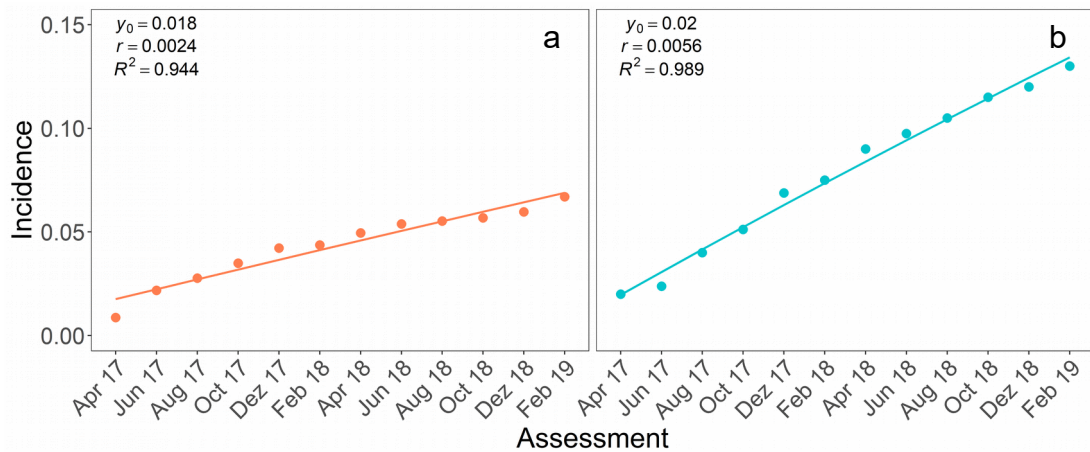
217 Management and monitoring of WB were carried out from May 2017 to  
218 February 2019. The overall number of FWB collected (median of 2.3 per trap) was  
219 higher than WB (median of 1.1 per trap) in each assessment ( $P < 0.001$ ). The number  
220 of WB was lower in the plot where WB was managed with *B. bassiana* (median of  
221 0.67 per trap) compared to the unmanaged plot (1.6 per trap) ( $P < 0.001$ ) (Fig 1a).  
222 Management with *B. bassiana* did not affect ( $P = 0.789$ ) the population of FWB in  
223 the same period (Fig 1b).



224 Fig 1. Biweekly monitoring of weevil borer (*Cosmopolites sordidus*, WB) (a); and  
225 false weevil borer (*Metamasius hemipterus*, FWB) (b) in fields with and without WB  
226 control, from May 2017 to February 2018, assessments 1 to 45, respectively.

227 Fusarium wilt incidence was lowest in first assessment with 0.9% and 2% in  
228 the plot with and without WB management, respectively (Fig 2). These two plots  
229 already had diseased plants when the assessments began. After 12 assessments,  
230 disease incidence reached 6.7% and 13% in plots with and without WB management,  
231 respectively (Fig 2). Monomolecular model best described the disease progress in

232 both plots (Table 1). Initial incidence did not differ for the two plots studied and the  
 233 disease rate was higher in the plot without management of WB ( $P < 0.001$ ) (Fig 2).



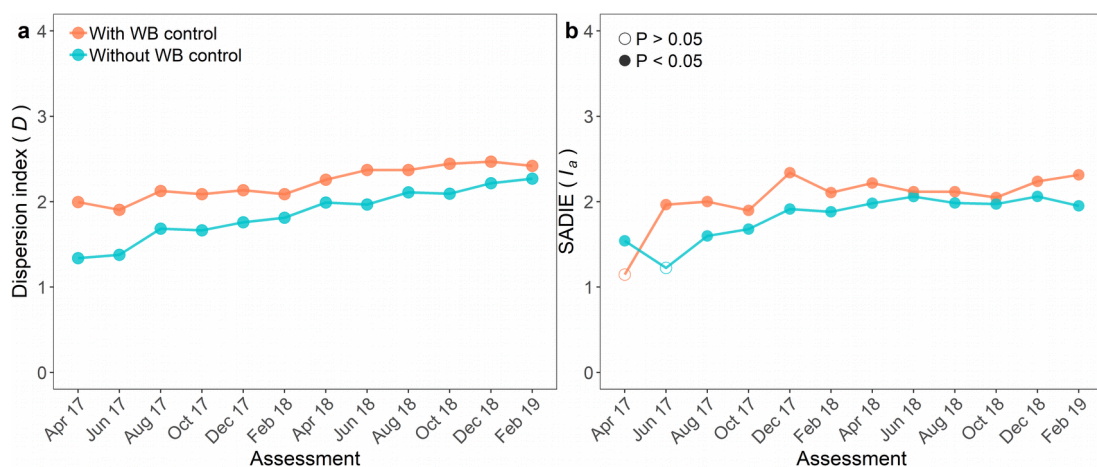
234 Fig 2. Incidence of Fusarium wilt of banana in plots with (a) and without (b)  
 235 management of weevil borer (*Cosmopolites sordidus*, WB) from April 2017 to  
 236 February 2019 (points). Monomolecular model adjusted to incidence data (curves)  
 237 The plots were located in Teixeiras, Minas Gerais state, Brazil. Estimated initial  
 238 incidence ( $y_0$ ), progress rate ( $r$ ) of epidemics and the measure of the quality of the  
 239 adjusted monomolecular model ( $R^2$ ) are presented.

240 Table 1. Summary of statistics used to evaluate the progress of Fusarium wilt of  
 241 banana in two plots, with and without weevil borer management, located in  
 242 Teixeiras, Minas Gerais state, Brazil, from April 2017 to February 2019.

Model	AIC	BIC	logLikelihood	Best adjust / $n$
Monomolecular	-219.95	-213.98	115.98	2/2
Logistic	-137.39	-131.41	74.69	0/2
Gompertz	-153.44	-147.47	82.72	0/2

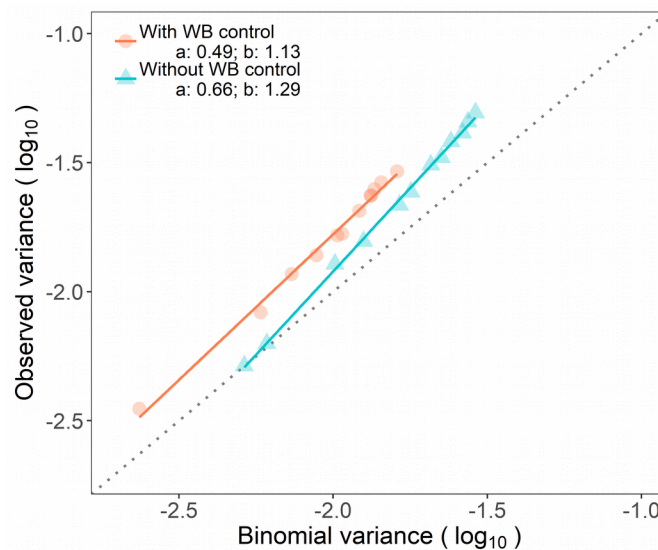
243 AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.

244 Spatial analysis were computed for both plots in quadrat- and distance-based  
 245 methods. FW aggregation was inferred based on dispersion index in all assessments  
 246 in both plots (Fig 3a). Aggregation was lowest in the first two assessments and  
 247 highest in the last. Aggregation was higher in the plot with management of WB and  
 248  $D$  ranged from 1.90 to 2.47 with a mean of 2.23 than in the unmanaged field ( $P <$   
 249 0.001). In the plot without management,  $D$  ranged from 1.34 to 2.27 with a mean of  
 250 1.86 (Fig 4a). Random pattern was detected using *SADIE* in the first two assessments  
 251 only when the  $I_a$  values were low (1.15 and 1.23) (Fig 4b). The highest  $I_a$  value (2.34)  
 252 was observed in the plot with management of WB. The degree of aggregation  
 253 obtained by *SADIE* differed between the plots: aggregation index was higher in the  
 254 managed (2.04) compared to the plot without WB management (1.82;  $P = 0.016$ ; Fig  
 255 4b).



256 Fig 4. Dispersion index ( $D$ ; a) and aggregation index ( $I_a$ ) of Spatial Analysis by  
 257 Distance Indices (*SADIE*; b) of incidence of Fusarium wilt of banana in two plots,  
 258 with and without management of weevil borer (*Cosmopolites sordidus*, WB), from  
 259 April 2017 to February 2019. The plots were located in Teixeiras, Minas Gerais  
 260 state, Brazil.  $P$ -value was represented by empty ( $P > 0.05$ ) or filled ( $P < 0.05$ )  
 261 symbols.

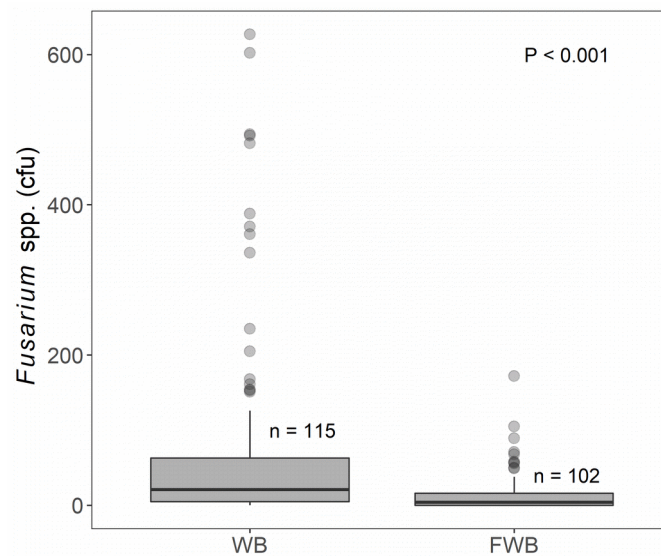
262 Binary power law express the relationship between the logarithm of observed  
 263 variance and logarithm of theoretical variance assuming a binomial distribution, and  
 264 was well adjusted in plots with ( $R^2 = 0.992$ ) and without ( $R^2 = 0.998$ ) WB  
 265 management (Fig 5). Parameters for power law,  $A$  and  $b$ , were significantly ( $P <$   
 266  $0.001$ ) different 1 for both plots. Aggregated patterns that increased with incidence  
 267 were observed.  $\log_{10}(A)$  and  $b$  also differed between plots ( $P < 0.001$ ). The plot  
 268 without WB management had higher degree of aggregation ( $\log_{10}(A) = 0.66$ ) than the  
 269 plot with management and was strongly ( $b = 1.29$ ) affected by the increase of  
 270 incidence over time (Fig 5).



271 Fig 5. Binary power law of successive assessments for incidence of Fusarium wilt of  
 272 banana from April 2017 to February 2019 in two plots, with and without  
 273 management of weevil borer (*Cosmopolites sordidus*, WB). The plots were located in  
 274 Teixeiras, Minas Gerais state, Brazil.

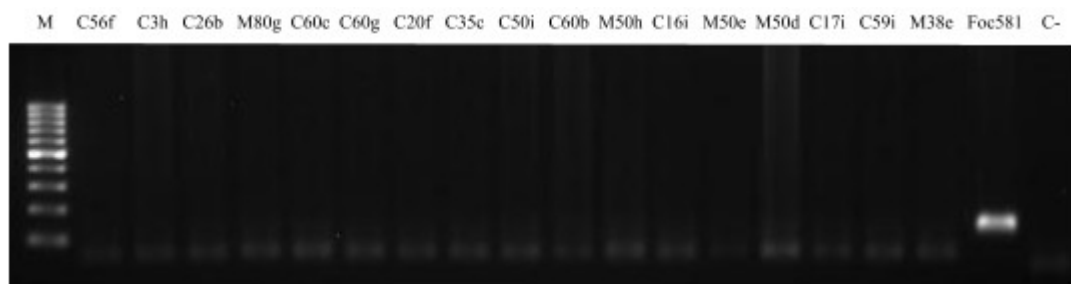
275 **Association between *Fusarium oxysporum* f. sp. *cubense* and weevil borer**

276 A total of 115 WB and 102 FWB were collected from April 2017 to February  
277 2019. All of them were washed and a total of 9,347 colony forming units (cfu) were  
278 formed in selective medium for *F. oxysporum*. Colony forming units were higher in  
279 WB (median = 21) than FWB (4) ( $P < 0.001$ ) (Fig 6).



280 Fig 6. Number of colony forming units (CFU) in selective medium for *Fusarium*  
281 *oxysporum* associated to weevil borer (*Cosmopolites sordidus*; WB) and false weevil  
282 borer (*Metamasius hemipterus*; FWB).

283 From the total colonies observed, 370 subcultures were selected, purified and  
284 analyzed by PCR, but none was *Foc* (Fig 7). Morphological characterization was  
285 performed for 154 strains and 61% ( $n = 94$ ) were classified as *F. oxysporum*.



286 Fig 7. PCR analysis using *Foc*-UFV primers to amplify a conserved region of 122 bp  
 287 of 17 *Fusarium* spp. strains associated with weevil borer collected in fields with  
 288 epidemics of Fusarium wilt. M is a 100pb marker. Lanes 2 to 18 are PCR products  
 289 from weevil borer (*Cosmopolites sordidus*; code starts with C) and false weevil borer  
 290 (*Metamasius hemipterus*; code starts with M). Foc581 refers to a positive control  
 291 (pathogenic strain) collected from diseased plant in the same field and stored at *Foc*-  
 292 UFV collection with code *Foc*-UFV581. Negative control is identified as C-.

## 293 DISCUSSION

294 Currently, there is high interest in the dispersal mechanisms of *Foc* (Dita et  
 295 al. 2018; Ploetz et al. 2015). This information is crucial for management of FW in  
 296 already infested areas as well as for setting exclusion and mitigation actions in  
 297 disease-free fields. The role played by pests that are present in banana fields still  
 298 needs to be elucidated. Epidemiological information can be useful to develop  
 299 management strategies to effectively reduce the spread of *Foc* and reduce the  
 300 damage caused by FW. In this study, two approaches were used to study the role of  
 301 the vector on disease development: a comparative epidemiology study under field  
 302 conditions; and an association study involving the capture of insects potentially  
 303 involved in *Foc* transmission.

304 The management of banana weevil (*C. sordidus*) was performed using *B.*  
305 *bassiana* an entomopathogenic fungus widely used to control banana weevils and  
306 FWB (Akello et al. 2008; Kaaya et al. 1993; Mesquita et al. 1981; Pauli et al. 2011).  
307 The fungus enter the insect through the spiracles, digestive system or insect cuticle  
308 and grows in the haemocoel and muscle tissues, destroys tracheal taenidia and fat  
309 bodies (Kaaya et al. 1993). In both plots, the population of FWB was higher than that  
310 of WB. False weevil borer is considered a secondary pest in banana and other crops  
311 (Fancelli et al. 2012). However, in high population it damages the banana plantations  
312 and management needs to be considered (Fancelli et al. 2012). In this study, the  
313 management did not affect the population of *M. hemipterus* even though many  
314 infected individuals were found in traps after the application of *B. bassiana*. An  
315 abandoned banana plantation close to the plot with management probably masked the  
316 counts of FWB in the traps due to their high mobility. This could have increased the  
317 chance of FWB to be attracted to the pseudostems traps (Dolinski and Lacey 2007).

318 Differences in the dynamic of FW incidence could be seen between the two  
319 plots. The incidence was lowest in the first assessment and increased over time,  
320 reaching up 13% in the plot without WB management and reached 6.7% in the plot  
321 with control of WB. These values can be considered low when compared with  
322 reports in Tanzania and Indonesia where the incidence reached up to 77% and 100%,  
323 respectively (Hermanto et al. 2011; Karangwa et al. 2016). However, the stage of  
324 FW epidemics, cultivars, environmental conditions and cultural practices could affect  
325 the incidence observed. The plots studied were cultivated with a Prata type cultivar  
326 (AAB genome) that shows intermediate resistance to race 1 of the pathogen when  
327 compared to Gros Michel or Silk subgroups. This fact probably reduced the disease  
328 progress (Dita et al. 2018). FW progress was described with the monomolecular

329 model. Differences between the initial incidences were not detected and the disease  
330 rate was higher in the plot with higher population of WB. This fact indicated that the  
331 dynamic of FW epidemics may have been affected by the insect population, probably  
332 acting as dispersal agent or predisposing the banana plants to infection by *Foc*  
333 (Meldrum et al. 2013).

334 Both fields showed an aggregated pattern during the study, but a higher  
335 degree of aggregation was observed in plot with lower populations of WB. Higher  
336 spatial heterogeneity was observed in the plot with management of WB when  
337 compared with the plot without management. The higher degree of aggregation could  
338 be assigned to the plant-to-plant transmission. A diseased plant acts as an inoculum  
339 source to the closest plants, i.e. the neighbours plants. Root-to-root was the main  
340 dispersion way of *F. oxysporum* f. sp. *radicis-lycopersici* in tomato fields (Rekah et  
341 al. 1999). The same pattern was observed by the distance-based method, *SADIE*.  
342 The clusters of diseased plants were closest in WB managed field than in  
343 unmanaged. In addition, the degree of aggregation increased over time showing  
344 higher values in the last assessments for both,  $D$  and  $I_a$ . Initial infections of stem  
345 bleeding disease of coconut palm had a random pattern in the first assessments, but  
346 evolved to aggregated pattern in the last (Carvalho et al. 2013).

347 In the spatio-temporal approach, at low levels of incidence, the plot managed  
348 for WB presented higher aggregation of FW. However, as incidence increases, the  
349 level of aggregation increases at higher rates in the plot without management.  
350 Probably, reducing the population of a potential vector, WB, the pathogen dispersal  
351 at greater distances would be reduced and the nearby plants get infected more easily.

352 It is important to highlight that the behaviour of WB and FWB presented  
353 great differences that can impact the spatio-temporal dynamic of FW epidemics. *C.*

354 *sordidus* adults have limited mobility. Even though they have functional wings, flight  
355 is rare, movement by crawling is limited and attracted by host volatiles (Gold et al.  
356 2001). Unpublished studies performed in Uganda demonstrated that 81% of the *C.*  
357 *sordidus* released moved a maximum of 15 m in six months, and only 3% moved  
358 more than 25 m (Gold et al. 2001). On the other hand, the movement of *M.*  
359 *hemipterus* is much more common, they are good flying insects and are attracted by  
360 wounds and plant debris, but can feed in healthy banana plants in higher populations  
361 (Fancelli et al. 2012; Molet 2013). Although WB had limited movement, differences  
362 in spatial patterns were detected between the two fields studied and could bring new  
363 insights about the impact of these two pests in FW epidemics.

364         In this study a great number of *Fusarium* spp. were externally associated with  
365 *C. sordidus* and *M. hemipterus*. The number of *Fusarium* spp. associated with WB  
366 was higher than FWB. Many species of *F. oxysporum* are soilborne fungi (Leslie and  
367 Summerell 2006) and due to the crawling habit of WB (Gold et al. 2001), soil  
368 particles can easily be found in their exoskeleton. As FWB is a good flier, probably  
369 their movement in soil is not as common as WB (Molet 2013). In this way, it was  
370 expected that WB, at individual level, had higher potential to carry *Fusarium*  
371 propagules than FWB. In addition, it is hypothesized that WB, as larvae have a  
372 preference to feed in rhizome (Gold et al. 2001) while larvae of FWB prefer to feed  
373 in stems or plant debris (Fancelli et al. 2012; Molet 2013), thus the quantity of  
374 *Fusarium* propagules carried by WB may be higher. Further studies needs to be  
375 performed to test this hypothesis.

376         PCR amplifications using *Foc*-specific primers were not positive for any of  
377 the collected and purified *Fusarium* spp. isolates. Meldrum et al. (2013) identified  
378 ten percent of the WB collected in fields with FW epidemics carrying viable spores

379 of *Foc* TR4. *Fusarium oxysporum* f. sp. *cucumerinum* spores were found externally  
380 on the bodies of sciarid and shore flies in concentration that reached up  $1 \times 10^6$   
381 copies per individual artificially infested (Scarlett et al. 2014). The transmission was  
382 confirmed by pathogenicity tests in greenhouse trial (Scarlett et al. 2014). Although  
383 no *Foc* was detected, microscopy analysis identified approximately 61% of the  
384 strains ( $n = 154$ ) belonging to *F. oxysporum* species. The fact that the pseudostem  
385 traps were previously distributed in the plot at random, only one (out of 30) was  
386 ended up placed near to a symptomatic plant. Therefore, the fact that the majority of  
387 traps were located near by asymptomatic plants could have reduced the probability to  
388 associate *Foc* with WB. In addition, less than 4% of the total CFU grown in selective  
389 media for *F. oxysporum* were analyzed by PCR assay or microscopy.

390 This study showed a potential impact of the WB population in the spatio-  
391 temporal dynamic of FW epidemics under field conditions. Fields with lower WB  
392 population presented a more aggregated pattern, demonstrating that dispersal of *Foc*  
393 at greater distances was minimized. *C. sordidus* and *M. hemipterus* were able to  
394 carry viable propagules of *Fusarium* spp. on the external surface of their bodies.  
395 These results may direct new studies to clarify the interaction between *Foc* and their  
396 potential vectors. A better management to FW of bananas depends on the  
397 development of efficient strategies to reduce the dispersal of *Foc* in the fields.

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## GENERAL CONCLUSIONS

Fusarium wilt incidence in Brazil is moderate (~11%) and is higher in fields planted with Silk (14.3%) than Pome (4.4%) and Cavendish (2.7%) subgroups.

The epidemics of FW in Brazil can be considered as monocyclic, develop mostly in an aggregated pattern at small-scale level of observation, but clusters of diseased plants were randomly distributed in most plots. Additionally, FW seems be primarily affected by cultivar, nutritional state of the plants and soil physical factors.

Aerial dispersal of *Fusarium oxysporum* f. sp. *cubense* was confirmed.

Weevil borer (*Cosmopolites sordidus*) and false weevil borer (*Metamasius hemipterus*) can carry propagules of *Fusarium* spp. on the external body surface. Weevil borer affects the spatio-temporal dynamics of FW epidemics. In fields with high populations of the insect, FW epidemics developed at higher rates and aggregation was more evident.