Weather-disease relationships and future disease potential of leaf rust and powdery mildew in Saxony-Anhalt

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Bastian Stößel

Berlin, den 31.03.2015 Bastian Stößel

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1 Introduction

Wheat (*Triticum aestivum*) is one of the most important staple foods worldwide. About 16 % of the calories consumed globally are provided by wheat (Dixon et al. 2009 In: Morgounov et al. 2011). Similar to other crops wheat suffers from a broad range of plant diseases, which limit plant growth and reduce yield. Leaf rust (*Puccinia triticina*) and powdery mildew (*Blumeria graminis* f.sp. *tritici*) of winter wheat belong to the most hazardous global wheat diseases (Oerke 2006, Morgounov et al. 2011) and are responsible for severe crop yield losses (James et al. 1990). Severe leaf rust epidemics occurred in Bulgaria 1932, France 1961, Hungary 1958, Poland 1958, 1959, 1961, Romania 1940, Yugoslavia 1958 (Zadoks 1965), Kansas (USA) 2007 (Bolton et al. 2008), the Netherlands 1981, 1983 (Daamen et al. 1992), Mexico 1976/77 (Dubin & Torres 1981), India 1972, 1973 (Joshi et al. 1980) and showed crop yield losses up to 90 % in some regions.

Powdery mildew is characterized by less epidemic nature, occurs more frequently, and is responsible for a high amount of yield loss every year worldwide (Morgounov et al. 2011). Studies of James et al. (1990) for Great Britain and Ireland from 1970 to 1988, Zadoks & Rijsdijk (1984) covering continental Europe from 1961 to 1970 underline this behaviour. In Germany leaf rust and powdery mildew of winter wheat belong to the most important crop diseases, too. One reason is the area cultivated with winter wheat. One quarter of the arable land is used for wheat cropping (Statistisches Bundesamt 2015). Another reason are the climatic conditions in Germany, which regularly take values around the optimum for the development of both diseases. Meteorological variables like temperature, precipitation, leaf wetness, and radiation, to name just a few, play an important role for the development of plant pathogens under field conditions (Colhoun 1973). The influences can be divided into directly accelerating or inhibiting weather factors and indirect effects of weather and weather periods on the host plant, serving as nourishment for the pathogens.

Despite their importance the factors influencing the incidence and severity of both agricultural diseases are not sufficiently studied yet. Especially the influence of weather, weather periods, climate, and their respective changes on the incidence and severity of both diseases lack profound knowledge. Because of the scarcity of long-term monitoring data for agricultural pathogens (Coakley 1988, Hodson 2011) most of the recent studies are based on experiments under artificial conditions. Unfortunately, such experiments can not replicate the complex environment-host-pathogen system and thus concentrate on describing and exploring idealized parts of single system components. In addition, the relationships discovered by laboratory studies are the basis for most of the models simulating disease development and disease pressure (Waggoner 1974, Teng 1985, Campbell & Madden 1990). For the modelling of leaf rust infestation of wheat, many different empirical and simulation attempts already exist (Chester 1946, Burleigh et al. 1969, Dirks & Romig 1970, Burleigh et al. 1972a, Burleigh et al. 1972b, Daamen 1991, Daamen et al. 1992, Eversmeyer & Kramer 1996, Rossi et al. 1997, Eversmeyer & Kramer 1998, Moschini & Pérez 1999, Sache 2000, Räder et al. 2007, Franke et al. 2009, Wiik & Ewaldz 2009, Richerzhagen et al. 2013). The same applies to powdery mildew of wheat (Aust 1981, Daamen et al. 1992, Friedrich 1994, Te Beest et al. 2009, Wiik & Ewaldz 2009). But for powdery mildew the infestation of barley was emphasized more often (Polley & King 1973, Channon 1981, Channon 1983 (In: Jones & Clifford 1983), Aust et al. 1983, Stephan 1984, Hau 1985, 1988, 1990, Gutsche et al. 1986, 1987, Gutsche 1987, Kluge et al. 1989, Frahm & Volk 1993, Bruns 1997, Rossi & Giosue 2003).

In the course of projected climatic changes in the coming decades the weather conditions influencing development and occurrence of both diseases will change, too. Thus, plant diseases will develop better or worse in the future, increasing or decreasing the damage caused by them, respectively. But, most of the studies projecting the occurrence of leaf rust and powdery mildew of wheat under changing climatic conditions are based on speculation, incorporate empirical equations developed from studies under artificial conditions, or were not validated (Juroszek & von Tiedemann 2013). For Germany only very few studies concerning the occurrence of leaf rust and powdery mildew of winter wheat under changing climatic conditions exist (Jahn et al. 1996, von Tiedemann 1996, Volk et al. 2010, Racca et al. 2012, Bregaglio et al. 2013). Only one study (Jahn et al. 1996) worked with empirical data from field trials and none utilized empirical models that ran through a validation process.

2 Aims of the Study

This study will identify knowledge gaps regarding climatic influences on leaf rust and powdery mildew of winter wheat in Germany. To fill the gaps analysis of relationships between meteorological variables and plant disease incidence are conducted for a selected study region.

The federal state of Saxony-Anhalt is selected as the study region because monitoring data for both diseases for a time frame of 34 years, at 20 to 30 monitoring locations per year are available. It represents a unique data collection for Germany regarding spatial and temporal resolution.

The main aims of this work are the quantification of the influence of meteorological variables on the occurrence of leaf rust and powdery mildew of winter wheat and the projection of the results into the future using climate simulations.

In a first step the influence of meteorological factors on leaf rust and powdery mildew occurrence during the most vulnerable phase of wheat development in Saxony-Anhalt will be identified. Therefore a database of long-term monitoring data for disease occurrence of both pathogens is build. Relationships between single meteorological variables and disease occurrence are studied by using a shifting windows correlation approach.

As the second step the database will be utilized to calculate regression models to quantify the influence of combinations of meteorological variables on the incidence of both plant diseases. To account for non-climatic variables having a significant impact on disease occurrence, soil, crop, and cultivation specific variables are analysed and, if applicable, included in the model building process. The models are extensively validated by a nested cross-validation approach to guarantee adequate prediction accuracy.

The resulting empirical disease models will then be fed with climate scenario data derived by a statistical climate model, to generate scenarios for future disease occurrence under changed climatic conditions. These scenarios may be an important component for disease control strategies in the framework of an integrated pest management.

The results of this work can be helpful for analysis of climatic impacts on other plant diseases and/or other regions in Germany.

3 State of Research

3.1 Biology of leaf rust and powdery mildew of wheat

3.1.1 Biology of *Puccinia triticina*

Leaf rust of winter wheat is an obligate biotroph parasite belonging to the class *Basidiomycetes* and needs an alternate host to complete its complete sexual developmental cycle with 5 spore types. Alternate hosts can be species of the genus *Isopyrum*, *Thalictrum*, *Anchusa* and *Clematis* (Chester 1946, Zadoks 1965, d'Oliveira & Samborski 1966, Roelfs & Bushnell 1985, Samborski 1985, Leonard & Fry 1986, Bolton et al. 2008, Bockus et al. 2010). But the importance of alternate hosts for epidemic development of leaf rust infection is heavily debated. Referring to Roelfs & Bushnell (1985) the sexual reproduction of leaf rust on alternate hosts is not of great importance for the evolution of new leaf rust races. Because of the small abundance of alternate hosts and results from molecular genetics, Kolmer (2005) states only small importance of the sexual reproduction cycle for dissemination and genetic heterogeneity of the pathogen. However, alternate hosts play an important role in surviving, when the primary host *Triticum aestivum* (wheat) is not available during the vegetation period. Therefore the pathogen evolves sperms and aecidiospores to assure surviving on the intermediate host. But overwintering of spores on the primary host is also possible. To build up a part of the inoculum in spring of the next season teleutospores, forming basidiospores, can be developed, but during mild winters urediniospores are the main survival mechanism (Roelfs & Bushnell 1984).

Overwintering urediniospores, which are very important for an epidemic development of leaf rust infestation (Hogg 1969), occur in all European countries (Zadoks 1965). When temperature increases during spring the development of *P. triticina* accelerates and the polycyclism of the fungus shows its advantages. With higher temperatures the monocycles are evolving faster, latency and infection times become shorter. Urediniospores landing on a suitable host plant under suitable conditions build a germ tube, which searches for suitable locations to infiltrate the host and evolves an appressorium if such an infiltration point has been found. After several hours with suitable microclimatic conditions a penetration hypha is built to infiltrate the leaf. Stomata play an important role as suitable infiltration points. The next step of the infection process is the establishment of a network of fungal mycelia inside the leaf. Haustoria grow inside host cells and represent the knots of a network delineating the food structure of the fungus (Bolton et al. 2008). Uredinia, which produce urediniospores, are built by mycelia 7 to 10 days after the infection. The building of uredinia is an important stage of leaf rust development. They are the only structures visible from outside the plant and the symptom that is recorded by disease assessments. After ripening urediniospores are released by uredinia and transported to other hosts for infection. With liberation and transport of urediniospores the monocycle of the asexual leaf rust reproduction is completed. One monocycle lasts from inoculation until liberation of the new generation of urediniospores, called latency, and takes 10 to 14 days on average (Stubbs et al. 1986, Wójtowicz 2007). Latencies of 7 to 17 days are not uncommon (Eversmeyer et al. 1980).

Infection time, incubation time, latency, infection, germination, ripening, and liberation are factors which strongly depend on temperature and moisture conditions.

The short latency enables leaf rust to pass through multiple monocycles per vegetation period, which is called polycyclism, and grants an enormous epidemic potential under extremely favorable weather periods, causing great damages on wheat plants and yield losses over 50%. Epidemics shortly before or during anthesis can cause the highest yield losses (Bockus et al. 2010), because, the maximum infestation by leaf rust of winter wheat occurs during anthesis (BBCH stages 60 to 70). After its maximum, infestation drops quickly due to missing host plant material after harvest and temperatures exceeding the optimum for leaf rust. The remaining leaf rust individuals struggle to survive summer on volunteers or weeds until the emergence of newly sown wheat during autumn. The more individuals survive summer, the bigger the potential threat of yield loss during the next season (Eversmeyer & Kramer 2000).

3.1.2 Biology of *Blumeria graminis* f.sp. *tritici*

Powdery mildew of winter wheat is an obligate biotroph parasite, too. During most parts of the vegetation period powdery mildew reproduces asexually (imperfect phase) by conidia (Spencer 1978). After the deposition of conidia on the leaf surface of the host the germ tube is being built to search for suitable infiltration points. If the plant is compatible an appresorium is formed as soon as a penetration point is found. Through an enzymatic reaction with the cuticle of the host, the penetration hyphe later mechanically infiltrates the leaf to form a haustorium between the leaf cells. As already described for leaf rust the haustorium is responsible for the nutrition of the fungus by taking in nutrients from surrounding cells (Bélanger et al. 2002). After the formation of a network of haustoria inside the leaf conidiophores are built to produce new conidia for reproduction and dissemination of the parasite. After ripening the conidia can be released from the conidiophore by vibrations or wind and disseminate. One monocycle of *B.graminis* takes between 4 and 28 days according to Friedrich (1994). Temperature and humidity play a major role for all developmental stages of the monocycle.

B.graminis has a sexual reproduction cycle (perfect phase), too (Spencer 1978). Within this cycle a cleisthotecium, the main fruit of the fungus, which is responsible for producing ascospores, is built. The sexual cycle is important to guarantee the long term survival of the pathogen by overcoming resistances of host plants and developing resistances against fungicides. However, the importance of the sexual reproduction cycle of powdery mildew of winter wheat for the epidemic development of the pathogen is considered low (Yarwood 1957).

Periods without living plant material of the primary host are very important for an epidemic development of *B.graminis*. The fungus reaches its developmental minimum during high temperatures after harvesting during summer and very low temperatures in winter. Powdery mildew has to survive these periods as cleistothecium (Moseman & Powers 1957), fungal mycelium (Cherewick 1944), or conidium - the most important survival mode from an epidemiological point of view (Johnston 1974) – because it does not have a specialized survival form (sclerotia). Thus, volunteers and weeds are very important for powdery mildew populations to survive the summer months (Bélanger 2002). There is a higher infection potential for newly sown wheat in autumn, if large amounts of conidia survive during summer. If more conidia survive winter, more initial inoculum is available resulting in a higher infection potential in early spring.

3.2 Climatic influences on leaf rust and powdery mildew of wheat

The influence of environmental factors on the development of plant diseases has been known for a long time. The history of knowledge and investigations regarding the influence of environmental variables on plant disease development from ancient times until the 1950s is summarized by Colhoun (1973). Theophrastus (370-286 BC) was the first who speculated that weather conditions are influencing the occurrence of cereal rust diseases. It took about 2000 years until researchers (Berkeley 1846, de Bary 1861) accepted the existence of fungi as autonomous microorganisms for the first time and recognized them as the cause of many plant diseases. Plant pathogens were still a mystery when potato blight caused the Irish potato famine in 1845 resulting in immigration of Irish people to the United States. The same disease caused an epidemic in Europe 1918 and directly influenced the course of World War I, but knowledge of key factors influencing the disease was still scarce. After World War II studies targeting this topic increased. A summary of studies analyzing the climatic requirements and conducting statistical analyses on the influence of meteorological variables on leaf rust and powdery mildew will follow within the next sub-chapters

3.2.1 Climatic requirements for the asexual development of *P. triticina*

The influence of weather and weather periods on the development of leaf rust of winter wheat is well known. Books and review articles summarizing the most important findings from laboratory and climate chamber experiments are Chester (1946), Hassebrauk (1959), Zadoks (1965), Roelfs & Bushnell (1984) and Roelfs & Bushnell (1985). Temperature and moisture conditions are the most important variables for most of the developmental sub-processes. This chapter will start with summarizing the climatic influences on the infection process and end with the liberation of the ripened spores.

Wind systems play an important role in the short distance and large scale spread of the pathogen (Hassebrauck 1959, Sache 2000). The North African - European and the North American leaf rust pathways were described by Zadoks (1961), Hirst et al. (1967a, b) and Hogg (1969).

The urediniospores of leaf rust germinate at temperatures between 2 and 31°C with „good“ germination rates between 10 and 28°C (Asuyama 1939, Hassebrauk 1959, Givan & Bromfield 1964). The same authors mentioned optimal germination of urediniospores at a temperature of 20°C.

Experiments under field conditions showed, that low temperature during winter and spring limits germination stronger than high temperature in summer. Further results of Eversmeyer & Kramer (1994) unveiled, that 50% of the spores are still able to germinate after 120 hours under environmental conditions in autumn, 60% under summer conditions, only 10 to 20% in spring, and during winter no viable spores were left after 96 hours at temperatures under 0°C. The optimum of the germination rate appeared after 120 hours with 30°C. In comparison, the germination rates dropped drastically at 5°C and only a little at 35°C. In addition, the germination of urediniospores can be hindered and even inhibited by strong precipitation events washing the spores off the leaf surface (Sache 2000).

After germination the pathogen has to penetrate the leaf to build up its nutrition structures. Asuyama (1939) and Givan & Bromfield (1964) identified the optimum temperature of the penetration process being 20°C. After penetrating the leaf appressoria are built. Eversmeyer & Kramer (1994) revealed that more appressoria were built at 5°C compared to 10, 20, 30 and 35°C after 120 hours.

Concerning the time frame between infection and development of appressoria 3 to 6 hours at 15 to 25°C or 8 to 13°C, respectively, are required (Asuyama 1939). 3 to 6 hours at 15°C or 9 hours at 13°C are needed between infection and penetration of the leaf. The time needed for leaf infection decreases from 9 to 3 hours, if the temperature rises from 8 to 13°C up to 23°C. The optimal temperature for the general infection process differs between 18 to 25°C (Asuyama 1939) and 15 to 18°C (Straib 1940).

Regarding the length and optimal conditions of the latency period many differing results are present in literature. Obst & Paul (1993) present a value of 140 degree days. Eversmeyer et al. (1980) describes latencies between 157 and 500 hours at temperatures between 10 and 32.2°C, with the shortest latency at 26.7°C. The same optimal temperature was found by Tomerlin et al. (1983) on infected seedlings. For host plants infected during heading or anthesis latency gets shorter with rising temperature. The infection periods at 25°C are significantly shorter than at 10 to 20°C. For the amount of uredinia per square centimeter Eversmeyer & Kramer (1994) identify a maximum at a temperature of 20°C lasting 120 hours. At 5°C and 35°C the amount is considerably lower. Zadoks (1965) shows an optimal temperature of 25°C and urediniospore growth times varying between 6 and 60 days for a temperature range of 2 to 35°C. For the overall development of leaf rust nights with a temperature between 15 and 22°C and a leaf wetness period of at least 4 hours are optimal (Heitefuss et al. 1993, Obst & Paul 1993). Sunny days with 20 to 25°C have a beneficial effect on the development, too (Prigge et al. 2005).

3.2.2 Climatic requirements for the asexual development of *B. graminis* f.sp. *tritici*

This sub-chapter reviews knowledge on meteorological influences on the infestation of wheat plants by powdery mildew in general and on sub-processes of fungal development, starting with the infection process and ending with the liberation of the ripened spores.

The influence of temperature and moisture conditions in particular on the development of powdery mildew of wheat is well known. Scientific results of laboratory studies and experiments under artificial conditions focusing on the influence of meteorological variables on subprocesses of powdery mildew infestation on wheat plants are summarized in the articles of Spencer (1978), Friedrich (1994), Merchan-Vargas (1984), Yarwood et al. (1954), Braun (1995), Bélanger (2002) and Te Beest et al. (2008) and sometimes are blended with own results. Some of the results for other *formae specialis* of powdery mildew of cereals can be transferred to powdery mildew of wheat, because the fungi behave similar to meteorological influences (Friedrich 1994).

The flight of powdery mildew conidia is increased on days with maximum temperatures over 15.6°C, more than 5 hours of sunshine, less than 1mm of precipitation, and mean wind speed exceeding 2.85m/s (Polley & King 1973). For the infection process Pratt (1943), Cherewick (1944) and Arya & Gemawat (1953) identified a temperature interval of below 0°C to 40°C where infection is possible and Hammarlund (1925) and Cherewick (1944) determined an optimum between 15 and 20°C.

Germination of conidia was detected between 0 and 35°C by Cherewick (1944), Yarwood et al. (1954), Jones & Clifford (1983) and Wiese (1987). Results for optimal germination temperature vary strongly at values between 6°C (Cherewick 1944) and 17°C (Yarwood et al. 1954). More general results for the order *Erysiphales* presented limiting temperatures for the germination of conidia between 2 and 4°C for the minimum and 30 and 35°C for the maximum, with optimal conditions between 11 and 28°C (Yarwood 1957, Blumer 1967). Grainger (1947) and Nour (1958) added studies about the influence of moisture conditions on germination. They found out that more than 85% relative humidity were needed for germination. An optimum of 100% was determined by Manners & Hossain (1963), Jiafeng et al. (1976, cited in Merchan Vargas 1984) and Cherewick (1944). Further study results regarding moisture and germination of conidia were summed up by Friedrich (1994).

Studies about the influence of temperature on germ tube growth showed similar results. Minimum temperatures were identified at -2°C (Pratt 1943) and 0°C (Prabhu et al. 1962), respectively, maximum temperatures at 30°C (Pratt 1943) and 32°C (Graf-Marin 1934), and optimum temperatures between 20 and 25°C (Prabhu et al. 1962, Pratt 1943, Yarwood et al. 1954). Nour (1958) and Manners & Hossain (1963) found out that germ tube growth is supported by high atmospheric moisture contents with a remarkable germ tube growth over 98% and an optimum at 100% relative air humidity. For the

development of appressoria the same authors determined 98% relative humidity to be the minimum requirement for the process.
Under optimal conditions between 15 and 20°C the incubation time of powdery mildew lasted three days (Müller 1988, Last 1963) and was prolonged to 17.5 days with temperatures decreasing to -2°C. The latency was about 3 to 4 days under optimal conditions and prolonged to 9 to 10 days when temperatures decreased to 10°C and up to 28 days at -2°C (In: Friedrich 1994).
Conidia develop and sporulate at temperatures between 5 and 28°C (Prigge et al. 2005, Obst & Paul 1993). Conditions are optimal between 20 and 21°C (Last 1953, Aust 1973, Pauvert 1976, Stephan 1980, Aust 1981, Dutzmann 1985). Müller (1988) mentioned lower temperatures between 15 and 20°C as the optimum for both processes. Moisture conditions for both processes were optimal between 90 and 100% relative humidity according to Ward & Manners (1974) and Prabhu et al. (1962).
Aust (1981) found out that spores of barley powdery mildew built at temperatures between 18 and 22°C were showing the highest germination and infection potential. Infectivity declined slowly at lower temperatures above 10°C and more rapid at higher temperatures above 22°C. Spores built at a temperature of 25°C inherited only 10% of the germination and infection potential compared to spores built at 20°C (Ward & Manners 1974).
The development of *B. graminis* f.sp. *tritici* progressed between temperatures below 2°C and 30°C (Pratt 1943). Temperature was optimal around 20°C with differing values of 20°C (Pratt 1943), 21.5°C (Kocourek & Vechet 1984), and 15 to 20°C (Heitefuss et al. 1993, Hammarlund 1925). Bouma (2008) described the optimal conditions for powdery mildew being unstable and cloudy weather in May. Prigge et al. (2005) added temperatures between 18 and 22°C, high relative humidity, and alternating warm and moist days.

3.2.3 Statistical approaches for analyzing climatic impacts on the development of *P. triticina*

Numerous statistical and mathematical approaches have been used to model leaf rust infection of wheat plants. Some of these approaches dealt with modeling leaf rust infections statistically, ignoring climatic influences. These approaches were important to understand the nature of leaf rust epidemics, but won't be listed in detail, because they are not important in the framework of this essay. Most of the statistical approaches dealing with climatic influences on leaf rust modeled specific sub-processes of the infection process under the influence of changing climatic conditions, e. g. temperature, precipitation, wind speed, or at specific growth stages of the host plant. Some of the models were created for a better understanding of the influence of changing environmental variables on leaf rust development and others for short- to medium-term predictions. The most important studies worth mentioning are the studies of Eversmeyer, Kramer, and Burleigh, who built statistical models for leaf rust prediction for the United States wheat belt. In this sub-chapter the most important studies concerning statistical and mathematical modeling approaches for leaf rust will be summarized in chronological order, beginning with the oldest studies.

First findings from statistical analysis of climatic influences on the incidence of wheat leaf rust were summarized by Chester (1946) and blended with his own results. Chester created the theory of the critical month. His results indicated that weather conditions in March with average daily temperatures exceeding 10°C were crucial for the reactivation of dormant uredinia supporting the spread of leaf rust in spring. The works of Chester (1946), Bryzgalova (1937), and others were summarized in a report of the „World Meteorological Organisation“ (Hogg 1969).

Eversmeyer & Burleigh (1970) worked on a linear model to predict leaf rust incidence on wheat in the United States. They used maximum and minimum temperature, precipitation and free moisture per day from a time interval between 8 and 14 days before disease assessment. Burleigh et al. (1972a) created statistical models to analyze dependencies between leaf rust incidence and crop yield. Burleigh et al. (1972b) built a linear model to predict leaf rust of winter wheat 7 to 30 days in advance. They found out, that heat accumulation estimated from the days with base temperature above 12°C and relative humidity over 70% without precipitation were good indicators. Furthermore, incidence increased when the amount of days with average temperature between 12 and 18°C and relative humidity over 49% increased during spring.

For leaf rust intensity on wheat in May (around the beginning of stem elongation and 1 to 2 nodes visible) and July (milky ripe) Daamen et al. (1992) developed statistical models. Disease prevalence measured in July was positively influenced by March temperatures and the amount of precipitation during April and May. An early onset of spring was more important for leaf rust epidemics than mild temperatures during winter.

In another study, Eversmeyer & Kramer (1996) focused on the overwintering of urediniospores using statistical models. They found out that minimum temperature in

August had a negative influence and minimum temperature in March and snow cover during February a positive impact on inoculum levels at mid-March. Snow cover in December showed the strongest positive relationship with overwintering inoculum. In addition, the authors modeled inoculum levels in September, October, November, December, January, and February and found out that precipitation anomalies in July were an important predictor. This underlined the importance of moisture at the time of the emergence of volunteers and its significance for the amount of inoculum available at the beginning of the next vegetation period.

The only study using German leaf rust data was conducted by Jahn et al. (1996). They used correlation and simple regression analyses to measure the influence of mean annual temperature and precipitation sums of spring and summer on leaf rust infestation. They identified temperature having a positive and precipitation a negative effect on infestation. The study of Eversmeyer & Kramer (1998) supported the theory of the importance of winter temperatures on the overwintering of leaf rust urediniospores. They revealed that warmer winters allowed inoculum to survive until early spring, which gave leaf rust an early start into the growing season. Exogenous inoculum was needed to increase the population in spring. After a very cold winter less inoculum survived and the number of generations built during the vegetation period was reduced by four, which resulted in varieties of medium resistance to escape epidemic infections. Furthermore, cold and moist conditions during fall foster the emergence of volunteers and the time infected leaves remained attached to the host plant. This led to more infections on volunteers and early sown wheat and increased the inoculum potential for the next year.

Moschini & Perez (1999) used linear regression to model the maximum leaf rust intensity on wheat plants at 4 stations during 22 years in Argentina. In their analyses they incorporated early and late sown wheat as well as a resistance index. For early sown wheat they determined cumulative degree days for base temperatures 11, 12, and 18°C at a relative humidity over 50%, days with less than 0.2 mm precipitation, relative humidity over 70%, and the resistance index as the most influential factors. For late sown wheat the degree of explanation of the meteorological variables decreased. The degree of explanation of the resistance index increased. Overall their results confirmed those of Chester (1946). Temperatures between the emergence of the first leaves on the host plant and the end of tillering played an important role for inoculum production.

Mahir (2000) used data of two vegetation periods for uni- and multivariate linear regression models to study the influence of meteorological variables on leaf rust severity.

He determined relative humidity, hours with relative humidity over 80%, and maximum temperature as the most important factors.

A similar study using correlation analyses, simple and multiple linear regression models was conducted by Wiik & Ewaldz (2009). The authors studied the influence of monthly temperature means and precipitation sums on the incidence and severity of leaf rust of winter wheat between 1983 and 2007 in southern Sweden. Their correlation analyses and simple linear regression models showed that January and April temperatures had a positive influence on disease incidence during anthesis and milky ripe (GS 65 to 75). Precipitation of December and July had a positive influence on severity at maximum attack. The multiple linear regression model revealed a positive influence of April and February temperatures and a negative influence of March precipitation on incidence at GS65.

Further studies were conducted under more special conditions and used a smaller database compared to those summarized above. Jaczewska-Kalicka (2007) and Vechet (2003) compared time series of weather and disease occurrence of leaf rust in Poland and the Czech Republic, respectively. They identified the average temperature in June and the number of days with maximum temperature over 25°C during the second and third week of June having a significant impact on leaf rust severity. Kolesnikov et al. (2009) used correlation analyses to identify meteorological important months for leaf rust development on wheat. They found out that temperatures in January, April, June, July, and October had a positive correlation and precipitation in December, January, and June a negative correlation with disease development.

3.2.4 Statistical approaches for analyzing climatic impacts on the development of *B. graminis* f.sp. *tritici*

Compared to leaf rust only few statistical modelling approaches exist for studying climatic impacts on powdery mildew of winter wheat. The most important studies are Daamen et al. (1992), Vechet (2003), Jaczewska-Kalicka (2007), Te Beest et al. (2008), Kolesnikov et al. (2009), Wiik & Ewaldz (2009), and Cao et al. (2012). Additionally, the results of studies concerning powdery mildew of barley (Polley & King 1973, Aust 1981, Stephan 1984, Lindner 1989) can be transferred to powdery mildew of winter wheat, because of the similarities of both subspecies (Friedrich 1994, p.10). The results of Sache (2000) can be transferred to powdery mildew, too. He studied the influence of wind on the dispersal of fungal spores utilizing statistical methods.

The first memorable study was conducted by Polley & King (1973) and dealt with the identification of logical rules explaining the amount of powdery mildew spores in the air in dependence of meteorological factors. The critical values for the logical rules were maximum temperature over 15.6°C, precipitation sum below 1mm, sunshine duration above 5 hours, and wind run above 246 km. Maximum values of spore numbers were detected, when all criteria were met on one day, three criteria on two consecutive days, or two criteria on three consecutive days.

Aust (1981) used climate chamber experiments in combination with field data to identify critical values for powdery mildew development. He analyzed the field data statistically and compared the results with those of the laboratory part. The study identified the influence of temperature, relative humidity, precipitation, sunshine duration, and wind speed as important variables for powdery mildew development on barley. The fungus showed compensation effects under unfavourable developmental conditions. Two other studies dealing with the development of powdery mildew of barley using field data were conducted by Stephan (1984), Lindner (1989), and Kluge (1990). Simple linear and quadratic regression models revealed a positive impact of temperature on the reproduction rate of the fungus (Stephan 1984). Lindner (1989) compared weekly disease incidence with temperature and host plant development in a qualitative analysis. Kluge (1990) identified precipitation during April and May to hamper powdery mildew development.

The study of Jahn et al. (1996) utilized German disease data, too. They used similar methods for powdery mildew and leaf rust and identified temperature and precipitation having a negative impact on mildew infestation.

Daamen et al. (1992) did a thorough study of the impact of meteorological variables on severity and incidence of powdery mildew of winter wheat. They used linear regression models and correlation analyses and integrated a resistance index to represent the resistance characteristics of the varieties used as an additional independent variable for the regression equations.

Vechet (2003) analyzed the influence of weather on powdery mildew. He did not observe significant influences of weather variables. Jaczewska-Kalicka (2007) observed that years with higher rainfall amounts between April and July resulted in a higher powdery mildew severity.

Te Beest et al. (2008) used a combined approach to analyze weather-disease relationships. The authors identified weather variables important for the occurrence of a damaging epidemic using discriminant analyses. In case of a damaging epidemic they estimated the severity of the epidemic separately by utilizing correlation analyses in combination with a window-pane approach. In the following step they built linear regression models to quantify the impacts of different weather variables. The number of days with more than 200 km of wind run between December and March, the number of days with a maximum of 2 hours of sunshine, and radiation accumulation at temperatures below 4°C between January and March lower the possibility of a damaging epidemic to occur. The number of consecutive days with a minimum of 95% humidity, rain accumulation above 10 mm, and the number of days with maximum temperature of 20°C or above between April and mid June held positive correlations with disease severity in case of a damaging epidemic. Kolesnikov et al. (2009) found out that mean temperature between October and January and mean monthly temperature in April were negatively correlated and May temperature positively correlated with powdery mildew development by using correlation analyses. Precipitation sums of December and January had a negative correlation with powdery mildew development.

In the study of Wiik & Ewaldz (2009) correlation and linear regression analyses were conducted to identify the impact of monthly weather variables on powdery mildew incidence and severity. They revealed that mildew incidence at growth stage (GS) 65 (mid anthesis) was positively correlated with August temperature and negatively with January temperature. Mildew severity at maximum attack showed a positive correlation with September temperature.

In a recent study Cao et al. (2012) performed correlation and regression analyses to identify meteorological variables influencing conidia concentrations of powdery mildew in the air on a daily basis. They identified a positive influence of temperature and radiation and a negative impact of wind speed and vapour pressure deficit on conidia concentrations. In addition, high temperatures lowered conidia concentrations in some years.

3.3 Non-climatic influences on the development of leaf rust and powdery mildew

Along with climatic factors non-climatic influences have a reasonable impact on plant disease development. They can be classified as factors modifying the crop, the pathogen development, or the environment (Krupinsky et al. 2002). But influences on diseases are hard to classify into those three categories, because some of them impact diseases in more than one way.

The resistance of wheat represents the most important factor for disease development by modifying the host. Partial resistances of wheat varieties to leaf rust and/or powdery mildew hinder the establishment of fungal structures inside the leaves and thus reduce disease incidence and severity. But genes responsible for the resistance of a wheat variety may only work in a specific temperature range (Leonard & Fry 1989). Furthermore, incidence and severity of both diseases are influenced by factors modifying the pathogen abundance, e.g. crop rotation in general and the preceding crop specifically. Crop rotation is a classical method to reduce the severity of diseases by rotating to non-host crops for the pathogen. Without suitable host material leaf rust and powdery mildew lack their basis for survival and nutrition and thus can not retain nor increase their population anymore. Some preceding crops support the abundance of bacterial or other pathogenic populations by inducing susceptibility for specific pathogens like powdery mildew on the subsequent crop (Newton et al. 2004). In addition the preceding crop influences the planting and harvesting dates of the subsequent crop and thus modifies the time available for an accumulation of inoculum in the subsequent crop. Sugarbeet for example is harvested late, thereby postponing the sowing of wheat and hampering powdery mildew development (Kluge 1990).

Another important factor is the canopy architecture of the wheat variety chosen to be sown. Recent studies assigned the canopy architecture an important role and presented ways to reduce pesticide usage by manipulating the plant canopy. In addition, canopy architecture impacted the senescence of plant tissue and thereby modified tissue receptivity to infection (Tivoli et al. 2012). But research on the influence of faster senescing leaves on disease development is only at the beginning. Furthermore, the development of the plant canopy has a strong impact on micro-climatic conditions in the crop stand by altering humidity and temperature below the canopy (Russell et al. 1989). The micro-climate is important for disease development during most developmental stages of the host plant. Another factor influencing in-field micro-climate and disease development is the stand density (Werner 1992). In crops sown with a higher stand density the temperature is higher, because of the reduced exchange with atmospheric layers above the canopy. In contrast, it can be lower, because of reduced insolation. In addition, higher air humidity may be present, because of reduced insolation leading to less evaporation.

Stand density is predefined by the distance between seed rows and can additionally be influenced by fertilization. Koch (1991) showed that the use of organic instead of mineral fertilizer lowered the stand density and thus powdery mildew severity.

More influences modifying the environment for the disease are cultivation practices, the application of nutrients (e.g. N, S, P, Ca), growth regulator, and fungicides. Chemical synthetical fungicides are often developed to prevent disease development of a specific disease on the plant, to reduce the impact of the disease, or to reduce the impact of multiple diseases on the crop. Biological fungicides serve the same purpose but with a different mode of action. For example micro-organisms of the *Streptomyces* species were identified having an antifungal effect on wheat leaf rust (Yi et al. 2004). Growth regulators are influencing the developmental speed of the host plant and thereby modify the micro-climate inside the stand. Additionally, the regulator disturbs the synchrony between host plant growth and disease development and thus may hamper the latter one. The application of nutrients as fertilizer has a considerable impact on disease development. The influence of different nutrients on plant disease development was reviewed by Dordas (2008).

Especially the influence of nitrogen fertilizer on powdery mildew incidence and severity was an often discussed topic in agricultural literature. Several studies showed that higher N supply increased the severity and incidence of powdery mildew (Kluge 1990, Kádár et al. 1999) by decreasing the resistance of the host plant (Kiraly 1976, In: Wiese et al. 2003). Besides powdery mildew leaf rust intensity was enhanced by higher N rates, too (Krauß 1969, Howard et al. 1994). But the effect of N applications depended on the timing. N applicated late in the growing season had only a reduced effect on powdery mildew development. Olesen et al. (2003) identified a split of the N application being the best strategy, promoting the tillering and development of the crop canopy at an early point in time, but reducing the beneficial effect for powdery mildew at the same time.

No consistent results are presented in the literature regarding the influence of K supply on the development of powdery mildew. High K supply hampered the development of leaf rust on wheat (Krauß 1969) and hindered powdery mildew under specific soil conditions (Kádár & Elek 1999, Kádár et al. 1999, Brennan & Jayasena 2007) and by increasing resistance (Dordas 2008). Another nutrient influencing powdery mildew development on wheat was sulphur. Hussain & Leitch (2005) found out that S applications reduced powdery mildew severity on wheat ears by delaying senescence and extending green leaf duration.

The studies mentioned underlined the importance of nutrients for plant diseases in general and leaf rust and powdery mildew of wheat specifically. However, the nutrient supply of wheat plants can not only be modified by nutrient applications. It also depends on the nutrients supplied by the soil beneath the crop, which is characterized by a specific soil type and structure. The influence of different soil types and structures on powdery mildew development was studied by Kluge (1990). The properties of the underlying soil can be modified by cultural practices, for example the addition of straw and manure to the soil (Rodgers-Gray & Shaw 2000). Under high disease pressure straw addition reduced powdery mildew and leaf rust incidence. The addition of manure decreased leaf rust incidence by increasing the resistance of the host plant against the diseases. The exact mechanism is not sufficiently studied yet, but silica levels in the plants may play an important role. Rodgers-Gray & Shaw (2004) observed reduced powdery mildew occurrence on plants treated with silicon on two different soils and related the effect to increased plant resistance to the disease. The additional silicon acted as a barrier inside the leaves against the penetration by the pathogen. Similar results were obtained by Aust (1981), who observed that age-related resistance manifested itself as a silification of epidermal cells and an increased number of stomata on the upper two leaves.

The influence of tillage practices on disease development is unclear. Charles et al. (2011) did not detect an influence of tillage on leaf rust and powdery mildew. In contrast, Ditsch & Grove (1991) found slightly higher powdery mildew incidence under no-tillage conditions. Besides influencing disease development by modifying host nutrition and the availability of volunteers and stubble, Han et al. (2013) showed that tillage practices could impact disease development by modification of micro-climatic conditions. The authors found out that in a no-tillage system illumination and air temperature were reduced during heading and increased during filling. The relative humidity of the canopy was higher under no-tillage. The mechanisms behind these results are still unknown as well as its relevance for disease development.

The last influential factor on the stand micro-climate worth mentioning is the exposition of the host plant. Depending on the exposition of the field various weather variables (e.g. temperature, precipitation, wind speed) may differ from those measured at the weather station. Kluge (1990) demonstrated that powdery mildew severity was higher at sheltered locations compared to exposed ones.
This leads to another important topic regarding the calculation of weather influences on disease severity. Causes and consequences of differences between field weather conditions and weather station data will be described in the following sub-chapter.

3.4 Field weather conditions versus weather station data

Pathogens are heavily influenced by weather conditions throughout the vegetation period. The closer the weather conditions to optimal conditions for disease development are, the faster a pathogen is able to reproduce itself, increase its population size, and potentially form an epidemic. Optimal conditions for disease development normally refer to the micro-climate in the crop stand. To analyse the impact of micro-climatic conditions on disease development the micro-climate in every surveyed crop stand needs to be measured. Unfortunately, this is not possible due to financial and logistical reasons. Thus, micro-climatic data only exists for some selected locations and rather short time frames. Additionally, equipment failures thin out the already sparse database of micro-climatic measurements (Coakley 1989). Hence, macro-climatic weather data of official measuring stations are commonly used to conduct these analyses. Unfortunately, official weather stations are not necessarily situated in the vicinity of the crop stand of interest. It has to be validated if the data collected at some weather station represents the weather conditions at the location of the crop stand sufficiently. Additionally, the upper leaves of the crop stand represent an isolation layer, shielding the lower parts of the crop stands from insolation, precipitation and wind leading to differences between observed weather at the station and in-field micro-climate. Up to 6°C difference between in-field and outside temperature can be measured during the year. Especially during summer, when the canopy is fully developed, the temperature on the ground of a wheat field can be 6°C lower compared to the outside (Krédl et al. 2012). Hence, the influence of the crop canopy on the micro-climate inside a crop stand depends on the weather and changes with the development of the crop throughout the vegetation period. The influence of the crop

canopy gets even more complex considering the factors influencing a crop canopy listed in Chapter 3.3.
Apart from all variables influencing micro-climate and factors modifying them the macro-climate always represents the general framework for disease development inside a crop stand. Thus, weather station data represents a very useful database for analysing weather- disease interactions and is the only reliable source for long-time weather observations.

3.5 Climate change in Saxony-Anhalt

Due to rising concentrations of carbon dioxide in the atmosphere the global climate will be subject to significant changes in the coming decades. This change will manifest itself as a change in global circulation patterns, and hence will alternate air temperature, precipitation, air humidity, sunshine duration, and wind fields to name just a few (IPCC 2013). In the past 20 years numerous climate studies were conducted to elaborate on the influence of rising greenhouse gas (GHG) concentrations on the global climate and the magnitude of changes to be expected. General circulation models (GCMs), simulating the general atmospheric circulation played an important role in performing these analyses. But climate change is not only a global phenomenon. It is the sum of changes happening on much smaller scales (countries, states, regions, municipalities, etc.) all around the globe. To quantify the regional impacts of global climatic changes regional climate models (RCMs) are used to downscale changes in atmospheric phenomena on smaller scales like the state of Saxony-Anhalt (IPCC 2013, Kotlarski et al. 2005).

3.5.1 Projections for atmospheric phenomena

The important atmospheric phenomena for the central European climate region are the North-Atlantic Oscillation (NAO), extratropical Cyclones (ETCs), and blocking activities by high pressure systems (IPCC 2013). Additionally, interactions with phenomena like the Atlantic ocean-atmosphere phenomenon, which is a multidecadal oscillation of North-Atlantic sea surface temperatures (SSTs), and the Barents-Kara-Sea sea-ice teleconnection (Petoukhov & Semenov 2010) are suspected to influence the central European climate.
Simulation results for future development of the NAO index indicated a slight increase. But the index was subject to large natural variations lowering the confidence in simulation

results. Supposing a slight increase more westerly weather situations were projected to occur in central Europe in the future. The IPCC indicated that it is unlikely that future ETC frequency will decrease. Regarding storm tracks, there is medium confidence in a poleward shift for the northern hemisphere. It is unlikely that North Atlantic storm tracks will simply shift polewards. A more complex reaction to climate change is to be expected. Blocking events, interrupting the westerly winds of the middle and high latitudes, play an important role for cold spells in winter and heat waves during summer in Europe. Transient eddy activity is supposed to be a key factor for these events. Long-term observed trends show a decrease in blocking events during winter over the North Atlantic, which are consistent with NAO-trends. Simulations do not show a clear tendency regarding intensity and persistence, but there is medium confidence that no increase in blocking events will occur in the future (IPCC 2013). The results for major atmospheric phenomena important for central Europe show that the future climate development in central Europe is subject to large natural variations and regional projections for most meteorological variables can only be made with large insecurities.

3.5.2 Observed and projected changes in climatological variables for central Europe

Implications for some variables, especially for temperature and extremes, for Europe in general and Saxony-Anhalt in particular are presented in the literature. For Europe an increase in the mean annual temperature was observed since the 1980s. Mean annual temperature is projected to increase further in the future. The seasonal distribution of the warming trend shows a summer warming in Southern Europe and a winter warming in Northern Europe (IPCC 2014). For central Europe a less intense warming in summer and winter is projected. During recent decades mean wind speeds declined for Europe. Projections of the future development are subject to large insecurities. Trend calculations for future precipitation amounts are unclear for central Europe due to the insecurities about the future development of the NAO, ETCs, and blocking events. Projections are subject to large regional and seasonal variations. Another observed change, despite a high natural variability, was the increased frequency of high temperature extremes and the decreased frequency of low temperature extremes over Europe. Simulations projected a marked increase in heat waves, droughts, and heavy precipitation events for Europe. There is high confidence in the changes of temperature extremes in Europe and high confidence in increased precipitation extremes in continental Europe, due to increased atmospheric moisture, moisture convergence, and an intensification of ETC activities during winter (IPCC 2014).

3.5.3 Projected changes in meteorological variables for Saxony-Anhalt

Climate projections for Saxony-Anhalt confirm the temperature trends from GCM calculations for Europe mentioned above. Mean annual temperature is projected to increase by 2 and 3°C until the end of the 21st century under the A1B and A2 scenarios, respectively, according to the climate models WETTREG (Spekat et al. 2007) and REMO (Jacob et al. 2001). The warming trend in WETTREG was spatially homogenous. In REMO the south-eastern part of the state showed a stronger warming trend than the northern part and the area around the Harz Mountains. For annual precipitation sums the WETTREG model projected a decrease for all scenarios used (A1B, B1, A2), the REMO model an increase for all scenarios. In comparison with WETTREG, REMO showed a much larger inter-annual variability of precipitation sums. Spatial precipitation trends varied between scenarios and time frames considered for WETTREG and REMO. For the most prominent scenario - A1B - WETTREG simulated a slight decrease in annual precipitation for the whole state between 2011 and 2040, a slight decrease in the north and the eastern Harz mountains, and a decrease in rainfall up to 60mm for the other parts of the state between 2041 and 2070, an increase up to 40mm in the north and the southeastern Harz mountains, and a decrease in precipitation up to 60mm for the remaining parts between 2071 and 2100. For the A1B-scenario, REMO simulated a decrease in annual precipitation sums in the northern part of the state and an increase up to 60mm for the remaining parts between 2011 and 2040, an increase in rainfall for the whole state, especially for the central parts and the central Harz mountains with values up to 120mm/a between 2041 and 2070, and a moderate increase in the central state parts and central Harz mountains with up to 80mm/a, a slight decrease at the northern border, and a slight increase in the remaining parts between 2071 and 2100 (Kropp et al. 2009).
The change in annual values was not only subject to spatial variations but developed differently during the course of the year. WETTREG simulations using the A1B emission scenario showed a slight rise in minimum, maximum and mean temperature during the whole year. A more intense increase during winter is the main reason for the annual increase in temperature for Saxony-Anhalt. In addition the model projected a decrease in summer and increase in winter precipitation, which balanced the summer maximum for the base scenario. In comparison, REMO showed the same response for temperature

variables but with higher magnitude. In addition REMO simulated a higher increase in summer temperature than WETTREG. For precipitation REMO simulated tendencies comparable to those of WETTREG with a less pronounced decrease in summer and increase in winter. Both models agreed in the number of frost days decreasing strongly towards the end of the century. The number of extremely hot days would increase for all emission scenarios considered according to both models (Kropp et al. 2009). Overall the simulations projected a temperature increase of Saxony-Anhalt, especially during winter and summer. Deviations for mean wetness would become more pronounced in the future (Bernhofer et al. 2008).

3.6 Impact of climatic changes on plant diseases

Besides meteorological variables the environment in general will be influenced by climatic changes on different complexity levels (IPCC 2014). Plant diseases and their host plants are significantly influenced by climatic conditions as demonstrated through the disease triangle (Jeger & Pautasso 2008). As a result of changing climatic conditions the plant growth of agricultural crops and the abundance of insects and plant pathogens will be subject to changes. The possible impacts of climatic changes on plant diseases according to the literature will be summarized in the following chapter. A short summary of climate change impact studies regarding the future development of leaf rust and powdery mildew in Germany will follow.

3.6.1 How do climatic changes impact plant diseases?

A respectable amount of studies concerning the impact of changing climatic conditions on plant pathogens were conducted (Juroszek & von Tiedemann 2013). Unfortunately, most of them based on pure speculation and not on proper models or statistical analyses of the investigated diseases. However, most of the studies described only the influences of single climatic factors on pathogen development. The studies mentioned were scattered on a large number of plant diseases. Hence, little is known about the development of leaf rust and powdery mildew under changing climatic conditions. The main reasons for the lack of climate impact studies are a lack of process-based models for most plant diseases (Bregaglio et al. 2013), a lack of long-term monitoring data (Luck et al. 2011, Shaw & Osborne 2011), and difficulties in linking epidemiological and climate models (Garrett et

al. 2011) mainly because of the high temporal resolution of weather data needed by epidemiological models.
Hourly resolution of weather data is often supported by weather station data, but most climate models only support daily or 6-hour data. Additionally, climate models generate reasonable results simulating longer time-periods, e. g. simulation of monthly and annual mean values. Hourly climate simulation data has to be used with caution. The physics behind the simulation results stay the same, but hourly simulations are subject to random processes. Natural variability exhibits large uncertainties (Motha 2007), especially when precipitation is the variable of interest (Ghini et al. 2008, Shaw & Osborne 2011).
Despite these difficulties climate model scenarios present a solid base for projecting the future development of meteorological factors influencing disease abundance (Motha 2007). The literature contains interesting, alarming, and speculative projections for the future development of plant pathogens under changed climatic conditions. Climatic changes will affect pathogens directly and indirectly by influencing the host plant. The possible reactions of pathogens will include changes in the geographical distribution, the seasonal phenology, and population dynamics (Coakley et al. 1999, Boonekamp 2012, Decker et al. 1986 cited in Jahn et al. 1995, Pangga et al. 2011, Shaw & Osborne 2011). In detail, the changes regarding population dynamics for plant diseases will manifest themselves in a higher infection rate, shortened latent and incubation periods (Eastburn et al. 2011), a higher amount of overwintering and oversummering inoculum (Coakley et al. 1999), followed by a faster development of the disease, and hence a higher reproduction rate causing more generations to be built during the vegetation period under increased temperatures (Chakraborty et al. 2011). A decrease in moisture availability may counter the potential increase in disease abundance (Boland et al. 2004). Dissemination from and deposition of spores on host plants will be impacted (Garrett et al. 2011). Indirect influences will affect plant diseases through climate impacts on crops. According to Eastburn et al. (2011) the colonization of plant tissue may be altered as a response to changes in host physiology due to rising CO_2 levels. In addition, an elevated CO_2 level alters host plant growth and canopy structures, which will induce changes in micro-climatic conditions and developmental conditions of pathogens (Pangga et al. 2011). On a larger scale, changes in atmospheric circulation patterns will alter dissemination pathways for fungal spores (Rosenzweig et al. 2005 cited in Chakraborty et al. 2011). Thus, regions will get connected to new inoculum sources of pathogens which are not endemic yet or may become disconnected from inoculum sources resulting in lower

disease abundances. The temporal gap at the end of the vegetation period without living host material will narrow and a “green bridge” could support the survival of inoculum until the next season. Changes in the seasonal phenology will disturb the synchronization between host and pathogen, but the consequences are difficult to estimate. For example, host plants will evolve faster and escape their pathogens by faster development and earlier senescence (Gregory et al. 2009). Furthermore, host plants will get stressed by extreme weather conditions, e. g. high temperatures and drought, and thus susceptibility to plant pathogens will change (Coakley et al. 1999, Eastburn et al. 2011, Boyer 1995 cited in Eastburn et al. 2011). Resistance genes shielding the host plant against a number of pathogens will become more or less effective under changed climatic conditions due to physiological alterations in response to altered CO_2 levels and due to changes in the efficiency of these genes (Gregory et al. 2009, Juroszek & von Tiedemann 2011). In addition, susceptibility can be influenced by changing levels of ozone exposure of host plants (Boland et al. 2004). Besides ozone a change in other gaseous components of the atmosphere may influence disease incidence and severity of plant diseases, as summarized by Fitt et al. (2011).

3.6.2 Climate change studies of leaf rust and powdery mildew for Germany

Overall very few studies were found concerning the impact of climatic changes on plant pathogens in Germany. All studies dealt with impacts on multiple diseases including leaf rust and powdery mildew of wheat, except for Bregaglio et al. (2013). Only the findings for leaf rust and powdery mildew will be summarized in this chapter.
Jahn et al. (1996) were the first authors examining disease data recorded by the plant protection service of the former German Democratic Republic with regard to the influence of climate change on plant diseases. They used correlation and simple regression analyses to measure the influence of the mean annual temperature and precipitation sums of spring and summer on leaf rust and powdery mildew infestation. The regression equations were used to extrapolate into the future assuming mean annual temperature to increase by 1K or 2K, respectively, or spring or summer rainfall amounts to decrease by 30% or 60%, respectively. They tried to combine both effects and calculated future disease scenarios. They identified a supporting effect of higher temperature and decreased precipitation for single variables and for the combination of both for leaf rust of winter wheat. The powdery mildew infestation decreased slightly for

elevated temperature and increased for lowered precipitation. In combination a slight decreasing effect was found.

Von Tiedemann (1996) used climate projections of the IPCC for temperature and precipitation changes until 2030 to discuss the potential changes in disease occurrence based on expert knowledge about both diseases. He concluded that powdery mildew of wheat will lose importance. Leaf rust of wheat will become more important for future agriculture in temperate Europe.

Another important study is the “Befallsatlas – Atlas der potentiellen Befallsgefährdung durch wichtige Schadorganismen im Ackerbau Deutschlands“ by Kluge et al. (1999). The work reports the actual damaging potential of various plant diseases and pests in Germany based on climate data of 412 weather stations between 1951 and 1980. As a basis for the calculation of the disease potential logical rules, on the basis of expert knowledge were defined incorporating meteorological variables. The rules, similar to a fuzzy approach, were then used to calculate the disease potential. Despite not being intended to be used for a climate change impact assessment these rules can be utilized to deduct future disease potential and changes in disease potential by feeding the equations with climate simulation data. The results of this experiment served as the basis for forming hypotheses about the impact of climatic changes on disease potential in Germany and are listed in chapter 6.6.

Volk et al. (2010) calculated disease projections for the time frame 2001 to 2050 for the German federal state North Rhine-Westphalia. They used the already existing disease warning system “proPlant expert” (Johnen et al. 1995) and ran the model with A1B climate scenario data calculated by the WETTREG model (Spekat et al. 2007). The results showed that the infection risk between November and March increased for leaf rust and powdery mildew for all considered subregions. The low-lying regions of the state held a stronger increasing trend compared to the higher elevated areas for both diseases.

Another regional study for the German state of Lower Saxony was conducted by Racca et al. (2012). They ran the disease model “SIG-Getreide” in combination with the ontogenesis model SIMONTO-WW and the REMO climate model developed by the Max-Planck-Institute for Meteorology (Jacob et al. 2001). No information on the emission scenario used was given. The authors calculated differences of the length of the vegetation period (BBCH 30 to 69) and of the infection probability of leaf rust and powdery mildew of winter wheat between the base period (1971-2000), a short-term projection (2021-2050), and a long-term projection (2071-2100). The simulated infection probabilities for powdery mildew showed no significant trend but a slight decreasing tendency. The infection probability for leaf rust increased significantly between the base period and the long-term projection. A prolongation of the vegetation period under future climatic conditions resulted (Richerzhagen et al. 2013).

In the most recent study Bregaglio et al. (2013) calculated disease scenarios for whole Europe and discussed the results on a regional basis, including Germany. They used the generic potential infection model by Magarey et al. (2005) in combination with the A1B emission scenario of the HadCM3-GCM nested within the HadRM3-RCM (van der Linden and Mitchell 2009). Infection events for the baseline time frame (1993-2007) were compared with a short-term scenario (2025-2034) and a long-term scenario (2045-2054). The results revealed a considerable increase in leaf rust infection events for northern Germany, including Saxony-Anhalt for the short-term scenario and an increase in the number of leaf rust infections by up to 100% for the long-term scenario.

4 Materials and Methods

4.1 Data used

4.1.1 Disease data

In the analyses data on the occurrence of leaf rust (*Puccinia triticina*) and powdery mildew (*Blumeria graminis* f.sp. *tritici*) on winter wheat, collected from untreated plots by the Federal Plant Protection Service of Saxony-Anhalt according to methodological specifications of the pest monitoring system of the former German Democratic Republic (Schwähn & Röder 1982) was used. Infestation levels were determined on 40 plants per plot for each site and year and the mean disease incidence for each monitoring site was calculated as the percentage of infected plants. The infestation data were collected from 1976 to 2010 at several sites (up to 35) per year and transferred into a database. As the monitoring sites were randomly selected, the locations varied over time. Because monitoring sites could not be identified by municipality from 1976 to 1990, the district capitals of the former German Democratic Republic were used as substitute monitoring sites during this period. From 1991 to 2010 the capitals of the municipalities were defined as monitoring sites. Because the maximum infestation level represents the best indicator of the damage caused by both diseases, only data from the beginning of anthesis until early ripening (Feekes stage 16 or BBCH stage 60 to 70) were included in the analyses. In case of multiple measurements during anthesis the value recorded on the latest monitoring date was used. Overall, 989 infestation measurements for leaf rust and 1180 for powdery mildew were included (Tab. 4-1). Additional information included the sowing date and the monitoring date as day of the year (doy). The median monitoring date for both diseases was 16th of June. Furthermore the sown wheat variety was recorded for the majority of the plots. The susceptibility of each variety of winter wheat, divided into nine susceptibility classes, was extracted from the National Lists of the German Federal Plant Variety Office (1990-2010) and variety lists of the "ZENTRALE FÜR SORTENWESEN DER DEUTSCHEN DEMOKRATISCHEN REPUBLIK" (1976-1989).

Tab. 4-1: Annual numbers of monitoring sites for leaf rust and powdery mildew on winter wheat in Saxony-Anhalt during 1976 to 2010.

Leaf rust						Powdery mildew					
Year	**N**	**Year**	**N**	**Year**	**N**	**Year**	**N**	**Year**	**N**	**Year**	**N**
1976	48	**1989**	44	**2000**	31	**1976**	50	**1987**	26	**1999**	35
1977	43	**1990**	39	**2001**	35	**1977**	45	**1988**	43	**2000**	31
1978	31	**1992**	28	**2002**	37	**1978**	33	**1989**	34	**2001**	35
1979	40	**1993**	38	**2003**	30	**1979**	41	**1990**	34	**2002**	37
1981	20	**1994**	39	**2004**	29	**1980**	47	**1992**	28	**2003**	30
1984	26	**1995**	34	**2005**	29	**1981**	47	**1993**	38	**2004**	30
1985	28	**1996**	19	**2006**	30	**1982**	38	**1994**	39	**2005**	30
1986	13	**1997**	37	**2007**	30	**1983**	42	**1995**	34	**2006**	30
1987	24	**1998**	17	**2008**	19	**1984**	20	**1996**	19	**2007**	30
1988	43	**1999**	37	**2009**	36	**1985**	45	**1997**	37	**2008**	19
				2010	35	**1986**	45	**1998**	17	**2009**	36
										2010	35

4.1.2 Weather data

Daily measurement data collected by the German Weather Service (DWD) were available at 1,218 stations distributed over Germany for the timeframe 1951 to 2010. Missing or inhomogeneous data were replaced or corrected by interpolation by the Potsdam Institute for Climate Impact Research (PIK, Orlowsky et al. 2008). The regression analyses of data from Saxony-Anhalt were performed using daily measurements for the variables mean temperature, precipitation, and wind speed collected at 61 weather stations. For the correlation analyses the daily variables maximum and minimum temperature, relative humidity, sunshine duration, and air pressure, corrected to sea level, were added. The number of days with precipitation (daily precipitation sum above 0 mm), freezing days (daily minimum temperature under 0°C), days with snowfall (daily precipitation sum above 0 mm and daily mean temperature under 0°C), and days with mean temperature between 17 and 23°C (including the optimal temperature for leaf rust and powdery mildew development) were calculated as additional variables for the weather stations used.

The monitoring sites (Fig. 4-1) were connected with weather data from the corresponding weather stations by calculating Thiessen polygons using inverse distance weighting to interpolate the climatic data between weather stations (Shepard 1968). The software ArcGIS 10.0 was used for this purpose.

4.1.3 Other data

Beside weather variables 12 other environmental variables possibly related to disease occurrence in the field were collected and analysed. The 12 non-climatic variables covered disease resistance, the preceding crop (PC), the previous preceding crop (PPC), the length of the vegetation period (calculated as the difference, in days, between the monitoring and sowing date), the doy of disease assessment, sowing, and emergence, and mean values of the field capacity, useable field capacity, air capacity, total pore volume, and potential cation exchange capacity of the upper soil layers. The soil properties were estimated by using the BÜK 1000 N2.3 soil dataset (BGR 2007). Mean values of all soil variables were calculated by aggregating the variables for the upper two meters of the soil.

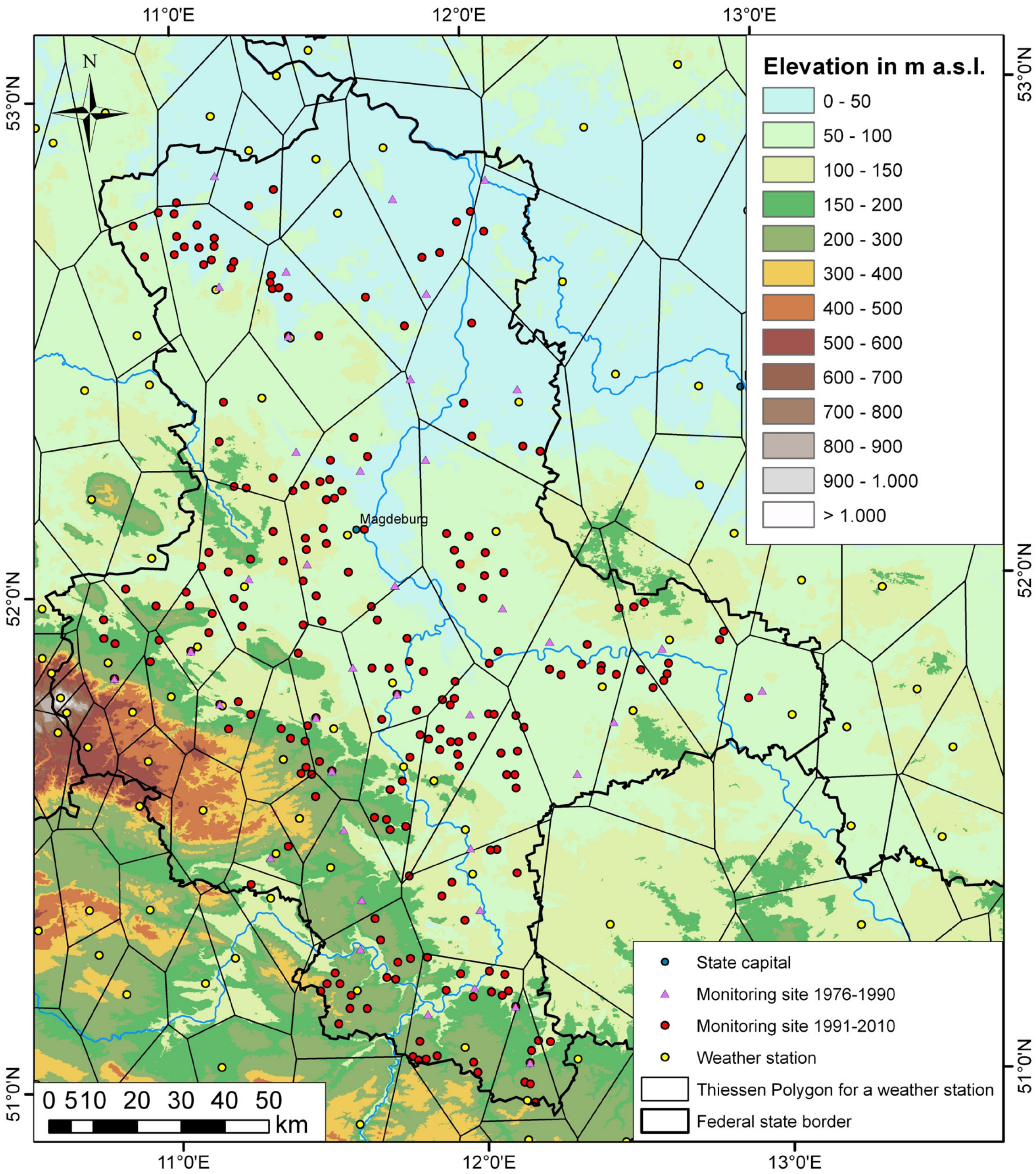


Fig. 4-1: Monitoring sites for leaf rust and powdery mildew on winter wheat and weather stations with corresponding Thiessen polygons in Saxony-Anhalt between 1976 and 2010. Source of the digital elevation model data: Hole-filled seamless SRTM data V4 (Jarvis et al. 2008).

4.2 Interval-based correlation

The “Window Pane” algorithm proposed by Coakley and colleagues (Coakley et al. 1988, Coakley 1989) was used to perform the analyses. A flow chart of the program was published by Coakley et al. (Fig. 1, 1985). The approach dealt with the calculation of correlation coefficients between disease values measured at a similar point in time every year and weather variables averaged or summarized over a shifting time window. The window is defined by its length, its starting point, and an increment for shifting. Coakley used the algorithm to identify highly correlated time windows for each meteorological variable and to narrow the interesting windows further by decreasing the length or the increment of the procedure.

In this study the algorithm was applied with starting days ranging from day 1 to day 295 and ending days ranging from day 5 to day 300 before disease monitoring and window lengths of 5 to 300 days. The increment was one day for all analyses. Thus, all possible time intervals between day 1 and day 300 before the disease assessment with a minimum length of five days for all 13 meteorological variables were investigated regarding their correlation with the disease data for leaf rust and powdery mildew. The results were presented as correlograms (Goldwin 1982), which are perfectly suited for presenting the results of the “Window Pane” algorithm in its entirety. In contrast to the aforementioned publications describing the “Window Pane” and Goldwin’s correlogram, Kendall correlation coefficients were calculated to derive the correlation matrices. Kendall’s correlation coefficient was used to account for the non-normal distribution of the disease data. Non-parametric tests were performed to derive information on the significance of the coefficients (Noether 1967, Hartung et al. 2009).

The number of correlation coefficients calculated was about 45,000 per plant disease and weather variable, which amounts to about 1.2 million correlations investigated. SAS statistical analysis software (Version 9.2) was used to perform the time-consuming calculations (SAS Institute Inc. 2008).

4.3 Analysis of non climatic variables

To analyse non-climatic influences on disease incidence of leaf rust and powdery mildew of winter wheat correlation coefficients of Kendall were calculated for the length of the vegetation period, the doy of disease assessment, sowing, and emergence, and mean

values of the field capacity, useable field capacity, air capacity, total pore volume, and potential cation exchange capacity of the upper soil layers. For significance testing the nonparametric z-statistic (Noether 1967) was calculated to determine the p-values.
The calculation of correlation coefficients were not suitable for the discrete variables resistance, PC and PPC. Hence, the mean values and distributions of disease incidence between the characteristic features were compared. Equal methods for all three variables were applied. The methodology for disease resistance is summarized in chapter 4.4.1. Disease resistance was included as a predictor in the model procedures and resistance classes had to be aggregated before. To compare the mean values of PC- and PPC-classes multisample Kruskal-Wallis tests and two-sample Wilcoxon rank-sum tests were conducted to identify the significance of differences between all and single class means, respectively. In addition, Kolmogorov-Smirnov tests were carried out to identify significant differences between the distributions of two classes. Every combination of classes was analysed.
Autocorrelation functions were calculated for annual means of leaf rust (LRI) and powdery mildew incidence (PMI) to test time-series of both pathogens for recurring patterns. 95%-Quantiles of the normal distribution were calculated to test the significance of the autocorrelation coefficients. Lags between 0 and 15 years were analysed using this method. Years with missing values were left out. Furthermore, the correlation between yearly LRI and PMI means was assessed using Spearman’s correlation coefficient in combination with a t-test for significance.

4.4 Logistic regression model

4.4.1 Grouping varieties by resistance

The observations were filtered for the resistance of the variety. Observations without information on the degree of resistance were excluded, resulting in 837 incidence measurements available for leaf rust and 950 for powdery mildew. Kruskal-Wallis and Kolmogorov-Smirnov tests (Hartung et al. 2009) were run using the NPAR1WAY procedure of the SAS system (Version 9.2) to compare mean values and distributions of disease incidence between all nine susceptibility classes for both diseases. Varieties without significant differences in incidence mean values and/or distributions were aggregated. The observations were grouped by dividing the samples into two groups: more resistant and more susceptible varieties - in the following referred to as resistant and susceptible varieties. Based on the results of the aforementioned statistical tests and under the condition of groups with a nearly equal number of observations, susceptibility classes one to five were grouped as resistant and classes six to nine as susceptible for leaf rust. For powdery mildew classes one to four were grouped as resistant, and classes five to nine as susceptible.

4.4.2 Preparation of the predictor variables

The weather data were aggregated for the regression analyses by calculating mean values and sums of meteorological variables, respectively, for 15-day periods extending backwards from the monitoring date to the earliest sowing date of the previous year. Meteorological variables like temperature showed a strong autocorrelation with a persistence of up to 60 days. The meteorological variables were deseasonalized by subtracting the long-term daily mean values from each observation before aggregating the data by intervals to reduce autocorrelation effects. In addition the length of the intervals for aggregating the weather data was set to 15 days to further reduce autocorrelation. The resulting aggregated meteorological variables were defined as independent. In the next step, the three meteorological variables were aggregated for 20 intervals yielding a total of 60 weather variables for regression analysis covering 300 days of the year. The starting and ending dates for each interval are shown in Tab. 4-2. Interactions between susceptibility and the 60 weather variables were included as 60 additional variables for the analyses to account for an influence of plant resistance in combination with weather variables on disease incidence. In combination with the susceptibility groups as a categorical variable 121 predictors were available for the regression procedures.

Tab. 4-2: Relationships between 15-day intervals used as the basis for aggregating meteorological variables for the regression procedure and real dates.

Interval	1	2	3	4	5	6	7	8	9	10
Start	16.6	1.6	17.5	2.5	17.4	2.4	18.3	3.3	16.2	1.2
End	2.6	18.5	3.5	18.4	3.4	19.3	4.3	17.2	2.2	18.1
Interval	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Start	17.1	2.1	18.12	3.12	18.11	3.11	19.10	4.10	19.9	4.9
End	3.1	19.12	4.12	19.11	4.11	20.10	5.10	20.9	5.9	21.8

4.4.3 Preparation of the validation datasets

The dataset consisted of 121 predictors and one predictand. It was split up into training, validation, and test samples (Hastie et al. 2009). In a first step the data were split into 10 outer samples with an equal number of observations using a stratified random sampling approach (Cochran 1977) for the outer 10-fold cross-validation. For the outer cross-validation 9 of the 10 samples were chosen as training data (further split up into training and validation sample for the inner cross-validation) and one sample as validation data (representing the test sample for the overall validation approach). The procedure was repeated 10 times until all samples were used exactly once for validation and 9 times for training. The stratification was handled differently for raw and binary disease data. For the raw disease data the restriction on the random splits demanded the resistant to susceptible ratio to be equal for both training and test samples. For the dichotomized disease data the ratio of observations exceeding the threshold and those below the threshold had to be equal for training and test samples, in addition to the restriction mentioned before. The second step dealt with the construction of the inner samples for the leave-one-out cross-validation. Therefore, each outer sample was split into n inner samples with n being the number of observations in the sample using simple random sampling (Cochran 1977). For the inner cross-validation $n-1$ observations were used for training and one observation for validation. The procedure was repeated n times until all observations were used once for validation and $n-1$ times for training. No stratification was used for selecting the samples.

4.4.4 Modelling and parameter estimation

The logistic regression models were built (Harrell Jr. 2010) to explain functional relationships between environmental variables and disease incidence of the two pathogens. Maximum-likelihood estimates of the parameters were calculated using the LOGISTIC procedure of the SAS System (Version 9.2, SAS Institute Inc. 2008). All other steps of the analysis were programmed manually, because they were not integrated in the procedure used.

Besides analyzing the influence of weather variables and variety susceptibility on raw leaf rust (LRI) and powdery mildew incidence (PMI) the study assessed the influence on the probability of the diseases exceeding different incidence thresholds. According to thresholds defined by Beer (2005) disease incidence was dichotomized in four different ways. Incidence thresholds of 0% (non-diseased and diseased) for both diseases (LRI0, PMI0), 30% (≤ 30% and >30%) for leaf rust incidence (LRI30), and 50% (≤ 50% and >50%) for powdery mildew incidence (PMI50) were applied. One logistic regression equation was identified for the raw disease data and two logistic regression models were

developed for the dichotomized incidence data for each disease. Susceptible varieties were defined as the reference category coded as "-1" and resistant varieties were coded as "1" (Allison 2012) when interactions with disease susceptibility were included in the model.
The dichotomized incidence data were analyzed using the standard binary logistic regression procedure. The raw disease data were analyzed using a modification by Piepho (1998). Maximum-likelihood estimates were derived using the Fisher scoring method. As a scale parameter to account for overdispersion, the Pearson chi-square statistic divided by the degrees of freedom was used.

4.4.5 Variable selection

The logistic regression models for raw disease data were calculated for each possible number of predictors using forward variable selection. The variables considered for the model were selected using leave-one-out cross-validation (Efron & Tibshirani 1998, Hastie et al. 2009, Sen & Srivastava 1990). The selection started with the predictor minimizing the mean squared error in the training dataset (MSE-T) averaged over all inner cross-validation samples. The step was repeated until a stop criterion was met. One criterion included the addition of an additional variable included in the model not decreasing the mean squared error of the validation dataset (MSE-V) further. The second criterion stated that no predictor candidate exhibiting a significant parameter estimate upon inclusion was found. According to Harrell Jr. (2010) and Wilks (1995) the minimum MSE-V equals the number of variables in the model from which on overfitting occurs. Thus, the maximum amount of possible predictors that can be added without overfitting the model was determined and the variable selection stopped. To exclude meaningless parameters from the models only parameters significantly different from zero were considered. Significance for all parameter estimates was tested using empirically derived cross-validation confidence intervals at $\alpha = 0.1$. In the last step, the estimated parameters and the corresponding confidence intervals for the best model were extracted.
The logistic regression proceeded similar for the dichotomized disease data but used another variable selection statistic instead of MSE, called the f-measure, proposed by Torgo & Ribeiro (2006). The basic principle for calculating the f-measure is a 2x2 table in which the real situation (value below or above threshold) is contrasted with the situation predicted by the model. There are four possible outcomes of this test:
1. True positive (TP): threshold was exceeded and this was detected by the model,

2. True negative (TN): threshold was not reached and this was detected by the model,
3. False negative (FN): threshold was exceeded but the model detected a value below the threshold), and
4. False positive (FP): threshold was not reached but the model detected a threshold exceedance.

The f-measure is defined as a weighted harmonic mean of precision (positive predicted value) and recall (sensitivity) with $0 \leq \beta \leq 1$

$$F = \frac{1+\beta^2}{\frac{1}{Precision} + \frac{\beta^2}{Recall}} \tag{1}$$

where

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

and

$$Precision = \frac{TP}{TP + FP} \tag{3}$$.

The β values are weights that allow the researcher to adjust the equations according to the importance of recall in comparison to precision. In this study, β was set at 0.5, which means precision was weighted four times higher than recall for variable and model selection. Thus, the maximum f-measure was calculated as the variable selection statistic to pick variables for integration in the logistic regression models for binary transformed disease data. Additionally, the maximum f-measure determined the amount of variables from which on overfitting occurs and served as a stop criterion for the variable selection algorithm similar to the MSE-V. To calculate the f-measure, all prediction results from each step of the variable selection for the logistic regression procedures for dichotomized incidence were transformed. The transformation dichotomized the predicted probabilities into binary outcomes with values 0 and 1. For the transformation into binary outcomes a predicted probability of 0.5 was used as the classification threshold. Observations exceeding the threshold were assigned the value 1, values below the threshold the value 0.

4.4.6 Model selection and validation

After selecting the best parameters and calculating the estimates the resulting models were validated. For the validation independent data not involved in the variable selection process were used to assess the predictive ability of each model. Unfortunately, the validation samples of the inner cross-validation procedure were already used for the variable selection. Hence, a second, outer cross-validation loop around the model fitting part was built applying 10-fold cross-validation to the test samples described before. The best model for raw disease data from the resulting ensemble was selected by calculating the MSE-T and picking the model with the minimum value. For the dichotomized disease data the same procedure was performed using the maximum f-measure as the model selection criterion.

To assess the overall quality of the selected "best" model the models were validated using the original input data. For raw incidence data errors of the overall mean for the period 1976 to 2010 and root-mean-square errors (RMSEs) of the annual and station-wise mean values were analysed for each pathogen. In addition, the RMSE over all observations was examined for the final models working with raw disease data. The quality of the final models using dichotomized disease data was assessed using precision, recall, and the f-measure. In addition, annual, station-wise, and dataset mean differences of the probability of exceeding the defined threshold were calculated between observed and predicted values. To obtain the differences, mean probabilities for the observed data were calculated utilizing the binary threshold exceedance values. Mean probabilities for the predicted data were calculated using the non-dichotomized probabilities resulting from the logistic regression equations. The residuals of both model types were investigated by plotting the Pearson residuals against the linear predictor. Furthermore, the area under the receiver under the operator curve (ROC AUC) was calculated to determine the model quality.

4.5 STARS – a statistical resampling scheme

To calculate the scenarios for leaf rust and powdery mildew the STARS model (Orlowsky et al. 2008), developed by the Potsdam Institute for Climate Impact Research, was used. The abbreviation STARS stands for "statistical analogue resampling scheme" and names a regional statistical climate model. The STARS model uses observed weather periods from the years 1951 to 2003 and reorders them under specific constraints to meet a prescribed temperature trend. The prescribed temperature trend is determined by inspection of possible future temperature scenarios from multiple runs of GCMs.

Under the restriction to meet the prescribed temperature trends STARS reorders monitored weather time-series to construct scenario time-series. In a first step, years of the observed weather data are reordered using Monte-Carlo-simulations to meet the prescribed temperature trend. In the second step blocks of 12-day length are selected from the observed weather data for every year and used to replace blocks of the same length in the first approximated scenario time-series, which showed the strongest prohibiting influence on meeting the prescribed trend during the first approximation step. The block length of 12 days is chosen to assure realistic weather periods inside the blocks and to maintain the persistence of temperature, air pressure, and precipitation for each station. Furthermore, some blocks from the first approximation retain their position to preserve the basic structure of the observed years and the intra-annual variability. Hence, physically plausible series of weather periods during the course of the year are guaranteed.

The described steps are repeated for every reference station determined beforehand. To determine reference stations a cluster analysis identifies clusters of similar structures of meteorological variables. For each cluster one station is selected as its reference station. The temperature trend is only prescribed for reference stations and simulation time series of non-reference stations are constructed using the reorder information of the reference stations. Hence, the spatial structure of meteorological variables is retained.

In summary, the model fulfilled the following requirements to guarantee physical consistency of the scenarios:

1. The seasonal cycle for the scenarios is preserved.
2. The persistence of weather periods is preserved.
3. The spatial consistency of the meteorological parameters is preserved.
4. The physical plausibility is preserved.

Daily climate scenario data for 11 meteorological variables are produced by the model for each of the 1218 weather stations of the German Weather Service (DWD).
For this study scenario data of 61 weather stations from the federal state of Saxony-Anhalt were used. The data were part of climate simulations conducted for previous studies (Gerstengarbe & Werner 2013, PIK 2012). For each climate scenario STARS calculated 100 realizations to account for the range of possible future climate conditions. Seven climate change scenarios with different temperature trends from 2011 until 2060 were calculated by the model. The scenarios used incorporated prescribed temperature trends of 0, 1.0, 2.0, and 3.0K. The 2K-scenario is comparable to the A1B scenario used by WETTREG (Spekat et al. 2007) and REMO (Jacob et al. 2001).
The simulation results were analyzed calculating long-term mean values of mean temperature and wind speed, precipitation sums, and sums of freezing days, icy days, and days with rainfall. The calculations were conducted for annual and seasonal aggregates on scales of the whole federal state and single stations. The aggregates of the scenario period 2031 to 2060 were compared to aggregates of the base period 1981 to 2010 by calculating the differences. The differences were obtained by subtracting the base period values from those of the scenario periods for all STARS realizations. The median difference was used to compare the scenarios and 5%- and 95%-percentiles were calculated to test the significance of the differences. The significance of the differences was tested against the null hypothesis of no difference. Station-wise differences were only calculated for the meteorological variables mean temperature, precipitation, and wind speed under the 3K-scenario. Only aggregates calculated for the whole state were tested for significance.

4.6 Climate change disease scenarios

For calculation of the LRI and PMI scenarios the logistic regression models were run with climate model data provided by the STARS model. The climate scenario data were deseasonalized using the seasonal component of the base period (1981-2010) to meet the conditions of the meteorological data used as input for the regression modelling procedure. The six regression equations were fed with climate scenario data of all 100 realizations computed by STARS. In addition to the four climate change scenarios (0K, 1K, 2K, 3K), two susceptibility scenarios, containing two extreme presumptions about the amount of resistant varieties used in the future were applied. One scenario incorporated only susceptible varieties and the other only resistant varieties.

A simple linear regression was used to estimate the trend for each of the disease scenarios for both pathogens and each of the 100 realizations between 2011 and 2060. For the models generated with raw disease data, mean disease incidence was used as the predictand. The probability of exceeding the defined threshold was used as predictand for the models generated with dichotomized disease data. The thresholds for both pathogens were selected as defined in chapter 4.4.4. Trends were calculated on one hand for each Thiessen polygon in Saxony-Anhalt and on the other hand for the disease scenario data averaged over the whole federal state.

Trends of future disease occurrence were tested for significance with $\alpha = 0.05$ by interpreting the 100 realizations as bootstrap repetitions of each disease scenario. The 95% and 5%-percentiles for each disease scenario trend were calculated from the empirical distribution of the means, respectively. In case of zero not being part of the bootstrap confidence interval, a significant trend was identified. A total of over 300,000 trends were examined.

To identify significant changes between past and future disease incidence the LRI, LRI0, LRI30, PMI, PMI0, and PMI50 mean values of the period 1976 to 2010 were compared with the period 2031 to 2060 for the whole state. The differences were adjusted for errors by subtracting the validation errors to account for discrepancies between model validation results and observed values. The data of all 100 model realizations entered the analyses as mentioned above. The significance of changes was identified by calculating the empirical 5%- and 95%-percentiles of mean differences for LRI, LRI0, LRI30, PMI, PMI0, and PMI50 for each disease scenario.

The LRI, LRI0, LRI30, PMI, PMI0, and PMI50 mean values of the period 2031 to 2060 calculated for each Thiessen polygon were compared between the 0K-scenario, indicating no change in German mean temperature, and the 1K,- 2K-, and 3K-scenario, indicating an increase in German mean temperature, to identify regional differences in future disease incidence and threshold exceeding probability. Incidence was compared between both time periods for the disease scenarios originating from raw disease data. The probabilities of exceeding the defined thresholds were compared for the disease scenarios originating from dichotomized data. Significance was tested by comparing the 5%- and 95%-percentiles derived for the 0K-scenario with those calculated for the warming scenarios.

4.7 Fuzzy modelling

Logical expressions taken from the "Befallsatlas" (Kluge et al. 1999) were used to calculate the disease potential for both pathogens during the 1981 to 2010 timeframe and during the 2031 to 2060 timeframe for the mean of all STARS climate model realizations. The station weather data used as input for the fuzzy models were interpolated according to chapter 4.1.2. Actual and future disease potential were calculated for all Thiessen polygons in the study area.

The logical expressions for leaf rust of winter wheat were:

$$Low \leftarrow \boxed{\begin{array}{c} tmean(June) < 15.0°C \\ (15.0°C \le tmean(June) \le 15.7°C) \wedge (prec(June) < 65mm) \end{array}}$$

$$Medium \leftarrow \boxed{\begin{array}{c} (15.0°C \le tmean(June) \le 15.7°C) \wedge (65mm \le prec(June)) \\ 15.7°C < tmean(June) \le 16.2°C \\ (16.2°C < tmean(June)) \wedge (prec(June) < 65mm) \end{array}} \quad (4).$$

$$High \leftarrow \boxed{(16.2°C < tmean(June)) \wedge (65mm \le prec(June))}$$

The logical expressions for powdery mildew of winter wheat were:

$$Low \leftarrow \boxed{12.6°C < tmean(May)}$$

$$Medium \leftarrow \boxed{11.6°C \le tmean(May) \le 12.6°C}$$

$$(5).$$

$$High \leftarrow \boxed{11.0°C \le tmean(May) < 11.6°C}$$

$$Very\ high \leftarrow \boxed{tmean(May) < 11.0°C}$$

For leaf rust potential the third expression was changed due to a typing error in the original document. The class "very high" disease potential was added for powdery mildew, to account for areas with temperatures outside the limits of the original definition. Differences between both timeframes were assessed and used as a basis for building hypotheses about future disease potential.

5 Study Area

In this chapter the climatic and disease situation of Saxony-Anhalt are presented. A characterization of the state and its placement in context to the general atmospheric circulation according to the literature will be given. After that the climatic characterization based on own weather data will be presented. Finally, the disease situation based on monitoring data between 1976 and 2010 will be summarized.

5.1 Climatic Conditions

The federal state of Saxony-Anhalt is located in central Germany between 51° and 53° latitude. It is characterized by a temperate climate. The state is situated at the border of the maritime western parts of Europe and the continental East (Metzger et al. 2005). The relief is characterized on one hand by the dry central German flats and on the other by the strongly exposed mountain ranges of the Harz. Inside the general atmospheric circulation Saxony-Anhalt is located in the zone of extratropical westerlies and circulation patterns with western winds dominating the flow patterns during the year. Where air masses are not deflected by mountain ridges, weather periods are mainly influenced by the Atlantic Ocean.

Saxony-Anhalt is divided into two climatic zones with a borderline from the Harz to the Fläming. North of this line north, northwest, west, and southwest weather conditions dominate. The maritime influence is high and high pressure situations over central Europe only have limited impact. South of the border, the importance shifts in favor of high pressure systems, especially during winter. The maritime influence decreases and the climate becomes more continental. Additionally, low pressure systems moving from the Mediterranean to the Baltic states have a stronger influence and precipitation is more intense (Schröder 2000).

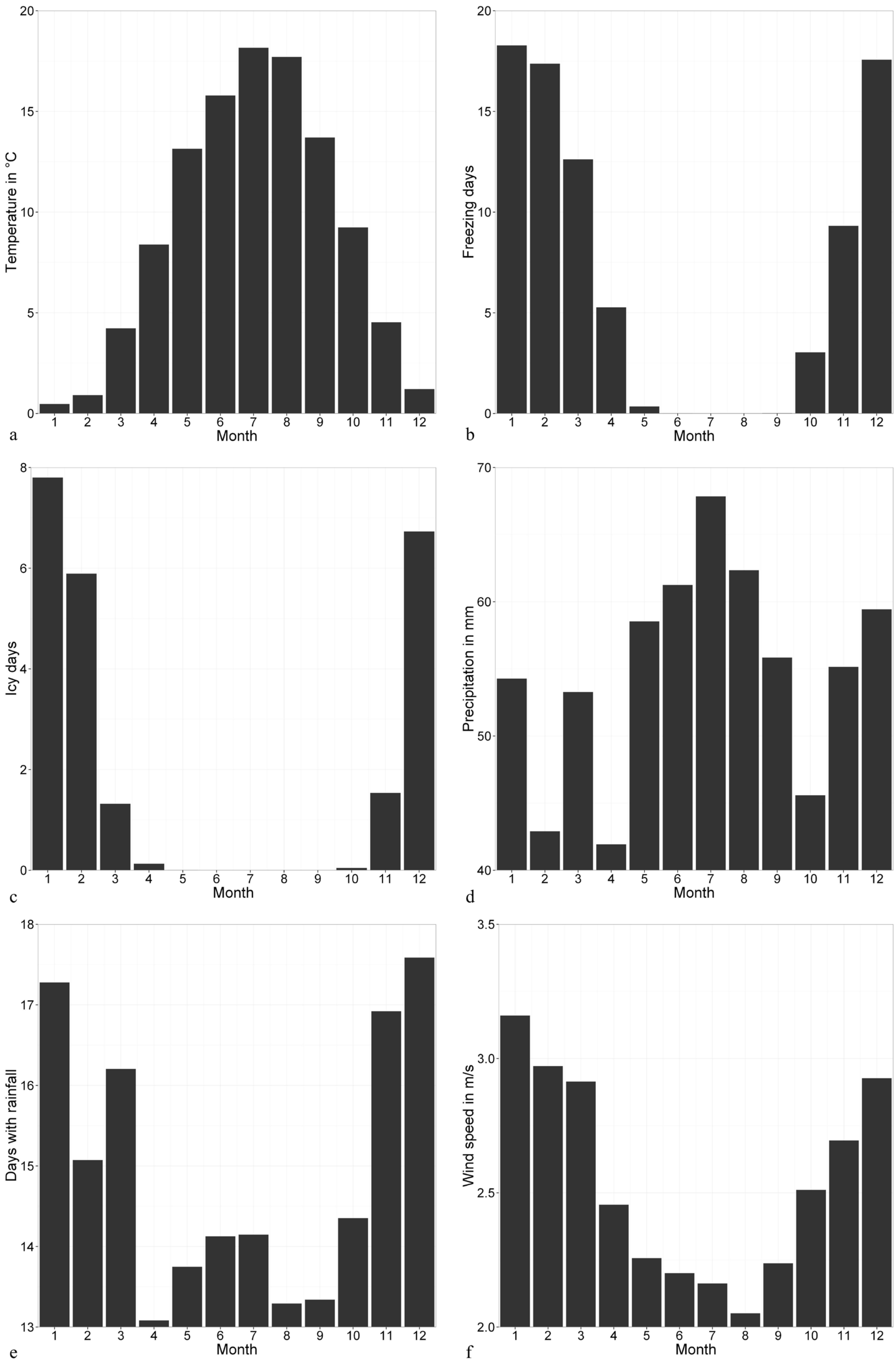


Fig. 5-1: Long-term averages of monthly aggregated mean temperature (a), freezing days (b), icy days (c), precipitation (d), days with rainfall (e), and wind speeds (f) during 1981 to 2010.

The climatological characteristics presented in the following section were calculated for the federal state using weather data of the DWD from 1981 to 2010. The data were error corrected and homogenized by the PIK. The abovementioned influences of the atmospheric circulation result in a long-term annual mean temperature of 8.9°C with 84 frosty days (minimum temperature below 0°C) and 24 icy days (maximum temperature below 0°C). Long-term precipitation sums are 681mm distributed on 182 days with precipitation. Mean temperatures reach their minimum of 0 to 1.5°C between December and February (Fig. 5-1a). During this timeframe about 70% of the freezing days (Fig. 5-1b) and 90% of the icy days (Fig. 5-1c) occur. The warmest months are June, July, and August with long-term mean temperatures between 16 and 18°C (Fig. 5-1a). The precipitation distribution during the course of the year has a bimodal structure with a slight maximum in winter and a stronger maximum between May and August (Fig. 5-1d). The summer maximum is defined by monthly precipitation sums between 60 and 70mm, the winter maximum has monthly precipitation values of 55 to 60mm. Rainfall during summer is distributed over 14 days with precipitation per month and 17 days per month during winter, which demonstrates the higher intensity of summer compared to winter rainfall in the study area (Fig. 5-1e). The distribution of mean wind speed is characterized by a maximum during winter with values of 3.0 m/s and a summer minimum with values between 2.0 and 2.2 m/s (Fig. 5-1f).

According to the regional distribution of mean temperature, Saxony-Anhalt is split into four subdivisions (Fig. 5-2a). The northernmost part is almost identical to the northern subdivision described by Schröder (2000). The atlantic influence has a cooling effect during summer in this area, which results in a mean annual temperature between 8.5 and 9.5°C. During winter the atlantic influence weakens and frosty days occur nearly as often as in the Harz mountains. The atlantic influence during the course of the year can be recognized when examining the annual precipitation sums and the number of rainy days for Saxony-Anhalt (Fig. 5-2d & 5-2e).

Precipitation sums are around the statewide mean or slightly below with 550 to 750mm/a. Despite some outliers the rainfall is distributed over 175 to 208 days. Wind speed reaches higher values in the northeast compared to the central, southern, and eastern parts of the state (Fig. 5-2f).

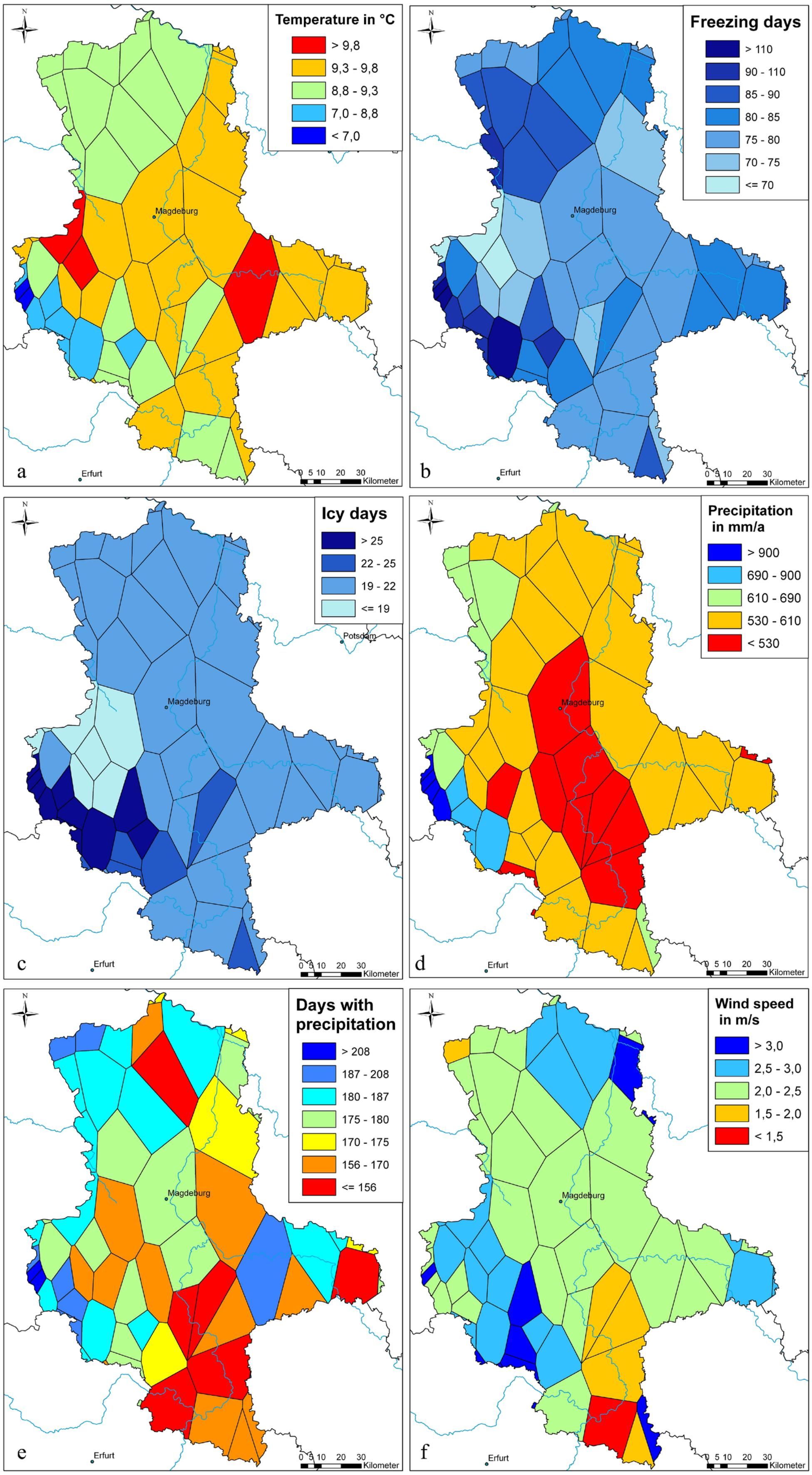


Fig. 5-2: Long-term station-wise averages of annually aggregated mean temperature (a), freezing days (b), icy days (c), precipitation (d), days with rainfall (e), and wind speeds (f) during 1981 to 2010.

According to Schröder (2000) the southern part can be split into three distinct temperature subdivisions. The central and eastern part of the state shows a mean annual temperature above 9.5°C, the southernmost part exhibits mean annual temperatures around 9°C at the northern rim of the Thuringian Forest, and the area directly influenced by the Harz mountains shows a mean annual temperature below 7°C in the center of the mountain range and 8 to 8.5°C at the rim. The central part, often referred to as the central German dry zone (Fabig 2007), shows the lowest amounts of annual rainfall with 500 to 600mm. In some areas annual rainfall is even below 500mm. The regional rainfall distribution is very heterogeneous. The rainfall is distributed on 156 to 180 days. In the southernmost area near the Thuringian Forest precipitation is higher again. Annual rainfall amounts up to 550 to 750mm distributed on 150 to 170 days. The area around the Harz Mountains is the wettest in Saxony-Anhalt and whole central Germany (Schröder 2000) with annual precipitation sums between 750 and more than 1100mm. In contrast to the more central areas of the state, rainfall is distributed on a larger amount of days (180 to more than 208 rainy days). In addition this region is the coldest in the state, which is underlined by 85 to more than 110 freezing days per year (Fig. 5-2b) and more than 25 icy days per year in the long term mean (Fig. 5-2c). Wind speed is lowest in the southeastern part of the state near the Thurinigian Forest. The highest wind speeds are detected at the Brocken station and the eastern to south eastern areas of the Harz Mountains (Fig. 5-2f).

5.2 Disease Situation

The time series of LRI on winter wheat presents two distinct periods in Saxony-Anhalt (Fig. 5-3a). The first period covers the time before 1993 with very low LRI means and very few regions exceeding 10% LRI every year. Beginning in 1993 LRI shows an overall increasing trend with mean values up to 35% LRI, a maximum LRI of 100% in some years at some stations, and a higher interannual and intraannual variability. The years with higher LRI concentrate around the years 1994, 2001, and 2007, always interrupted by phases with lower LRI. Figures 5-6a & b show annual time series of LRI0 and LRI30 during the same timeframe. The tendency towards higher leaf rust incidence after 1993 becomes more obvious. Observations indicating a damaging epidemic were scarce before 1993 and became much more frequent after 1993. In 2007 the observations exhibiting a damaging epidemic reached its peak with 40%. The frequency distribution of LRI reveals that the majority (around 75%) of the 837 incidence measurements has a value between

0 and 5% (Fig. 5-4). The remaining 25% distribute on values above 5% with the majority between 5 and 15% LRI.

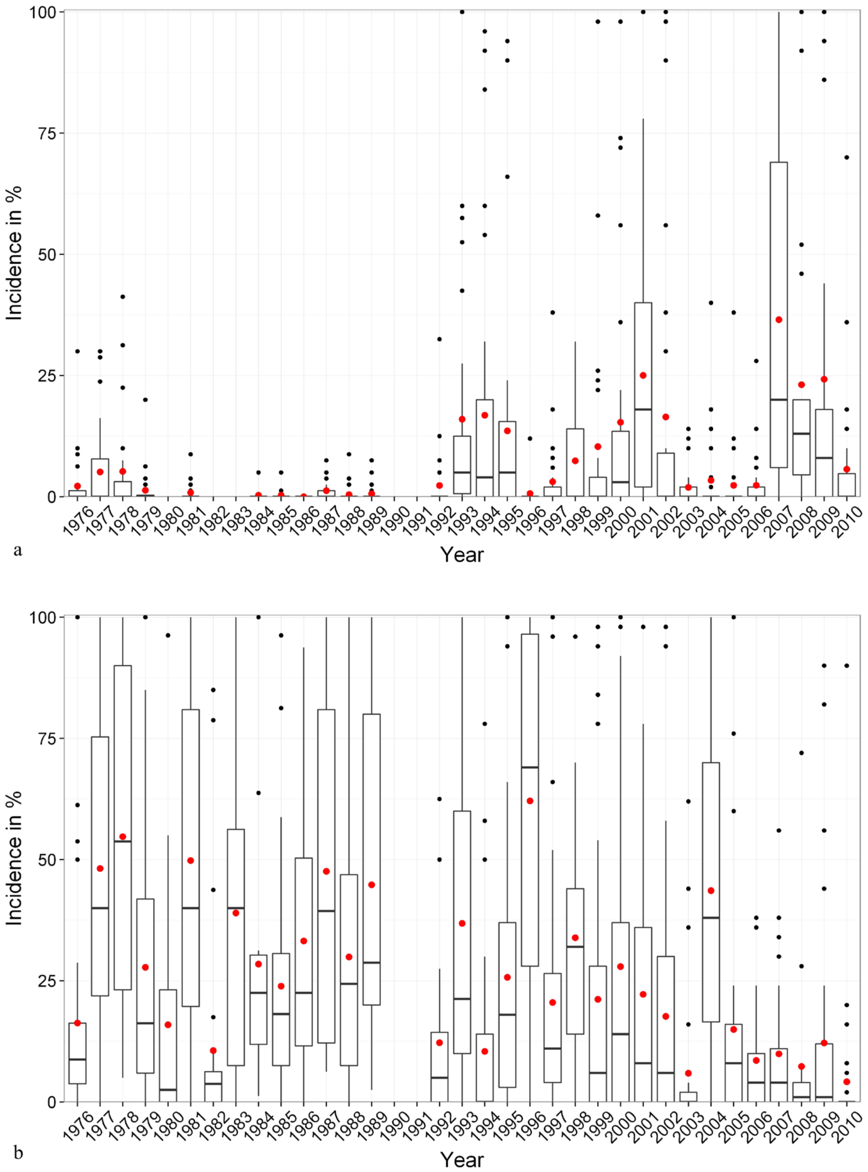


Fig. 5-3: Disease incidence of leaf rust (a) and powdery mildew (b) on winter wheat in percent during the period 1976 to 2010: The mean values (red dots), medians (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers), and outliers (black dots) are shown.

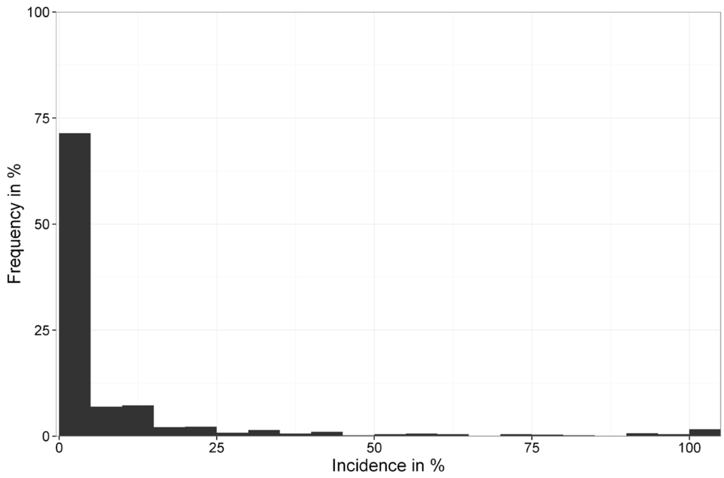


Fig. 5-4: Frequency distribution of leaf rust incidence in percent.

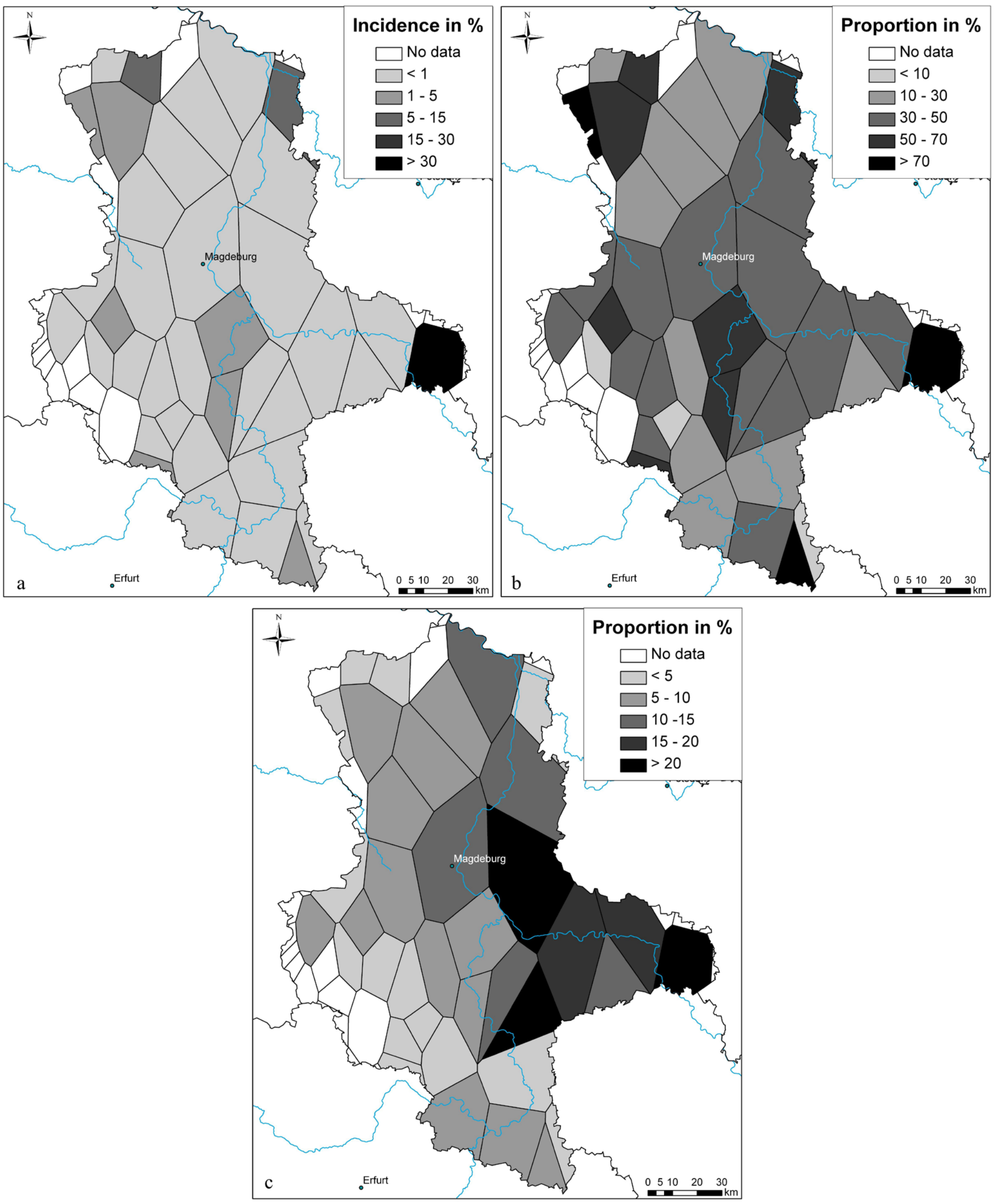


Fig. 5-5: Median leaf rust incidence (a) and proportion of observations exceeding 0% (b) and 30% (c) incidence during the period 1976 to 2010.

The spatial distribution of median LRI reveals only small regional differences (Fig. 5-5a). The median LRI0 shows more pronounced regional differences (Fig. 5-5b). Values are higher in a band stretching from the Harz Mountains eastwards to the eastern and northeastern border of the state compared to most of the northern and southern areas. The highest values with LRI0 above 50% are located in the farthest northwestern, eastern, and southern parts of the state. The median LRI30 is lowest near the Harz Mountains with LRI30 below 5% (Fig. 5-5c). Values above 10% and even above 20% are reached in the northeastern and eastern parts of the state.

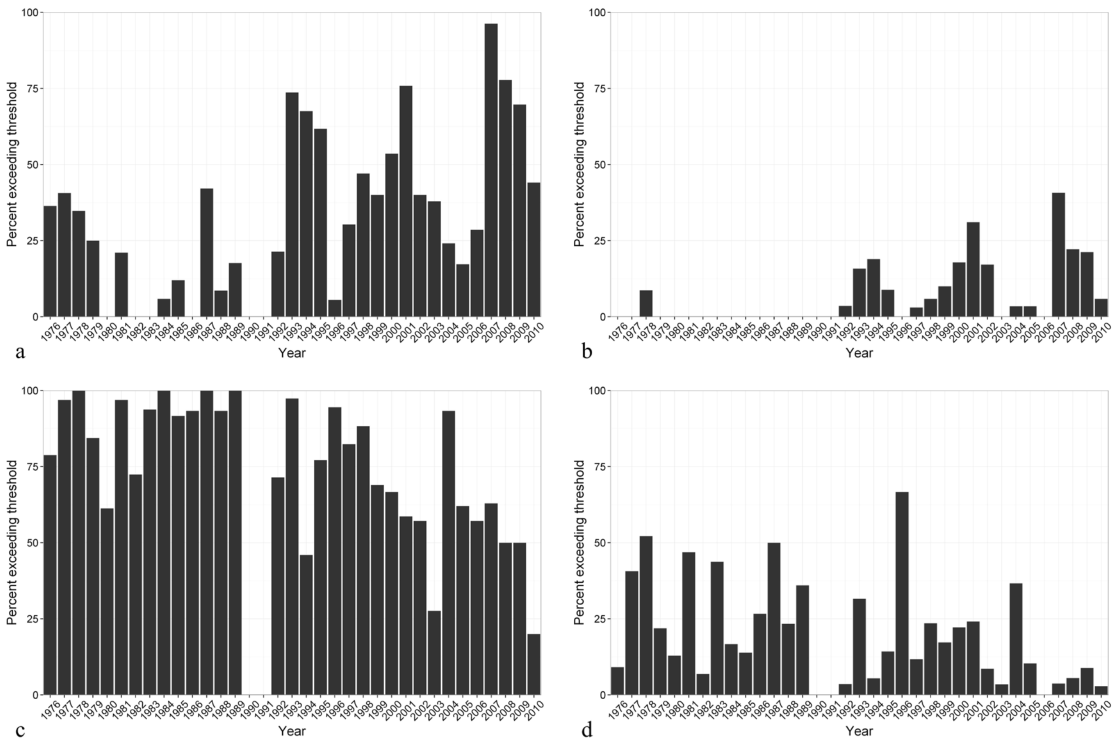


Fig. 5-6: Relative annual frequency of observations exceeding 0% (a, c), 30% (b), and 50% (d) incidence during the period 1976 to 2010 at monitoring sites for leaf rust (a, b) and powdery mildew(c, d) in percent.

Compared to LRI, powdery mildew incidence (PMI) shows a decreasing trend considering the whole timeframe 1976 to 2010 (Fig. 5-3b). The negative trend is visible during the whole period, but becomes especially obvious after 1991 with mean PMI only rarely exceeding 30%. Especially after 2004 mean values reach a continuously low level between 10 and 15% PMI. The decreasing tendency is underlined by figures 5-6c & d, presenting annual time series of PMI0 and PMI50.

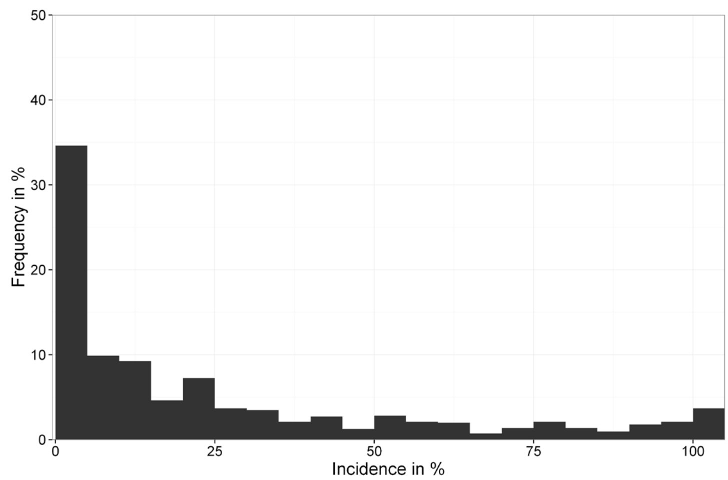


Fig. 5-7: Frequency distribution of powdery mildew incidence in percent.

Compared to the early years damaging epidemics, indicated by exceeding the 50% PMI threshold, occur at much fewer monitoring sites. The frequency distribution of PMI shows, that about one third of the 950 measurements has a value below 5% incidence (Fig. 5-7). The second third of the data exhibits values between 5% and 25% PMI and the last third distributes on 25% to 100% PMI. The spatial distribution reveals high median PMI values between 5 and 30% for most parts of Saxony-Anhalt (Fig. 5-8a). The southeastern and northwestern parts of the state exhibit the highest values with PMI over 15%. The median PMI0 holds high values above 70% for nearly the whole state (Fig. 5-8b). Areas with lower PMI0 aggregate in the southern and southwestern parts of the state. Fig. 5-8c, showing the median PMI50, reveals a split of the state into two parts. The central, eastern, and southern areas of the state belong to the part having higher PMI50 values above 20%. The northern areas and areas northeast of the Harz Mountains belong to the part characterized by PMI50 values below 20%, most of them even below 15%.

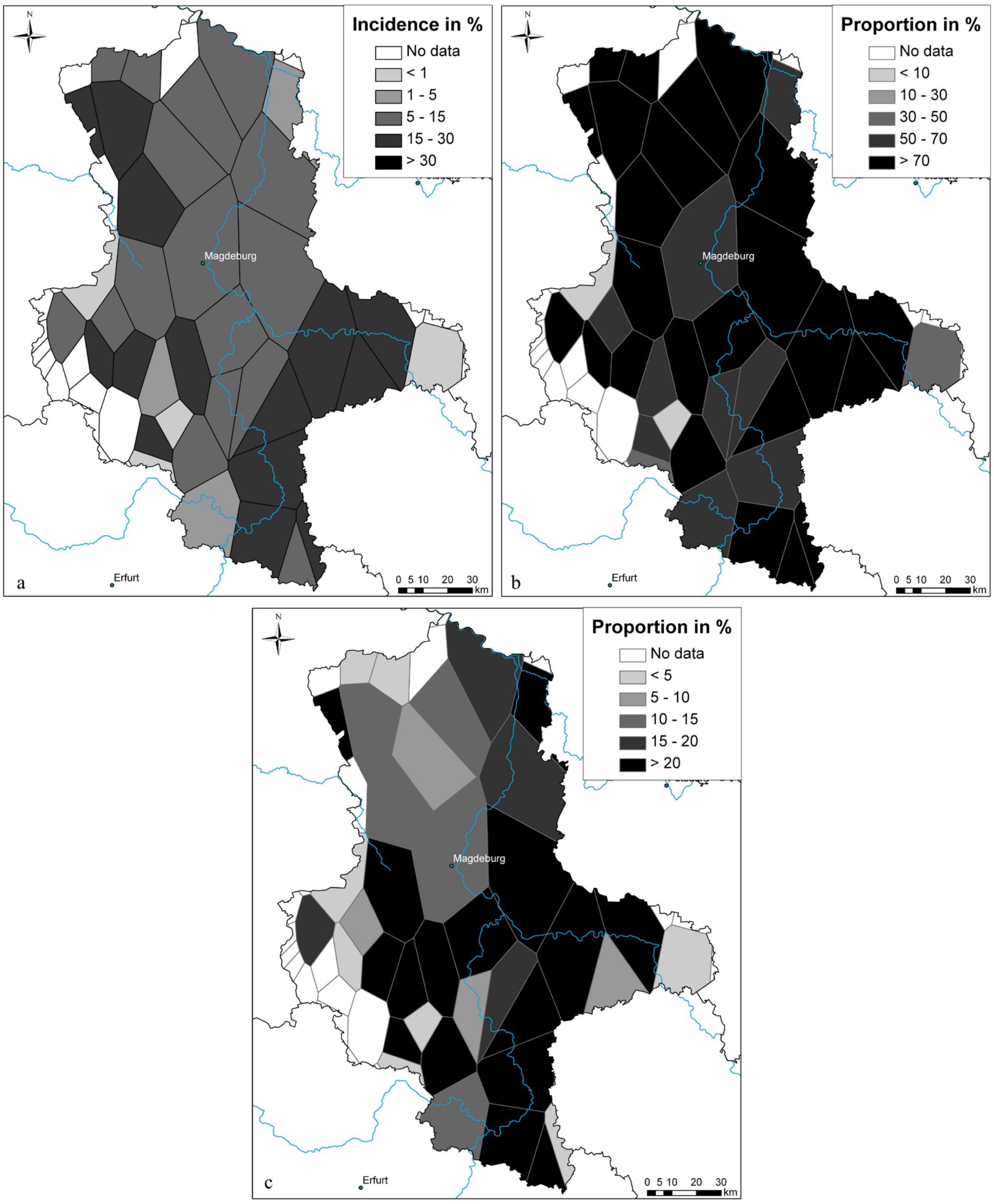


Fig. 5-8: Median powdery mildew incidence (a) and proportion of observations exceeding 0% (b) and 50% (c) incidence during the period 1976 to 2010.

6 Results

6.1 Interval-based correlation

The results described in this chapter were taken from the study of Stößel et al. (2013).

6.1.1 Leaf rust

The results of the analysis of the influence of selected weather parameters on leaf rust occurrence are presented in Figures 6-1 and 6-2. A positive correlation between daily mean temperature and leaf rust infestation level were detected for most investigated time intervals. The highest correlation coefficients were found for longer time periods (e.g., from day 1 to day 300 before the monitoring date) (Fig. 6-1a). Another finding was that correlation coefficients for short 5- to 20-day periods around 120, 150, 200, 240, and 260 days before monitoring were lower than those obtained averaging over these periods.

Short- to medium-term relationships prevailed for correlations between precipitation sums and leaf rust infestation (Fig. 6-1b). Positive correlations were observed from days 90 to 150 (mid-March to mid-January), around days 230 and 295, and in the first 20 to 40 days before monitoring. Short-term negative correlations were found around 60, 170, and 210 days before field monitoring.

The correlation analyses of sunshine duration and leaf rust infestation are shown in Fig. 6-1c. Sunshine duration had a significant positive influence on leaf rust incidence when averaged over 300 days. In contrast to Fig. 6-1a correlations on shorter time scales were higher than those for longer time periods. There were significant positive correlations from days 30 to 60 (mid-May to mid-April) and days 160 to 270 before monitoring (end of January to mid-September). No significant positive correlations were found from early spring to mid-winter (day 80 to 150). Significant negative correlations were observed between days 90 and 120 (March to February). No significant correlations were identified during the first 30 days before disease monitoring. Between days 290 and 300 significant negative correlations with leaf rust infestation were observed.

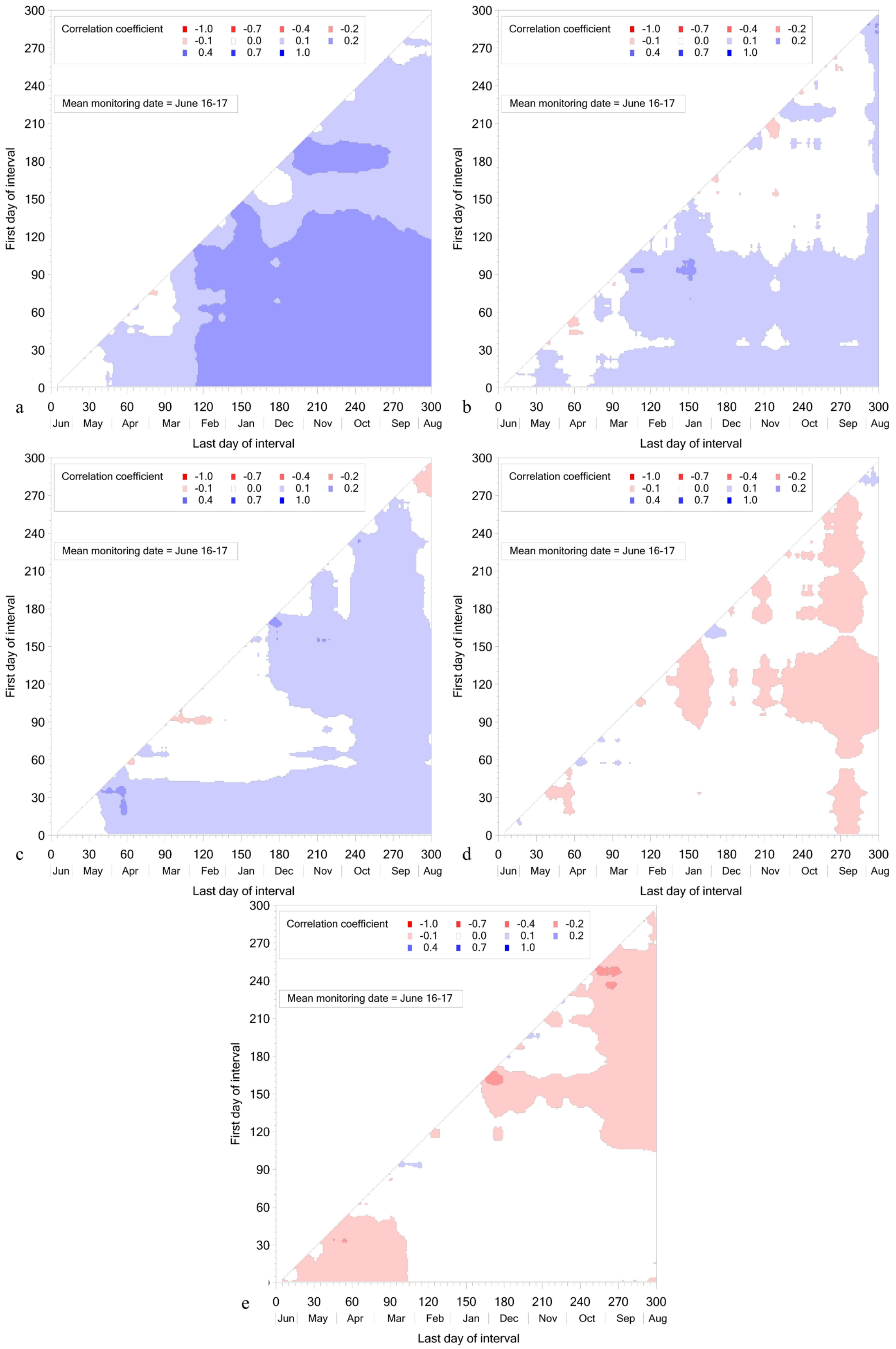


Fig. 6-1: Correlograms of significant correlation (α=0.05; Kendall's coefficient) between a) mean temperature, b) precipitation sum, c) sunshine duration, d) relative humidity, and e) wind speed and leaf rust severity on winter wheat in Saxony-Anhalt from 1976 to 2010. Legend elements represent the median of the interval of correlation coefficients. Day zero represents the monitoring day.

Correlations between leaf rust infestation and relative humidity revealed mainly short-term relationships, except during the period from day 140 to 270 (end of January to mid-September), when significant negative mid- to long-term correlations were observed (Fig. 6-1d). From days 30 to 60 (mid-May to mid-April) another negatively correlated period was observed.

Analysis of correlations between wind speed and leaf rust infestation showed almost exclusively negative relationships (Fig. 6-1e). Significant negative correlations were detected for mean wind speed in autumn (days 240 to 270 before monitoring), late autumn and winter (days 150 to 180), and during the first 60 days before monitoring (spring to early summer).

Analysis of correlations between leaf rust infestation and the number of days with precipitation (Fig. 6-2a) pointed out significant positive correlations from day 90 to day 150 (March to January), day 190 to day 240 (end of November to mid-October), and day 290 to day 300. Significant negative correlations occurred during the interval from days 35 to 60 and around day 170 before monitoring.

The influence of freezing days on leaf rust infestation in spring was mainly negative from the beginning of November (day 225) until mid-March (day 90) (Fig. 6-2b), especially during the winter until early spring. Analysis of correlations between the number of days with snowfall and leaf rust occurrence revealed the most negative correlation coefficients in the interval between days 90 and 210 (mid-March to mid-November) and further negative correlations during shorter time periods around day 210 (Fig. 6-2c).

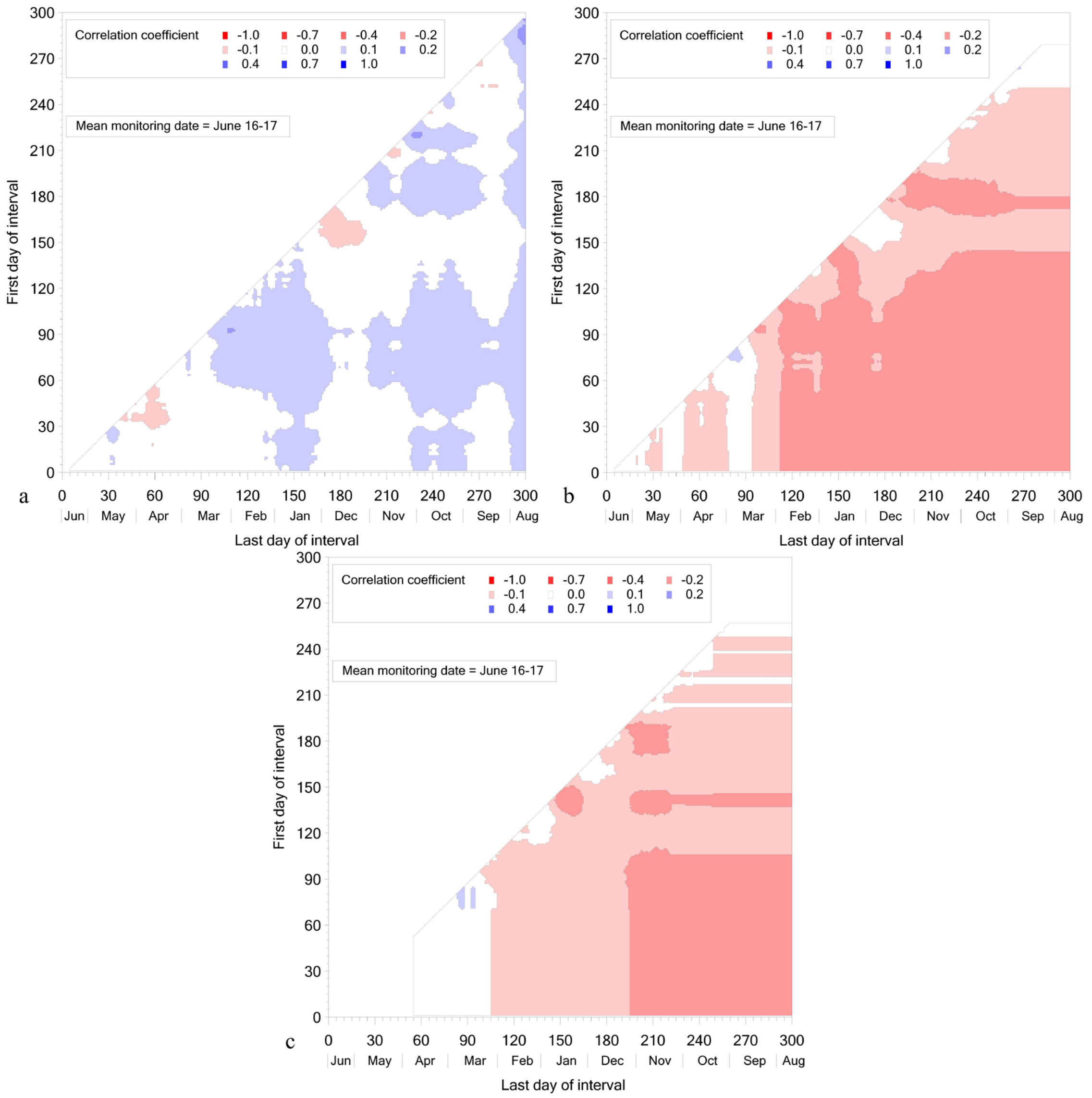


Fig. 6-2: Correlograms of significant correlation (α=0.05; Kendall's coefficient) between a) number of precipitation days, b) number of freezing days and c) number of days with snowfall and leaf rust severity on winter wheat in Saxony-Anhalt from 1976 to 2010. Legend elements represent the median of the interval of correlation coefficients. Day zero represents the monitoring day.

6.1.2 Powdery mildew

The results of the analysis of the influence of selected weather parameters on powdery mildew occurrence are presented in Figures 6-3 and 6-4. Powdery mildew infestation was not clearly affected by mean temperature throughout the whole vegetation period (Fig. 6-3a). Rather short intervals with significant correlation coefficients were observed. Periods around days 230, 290, and during the first two to three months before monitoring contained most of the negative correlations. Positive correlations were found for days 130 to 210 before disease monitoring.

Regarding relationships between minimum temperatures and powdery mildew infestation levels significant positive correlations appeared in the period from day 70 to day 110 (beginning in April until end of February) and during winter months (February to December) (Fig. 6-3b). Conversely, significant negative correlations were observed between mid-November and mid-October.
Two distinct patterns are shown by the correlograms for precipitation sums and powdery mildew occurrence (Fig. 6-3c). Firstly, precipitation sums from February to September and from days 20 to 40 before monitoring were negatively correlated with disease incidence. Secondly, time windows around 300 days before monitoring and during the first 10 to 15 days before monitoring included significant positive correlations.
Analysis of correlations between relative humidity and disease infestation revealed significant negative correlations from days 90 to 230 (mid-March to the beginning of November) and positive relationships during April and 10 to 15 days before disease monitoring (Fig. 6-3d).
Significant negative correlations between sunshine duration and disease occurrence for the time window from December until the monitoring date were observed (Fig. 6-3e). The strongest correlations were identified during the first 10 to 15 days before monitoring.
The correlogram for maximum temperature and incidence of *B. graminis* f.sp. *tritici* shows significant negative correlations in late summer (end of August) and between the beginning of February and the monitoring day (Fig. 6-3f). Between the end of January and the beginning of December significant positive correlations at interval lengths of 10 to 20 days were detected.
In late spring (days 20 to 60) and especially in autumn (days 210 to 270) the number of days with precipitation had a significant negative effect on powdery mildew incidence (Fig. 6-4a). Significant positive correlations were observed during the first 20 days before monitoring.
Regarding correlations between freezing days and powdery mildew occurrence (Fig. 6-4b) significant positive correlations were observed from mid-October to the end of November (days 240 to 200).
The analyses identified significant positive correlations between the number of days with mean temperatures of 17 to 23°C and powdery mildew occurrence for periods in early April, from days 70 to 80, and around mid-October. Significant negative correlations were located around 15 and 300 days before monitoring (Fig. 6-4c).

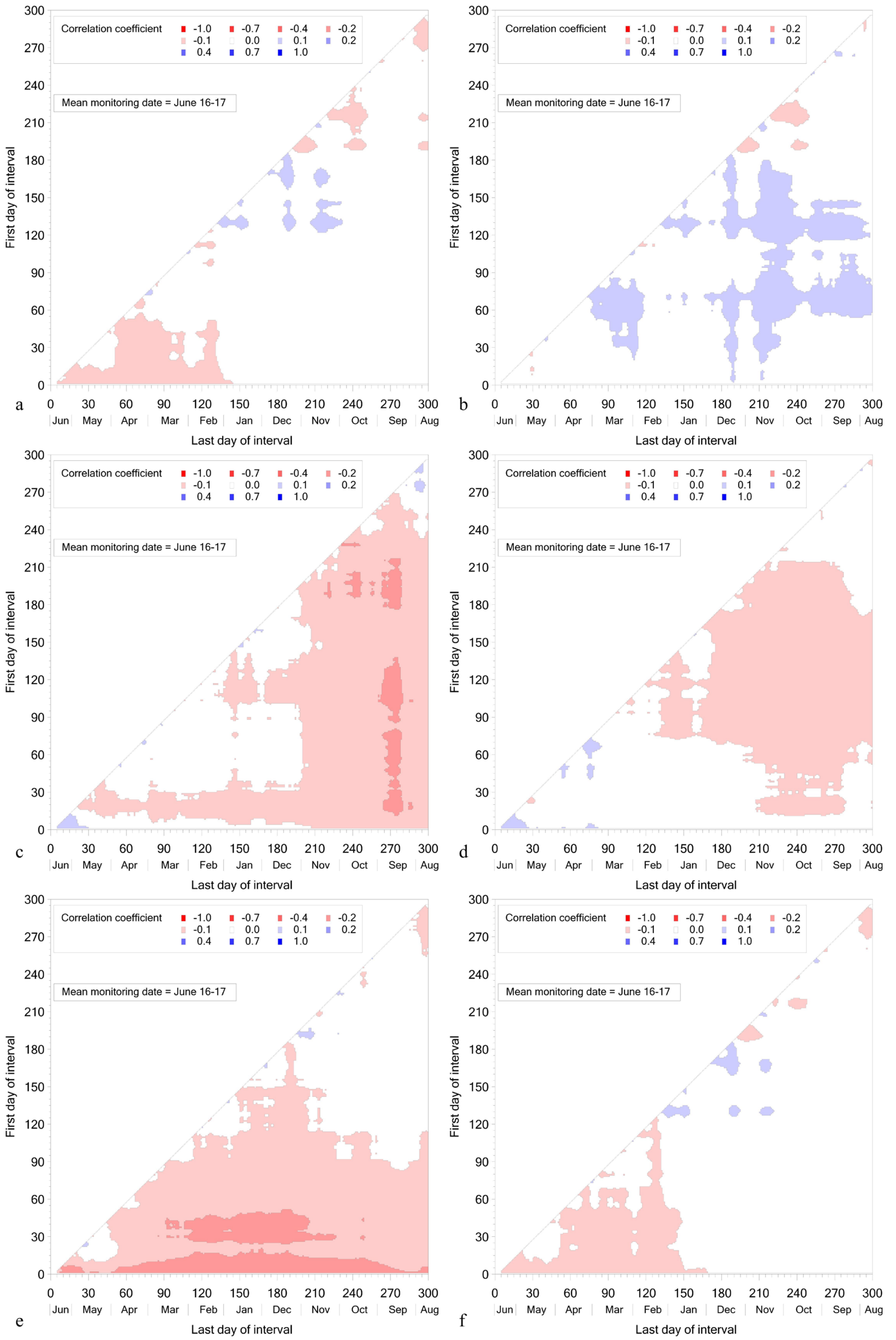


Fig. 6-3: Correlograms of significant correlation (α=0.05; Kendall's coefficient) between a) mean temperature, b) minimum temperature, c) precipitation sum, d) relative humidity, e) sunshine duration, and f) maximum temperature and powdery mildew severity on winter wheat in Saxony-Anhalt from 1976 to 2010. Legend elements represent the median of the interval of correlation coefficients. Day zero represents the monitoring day.

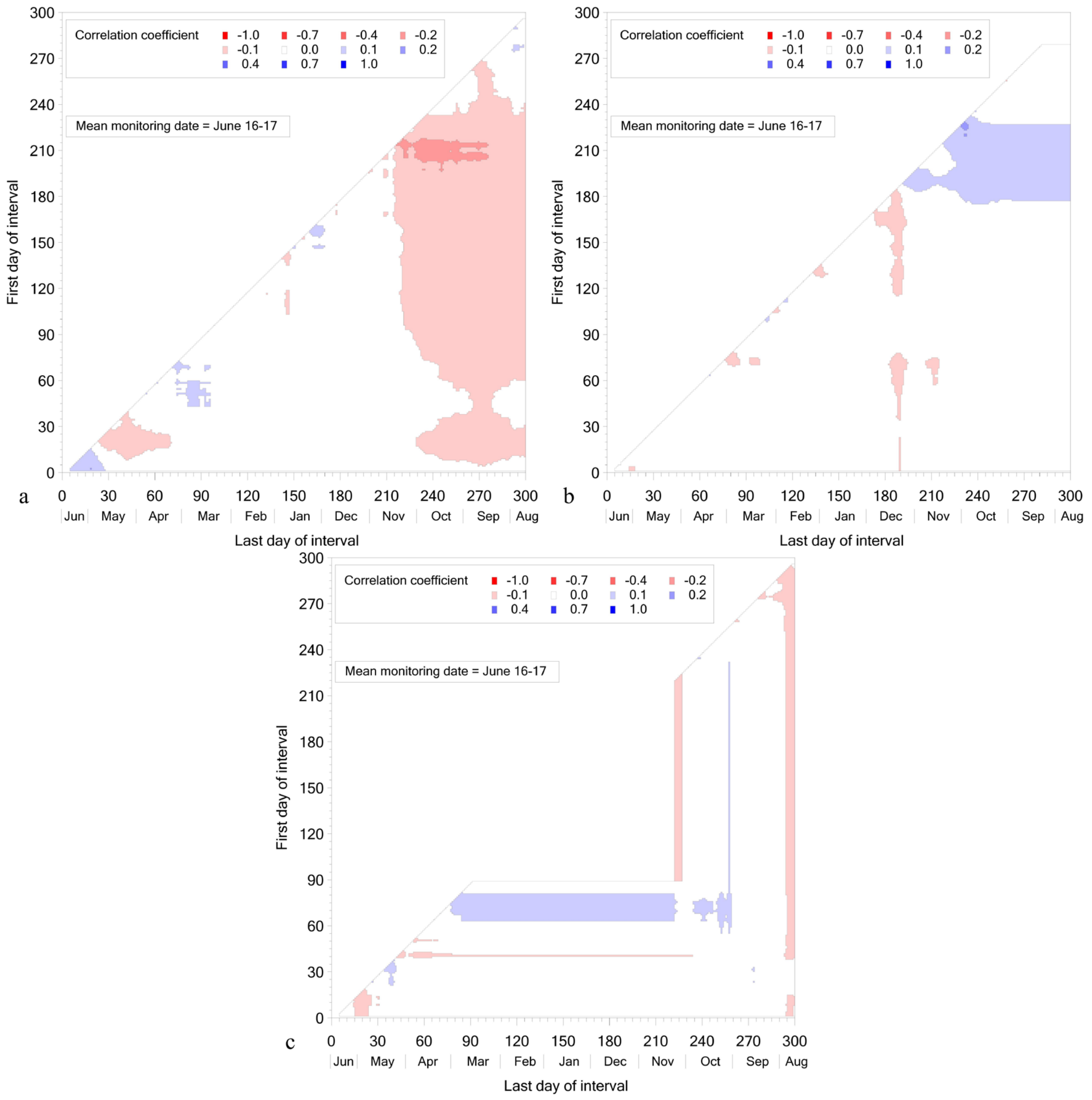


Fig. 6-4: Correlograms of significant correlation (α=0.05; Kendall's coefficient) between a) number of precipitation days, b) number of freezing days, and c) number of days with temperatures between 17 and 23°C and powdery mildew severity on winter wheat in Saxony-Anhalt from 1976 to 2010. Legend elements represent the median of the interval of correlation coefficients. Day zero represents the monitoring day.

6.2 Non-climatic influences

The correlation coefficients of Kendall, calculated between leaf rust incidence (LRI) and nine non-climatic variables for the timeframe 1990-2010, revealed only one significant relationship. The monitoring doy had a significant negative correlation ($r = -0.09$) with LRI and $p < 0.01$ (Tab. 6-1). In contrast to the results for leaf rust correlations with powdery mildew incidence (PMI) revealed significant correlations for all non-climatic variables: except soil air capacity (Tab. 6-1). The doy of sowing and emergence had a positive correlation with PMI, the monitoring doy, the length of the vegetation period, and mean values of the soil variables usable field capacity, field capacity, total pore volume, and potential cation exchange capacity a negative correlation.

Tab. 6-1: Kendall correlation coefficients and p-values between non-climatic variables and incidence of leaf rust (lr) and powdery mildew (pm).

Variable	corr (lr)	p (lr)	corr (pm)	p (pm)	n
Monitoring day	-0.0889	0.0049	-0.0959	0.0016	554
Day of sowing	-0.0384	0.2211	0.1467	0.0000	553
Day of emergence	-0.0422	0.1819	0.1487	0.0000	541
Vegetation period	-0.0197	0.5285	-0.1628	0.0000	553
Usable field capacity	0.0159	0.6205	-0.0818	0.0083	554
Field capacity	-0.0149	0.6439	-0.1315	0.0000	554
Air capacity	-0.0043	0.8957	0.0230	0.4624	554
Total pore volume	-0.0056	0.8630	-0.1120	0.0003	554
Potential cation exchange capacity	-0.0310	0.3357	-0.0692	0.0257	554

Tab. 6-2: Chi-Square values and p-values obtained by Kruskal-Wallis tests on differences between sample means of PC, PPC, and Resistance for leaf rust and powdery mildew.

Disease	Variable	Chi-Square	p
Leaf rust	PC	16.4894	0.8995
Leaf rust	PPC	17.9126	0.5283
Leaf rust	Resistance	19.8071	0.0060
Powdery mildew	PC	36.5693	0.0483
Powdery mildew	PPC	19.9622	0.3969
Powdery mildew	Resistance	38.8212	0.0000

The Kruskal-Wallis tests on differences between multiple class means revealed no significant influence of the PC on LRI and no significant influence of the PPC on LRI and PMI. But, a significant impact of the PC on PMI was identified with $p = 0.048$ (Tab. 6-2).

The Kruskal-Wallis tests applied on variety susceptibility revealed significant differences for LRI and PMI with $p < 0.01$. Susceptibility classes 3 to 5 had significant different LRI mean values compared to classes 7 to 9 with $p < 0.05$ according to the two-sample Wilcoxon rank-sum tests. Classes 2 and 6 had no significant different mean than any other class (Tab. 6-3). The Kolmogorov-Smirnov tests presented even less significant differences between the leaf rust susceptibility classes (Tab. 6-3). Susceptibility classes 1 and 2 had significant different PMI means compared to classes 3 to 8 with $p < 0.05$ according to the two-sample Wilcoxon rank-sum tests. The classes 3 and 4 had significant different means compared to most of the classes 5 to 8 with $p < 0.05$. The mean values of classes 5 to 8 were not significantly different from each other (Tab. 6-3). The Kolomogorov-Smirnov tests revealed similar patterns of difference between the susceptibility classes for powdery mildew (Tab. 6-3).

Tab. 6-3: P-values of two-sample Wilcoxon rank-sum tests (Wilc) and Kolmogorov-Smirnov tests (KS) to compare mean values and distributions of leaf rust and powdery mildew incidence between all combinations of resistance groups.

Leaf rust				Powdery mildew			
Group 1	**Group 2**	**p (Wilc)**	**p (KS)**	**Group 1**	**Group 2**	**p (Wilc)**	**p (KS)**
2	3	0.7997	0.9975	1	2	0.3533	0.7258
2	4	0.4526	0.8069	1	3	0.4340	0.5265
2	5	0.6011	0.9498	1	4	0.1670	0.2400
2	6	0.4459	0.9361	1	5	0.0281	0.0794
2	7	0.2250	0.3842	1	6	0.0249	0.0366
2	8	0.2132	0.3958	1	7	0.0272	0.0095
2	9	0.1060	0.3585	1	8	0.0261	0.1033
3	4	0.1053	0.3128	1	9	0.1203	0.2992
3	5	0.3404	0.8360	2	3	0.0046	0.0105
3	6	0.1539	0.6924	2	4	<.0001	0.0001
3	7	0.0007	0.0016	2	5	0.0001	0.0018
3	8	0.0026	0.0317	2	6	0.0014	0.0037
3	9	0.0191	0.1882	2	7	0.0028	0.0021
4	5	0.6259	0.9665	2	8	0.0090	0.0745
4	6	0.8820	0.6345	2	9	0.0771	0.2268
4	7	0.0208	0.0335	3	4	0.2812	0.7627
4	8	0.0777	0.3041	3	5	0.0308	0.1337
4	9	0.0964	0.3504	3	6	0.0261	0.0709
5	6	0.5865	0.9982	3	7	0.0448	0.0201
5	7	0.0181	0.0851	3	8	0.0280	0.1756
5	8	0.0455	0.2233	3	9	0.2613	0.5594
5	9	0.0789	0.3361	4	5	0.1274	0.4414
6	7	0.1249	0.1320	4	6	0.0593	0.1613
6	8	0.1864	0.4492	4	7	0.0922	0.0582
6	9	0.1492	0.6381	4	8	0.0438	0.2047
7	8	0.7034	0.8893	4	9	0.3787	0.7122
7	9	0.5797	0.9679	5	6	0.3494	0.7299
8	9	0.4724	0.8423	5	7	0.4803	0.4867
				5	8	0.1132	0.2453
				5	9	0.7628	0.9444
				6	7	0.8307	0.9614
				6	8	0.3839	0.5860
				6	9	0.6644	0.9525
				7	8	0.2647	0.2700
				7	9	0.6433	0.9639
				8	9	0.2683	0.5176

The annual amounts of susceptible and resistant varieties included in the dataset revealed different patterns for both pathogens. No varieties susceptible to leaf rust were detected before 1992 (Fig. 6-5a). Between 1992 and 1996 more susceptible than resistant varieties were used. Since 1996 a trend towards varieties with lower susceptibility was observed. In contrast to leaf rust varieties susceptible to powdery mildew were intensely used before 1992 (Fig. 6-5b). In most of the years more than 50% of the varieties were susceptible.

Starting in 1992 the amount of varieties susceptible to powdery mildew remained constant on a very low level.

The autocorrelation functions were significant for LRI at lags of one and seven years (Fig. 6-6a) and not significant for PMI (Fig.6-6b) according to the 95%-quantile of the normal distribution.

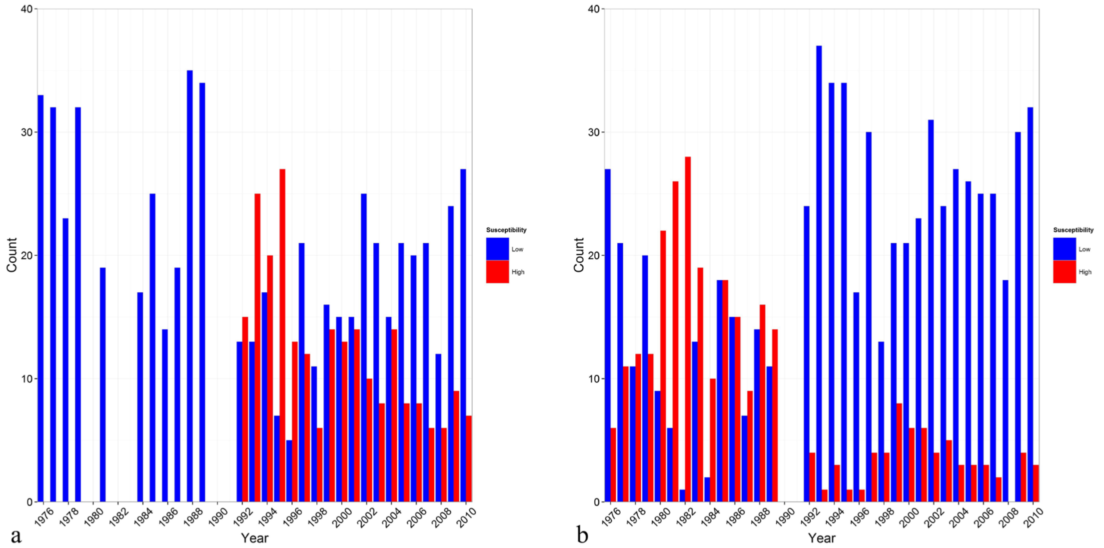


Fig. 6-5: Annual counts of wheat varieties susceptible (red) and resistant (blue) to leaf rust (a) and powdery mildew (b)for monitoring sites during 1976 to 2010 in Saxony-Anhalt.

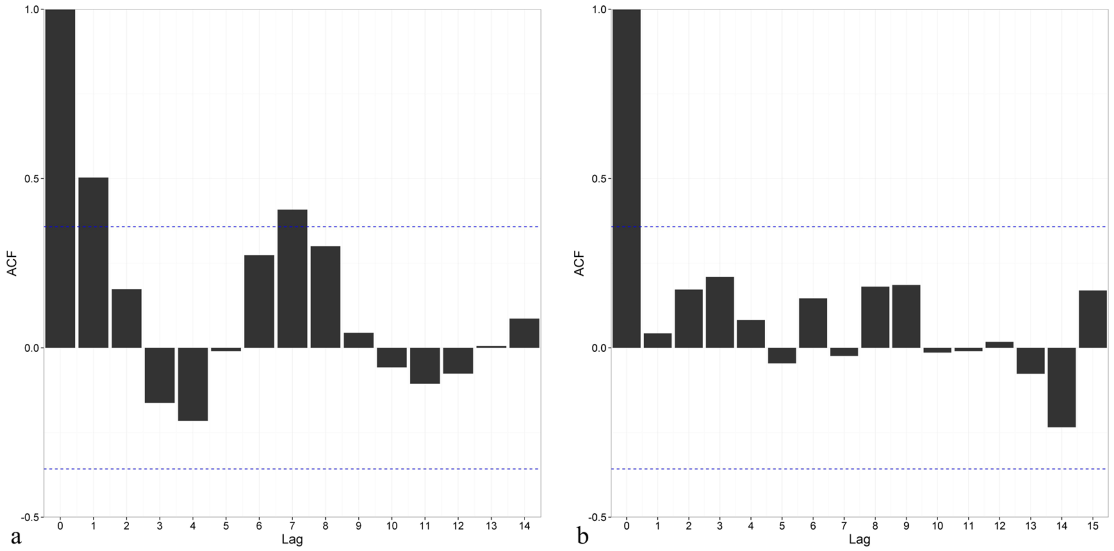


Fig. 6-6: Coefficients of the autocorrelation functions of leaf rust (a) and powdery mildew (b) for lags of 0 to 14 years. The confidence limits using $\alpha = 0.05$ are indicated as blue interrupted lines.

6.3 Logistic regression results

In this chapter the results of the logistic modeling approaches are presented. In addition to the tables presented below, all parameter estimates of the final selected models were compiled according to a calendar format in Tab. 6-4 & 6-5 to allow an easier overview of the selected variable-timeframe combinations.

Tab. 6-4: Calendar of parameter estimates included in the logistic regression models using leaf rust data. Interval number (Interv), real starting (Start), and ending (End) dates of the intervals are displayed. Res = x, if parameter estimate interacted with the resistance group, Res = value, if meteorological variable was selected with and without resistance as an interaction term. Negative (red) and positive (blue) parameter estimates are shown for the LRI-, LRI0-, and LRI30-model.

Date	Start	16.6	1.6	17.5	2.5	17.4	2.4	18.3	3.3	16.2	1.2	17.1	2.1	18.12	3.12	18.11	3.11	19.10	4.10	19.9	4.9
	End	2.6	18.5	3.5	18.4	3.4	19.3	4.3	17.2	2.2	18.1	3.1	19.12	4.12	19.11	4.11	20.10	5.10	20.9	5.9	21.8
	Interv	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Temperature	LRI					0.116					0.145			0.141							
	Res																				
	LRI0				0.120	0.110															
	Res				x																
	LRI30					0.229												0.238	0.153		-0.144
	Res																				
Precipitation	LRI		0.138			-0.173		0.301	0.297	0.300			-0.212		0.164						0.220
	Res		x							x					x						
	LRI0				-0.205			0.290			0.380						0.169				
	Res																				
	LRI30		0.172								0.286										
	Res		x																		
Wind speed	LRI						0.243					-0.343									
	Res																				
	LRI0												-0.217		0.312						
	Res																				
	LRI30					0.628	-0.395	0.690					-0.804								
	Res					x	x														

Tab. 6-5: Calendar of parameter estimates included in the logistic regression models using powdery mildew data. Interval number (Interv), real starting (Start), and ending (End) dates of the intervals are displayed. Res = x, if parameter estimate interacted with the resistance group, Res = value, if meteorological variable was selected with and without resistance as an interaction term. Negative (red) and positive (blue) parameter estimates are shown for the PMI-, PMI0-, and PMI50-model.

Date	Start	16.6	1.6	17.5	2.5	17.4	2.4	18.3	3.3	16.2	1.2	17.1	2.1	18.12	3.12	18.11	3.11	19.10	4.10	19.9	4.9
	End	2.6	18.5	3.5	18.4	3.4	19.3	4.3	17.2	2.2	18.1	3.1	19.12	4.12	19.11	4.11	20.10	5.10	20.9	5.9	21.8
	Interv	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Temperature	PMI	0.075		-0.042		-0.092		-0.065									-0.080		-0.080		-0.085
	Res	x				x		x											x		
	PMI0						-0.085								-0.112						
	Res						x								x						
	PMI50	-0.069		-0.109		-0.121	-0.108	-0.120								0.070					-0.139
	Res	0.105					x	x													x
Precipitation	PMI	0.091					-0.182				-0.204			-0.152			-0.373		-0.252		0.135
	Res																				
	PMI0				-0.189										-0.308		-0.459				
	Res																				
	PMI50	0.154			-0.190		-0.210	-0.428			-0.258	-0.167	-0.157				-0.278		-0.342		0.135
	Res	x			x			x				x	x								x
Wind speed	PMI			0.350	-0.413							-0.150			-0.192						
	Res																				
	PMI0								-0.165	0.215				-0.262							
	Res																				
	PMI50																				
	Res																				

6.3.1 Leaf rust

6.3.1.1 Raw incidence data

The MSE validation results obtained for the 10 regression models, identified by applying a 10-fold cross-validation on the test samples are presented in Tab. 6-6. The logistic model for the raw leaf rust incidence (LRI) with the minimum MSE value for the test sample was selected and included 14 variables (Tab. 6-7). Based on the parameter estimates (PE) precipitation had a positive influence on LRI between mid February and mid March and at the end of August and beginning of September and a negative influence during the second half of December. During the second half of May, the first half of February, and the second half of November precipitation had a positive impact on LRI on resistant varieties and a negative on LRI on susceptible varieties. In the first half of April precipitation had a negative influence on LRI on susceptible varieties and a positive one on resistant varieties. Mean temperature had a positive influence on LRI during the first half of April, the second half of January, and the first half of December. Wind speed had a negative impact on LRI during the first half of January and a positive one during the second half of March. The resistance group had a negative parameter estimate. With regard to the class coding this implies a positive PE on susceptible varieties and a negative PE on resistant varieties.

Tab. 6-6: MSE-V for the logistic regression model derived using raw leaf rust data for each repetition number according to the 10-fold cross-validation sample.

Repetition	MSE-V
1	0.031
2	0.040
3	0.039
4	0.049
5	0.031
6	0.023
7	0.042
8	0.038
9	0.043
10	0.046

Tab. 6-7: Parameter estimates and 5%- and 95%-confidence limits for the final selected leaf rust (lr) model using raw incidence data. The abbreviation “Resgr” stands for the resistance group. Interactions are indicated by *.The numbers linked with the abbreviated variable identify the 15-day interval over which the variable was aggregated.

Variable	Estimate	p5	p95
Intercept	-3.041	-3.235	-2.879
Resgr_lr	-0.588	-0.718	-0.465
prec_12	-0.212	-0.321	-0.107
prec_14*Resgr_lr	0.164	0.014	0.318
prec_2*Resgr_lr	0.138	0.042	0.225
prec_20	0.220	0.111	0.325
prec_5*Resgr_lr	-0.173	-0.308	-0.052
prec_7	0.301	0.193	0.424
prec_8	0.297	0.148	0.426
prec_9*Resgr_lr	0.300	0.103	0.463
temp_10	0.145	0.108	0.180
temp_13	0.141	0.096	0.184
temp_5	0.116	0.055	0.175
wind_11	-0.343	-0.468	-0.213
wind_6	0.243	0.032	0.430

6.3.1.2 0% incidence threshold

The f-measure validation results obtained for the 10 regression models, identified by applying a 10-fold cross-validation on the test samples are shown in Tab. 6-8. The binary logistic model for a threshold of 0% leaf rust incidence (LRI0) with the maximum f-measure for the test sample was selected and included 9 variables (Tab. 6-9). The PEs pointed out that precipitation had a negative impact on LRI0 in the second half of April and a positive during the first half of March and the second halves of January and October. Mean temperature had a positive influence during the first half of April. For the second half of April LRI0 had a positive PE on resistant varieties and a negative PE on susceptible varieties. Wind speed had a positive influence on LRI0 in the second half of November, and a negative influence during the second half of December.

Tab. 6-8: F-measure, recall, precision, predicted positives (ppos), observed positives (pos), and true positives (TP) for the logistic regression model derived for the probability to exceed 0% leaf rust incidence for each repetition number according to the 10-fold cross-validation sample.

Repetition	ppos	pos	tp	recall	precision	fmeasure
1	27	33	18	0.545	0.667	0.638
2	27	33	17	0.515	0.630	0.603
3	20	33	13	0.394	0.650	0.575
4	19	33	13	0.394	0.684	0.596
5	26	33	19	0.576	0.731	0.693
6	22	34	16	0.471	0.727	0.656
7	23	34	17	0.500	0.739	0.675
8	22	34	13	0.382	0.591	0.533
9	21	35	14	0.400	0.667	0.588
10	23	35	15	0.429	0.652	0.591

Tab. 6-9: Parameter estimates and 5%- and 95%-confidence limits for the final selected leaf rust (lr) model generated to model the probability to exceed 0% leaf rust incidence. The abbreviation "Resgr" stands for the resistance group. Interactions are indicated by *.The numbers linked with the abbreviated variable identify the 15-day interval over which the variable was aggregated.

Variable	Estimate	p5	p95
Intercept	-0.241	-0.358	-0.124
Resgr_lr	-0.460	-0.568	-0.360
prec_10	0.380	0.244	0.523
prec_16	0.169	0.064	0.274
prec_4	-0.205	-0.308	-0.103
prec_7	0.290	0.186	0.381
temp_4*Resgr_lr	0.120	0.069	0.170
temp_5	0.110	0.062	0.160
wind_12	-0.217	-0.346	-0.087
wind_14	0.312	0.162	0.479

6.3.1.3 30% incidence threshold

The f-measure validation results obtained for the regression models, identified by applying a 10-fold cross-validation on the test samples are presented in Tab. 6-10.

Tab. 6-10: F-measure, recall, precision, predicted positives (ppos), observed positives (pos), and true positives (TP) for the logistic regression model derived for the probability to exceed 30% leaf rust incidence for each repetition number according to the 10-fold cross-validation sample.

Repetition	ppos	pos	tp	recall	precision	fmeasure
1	1	6				
2	2	7	1	0.143	0.500	0.333
3	1	7				
4	1	7	1	0.143	1.000	0.455
5	1	7				
6	0	7				
7	4	7	2	0.286	0.500	0.435
8	1	7				
9	2	7				
10	3	8	2	0.250	0.667	0.500

The binary logistic model for a threshold of 30% leaf rust incidence (LRI30) with the maximum f-measure for the test sample was selected and included 10 variables (Tab. 6-11). The PEs revealed that precipitation had a positive impact during the second half of January. For the second half of May LRI30 had a positive PE on resistant and a negative PE on susceptible varieties. Mean temperature had a positive impact on LRI30 between 20th of September and 20th of October and during the first half of April. Mean temperature had a negative PE for late August and early September. Wind speed had a positive influence on LRI30 for the first half of March and a negative for the second half of December. During the second half of March wind speed had a negative PE on resistant varieties and a positive PE on susceptible varieties. For the first half of April wind speed had a positive influence on LRI30 on resistant varieties and a negative influence on susceptible varieties.

Tab. 6-11: Parameter estimates and 5%- and 95%-confidence limits for the final selected leaf rust (lr) model generated to model the probability to exceed 30% leaf rust incidence. The abbreviation “Resgr” stands for the resistance group. Interactions are indicated by *.The numbers linked with the abbreviated variable identify the 15-day interval over which the variable was aggregated.

Variable	Estimate	p5	p95
Intercept	-2.927	-3.191	-2.707
prec_10	0.286	0.052	0.498
prec_2*Resgr_lr	0.172	0.040	0.307
temp_17	0.238	0.131	0.358
temp_18	0.153	0.057	0.254
temp_20	-0.144	-0.250	-0.035
temp_5	0.229	0.134	0.329
wind_12	-0.804	-1.180	-0.453
wind_5*Resgr_lr	0.628	0.279	1.010
wind_6*Resgr_lr	-0.395	-0.724	-0.088
wind_7	0.690	0.421	0.943

6.3.2 Powdery mildew

6.3.2.1 Raw incidence data

The MSE validation results obtained for the 10 regression models, identified by applying a 10-fold cross-validation on the test samples are shown in Tab. 6-12.

Tab. 6-12: MSE-V for the logistic regression model derived using raw powdery mildew data for each repetition number according to the 10-fold cross-validation sample.

Repetition	MSE-V
1	0.086
2	0.079
3	0.076
4	0.091
5	0.074
6	0.092
7	0.094
8	0.078
9	0.094
10	0.070

The logistic model for the raw data on powdery mildew incidence (PMI) with the minimum MSE value for the test sample was selected and included 19 variables (Tab. 6-13). Precipitation had a positive effect on PMI during the last 15 days before the disease assessment and at the end of August and beginning of September. A negative effect of rainfall was identified for the second half of March, the latter half of January, the first half of December, the second half of October, and late September. Mean temperature had a negative influence on PMI during the first half of May, the second half of October, and late August. It had a negative influence on PMI on resistant varieties and a positive on susceptible varieties during the first halves of April and March and late September. A positive impact on PMI on resistant and a negative on susceptible varieties was detected for the 15-day period before the disease assessment. Finally, wind speed had a positive influence on PMI in the first half of May and a negative influence during the second half of April, the first half of January, and the second half of November. The resistance group had, similar to leaf rust, a negative parameter estimate, implying that a higher resistance had a negative effect on disease incidence.

Tab. 6-13: Parameter estimates and 5%- and 95%-confidence limits for the final selected powdery mildew (pm) model using raw incidence data. The abbreviation "Resgr" stands for the resistance group. Interactions are indicated by *.The numbers linked with the abbreviated variable identify the 15-day interval over which the variable was aggregated.

Variable	Estimate	p5	p95
Intercept	-0.999	-1.095	-0.911
Resgr_pm	-0.399	-0.478	-0.317
prec_1	0.091	0.035	0.148
prec_10	-0.204	-0.296	-0.109
prec_13	-0.152	-0.254	-0.061
prec_16	-0.373	-0.464	-0.283
prec_18	-0.252	-0.333	-0.174
prec_20	0.135	0.060	0.206
prec_6	-0.182	-0.262	-0.108
temp_1*Resgr_pm	0.075	0.039	0.110
temp_16	-0.080	-0.116	-0.043
temp_18*Resgr_pm	-0.080	-0.119	-0.042
temp_20	-0.085	-0.146	-0.031
temp_3	-0.042	-0.075	-0.004
temp_5*Resgr_pm	-0.092	-0.131	-0.053
temp_7*Resgr_pm	-0.065	-0.093	-0.039
wind_11	-0.150	-0.231	-0.066
wind_14	-0.192	-0.285	-0.105
wind_3	0.350	0.120	0.613
wind_4	-0.413	-0.565	-0.260

6.3.2.2 0% incidence threshold

The f-measure validation results obtained for the 10 regression models, identified by applying a 10-fold cross-validation on the test samples are presented in Tab. 6-14. The binary logistic model for a threshold of 0% powdery mildew incidence (PMI0) that achieved the maximum f-measure for the test sample was selected and included eight variables (Tab. 6-15). The model showed that precipitation had a negative impact on PMI0 during the second halves of April, November, and October. Mean temperature had a negative influence on PMI0 on resistant varieties and a positive one on susceptible varieties during the second halves of March and November. Wind speed had a positive influence on PMI0 in the first half of February and a negative one during the second half of February and the first half of December.

Tab. 6-14: F-measure, recall, precision, predicted positives (ppos), observed positives (pos), and true positives (TP) for the logistic regression model derived for the probability to exceed 0% powdery mildew incidence for each repetition number according to the 10-fold cross-validation sample.

Repetition	ppos	pos	tp	recall	precision	fmeasure
1	81	70	64	0.914	0.790	0.812
2	83	70	65	0.929	0.783	0.808
3	86	70	69	0.986	0.802	0.833
4	81	70	64	0.914	0.790	0.812
5	88	71	70	0.986	0.795	0.827
6	80	71	63	0.887	0.788	0.806
7	80	71	64	0.901	0.800	0.818
8	83	71	67	0.944	0.807	0.831
9	87	71	65	0.915	0.747	0.776
10	86	71	66	0.930	0.767	0.795

Tab. 6-15: Parameter estimates and 5%- and 95%-confidence limits for the final selected powdery mildew (pm) model generated to model the probability to exceed 0% powdery mildew incidence. The abbreviation "Resgr" stands for the resistance group. Interactions are indicated by *.The numbers linked with the abbreviated variable identify the 15-day interval over which the variable was aggregated.

Variable	Estimate	p5	p95
Intercept	1.111	1.005	1.223
prec_14	-0.308	-0.430	-0.190
prec_16	-0.459	-0.570	-0.356
prec_4	-0.189	-0.293	-0.091
temp_14*Resgr_pm	-0.112	-0.161	-0.063
temp_6*Resgr_pm	-0.085	-0.142	-0.022
wind_13	-0.262	-0.414	-0.099
wind_8	-0.165	-0.268	-0.066
wind_9	0.215	0.088	0.336

6.3.2.3 50% incidence threshold

The f-measure validation results obtained for the 10 regression models, identified by applying a 10-fold cross-validation on the test samples are shown in Tab. 6-16. The binary logistic model for a threshold of 50% powdery mildew incidence (PMI50) that achieved the maximum f-measure for the test sample was selected and included 18 variables (Tab. 6-17). Precipitation had a negative effect on PMI50 during the second halves of March, January, October, and September. During the second half of August and the 15-day period before the disease assessment precipitation showed a positive impact on PMI50 on resistant varieties and a negative impact on susceptible varieties. For the second halves of April and December and the first halves of March and January precipitation had a negative PE on resistant varieties and a positive PE on susceptible varieties. Mean temperature had a negative influence on PMI50 during the 15-day period before the monitoring date and the first halves of May and April. A positive PE was determined for the first half of November. In addition, mean temperature had a positive PE on resistant varieties and a negative PE on susceptible varieties during the 15-day period before disease assessment. During March and the second half of August mean temperature had a negative impact on PMI50 on resistant varieties and a positive impact on susceptible varieties.

Tab. 6-16: F-measure, recall, precision, predicted positives (ppos), observed positives (pos), and true positives (TP) for the logistic regression model derived for the probability to exceed 50% powdery mildew incidence for each repetition number according to the 10-fold cross-validation sample.

Repetition	ppos	pos	tp	recall	precision	fmeasure
1	5	19	3	0.158	0.600	0.385
2	3	19	2	0.105	0.667	0.323
3	5	19	4	0.211	0.800	0.513
4	4	19	3	0.158	0.750	0.429
5	1	19	1	0.053	1.000	0.217
6	5	19	1	0.053	0.200	0.128
7	6	19	5	0.263	0.833	0.581
8	5	19	4	0.211	0.800	0.513
9	8	19	2	0.105	0.250	0.196
10	4	20	3	0.150	0.750	0.417

Tab. 6-17: Parameter estimates and 5%- and 95%-confidence limits for the final selected powdery mildew (pm) model generated to model the probability to exceed 50% powdery mildew incidence. The abbreviation "Resgr" stands for the resistance group. Interactions are indicated by *.The numbers linked with the abbreviated variable identify the 15-day interval over which the variable was aggregated.

Variable	Estimate	p5	p95
Intercept	-1.377	-1.517	-1.244
prec_1*Resgr_pm	0.154	0.074	0.237
prec_10	-0.258	-0.456	-0.088
prec_11*Resgr_pm	-0.167	-0.297	-0.051
prec_12*Resgr_pm	-0.157	-0.264	-0.062
prec_16	-0.278	-0.448	-0.134
prec_18	-0.342	-0.489	-0.205
prec_20*Resgr_pm	0.135	0.023	0.236
prec_4*Resgr_pm	-0.190	-0.303	-0.072
prec_6	-0.210	-0.344	-0.094
prec_7*Resgr_pm	-0.428	-0.594	-0.284
temp_1	-0.069	-0.141	-0.004
temp_1*Resgr_pm	0.105	0.044	0.170
temp_15	0.070	0.014	0.127
temp_20*Resgr_pm	-0.139	-0.223	-0.055
temp_3	-0.109	-0.169	-0.057
temp_5	-0.121	-0.194	-0.054
temp_6*Resgr_pm	-0.108	-0.182	-0.040
temp_7*Resgr_pm	-0.120	-0.165	-0.074

6.4 Validation of the logistic regression equations

The leaf rust model using raw incidence data had a mean error of 17.2% and the powdery mildew model a mean error of 26.6%. Comparing predicted and observed mean values over all stations and years for the period 1976 to 2010 revealed an error of 0.05% for the LRI model and 0.36% for the PMI model. The annual mean values had a RMSE of 2.71% for the LRI model and 8.18% for the PMI model.

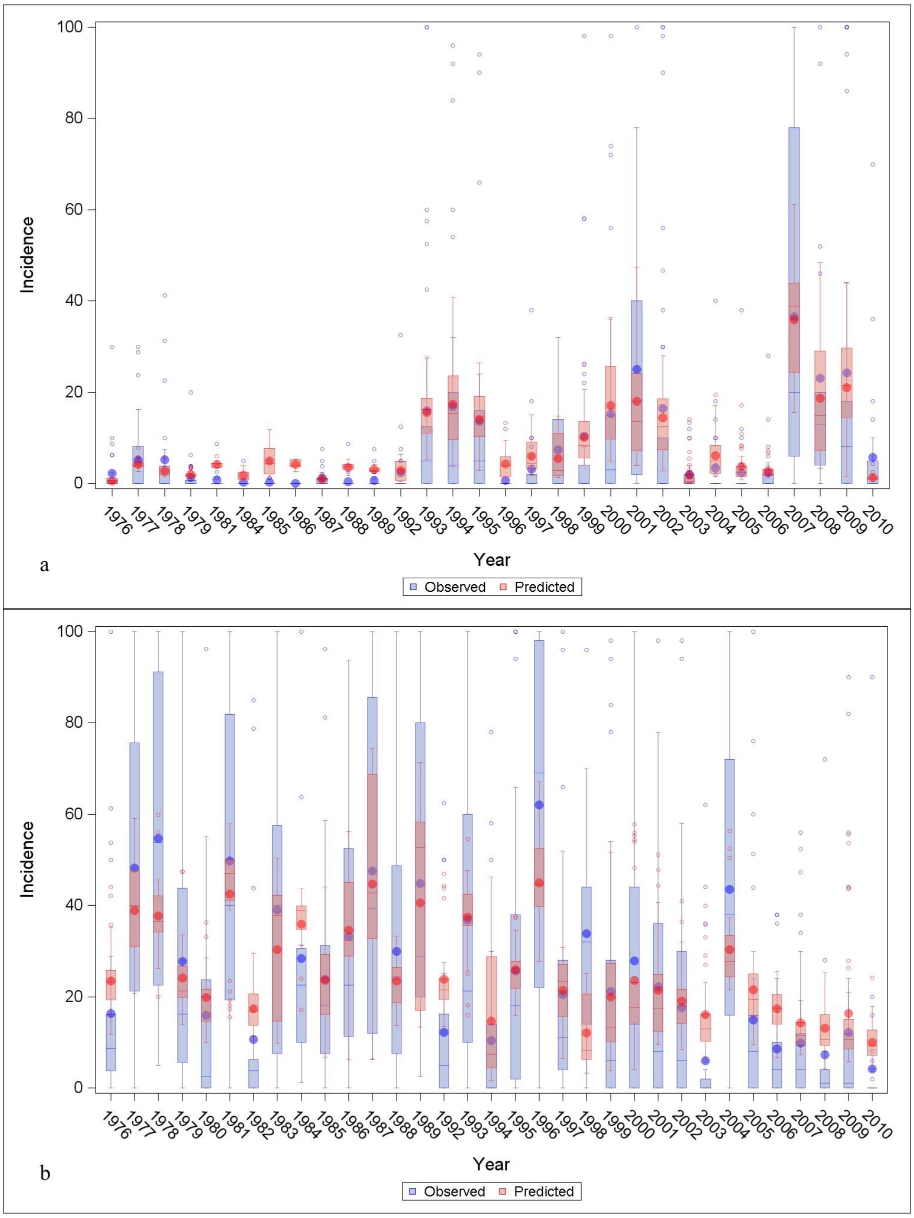


Fig. 6-7 Observed (blue) and predicted (red) disease incidence of leaf rust (a) and powdery mildew (b) on winter wheat in percent during the period 1976 to 2010: The mean values (filled dots), medians (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers), and outliers (circles) are shown.

Figure 6-7a reveals that mean annual LRI was slightly overestimated for smaller values and slightly underestimated for some of the larger values. The annual variability was underestimated for most years. Figure 6-7b shows the mean annual PMI being underestimated for high values and overestimated for smaller values. The annual variability was underestimated in every year. Station-wise mean values showed a RMSE of 7.56% for the LRI model and 8.18% for the PMI model.

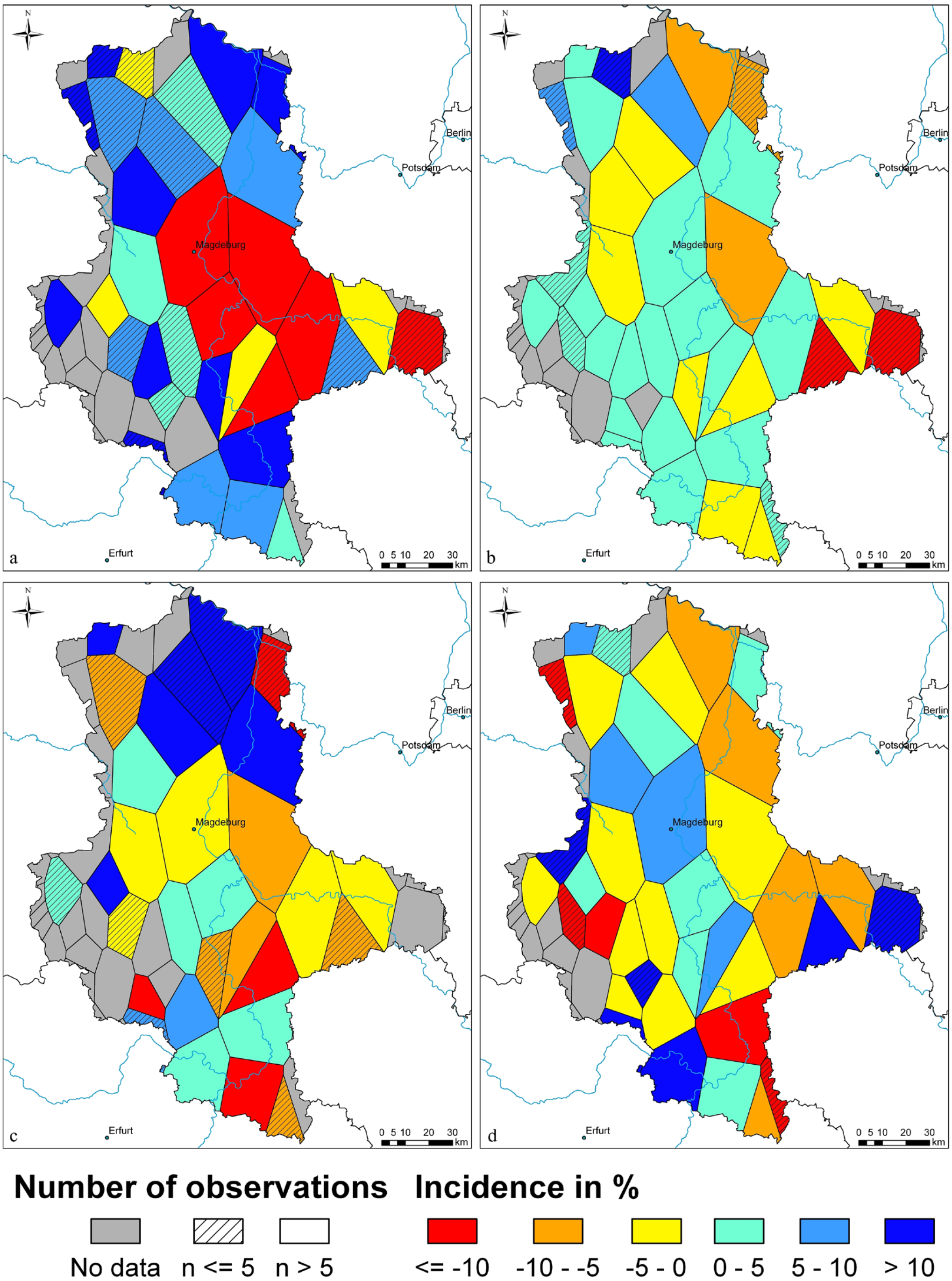
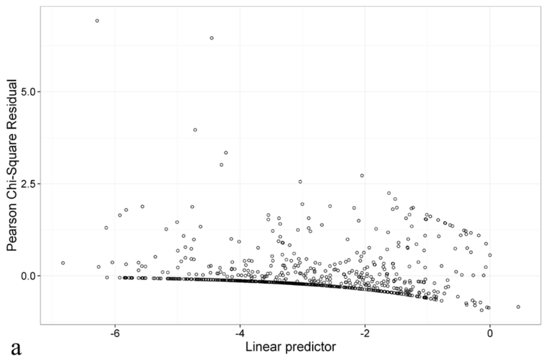


Fig. 6-8: Differences between observed and predicted station-wise mean disease incidence of leaf rust (a, b) and powdery mildew (c, d) on susceptible (a, c) and resistant (b, d) wheat varieties.

Figure 6-8 shows the regional differences between observed and predicted LRI and PMI on susceptible and resistant varieties. The LRI on susceptible varieties was underestimated in the central and eastern parts of the state and overestimated in the remaining parts. On resistant varieties the LRI was slightly over- or underestimated at most stations, but errors were smaller compared to susceptible varieties. The PMI on susceptible varieties revealed a rather heterogeneous pattern with a tendency towards underestimation in the central parts and overestimation in the northern part of the state. The PMI on resistant varieties showed heterogeneous distributed errors without a distinct pattern. The area under the receiver operator curve (ROC AUC) had a value of 0.80 for the LRI model and 0.71 for the PMI model. The plots of Pearson Chi-Square residuals show non-constant variance of the residuals with respect to the linear predictor for the LRI and PMI model (Fig. 6-9). In addition, the residuals for the PMI model identified a negative trend.



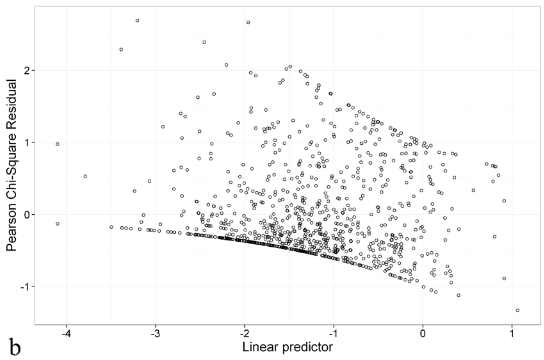


Fig. 6-9: Pearson Chi-Square Residuals plotted against the values of the linear predictor of the logistic regression model using raw leaf rust (a) and powdery mildew (b) incidence.

The model for LRI0 showed an f-measure of 0.67 with recall = 0.51 and precision = 0.73. The overall mean values of predicted and observed LRI0 for the period 1976 to 2010 revealed an error of 0.23%. The annual mean values had a RMSE of 15.68% and the station-wise means a RMSE of 18.97%. Annual mean LRI0 was underestimated for some of the years with higher probability and overestimated for most of the years with smaller probability (Fig. 6-10a). The differences between observed and predicted station-wise LRI0 averages on susceptible varieties (Fig. 6-11a) revealed a heterogeneous pattern with a strong tendency for underestimation in the central part of the state. On resistant varieties figure 6-11b shows a highly heterogeneous pattern with relatively high error for the whole state. The PMI0 model had an f-measure of 0.82 with recall = 0.97 and precision = 0.79.

Overall mean values of predicted and observed PMI0 showed an error of 0.06%. Annual mean values had a RMSE of 15.57% and station-wise mean values a RMSE of 22.25%. Annual PMI0 averages were mainly underestimated before 1998 and mainly overestimated after (Fig. 6-10b). Figure 6-11 shows that PMI0 was underestimated for most stations on susceptible varieties and strongly overestimated for most stations on resistant varieties. The ROC AUC had a value of 0.72 for the LRI0 model and 0.68 for the PMI0 model. The plots of Pearson Chi-Square residuals revealed non-constant variance of the residuals with respect to the linear predictor and a slight negative trend of the errors for the LRI0 and PMI0 model (Fig. 6-12).

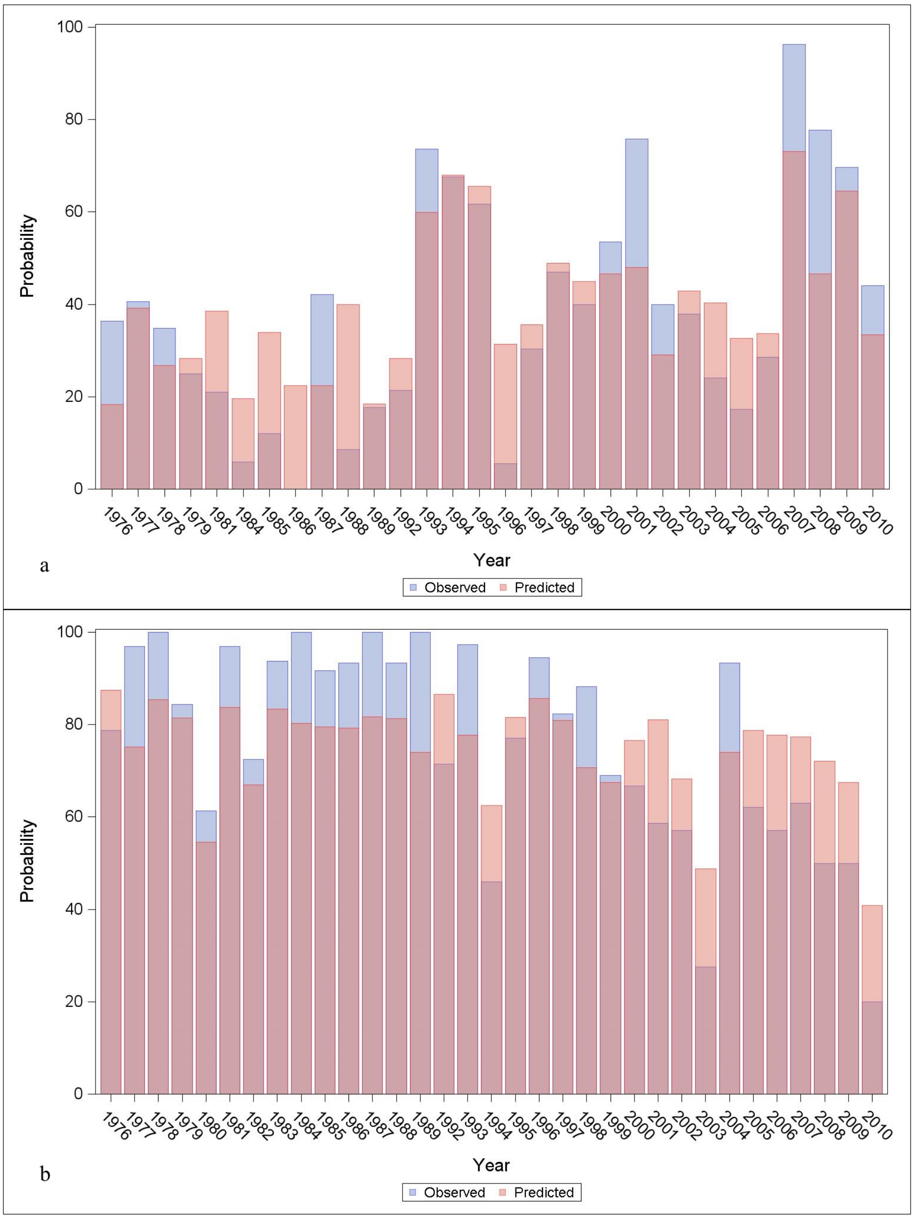


Fig. 6-10: Mean observed (blue) and predicted (red) annual probabilities of exceeding 0% leaf rust (a) and powdery mildew (b) incidence during the period 1976 to 2010 in percent.

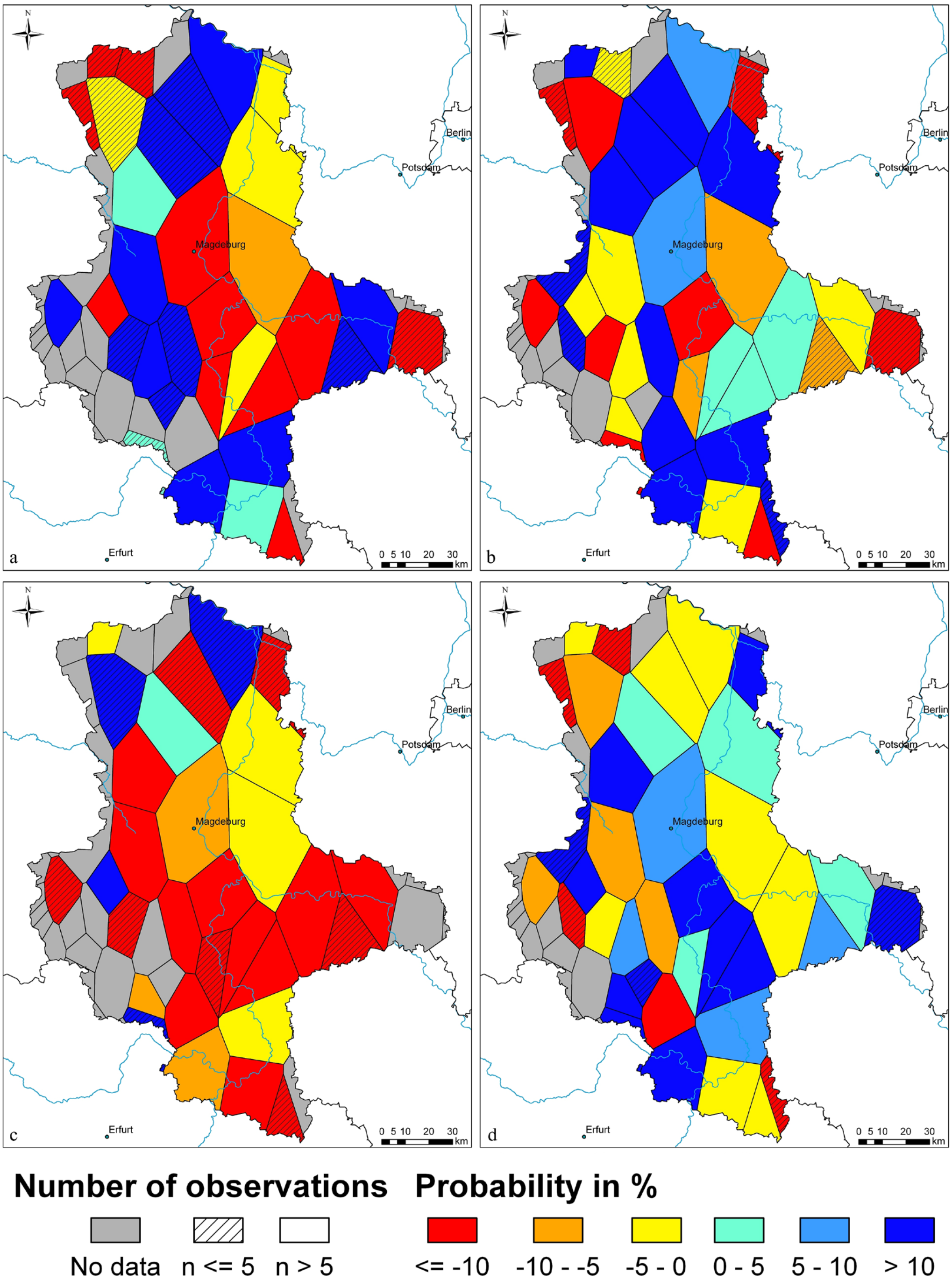
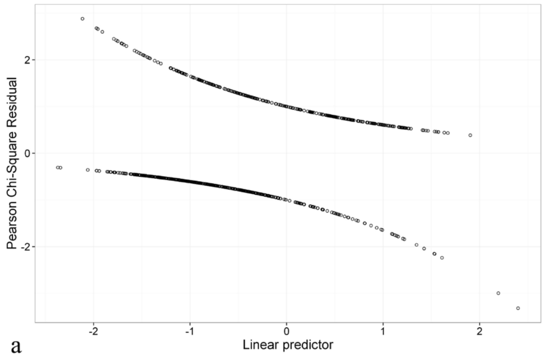


Fig. 6-11: Differences between observed and predicted station-wise mean probabilities to exceed 0% leaf rust (a, b) and powdery mildew (c, d) incidence on susceptible (a, c) and resistant (b, d) wheat varieties.



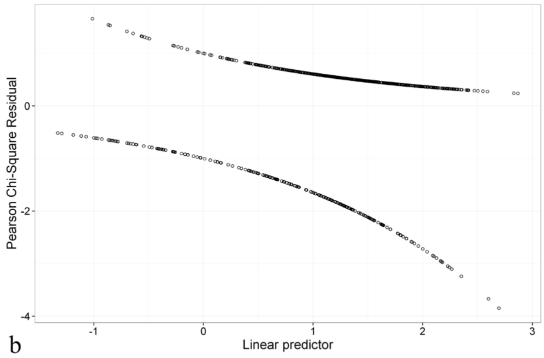


Fig. 6-12: Pearson Chi-Square Residuals plotted against the values of the linear predictor of the logistic regression model projecting the probability to exceed 0% leaf rust (a) and powdery mildew (b) incidence.

The f-measure for the LRI30 model was 0.42 with recall = 0.17 and precision = 0.67. The overall mean values of predicted and observed LRI30 for the period 1976 to 2010 identified an error of -0.37%. Annual means had a RMSE of 6.18% and station-wise mean values a RMSE of 11.17%. Annual mean values were overestimated for years with lower LRI30 and underestimated for most of the years with higher LRI30 (Fig. 6-13a). Fig. 6-15a shows that LRI30 on susceptible varieties was strongly underestimated in the central and eastern parts and overestimated in the northern and southern parts of the state. LRI30 on resistant varieties revealed smaller differences between observed and predicted values with a tendency towards overestimation in the central, western, and southern parts of the state (Fig. 6-15b). The PMI50 model had an f-measure of 0.51 with recall = 0.21 and precision = 0.78. The overall mean value of PMI50 showed an error of -0.36%. The annual mean values revealed a RMSE of 9.64% and the station-wise means a RMSE of 9.87%. Annual mean values were overestimated for years with smaller PMI50 and underestimated in years with higher PMI50 (Fig. 6-13b). The differences between observed and predicted PMI50 on susceptible varieties revealed a heterogeneous pattern with strong underestimation in the central and eastern parts and strong overestimation in the northern parts of the state (Fig. 6-15c). On resistant varieties fig. 6-15d shows a very heterogeneous pattern with slight to strong overestimation in the northwestern part and slight underestimation in the northeastern part of the state. The ROC AUC had a value of 0.77 for the LRI30 model and 0.74 for the PMI50 model. Both plots of Pearson Chi-Square residuals revealed non-constant variance of the residuals with respect to the linear predictor (Fig. 6-14).

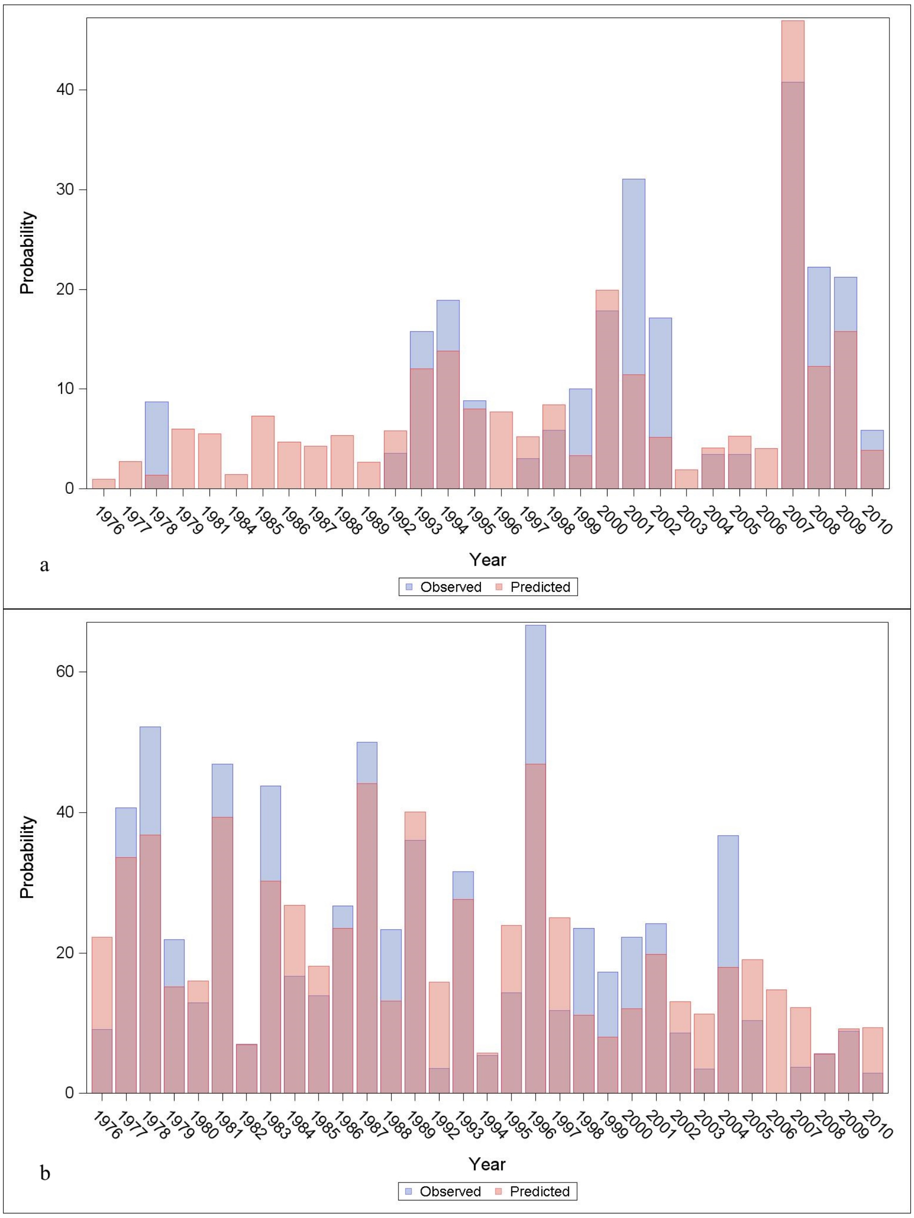


Fig. 6-13: Mean observed (blue) and predicted (red) annual probabilities of exceeding 30% leaf rust (a) and 50% powdery mildew (b) incidence during the period 1976 to 2010 in percent.

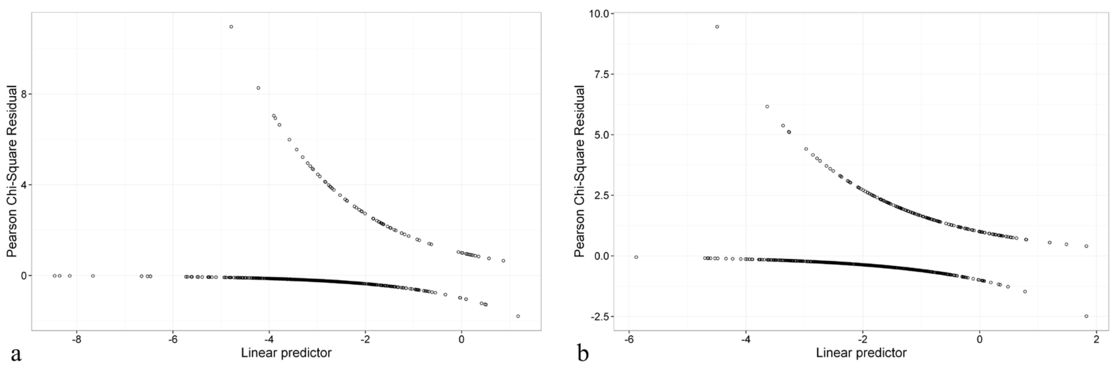


Fig. 6-14: Pearson Chi-Square Residuals plotted against the values of the linear predictor of the logistic regression model projecting the probability to exceed 30% leaf rust (a) and 50% powdery mildew (b) incidence.

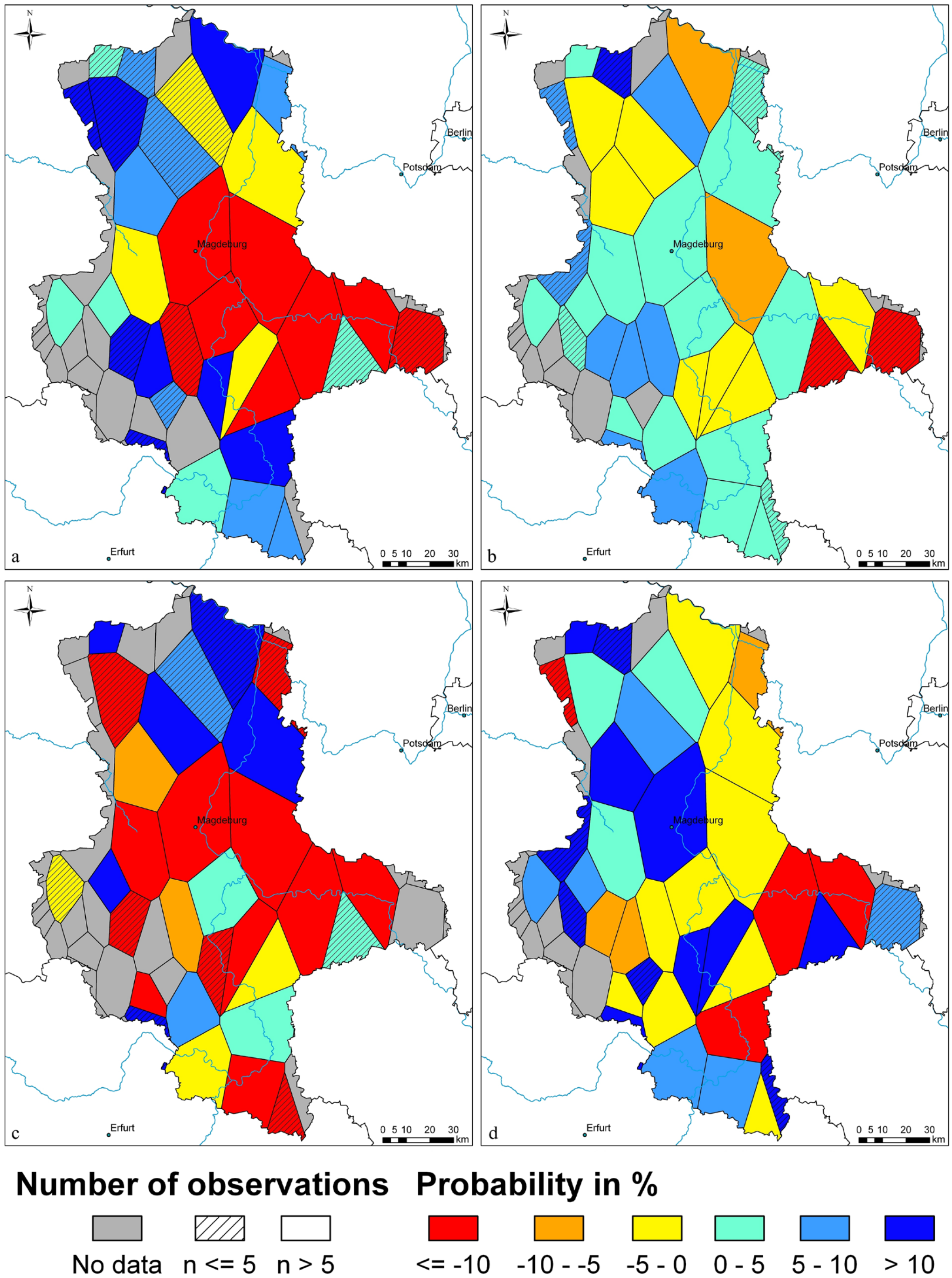


Fig. 6-15: Differences between observed and predicted station-wise mean probabilities to exceed 0% leaf rust (a, b) and 50% powdery mildew (c, d) incidence on susceptible (a, c) and resistant (b, d) wheat varieties.

6.5 Climate change scenarios

6.5.1 Changes of annual meteorological characteristics

Fig. 6-16 demonstrates a significant increase of annual mean temperature comparing the scenario period 2031 to 2060 with the base period 1981 to 2010 assuming an increase in the temperature forcing. The temperature rose stronger in the central German drylands, the Harz Mountains, and the northwestern part of the state under the 3K-scenario (Fig. 6-17). The amount of freezing and icy days decreased significantly with an increase in the temperature forcing. The decrease revealed values up to 35 freezing days and 15 icy days under the 3K-scenario (Fig. 6-18).

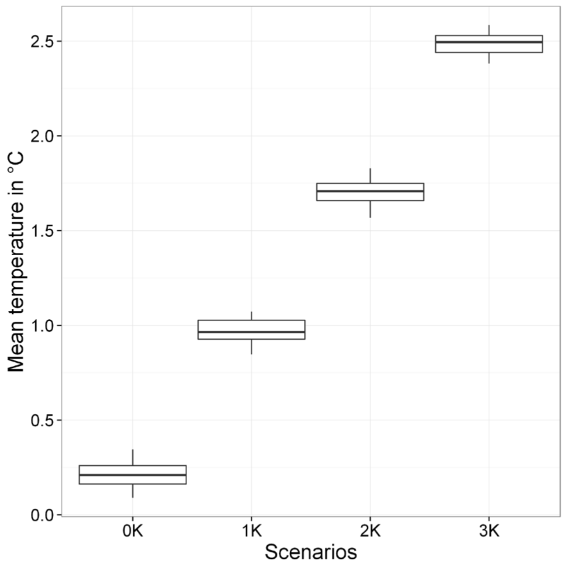


Fig. 6-16: Differences in mean temperature between long-term means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

Precipitation significantly decreased only under the 3K-scenario (Fig. 6-19). No significant differences were detected between the scenarios analyzed. Parallel to the reduction in rainfall the amount of days with precipitation decreased significantly with an increase in mean temperature (Fig. 6-20). The reduction was strongest under the 3K-scenario with a decrease by 27 days. Precipitation under the 3K-scenario decreased strongest in the Harz Mountains (Fig. 6-21). The weakest decrease was detected for the central, northwestern, and southeastern parts of the state.

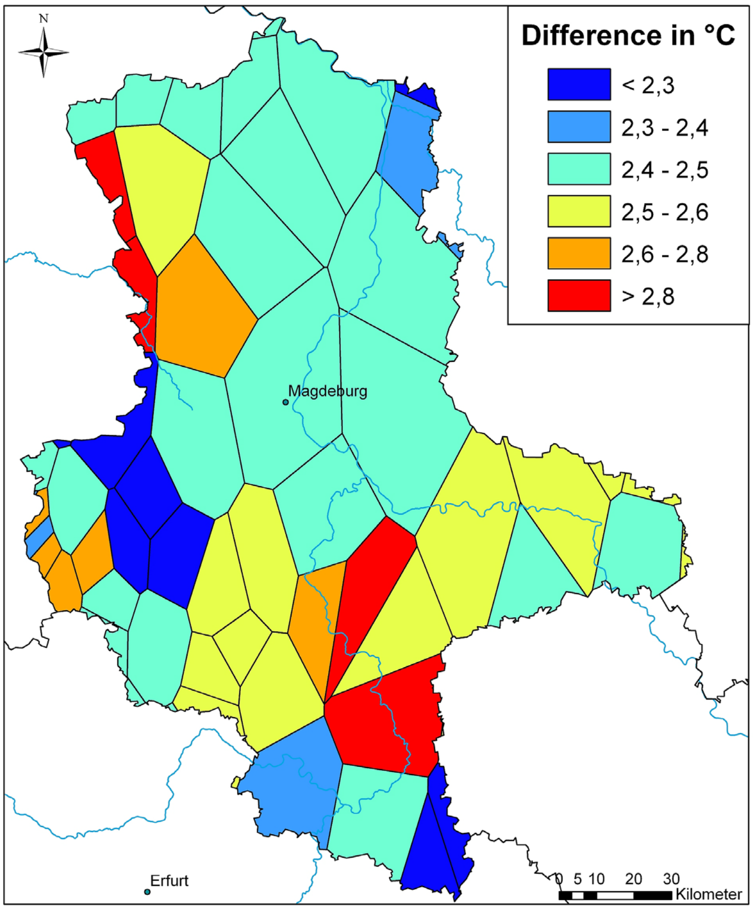


Fig. 6-17: Station-wise differences in mean temperature between long-term means calculated for the base period 1981 to 2010 and the scenario period 2031 to 2060 under the 3K-scenario.

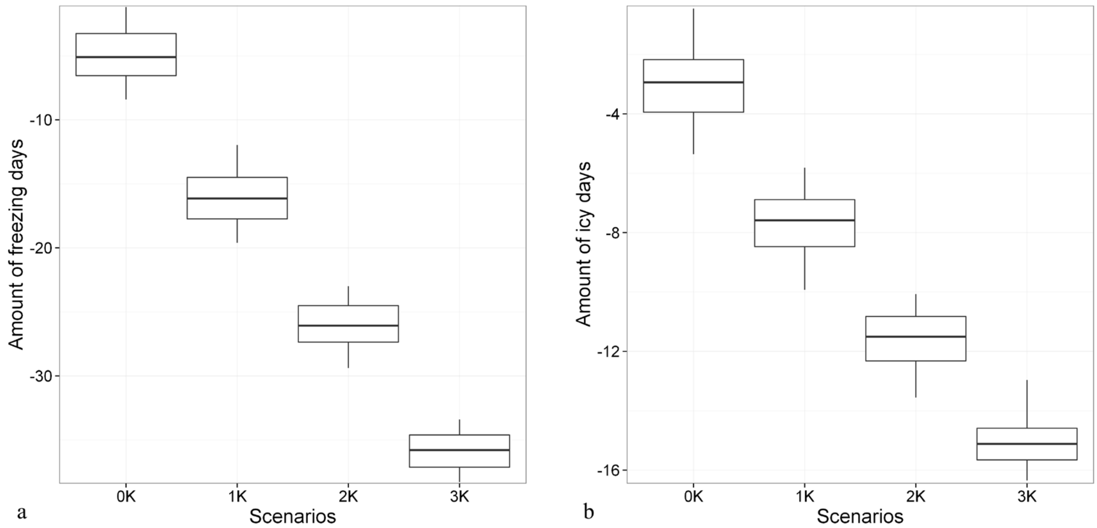


Fig. 6-18: Differences in the annual number of freezing days (a) and icy days (b) between long-term means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

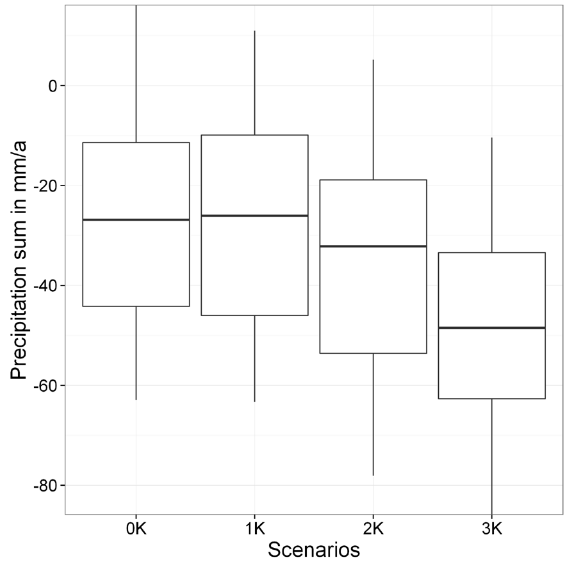


Fig. 6-19: Differences in annual precipitation sums between long-term means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

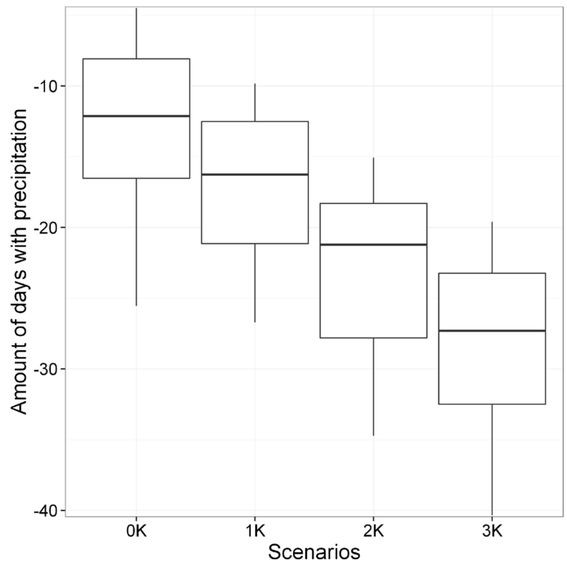


Fig. 6-20: Differences in the annual number of days with precipitation between long-term means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

The results for wind speed revealed no significant difference between both periods under any scenario (Fig. 6-22). A slight negative tendency was shown assuming a rise in mean temperature. Regional differences under the 3K-scenario revealed a decrease in mean wind speed for the northern part of the Harz Mountains and areas adjacent northwards

(Fig. 6-23). An increase in mean wind speed was detected for the southern parts of the state.

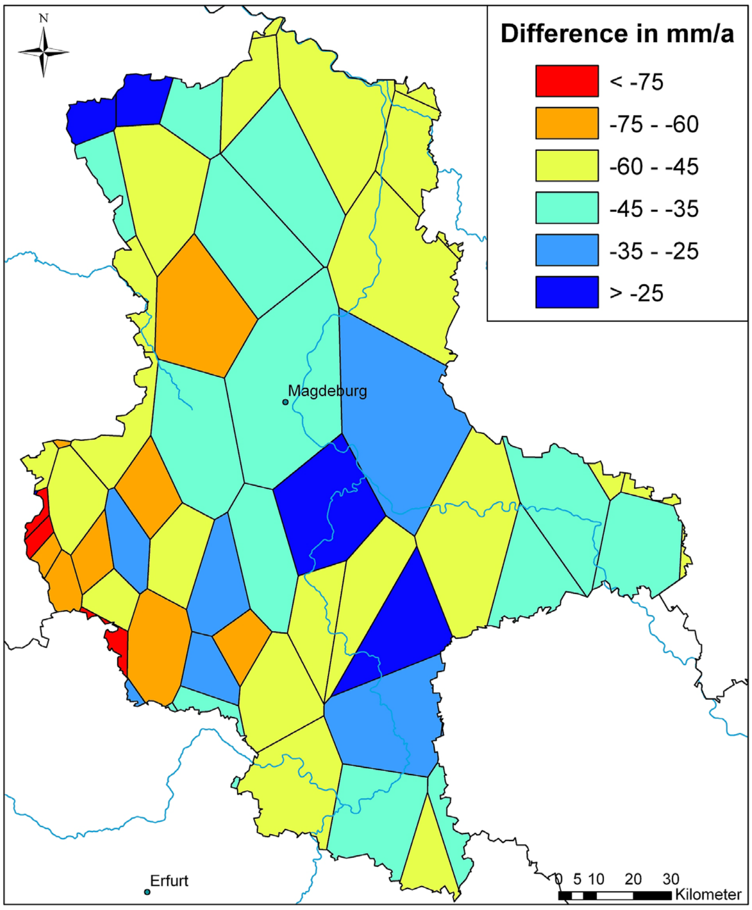


Fig. 6-21: Station-wise differences in annual precipitation sums between long-term means calculated for the base period 1981 to 2010 and the scenario period 2031 to 2060 under the 3K-scenario.

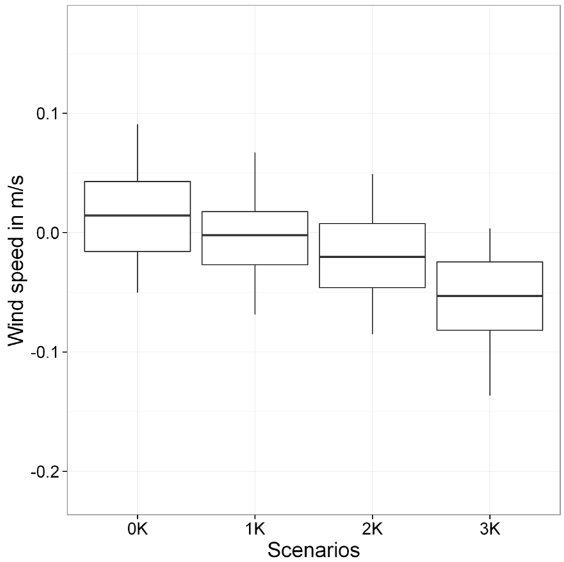


Fig. 6-22: Differences in wind speeds between long-term means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

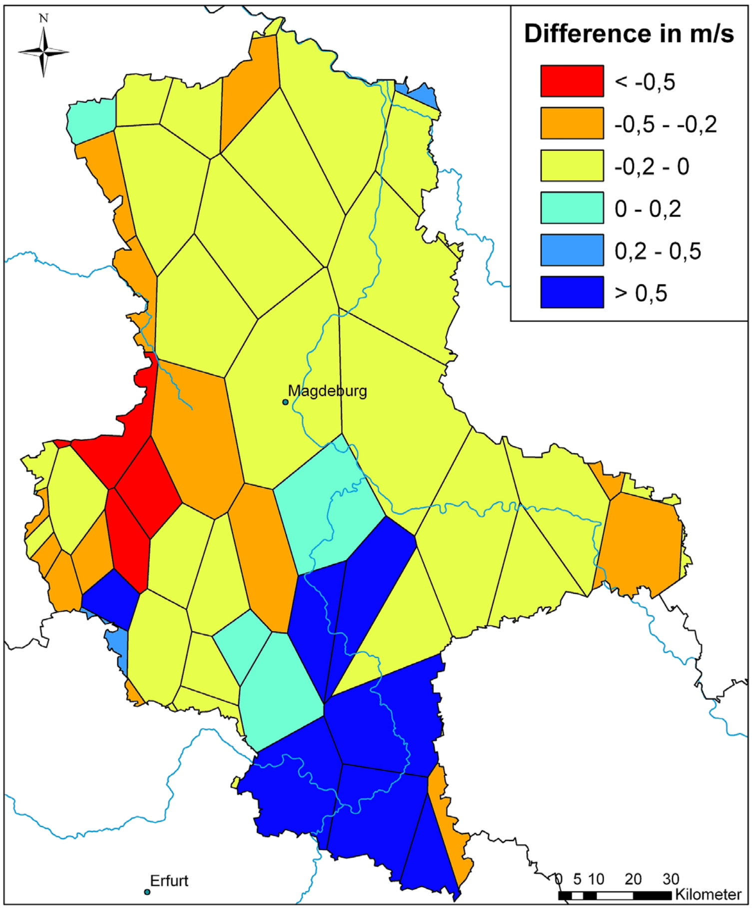


Fig. 6-23: Station-wise differences in wind speed between long-term means calculated for the base period 1981 to 2010 and the scenario period 2031 to 2060 under the 3K-scenario.

6.5.2 Changes of seasonal meteorological characteristics

A significant increase in mean temperature between base and scenario period was identified for all seasons analyzed (Fig. 6-24). The difference was larger for the winter months (DJF) and smaller for the summer months (JJA).

During winter temperature increased stronger for the central German drylands and the northwestern part of the state. The increase was weakest for the northern Harz Mountains. The strongest increase during spring (MAM) was revealed for the central Harz Mountains and the northwestern part of the state. The southern part exhibited the smallest increase. Summer temperature increased strongest in and around the Harz Mountains and in the northwestern part of the state. The northeast showed the slightest increase. In autumn the northern Harz Mountains and adjacent areas exhibited the weakest temperature increase. The largest differences were detected in the northwestern, southern, and eastern parts of the state (Fig. 6-25).

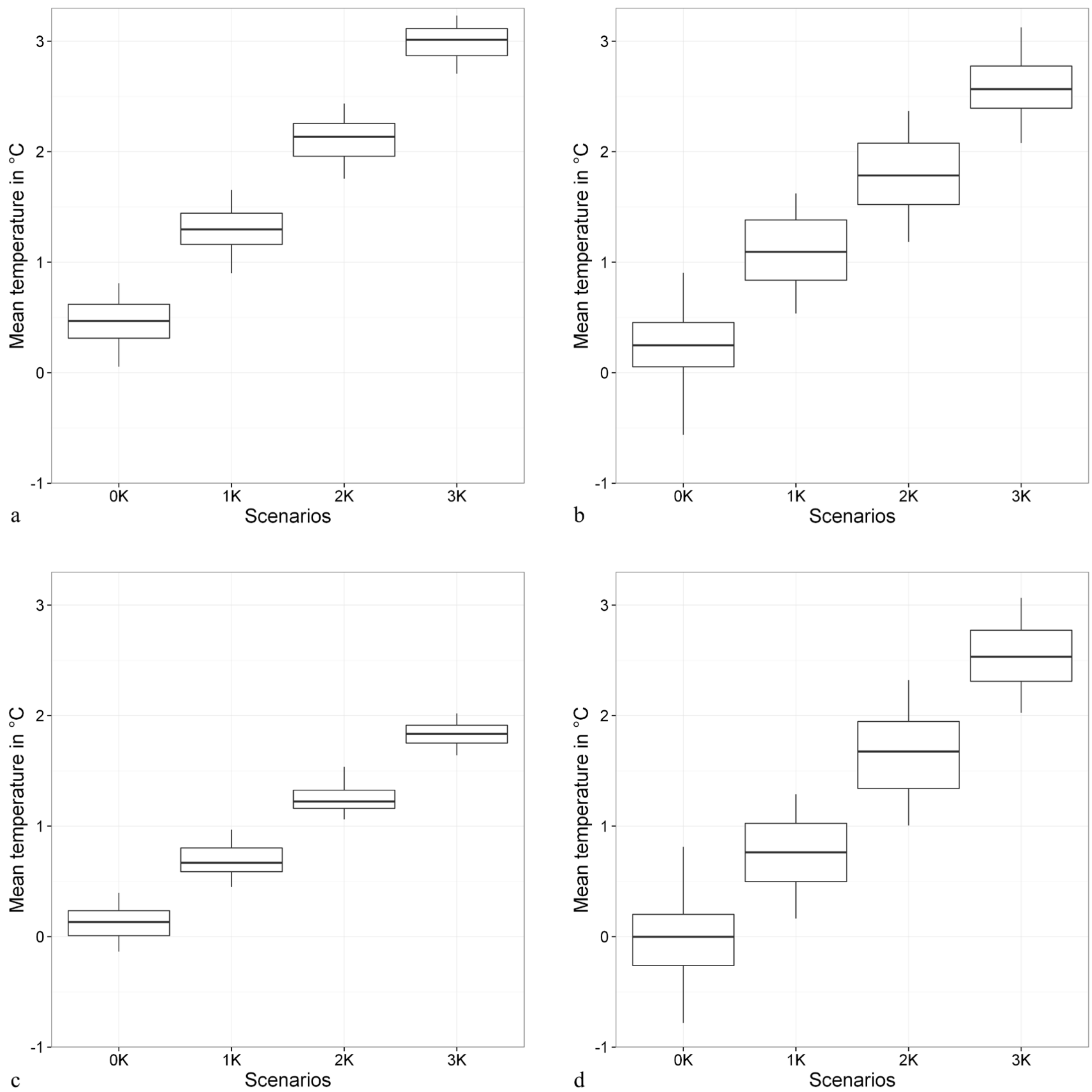


Fig. 6-24: Differences in mean temperature between long-term seasonal means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. Seasonal differences for winter (a), spring (b), summer (c), and autumn (d) are displayed. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

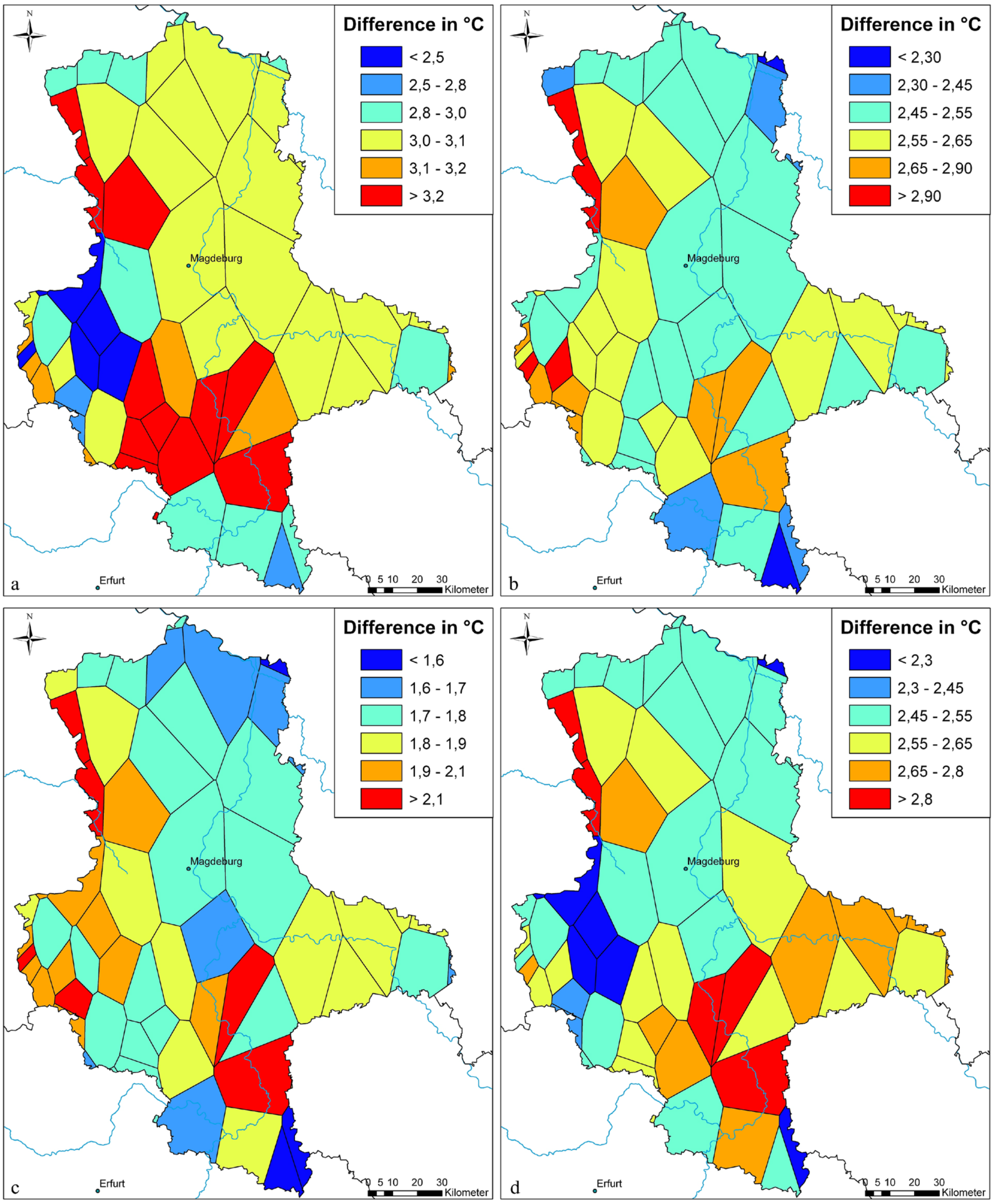
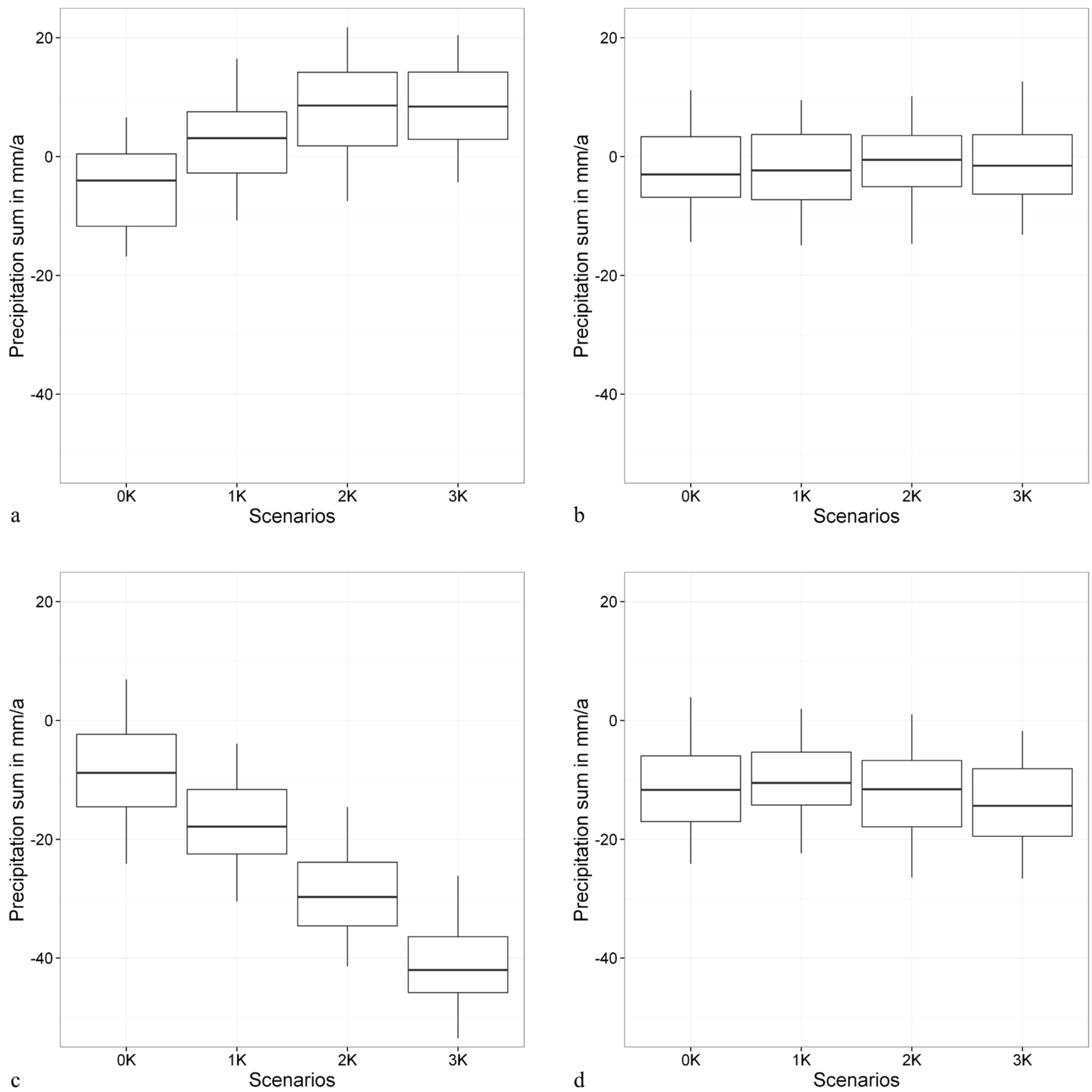


Fig. 6-25: Station-wise differences in mean temperature between long-term seasonal means calculated for the base period 1981 to 2010 and the scenario period 2031 to 2060 under the 3K-scenario. Seasonal differences for winter (a), spring (b), summer (c), and autumn (d) are displayed.

Analyzes comparing mean precipitation sums between base and scenario period showed differing results depending on the season focused on (Fig. 6-26). Rainfall was not significantly different during winter and spring under all scenarios. During summer precipitation was significantly lower for all warming scenario periods compared to the base period. The results exhibited a decrease up to 40 mm for the 3K-scenario. Precipitation differences in autumn were significant only under the 3K-scenario. All scenarios presented a negative difference and were not significantly different from each other.



a b c d

Fig. 6-26: Differences in seasonal precipitation sums between long-term means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. Seasonal differences for winter (a), spring (b), summer (c), and autumn (d) are displayed. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

Precipitation differences between base and scenario period during winter were positive for most parts of the state. The highest values were detected in the central Harz Mountains exhibiting an increase in precipitation up to 25 mm. Differences for spring precipitation revealed a smaller deviation from zero compared to winter. Rainfall decreased strongest in the Harz Mountains and increased strongest in the central and northwestern parts of the state. The summer season revealed the strongest differences overall and detected exclusively negative differences. Rainfall decreased strongest in parts of the Harz Mountains and slightest in the central and southern parts of the state. In autumn precipitation decreased for the whole state. The Harz Mountains showed the strongest decrease with values below -25 mm (Fig. 6-27).

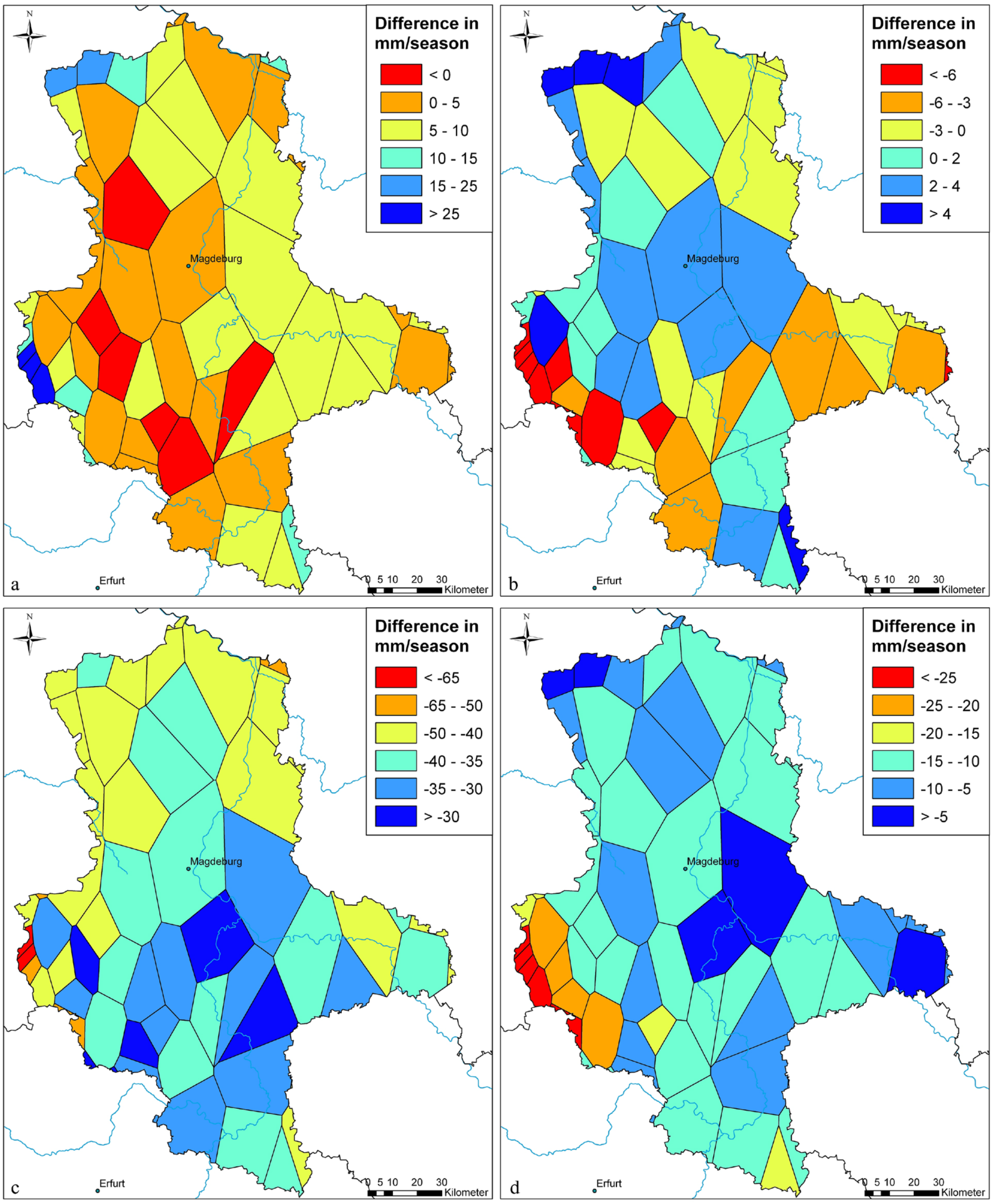


Fig. 6-27: Station-wise differences in seasonal precipitation sums between long-term means calculated for the base period 1981 to 2010 and the scenario period 2031 to 2060 under the 3K-scenario. Seasonal differences for winter (a), spring (b), summer (c), and autumn (d) are displayed.

Results for mean wind speed during winter revealed significant positive differences between base and scenario period under the 2K- and 3K-scenario (Fig. 6-28). The difference increased with an increase in mean temperature. Mean wind speed during the scenario period was lower compared to the base period during the other three seasons. The difference increased assuming an increase in mean temperature. Under the 3K-scenario the difference was significant during spring, summer, and autumn. Significant differences under the 1K- and 2K-scenario were only identified during summer.

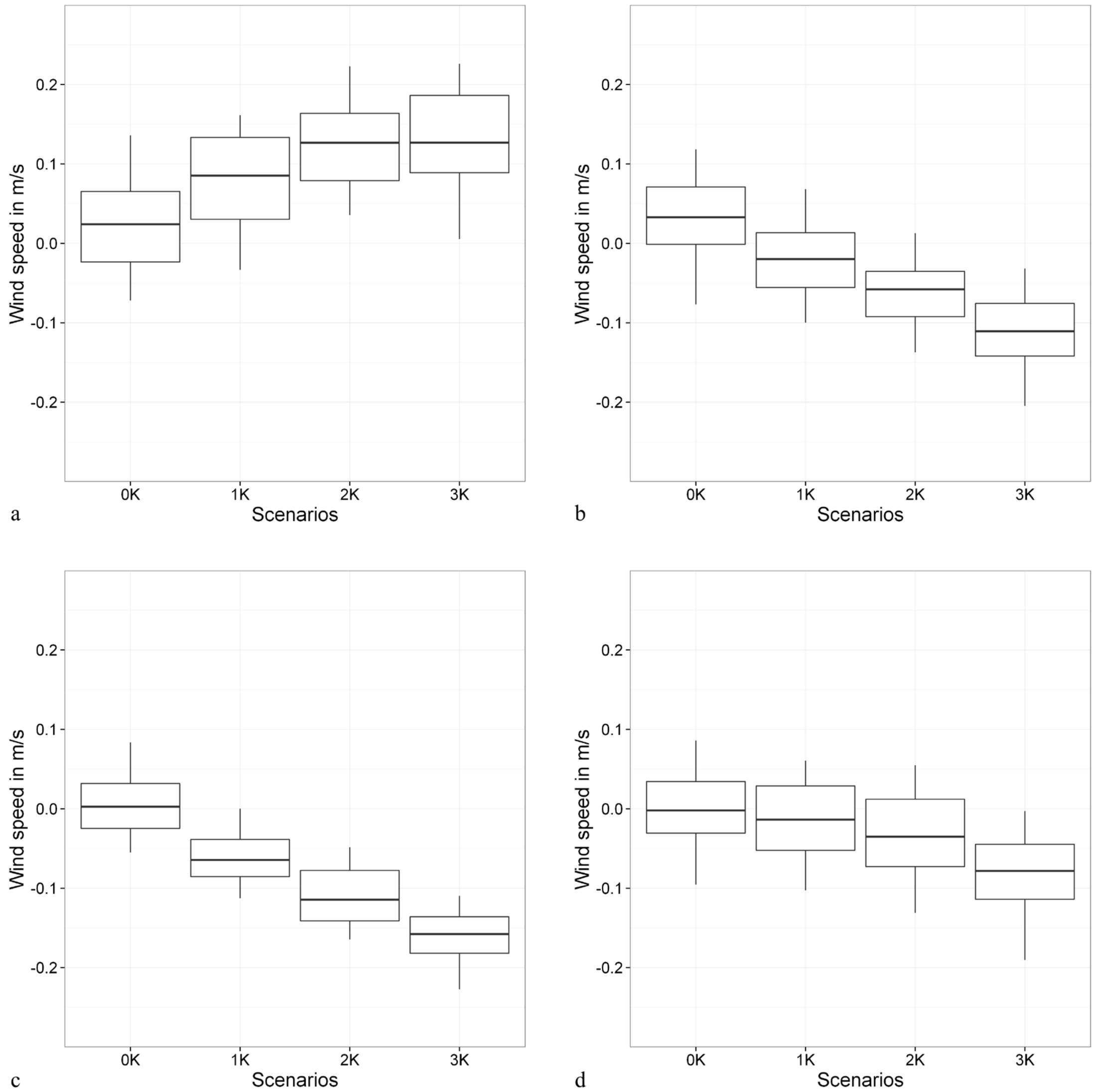


Fig. 6-28: Differences in mean wind speeds between long-term seasonal means calculated for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K-, 1K-, 2K-, and 3K-scenario. Seasonal differences for winter (a), spring (b), summer (c), and autumn (d) are displayed. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

The wind speed differences calculated for each weather station revealed positive and negative values for all seasons. During winter wind speed decreased strongest in the northern and northeastern part of the Harz Mountains. The strongest increase was detected for the southern parts of the state. The same patterns including similar values of the differences were identified during spring, summer, and autumn (Fig. 6-29).

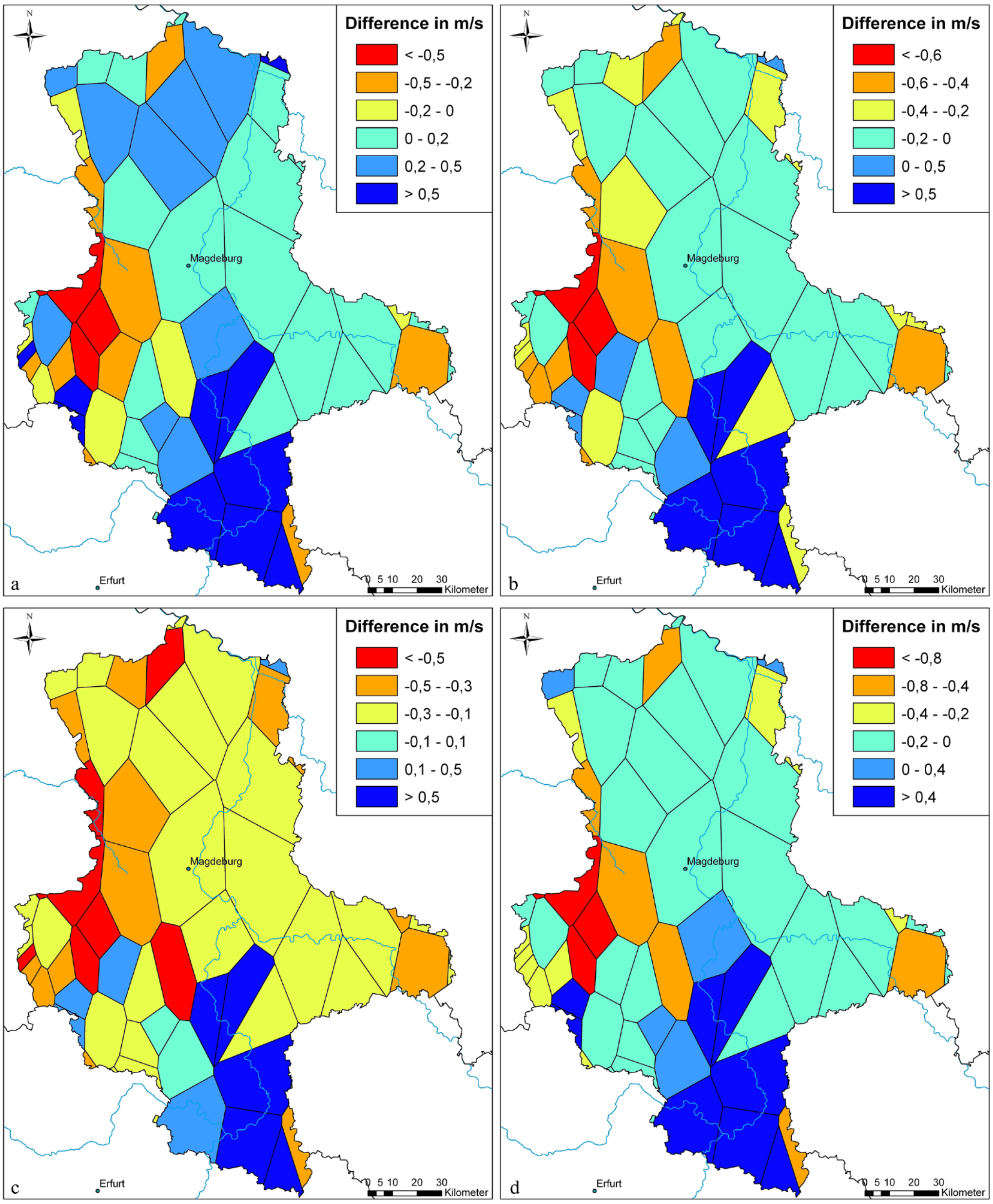


Fig. 6-29: Station-wise differences in wind speeds between long-term seasonal means calculated for the base period 1981 to 2010 and the scenario period 2031 to 2060 under the 3K-scenario. Seasonal differences for winter (a), spring (b), summer (c), and autumn (d) are displayed.

6.6 Disease potential according to the fuzzy approach

During the base period (1981 to 2010) the disease potential (DP) of leaf rust showed a clear dominance of medium potential. 48 of the 61 stations had medium, 12 stations low, and one station high DP. In contrast to the base period the distribution of DP changed towards more stations with medium DP and less stations with low and high DP during the scenario period (2031 to 2060) under the 3K-scenario. The number of stations exhibiting medium DP increased assuming a rise in mean temperature (Fig. 6-30a-d). The changes identified 11 stations less exhibiting low DP, 12 stations more having medium DP, and 1 station less showing high DP during the scenario period compared to the base period.

Concerning powdery mildew most stations (51 of 61) were characterized by low DP during the base period. The remaining stations distributed equally on medium to very high DP. Compared to the base period the potential during the scenario period shifted towards low DP (Fig. 6-30e-h). The number of stations exhibiting medium, high, and very high DP decreased with an increase in mean temperature. The number of stations showing low DP increased by 9 under the 3K-scenario. Only one station remained with very high DP. The station located at the Brocken, the highest mountain in northern Germany.

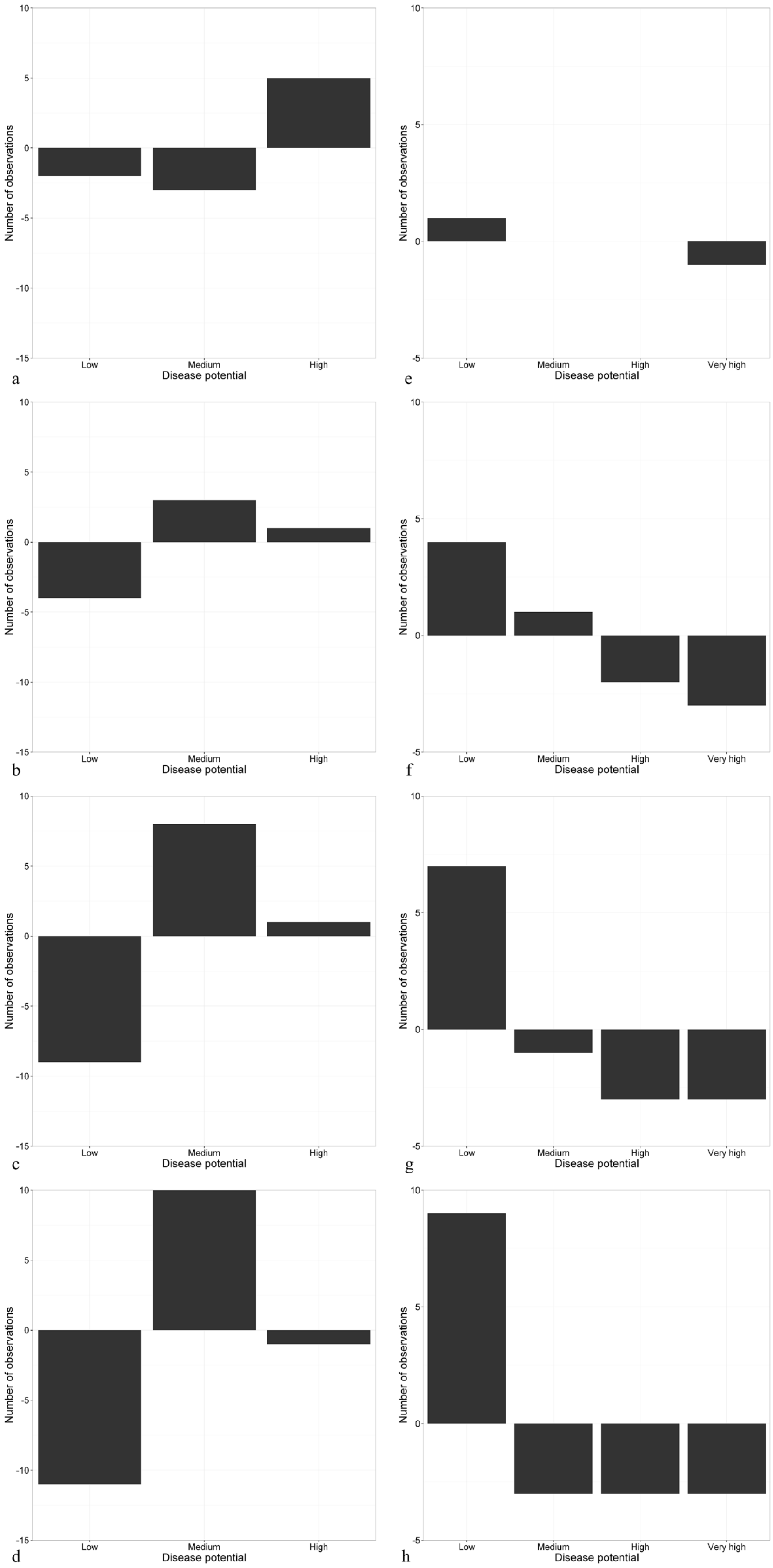


Fig. 6-30: Differences in station counts between disease potential classes calculated using long-term means of meteorological variables computed for the base period 1981 to 2010 and the scenario periods 2031 to 2060 under the 0K- (a, e), 1K- (b, f), 2K- (c, g), and 3K-scenario (d, h). Disease potential classes “Low”, “Medium”, and “High” for leaf rust (a-d) and including the additional class “Very high” for powdery mildew (e-h) are displayed.

6.7 Trends of mean disease incidence and threshold exceeding probability in Saxony-Anhalt between 2011 and 2060

6.7.1 Leaf rust

The time series of mean LRI on susceptible wheat varieties (Fig. 6-31a) revealed a strong increase under the 3K-scenario between 2011 and 2060, a slight increase for the 1K- and 2K-scenarios, and no increase for the 0K-scenario. Linear trend analyses of LRI development between 2011 and 2060 showed positive trends (ΔLRI) for all scenarios. Only the trend of the 3K-scenario showed a significant increase with ΔLRI = 14% and α = 5% (Fig. 6-32a). With regard to the four climate scenarios LRI patterns on resistant varieties were similar, but the increases in LRI for the 1K-, 2K-, and 3K-scenario were much smaller (Fig. 6-31d). This was supported by positive linear trends for all scenarios including a significant trend with ΔLRI = 8% and α = 5% for the 3K-scenario (Fig. 6-32d). The mean LRI0 on susceptible varieties did not change for the 0K-scenario but decreased slightly under the other scenarios (Fig. 6-31b). All linear trend estimates had a value close to 0 and none were significant (Fig. 6-32b). The mean LRI0 on resistant varieties showed no change for the 0K-scenario and strong increases for the other climate scenarios (Fig. 6-31e). Concerning all scenarios the trend estimates were positive. ΔLRI0 increased with an increase of the temperature forcing. The only significant trend was identified for the 3K-scenario with ΔLRI0 = 17% and α = 5% (Fig. 6-32e).
The mean LRI30 on susceptible varieties did not change for the 0K-scenario, increased slightly under the 1K- and 2K-scenario, and increased stronger under the 3K-scenario between 2011 and 2060 (Fig. 6-31c). The trend estimates revealed no significant trend for any scenario. But the trend for the 3K-scenario (ΔLRI30 = 10%) was much stronger compared to the 1K- and 2K-scenario (Fig. 6-32c). Similar change patterns were detected for the mean LRI30 on resistant varieties for all climate scenarios (Fig. 6-31f). Trend analyses showed no significant trend for any scenario, but positive trends strengthened with increasing temperature forcing (Fig. 6-32f).

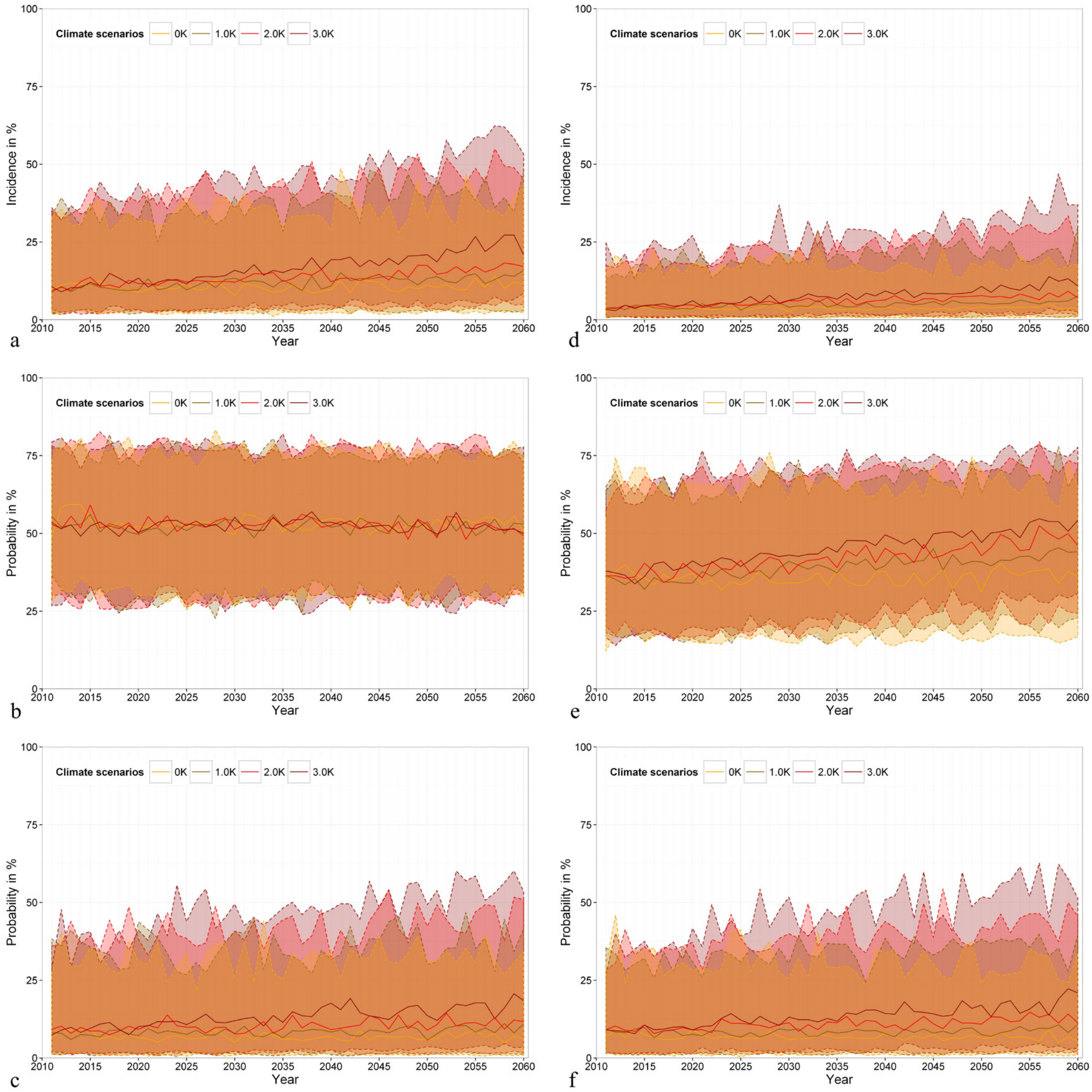


Fig. 6-31: Projected leaf rust incidence (a, d) and probabilities exceeding 0% (b, e) and 30% (c, f) incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent during the period 2011 to 2060 for the 0K-, 1K-, 2K-, and 3K-scenario: The annual median values (straight lines), 5%-, and 95%-percentiles (interrupted lines) are shown.

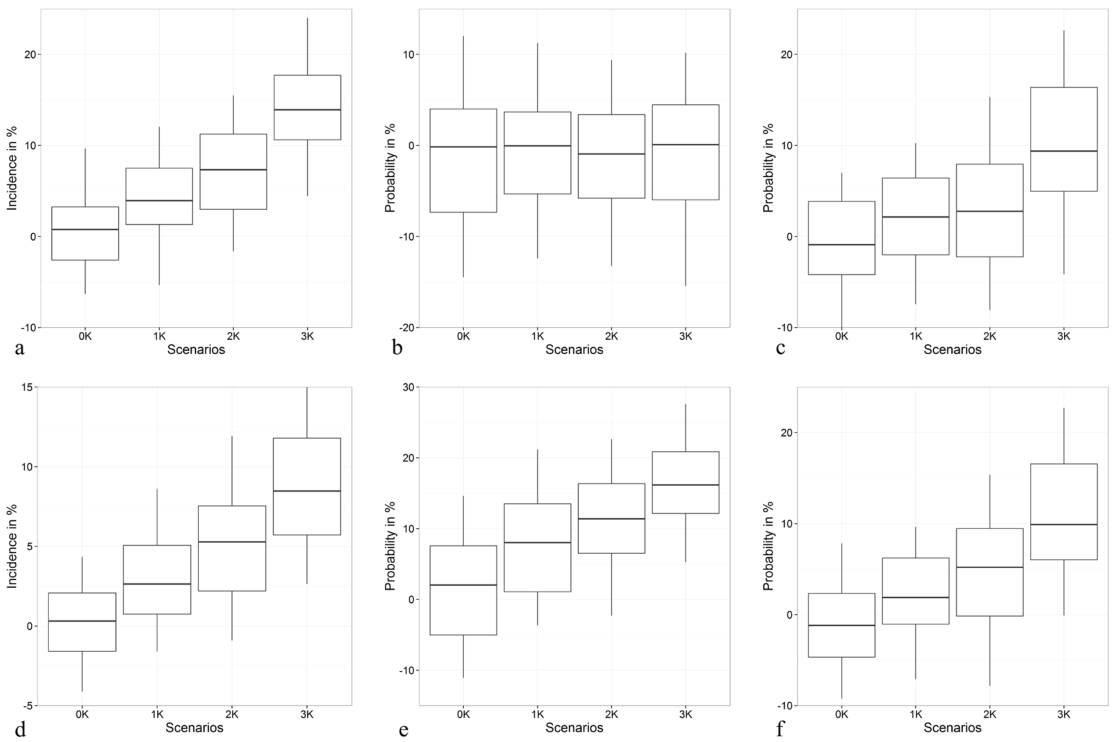


Fig. 6-32: Trends in leaf rust incidence (a, d) and probabilities exceeding 0% (b, e) and 30% (c, f) incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent during the period 2011 to 2060 for the 0K-, 1K-, 2K-, and 3K-scenario. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

6.7.2 Powdery mildew

The time series of mean PMI on susceptible wheat varieties showed no tendency for all climate scenarios between 2011 and 2060 (Fig. 6-33a). The mean trend estimates had a negative tendency in consequence to an increasing temperature forcing, but the estimates for all climate scenarios were not significant (Fig. 6-34a). A decreasing tendency was present on resistant varieties for all scenarios but the 0K-scenario (Fig. 6-33d). Trend estimates were negative for the 1K-, 2K-, and 3K-scenario and significant for the 2K- and 3K-scenario with $\Delta PMI = -9\%$ and $\Delta PMI = -13\%$, respectively, at $\alpha = 5\%$ (Fig. 6-34d). The mean PMI0 on susceptible varieties showed no tendency for the 0K-scenario, a slight increase for the 1K-scenario, and stronger increasing tendencies under the 2K- and 3K-scenario (Fig. 6-33b). The trend analyses confirmed these findings (Fig. 6-34b). The mean trend estimates revealed no trend for the 0K-scenario, a positive but not significant trend for the 1K- and 2K-scenario, and a significant positive trend for the 3K-scenario. The trend under the 3K-scenario was significant with $\Delta PMI0 = 8\%$ at $\alpha = 5\%$. The mean PMI0 on resistant varieties showed no tendency for the 0K-scenario, a slight negative one for the 1K-scenario, and a strong negative tendency under the 2K- and 3K-scenario (Fig. 6-33e). Trend estimates for all scenarios had a negative sign and decreased assuming a rise in mean temperature (Fig. 6-34e). The trend for the 3K-scenario was the only significant one with ΔPMI0 = -14% at α = 5%.

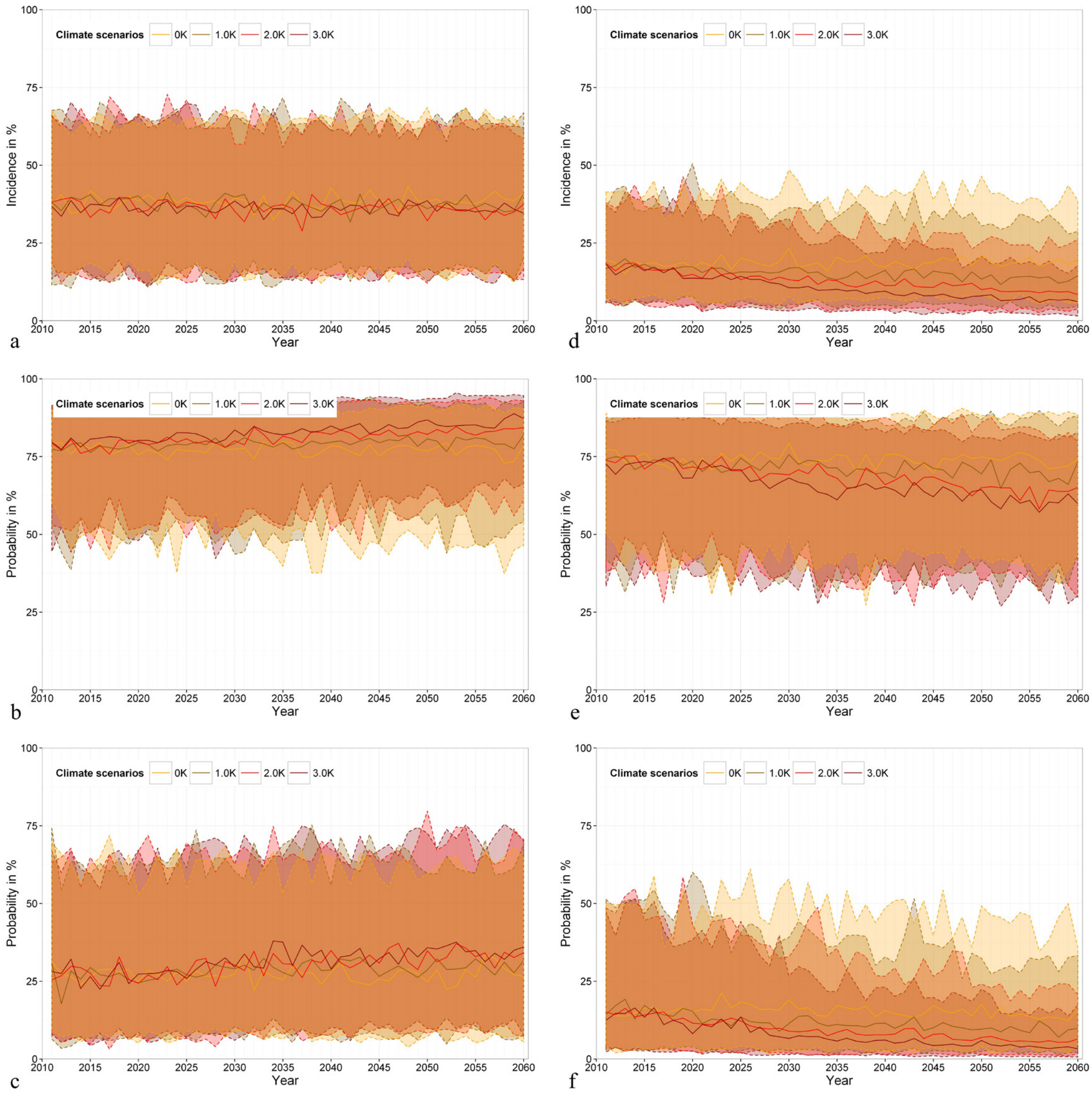


Fig. 6-33: Projected powdery mildew incidence (a, d) and probabilities exceeding 0% (b, e) and 50% (c, f) incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent during the period 2011 to 2060 for the 0K-, 1K-, 2K-, and 3K-scenario: The annual median values (straight lines), 5%-, and 95%-percentiles (interrupted lines) are shown.

The mean PMI50 on susceptible varieties did not change markedly for the 0K- and 1K-scenario and increased slightly for the 2K- and 3K-scenario between 2011 and 2060 (Fig. 6-33c). The mean trends for all scenarios, except the 0K-scenario, were positive but not significant at α = 5% (Fig. 6-34c). With increasing the temperature forcing the trend estimates increased, too. The mean PMI50 on resistant varieties decreased under all scenarios but the 0K-scenario, which showed no change (Fig. 6-33f). All trend estimates for scenarios of elevated temperature forcing were significantly negative and decreased as a result of increasing mean temperature (Fig. 6-34f). Trend estimates were significant at α = 5% with ΔPMI50(1K) = -9%, ΔPMI50(2K) = -12%, ΔPMI50(3K) = -15%.

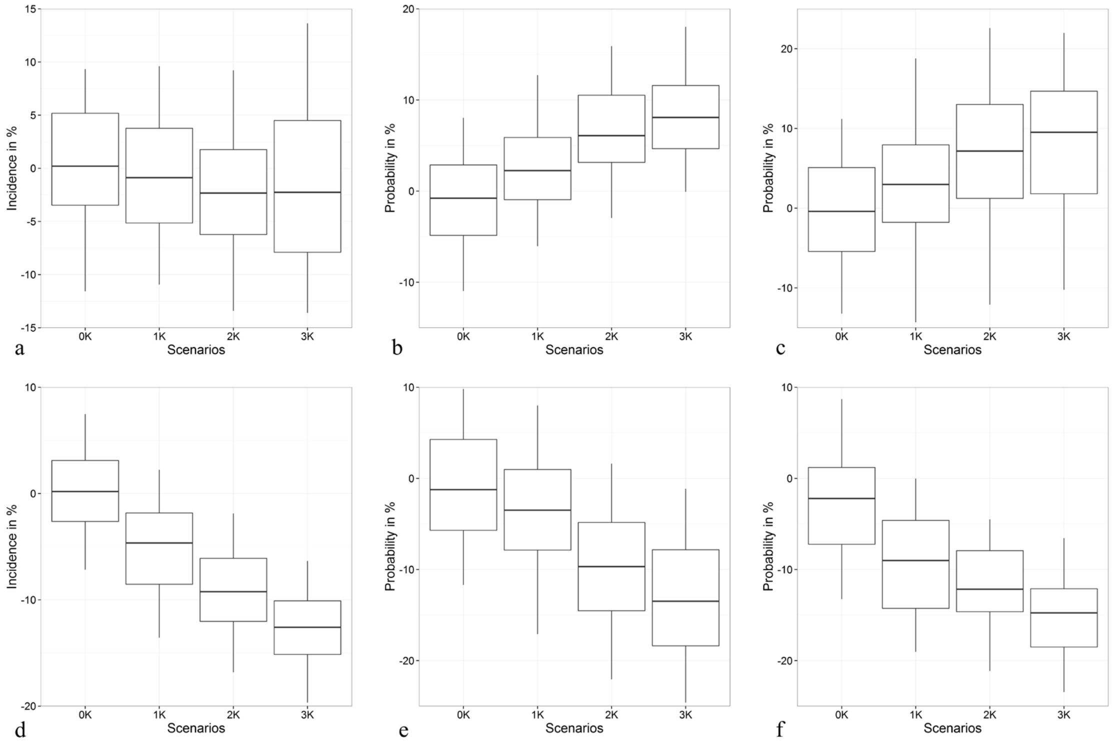


Fig. 6-34: Trends in powdery mildew incidence (a, d) and probabilities exceeding 0% (b, e) and 50% (c, f) incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent during the period 2011 to 2060 for the 0K-, 1K-, 2K-, and 3K-scenario. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

6.8 Comparing future and present mean disease incidence and threshold exceeding probability in Saxony-Anhalt

6.8.1 Leaf rust

A comparison of mean LRI values on susceptible varieties in Saxony-Anhalt between the periods 1976-2010 (base period) and 2031-2060 (scenario period) revealed a significant positive difference (α = 5%) for the 3K-climate scenario (Fig. 6-35a). The value of the mean difference between both periods (ΔLRI) increased from -4% ΔLRI(0K) to 6% ΔLRI(3K) in consequence to an increasing temperature forcing. Resistant varieties showed a similar behavior with significant positive differences (α = 5%) for the 2K- and 3K-scenario (Fig. 6-35d). The increasing temperature forcing elevated the mean differences from about -1% (0K-scenario) to about 6% (3K-scenario).

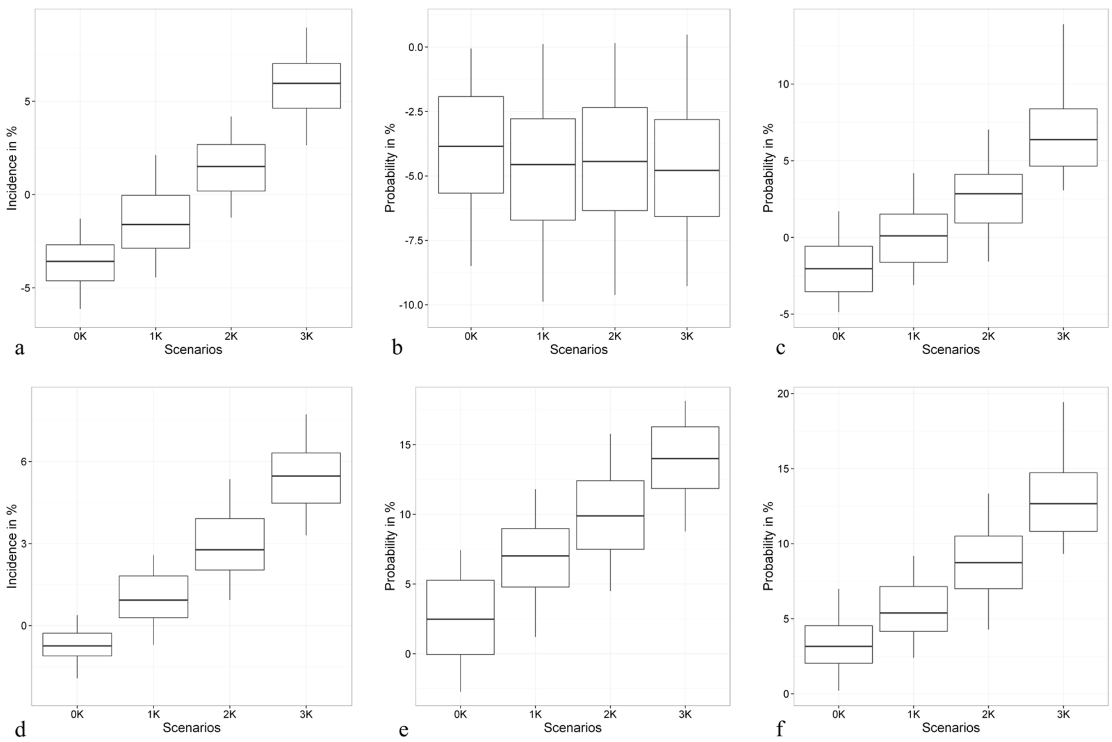


Fig. 6-35: Differences in leaf rust incidence (a, d) and the probability to exceed 0% (b, e) and 30% incidence (c, f) on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K-, 2K-, and 3K-scenario during the period 2031 to 2060. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

Comparing base and scenario period on susceptible varieties by calculating ΔLRI0 revealed no significant difference from zero for all climate scenarios, except the 0K-scenario, at α = 5% (Fig. 6-35b). All scenarios showed mean differences between -3% and -5%. On resistant varieties ΔLRI0 was significantly positive for all scenarios, but the 0K-scenario (Fig. 6-35e). The mean of ΔLRI0 increased from ΔLRI0(0K) = 2.5% to ΔLRI0(3K) = 14%, an increasing temperature forcing provided. ΔLRI30 was significantly positive for the 3K-scenario at α = 5% on susceptible varieties (Fig. 6-35c). The mean of ΔLRI30 increased from ΔLRI30(0K) = -2% to ΔLRI30(3K) = 6.5% for an increase in mean temperature. Resistant varieties showed a significant positive difference for all scenarios (Fig. 6-35f). The mean of ΔLRI30 increased from ΔLRI30(0K) = 3% to ΔLRI30(3K) = 12.5% assuming a rise in mean temperature.

6.8.2 Powdery mildew

The calculation of ΔPMI values between base and scenario period on susceptible varieties revealed no significant differences for all climate scenarios at α = 5% (Fig. 6-36a). Mean ΔPMI slightly decreased from ΔPMI(0K) = 1.5% to ΔPMI(3K) = -0.5% with increasing temperature forcing. On resistant varieties ΔPMI was significantly negative for the 1K-, 2K-, and 3K-scenario (Fig. 6-36d). Mean ΔPMI decreased from ΔPMI(0K) = 0% to ΔPMI(3K) = -11% for an increase in mean temperature. Differences in PMI0 on susceptible varieties were not significant for the 0K-, 1K-, and 2K-scenario and significantly positive for the 3K-scenario (Fig. 6-36b). Increasing the temperature forcing, mean ΔPMI0 increased from ΔPMI0(0K) = -3% to ΔPMI0(3K) = 5%. On resistant varieties ΔPMI0 was significantly different from zero for all climate scenarios, except the 0K-scenario (Fig. 6-36e). Mean ΔPMI0 decreased from ΔPMI0(0K) = -2% to ΔPMI0(3K) = -12% for an increase in mean temperature.

PMI50 values on susceptible varieties were significantly different between base and scenario period with $\alpha = 5\%$ for the 1K-, 2K-, and 3K-scenario (Fig. 6-36c). Mean ΔPMI50 rose from ΔPMI50(0K) = 3% to ΔPMI50(3K)=8.5% with increasing temperature forcing. On resistant varieties ΔPMI50 was significantly negative for the 2K- and 3K-scenario (Fig. 6-36f). Mean ΔPMI50 decreased from ΔPMI50(0K) = 1% to ΔPMI50(3K) = -10% assuming a rise in mean temperature.

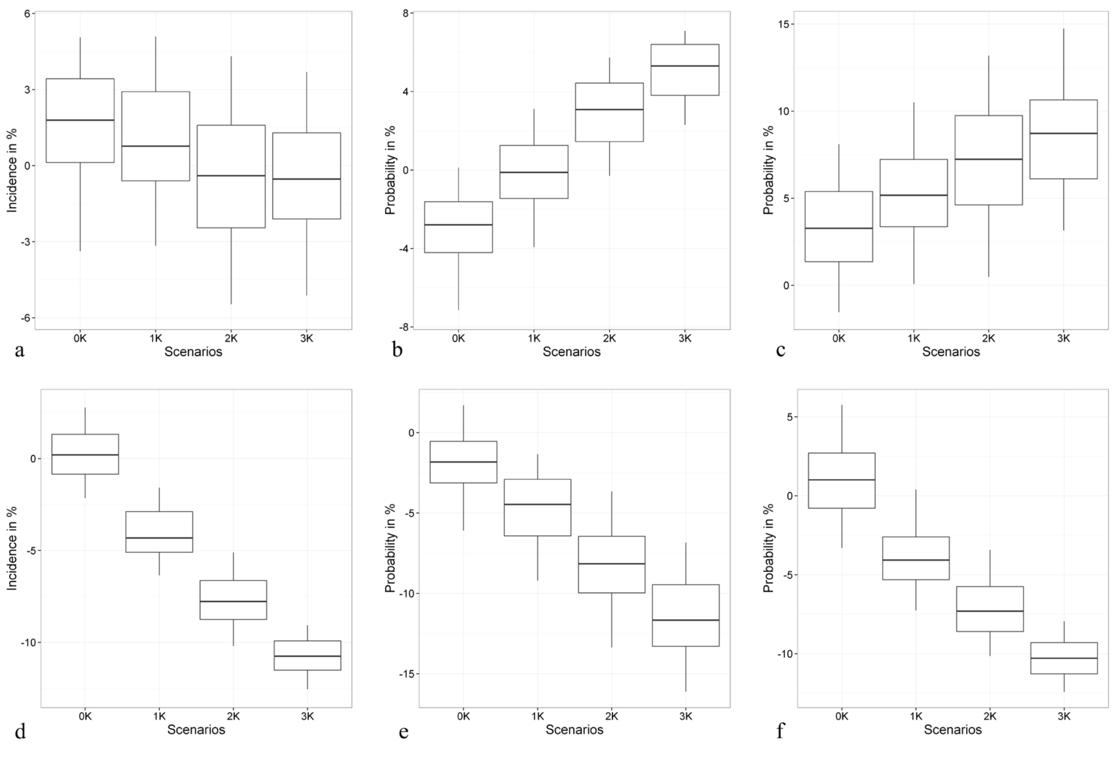


Fig. 6-36: Differences in powdery mildew incidence (a, d) and the probability to exceed 0% (b, e) and 30% incidence (c, f) on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K-, 2K-, and 3K-scenario during the period 2031 to 2060. The medians calculated over all STARS realizations (crossbars in the box), interquartile ranges (box heights), 5%- and 95%-percentiles (whiskers) are shown.

6.9 Spatial trend patterns of future disease incidence and threshold exceeding probability in Saxony-Anhalt

6.9.1 Leaf rust

No significant LRI trend was identified on susceptible and resistant varieties (Fig. 6-37) under the 0K- and 1K-scenario during the timeframe 2011 to 2060 for any Thiessen polygon. Trends for most parts of Saxony-Anhalt for the 0K-scenario were slightly positive with ΔLRI between 0% and 5%, except for the Harz Mountains and the most southern part of the state having a slightly negative trend. Trends for most parts of the state were slightly positive under the 1K-scenario, too, except for the region in the vicinity of the Harz Mountains showing a stronger positive trend. The 2K-scenario on susceptible varieties exhibited positive LRI trends for the whole state. Significance was demonstrated in some central areas of Saxony-Anhalt. The trends on resistant varieties were less positive than those on susceptible varieties for half of the polygons. Only few areas appeared to be significant. Nearly all polygons showed significant positive trends of LRI on susceptible varieties under the 3K-scenario with ΔLRI over 10%, except for the Harz Mountains with positive but not significant trends. The same spatial pattern of significance was prevalent on resistant varieties, but trends had smaller positive values with ΔLRI between 5% and 10%.

No significant trend was identified for all scenarios of LRI0 on susceptible varieties (Fig. 6-38). The trends for all scenarios and all areas were between 0% and -5%, except for some of the most western parts with values between 0% and 5%. The trends for LRI0 on resistant varieties were not significant for the 0K-, 1K-, and 2K-scenario (Fig. 6-38). The 0K-scenario had trends between 0% and 5% ΔLRI0, the 1K-scenario between 5% and 10% ΔLRI0, and the 2K-scenario between 10% and 15% ΔLRI0 for most of the polygons. The 3K-scenario revealed significant trends for most parts of Saxony-Anhalt with ΔLRI0 > 15%, except for single areas around the Harz Mountains.

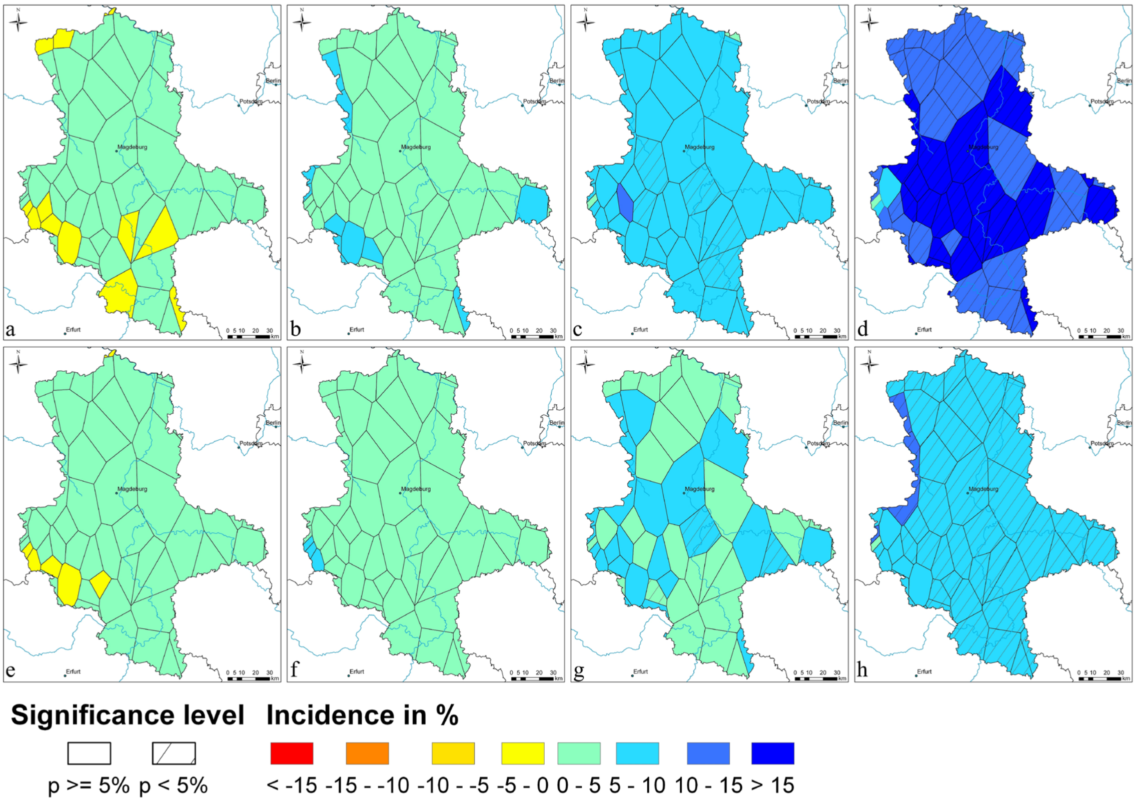


Fig. 6-37: Station-wise trends in leaf rust incidence on susceptible (a-d) and resistant (e-h) wheat varieties in percent during the period 2011 to 2060 for the 0K- (a, e), 1K- (b, f), 2K- (c, g), and 3K-scenario (d, h).

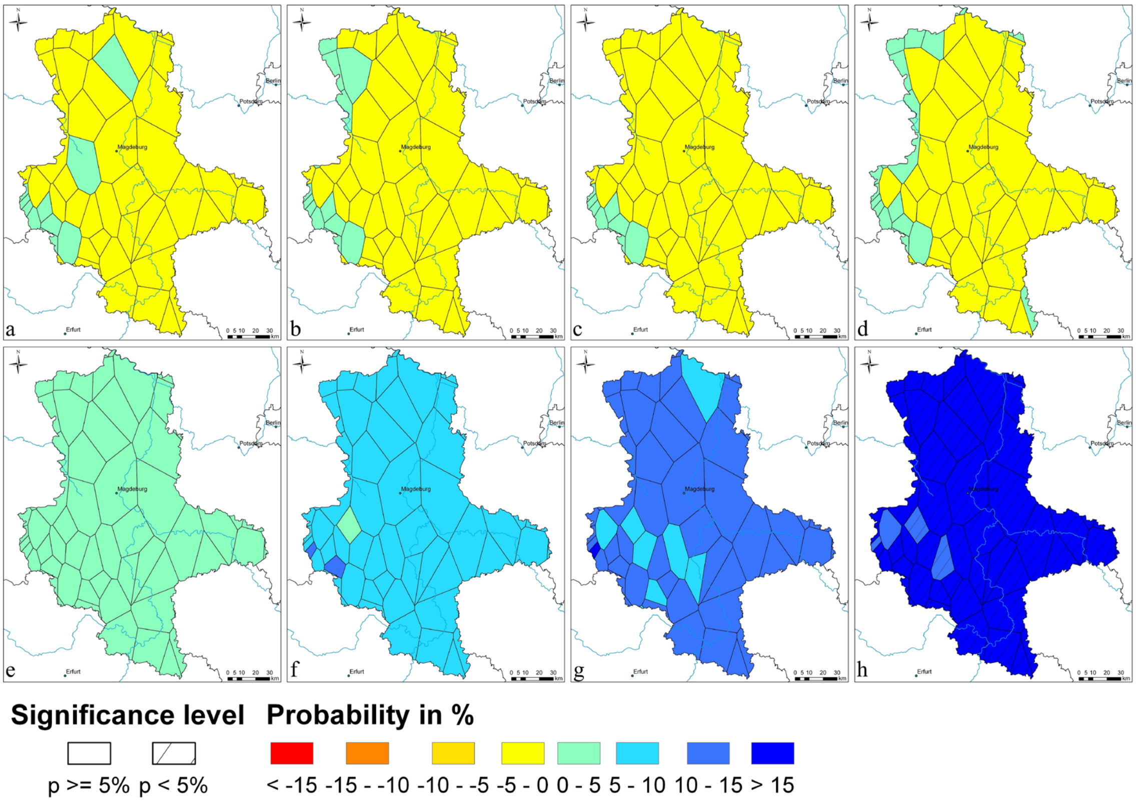


Fig. 6-38: Station-wise trends in the probability to exceed 0% leaf rust incidence on susceptible (a-d) and resistant (e-h) wheat varieties in percent during the period 2011 to 2060 for the 0K- (a, e), 1K- (b, f), 2K- (c, g), and 3K-scenario (d, h).

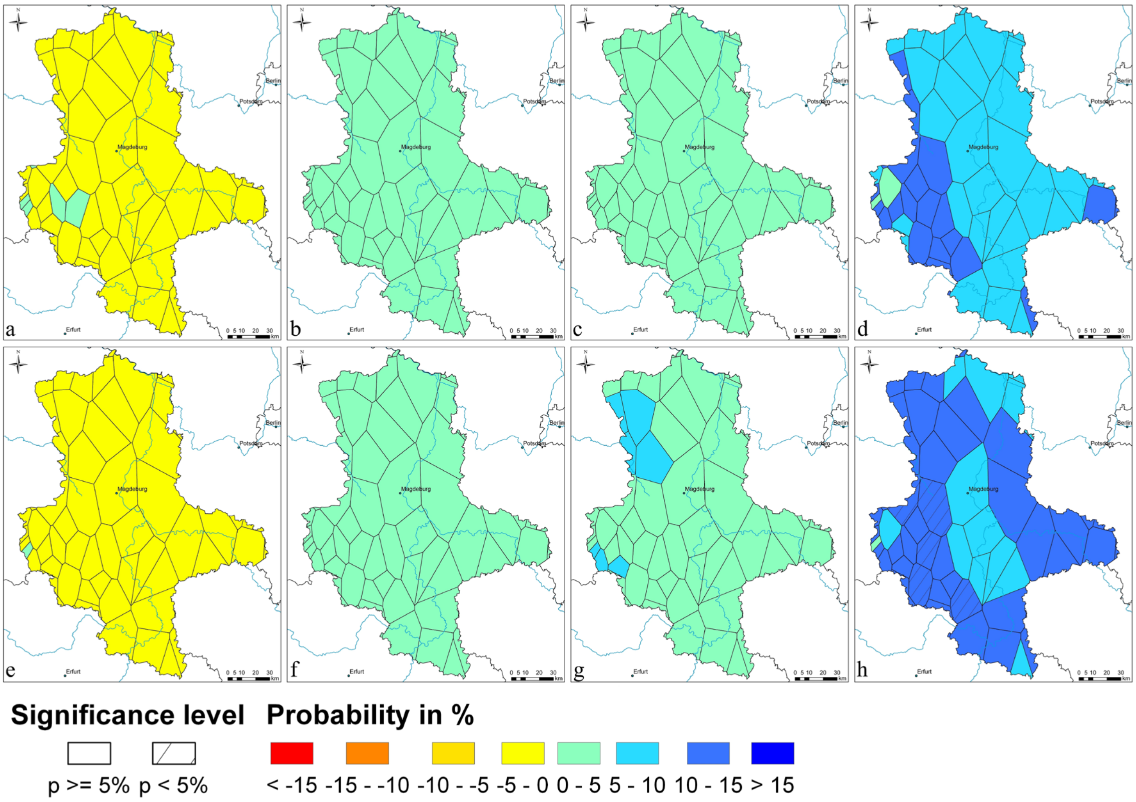


Fig. 6-39: Station-wise trends in the probability to exceed 30% leaf rust incidence on susceptible (a-d) and resistant (e-h) wheat varieties in percent during the period 2011 to 2060 for the 0K- (a, e), 1K- (b, f), 2K- (c, g), and 3K-scenario (d, h).

Figure 6-39 shows trends for LRI30 on susceptible varieties. All scenario trends were not significant and increased for all polygons with increasing temperature forcing. Trends in the Harz Mountains and the eastward adjacent highlands were higher compared to those of the lower areas under the 3K-scenario. Similar patterns were observed for the LRI30 trends on resistant varieties for the 0K-, 1K-, and 2K-scenario (Fig. 6-39). The 3K-scenario revealed lower ΔLRI30 values for the central part of the state compared to the remaining areas. Significant trends were detected for some areas east of the Harz Mountains.

6.9.2 Powdery mildew

The PMI trends on susceptible varieties showed no significant areas for all climate scenarios with ΔPMI between -5% and 5% (Fig. 6-40). PMI trends were not significant on resistant varieties under the 0K- and 1K-scenario and significant under the 2K- and 3K-scenario for most of the polygons (Fig. 6-40). Trends increased with increasing temperature forcing and trend patterns revealed higher trends east of the Harz Mountains compared to the remaining parts of the state under the 2K- and 3K-scenario.

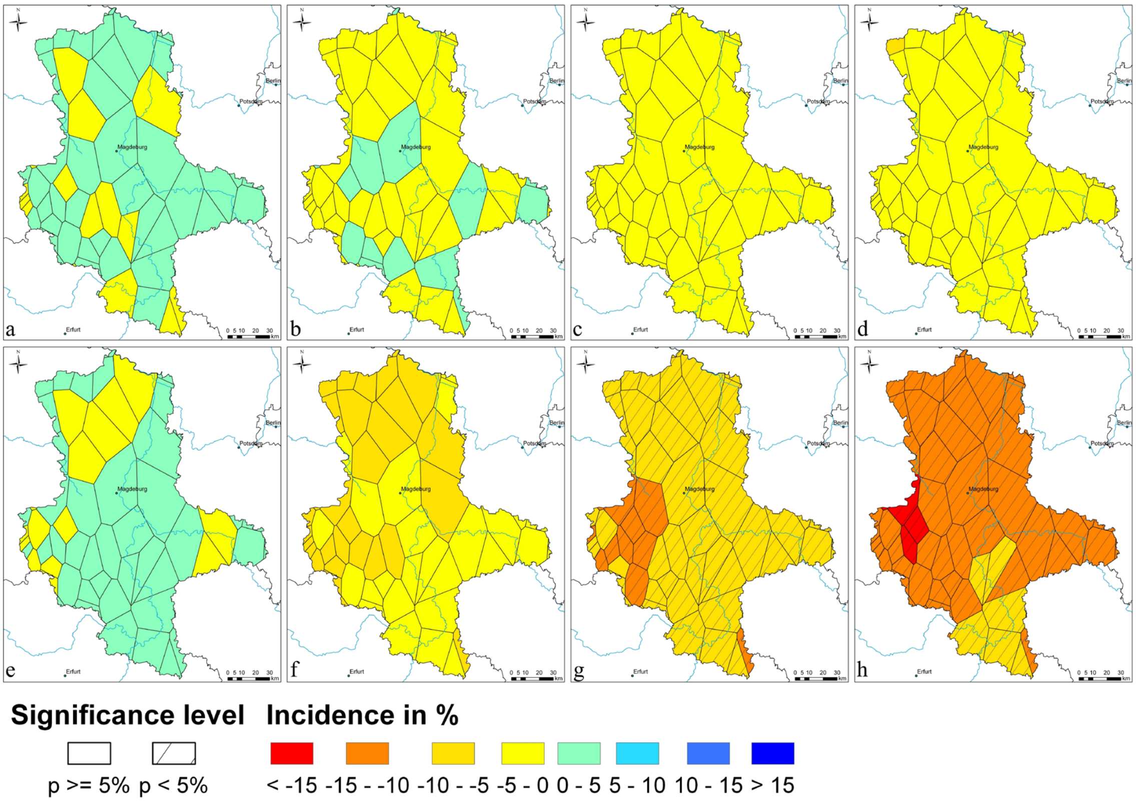


Fig. 6-40: Station-wise trends in powdery mildew incidence on susceptible (a-d) and resistant (e-h) wheat varieties in percent during the period 2011 to 2060 for the 0K- (a, e), 1K- (b, f), 2K- (c, g), and 3K-scenario (d, h).

PMI0 trends on susceptible varieties were not significant under the 0K-, 1K-, and 2K-scenario and significantly positive for some areas in central Saxony-Anhalt with ΔPMI0 between 5% and 10% (Fig. 6-41). ΔPMI0 increased for all areas with increasing temperature forcing. PMI0 trends on resistant varieties were not significant for the 0K- and 1K-scenario with negative values between 0% and -5%. Under the 2K- and 3K-scenario trend values decreased further and reached significance for certain areas in the central and northern part of the state with ΔPMI0 between -10% and -15% and in few areas even below -15% (Fig. 6-41).

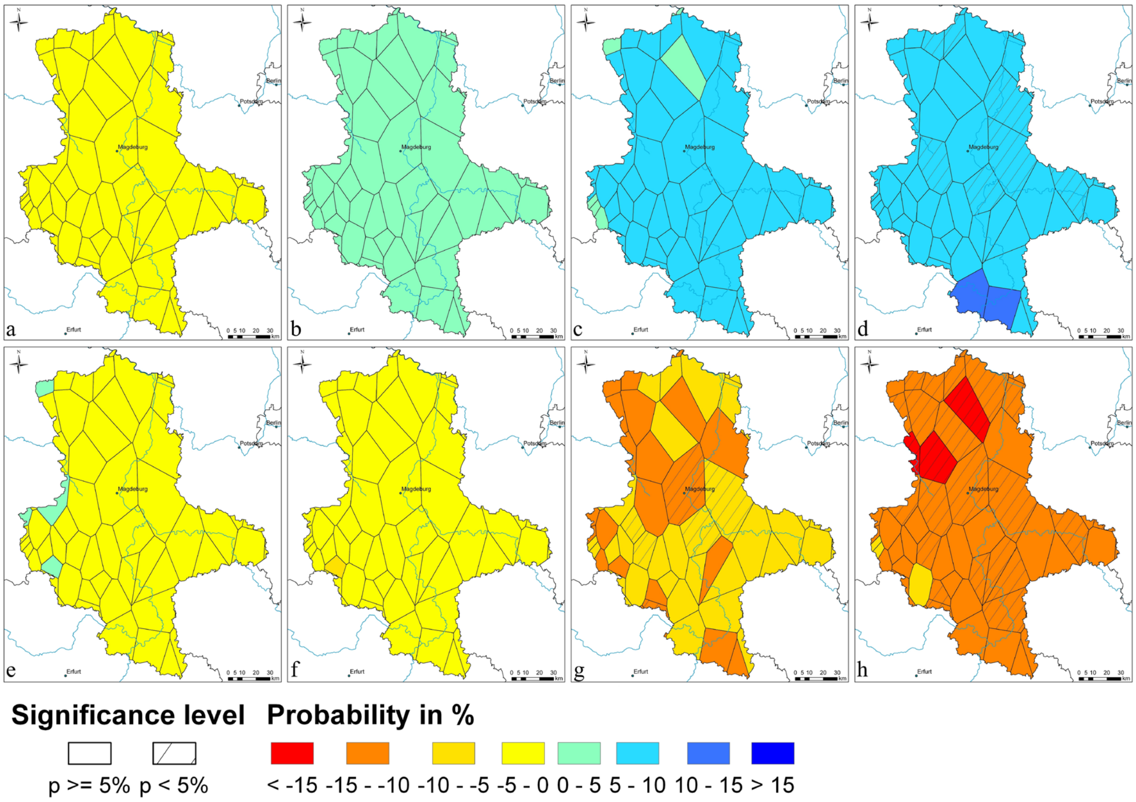


Fig. 6-41: Station-wise trends in the probability to exceed 0% powdery mildew incidence on susceptible (a-d) and resistant (e-h) wheat varieties in percent during the period 2011 to 2060 for the 0K- (a, e), 1K- (b, f), 2K- (c, g), and 3K-scenario (d, h).

PMI50 trends on susceptible varieties showed no significant trends for any area under any climate scenario (Fig. 6-42). Trend values increased with increasing temperature forcing, especially in the Harz Mountains. ΔPMI50 decreased on resistant varieties for all areas for an increase in mean temperature (Fig. 6-42). The 0K- and 1K-scenario had few to none areas with significant trends. The 2K- and 3K-scenario showed significance with ΔPMI50 values below -15% for all areas.

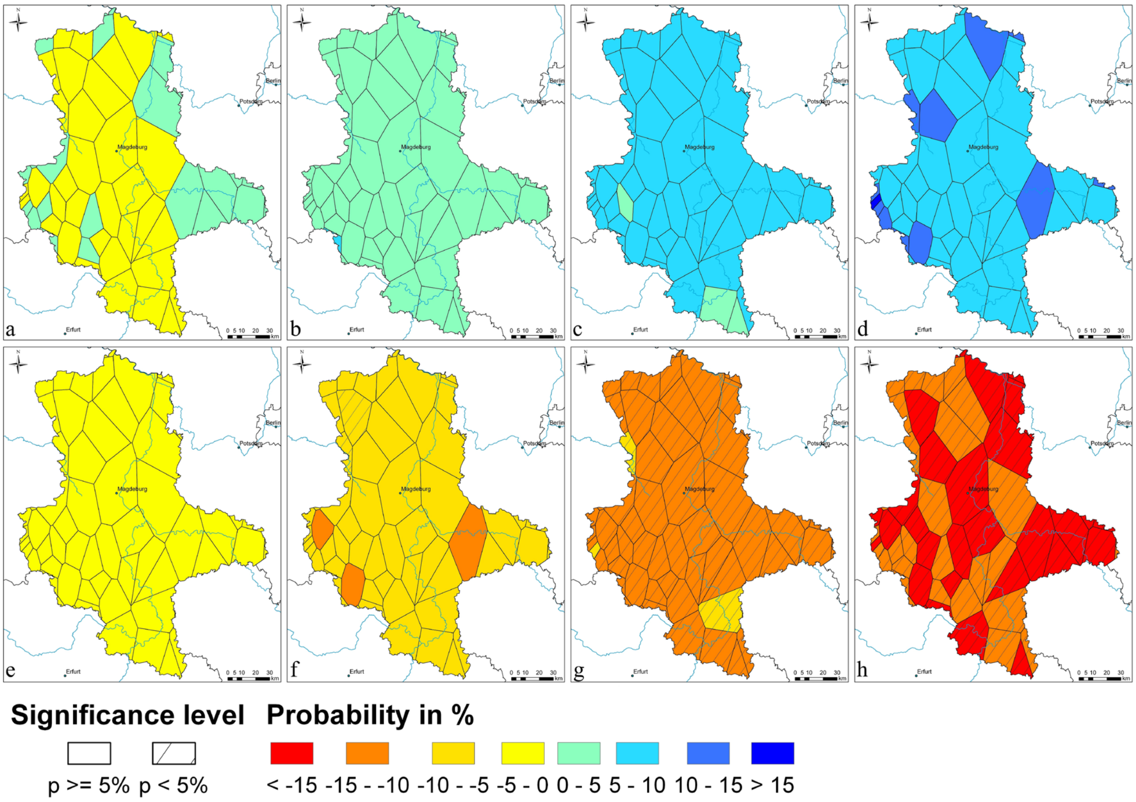


Fig. 6-42: Station-wise trends in the probability to exceed 50% powdery mildew incidence on susceptible (a-d) and resistant (e-h) wheat varieties in percent during the period 2011 to 2060 for the 0K- (a, e), 1K- (b, f), 2K- (c, g), and 3K-scenario (d, h).

6.10 Spatial differences of future disease incidence and threshold exceeding probability in Saxony-Anhalt

6.10.1 Leaf rust

The differences between the scenarios under elevated mean temperature and the 0K-scenario of LRI on susceptible varieties were increasingly positive for the whole state assuming an increase in mean temperature (Fig. 6-43). The increase in LRI was relatively uniform for the whole state, except for the Harz Mountains, where the increase was smaller. LRI even decreased for the Brocken station. For LRI large-scale significant increases were only detected under the 3K-scenario. LRI increased stronger in the lee of the Harz Mountains and the southern central part of the state. LRI showed a relatively uniform increase for the whole state on resistant varieties, except for the Harz Mountains exhibiting a smaller increase (Fig. 6-43). A significant increase of LRI was detected for the 2K-scenario in the central and southern parts of the state. The increase was significant for all but the stations situated in the Harz Mountains for the 3K-scenario. The increase was stronger for areas in the lee of the Harz Mountains and the polygons at the northwestern state border.

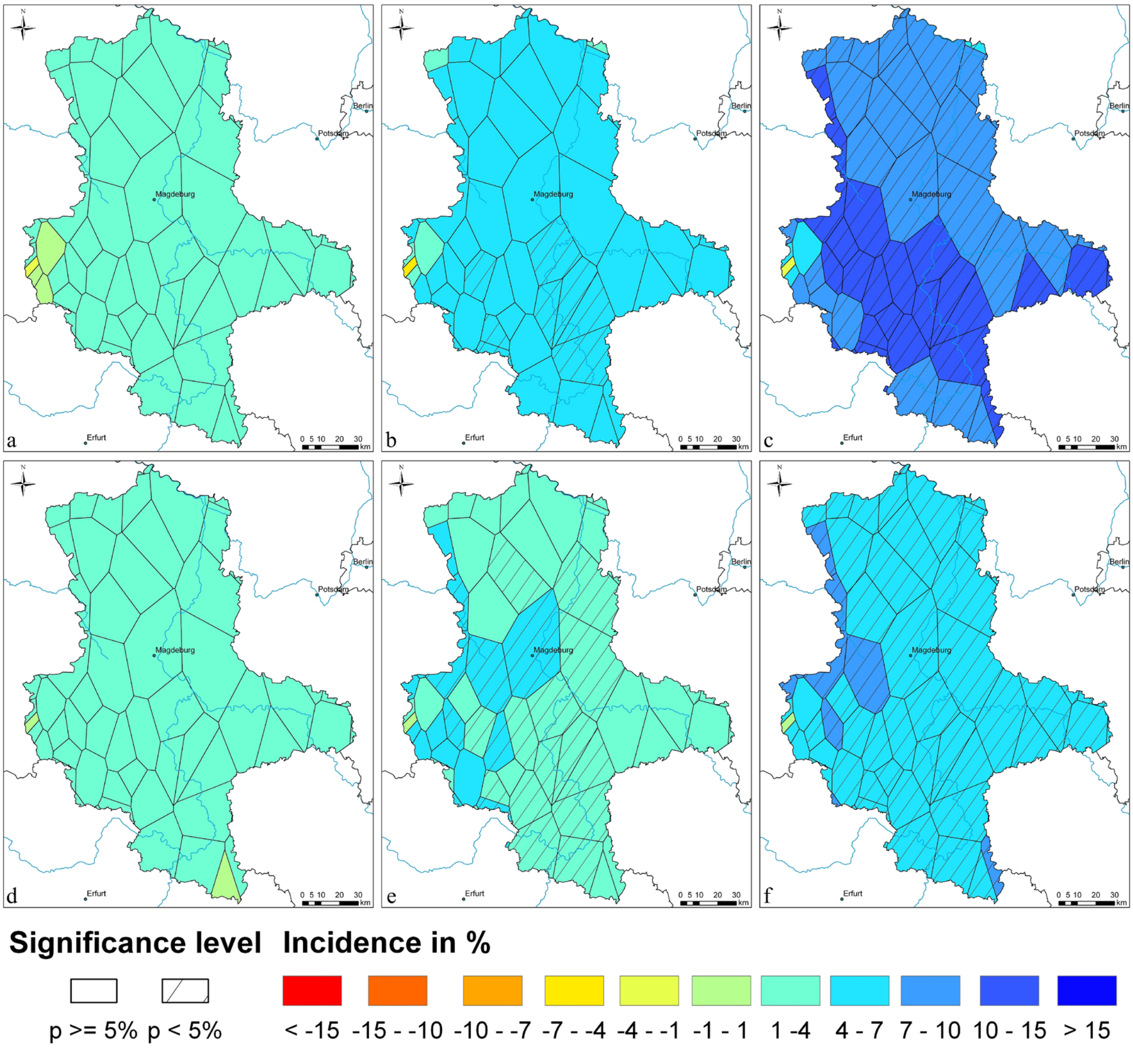


Fig. 6-43: Station-wise differences in leaf rust incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K- (a, d), 2K- (b, e), and 3K-scenario (c, f) during the period 2031 to 2060.

Comparing LRI0 on susceptible varieties for the 1K-, 2K-, and 3K-scenario with the 0K-scenario revealed no significances for the whole state (Fig. 6-44). ΔLRI0 fluctuated between zero and slight negative values for most areas. The 3K-scenario presented slight negative differences for all but the southern and southwestern parts of the state. ΔLRI0 on resistant varieties had positive values for all scenarios and increased with increasing temperature forcing for the whole state (Fig. 6-44). The increase was smaller in the lee of the Harz Mountains and in some central parts of the state for the 1K- and 2K-scenario. The 3K-scenario revealed a significant increase of LRI0 for most areas in Saxony-Anhalt, except the Harz Mountains, some adjacent areas, and the northeastern part of the state.

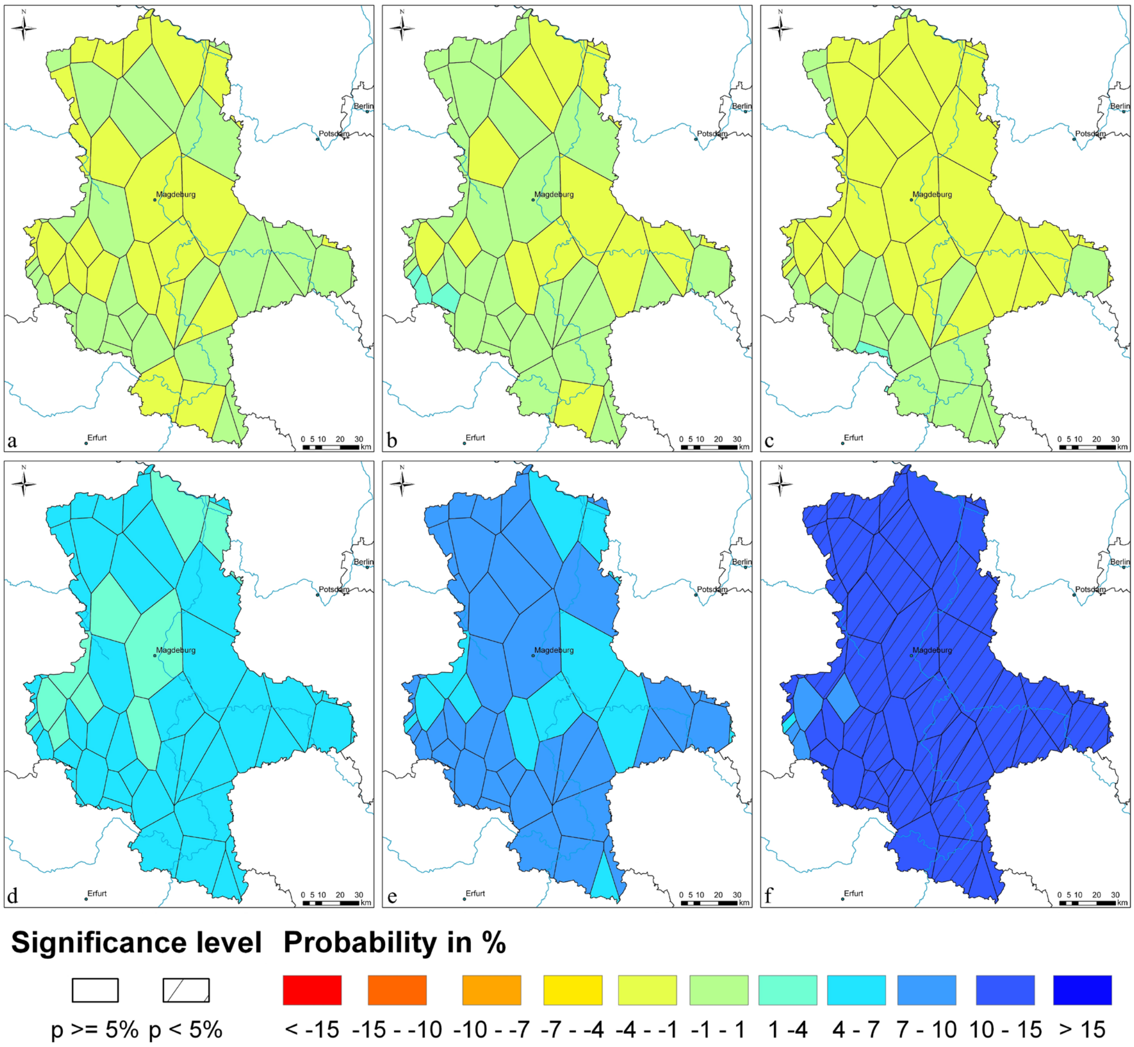


Fig. 6-44: Station-wise differences in the probability to exceed 0% leaf rust incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K- (a, d), 2K- (b, e), and 3K-scenario (c, f) during the period 2031 to 2060.

Differences between the scenarios of elevated mean temperature and the 0K-scenario of LRI30 on susceptible varieties were increasingly positive for the whole state with an increasing temperature forcing (Fig. 6-45). The increase was only significant under the 3K-scenario and only significant in most parts of the state, except the Harz Mountains and certain areas in the north. ΔLRI30 increased strongest in the areas east and northeast of the Harz Mountains. ΔLRI30 was positive for all scenarios on resistant varieties, but significance was only detected under the 3K-scenario (Fig. 6-45). The 1K- and 2K-scenario showed a uniform increase of LRI30 for the whole state. The 3K-scenario revealed regional differences. The strongest increase concerning the 3K-scenario was detected in the lee of the Harz Mountains, the northwestern, and southeastern parts of the state. Significant increases were detected for the whole state, except for two areas in the Harz Mountains and the southwestern part of the state.

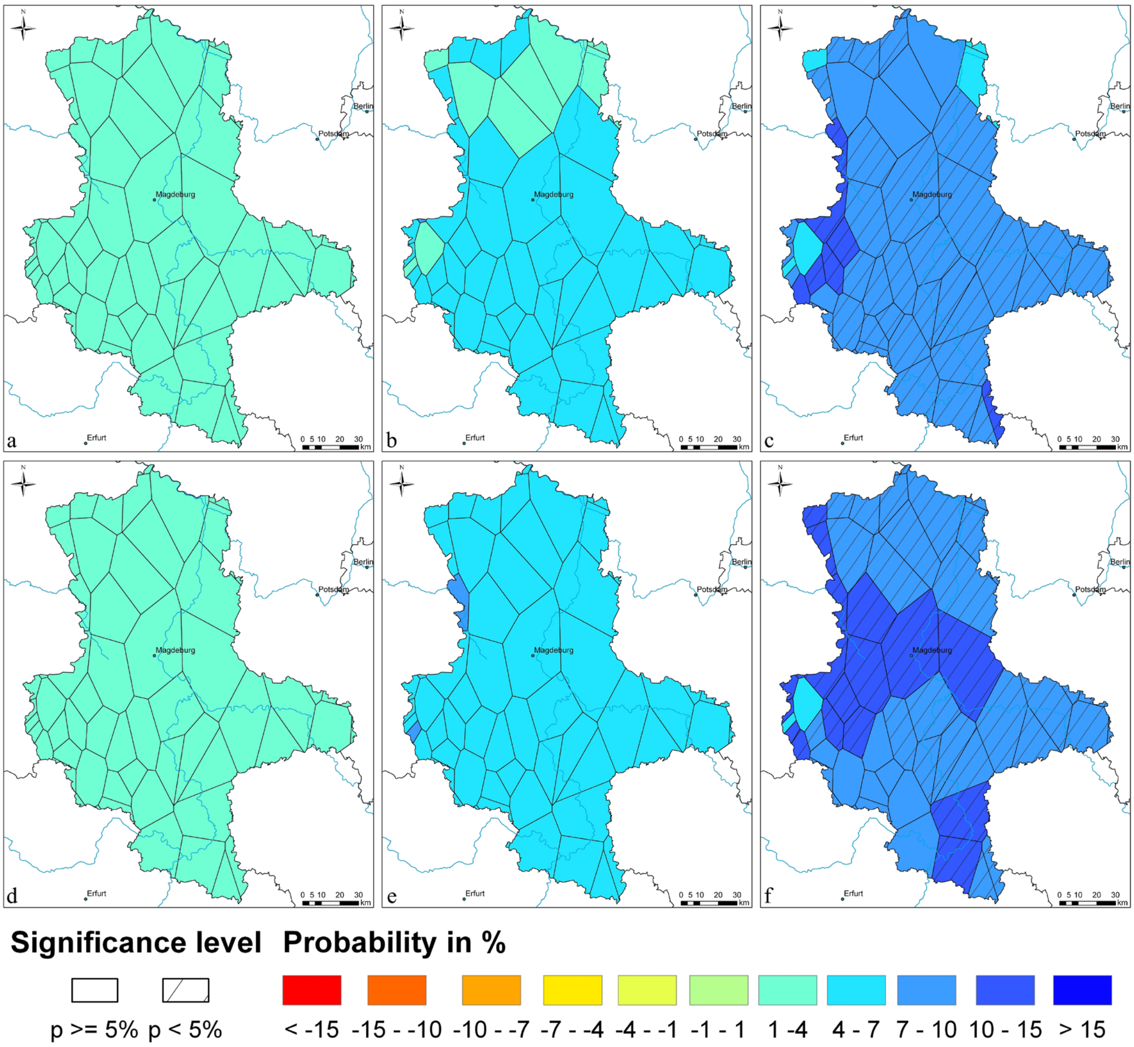


Fig. 6-45: Station-wise differences in the probability to exceed 30% leaf rust incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K- (a, d), 2K- (b, e), and 3K-scenario (c, f) during the period 2031 to 2060.

6.10.2 Powdery mildew

Comparing PMI on susceptible varieties for the 1K-, 2K-, and 3K-scenario with the 0K-scenario revealed no significances for the whole state (Fig. 6-46). ΔPMI fluctuated between zero and slight negative values in most areas. Under the 1K-scenario most areas had ΔPMI values around zero. Under the 2K- and 3K-scenario ΔPMI was slightly negative for most parts of the state, except some areas in the vicinity of the Harz Mountains. ΔPMI on resistant varieties was negative under all scenarios for the whole state (Fig. 6-46). The difference further increased for an increase in mean temperature. Differences were not significant under the 1K-scenario for the whole state and significant for the 2K- and 3K-scenario for most parts of the state. The strongest decrease was found for areas east and northeast of the Harz Mountains. The smallest decrease was detected in the southern part of the state.

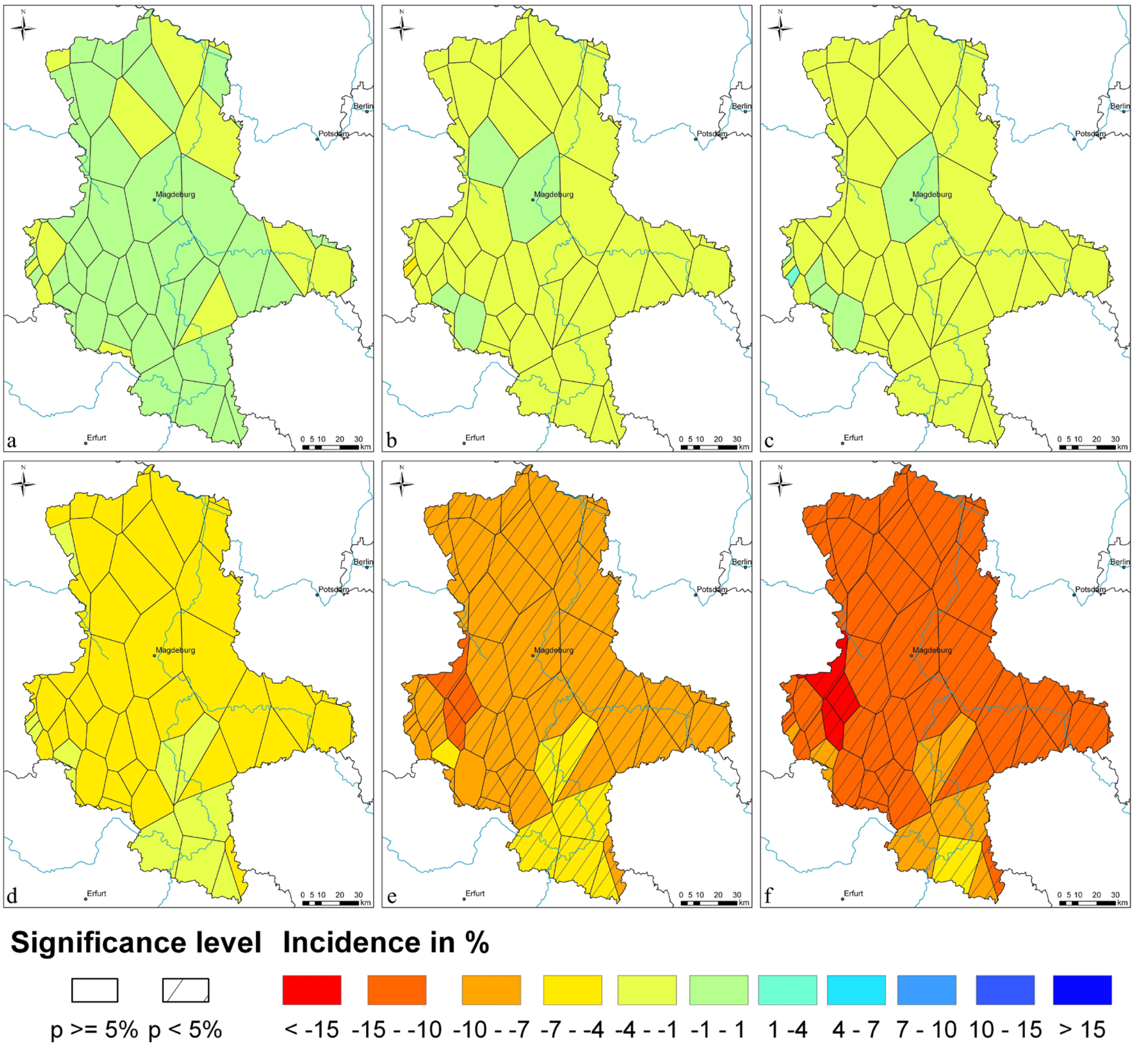


Fig. 6-46: Station-wise differences in powdery mildew incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K- (a, d), 2K- (b, e), and 3K-scenario (c, f) during the period 2031 to 2060.

Differences between the scenarios of elevated mean temperature and the 0K-scenario of PMI0 on susceptible varieties were increasingly positive for the whole state with an increasing temperature forcing (Fig. 6-47). For the 1K- and 2K-scenario ΔPMI0 showed few to none regional differences and no significances. The 3K-scenario revealed a pronounced regional difference in ΔPMI0 values. ΔPMI0 had the smallest increase in the northern part of the state and increased southwards. Differences were significant for the central, eastern, western, and northern part of the state, except for the Harz Mountains and the area around the capital. ΔPMI0 on resistant varieties was negative for the whole state, but showed no significant differences for the 1K- and 2K-scenario (Fig. 6-47). ΔPMI0 values further decreased with increasing temperature forcing for all polygons.

The difference was stronger for the northwest and one station in the south under the 2K-scenario. In contrast, differences were greater in the northern, central, and southern parts of the state and weakest in the Harz Mountains under the 3K-scenario. Most of the significant differences were located in the northern and central part of Saxony-Anhalt.

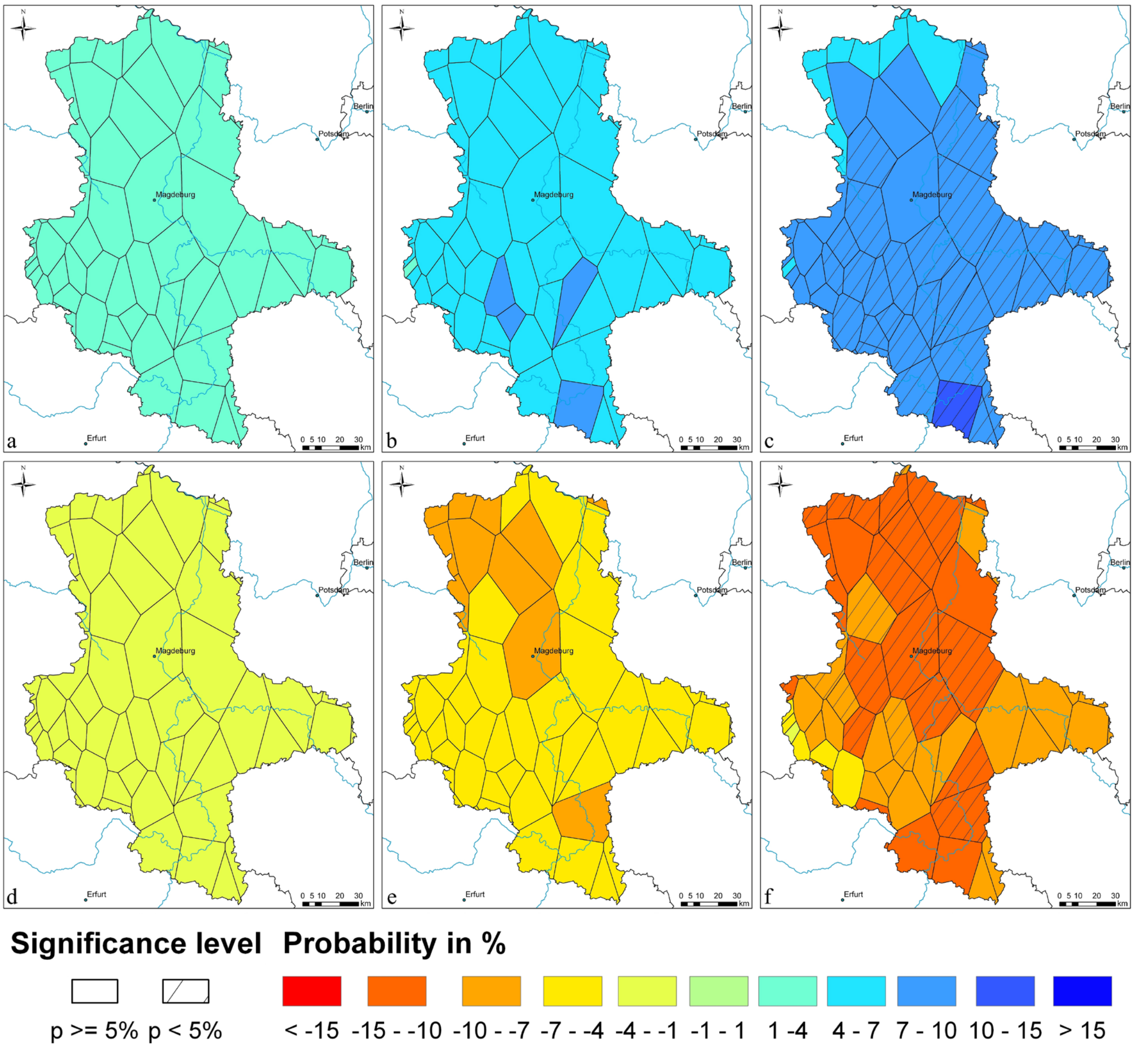


Fig. 6-47: Station-wise differences in the probability to exceed 0% powdery mildew incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K- (a, d), 2K- (b, e), and 3K-scenario (c, f) during the period 2031 to 2060.

Differences between the scenarios of elevated mean temperature and the 0K-scenario of PMI50 on susceptible varieties were increasingly positive for the majority of stations assuming an increase in mean temperature (Fig. 6-48). The increase in ΔPMI50 was strongest in the Harz Mountains, the northwestern part of the state, and the area around the capital. None of the differences were significant. ΔPMI50 on resistant varieties was negative for the whole state and for all scenarios (Fig. 6-48). The difference increased with increasing temperature forcing for all stations. The increase in ΔPMI50 was uniform across the state, except for certain stations in the Harz Mountains and the northwestern part of the state. Significant differences were detected for the northern, northeastern, eastern, and central parts of the state under 2K-scenario. Differences under the 3K-scenario were significant for the whole state.

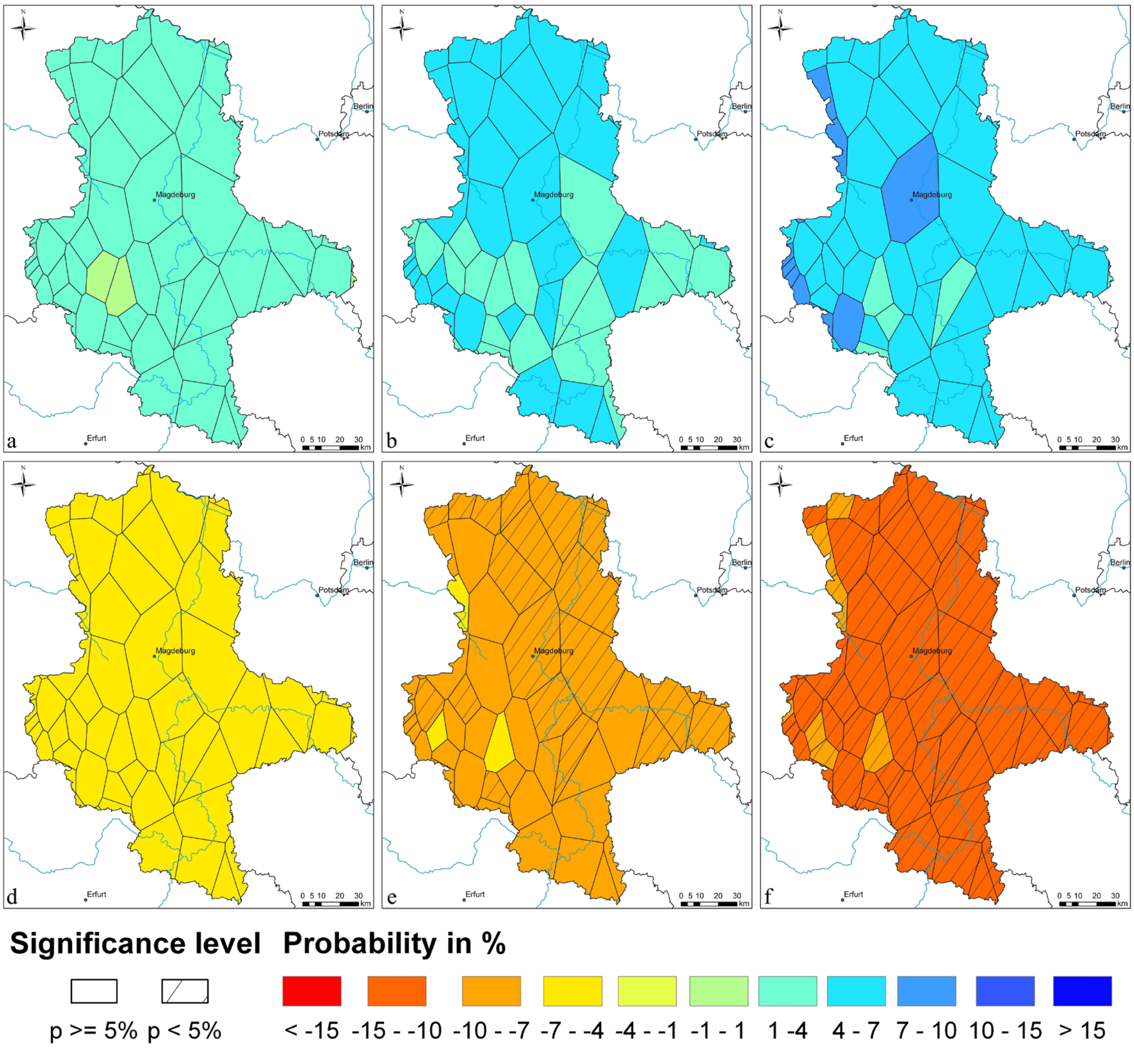


Fig. 6-48: Station-wise differences in the probability to exceed 50% powdery mildew incidence on susceptible (a-c) and resistant (d-f) wheat varieties in percent between long-term means calculated for the 0K-scenario and the 1K- (a, d), 2K- (b, e), and 3K-scenario (c, f) during the period 2031 to 2060.

7 Discussion

7.1 Influence of single meteorological variables on the pathogens

7.1.1 Leaf rust

Temperature

The positive influence of higher temperatures during most parts of the vegetation period on the development and incidence of leaf rust on winter wheat identified, agreed with the findings of laboratory studies (Chester 1946, Hassebrauk 1959, Zadoks 1965) and statistical analyses of monitored data (Chester 1946, Hogg 1969, Burleigh et al. 1972a, b, Daamen et al. 1992, Jahn et al. 1996, Eversmeyer & Kramer 1998, Moschini & Pérez 1999, Wiik & Ewaldz 2009). The results of the regression analyses confirmed the importance of temperature and pointed out the most influential periods during the vegetation period. Especially in winter and spring, temperatures play a major role in determining the amount of urediniospores managing to overwinter and increasing the amount of initial inoculum available for epidemic development on host plants in spring (Burleigh et al. 1969; Eversmeyer & Kramer 1994, 1995, 1996, 1998). Higher spring temperatures can accelerate the development of uredia and urediniospores, shorten latency and incubation times, and increase the number of leaf rust generations until anthesis of wheat. Lower temperatures slow down the development of leaf rust and decrease the amount of disease cycles until anthesis (Roelfs & Bushnell 1985, Eversmeyer & Kramer 1996). The identified correlations showed the importance of air temperatures during the transition from autumn to winter and from winter to spring, when temperatures are at the lower limit of leaf rust development (Chester 1946).

Precipitation

The influence of precipitation on the development of leaf rust spores was often described in the literature (Daamen et al. 1992, Heitefuss et al. 1993, Wiik & Ewaldz 2009). Precipitation is an important source of humidity and is essential for urediniospore germination and infection. This was confirmed by the positive correlated periods in August, October, and May. The findings for August agreed with those of Wiik & Ewaldz (2009). In late summer, humidity is an important prerequisite for leaf rust survival throughout the crop-free period as it provides moisture for volunteers. Precipitation in late summer results in lower insolation, raising the chances for leaf rust to over-summer (Zadoks 1965, Eversmeyer & Kramer 1998).

In autumn, leaf rust infects newly sown winter wheat. Its population size and spatial distribution can expand if weather conditions are good enough. Sufficient precipitation is needed as a source of moisture for leaf wetness, a major determinant of optimal infection and germination. The results revealed that these conditions seem to be similarly important in spring and especially in May. During spring leaf rust is in the crucial phase determining disease incidence during anthesis. The wetter and warmer the conditions during this period are, the shorter the latency and infection periods get, and the more generations are produced (Hogg 1969).

Snowfall

The positive correlations between precipitation in January and February and leaf rust incidence cannot be completely explained as a result of the presence of the necessary humidity, but rather with an isolating effect of snowfall at lower temperatures in contrast to freezing temperatures without snowfall. However, this isolating effect was not observed in the correlogram for snowfall days. The results showed the exact opposite of an isolation effect by snow cover. Snow-free periods during winter are needed for re-infection of host material and are important for leaf rust survival (Eversmeyer & Kramer 1998). As the results only presented correlograms for snowfall and disease incidence no conclusions could be drawn regarding the influence of snow cover on urediniospores. The amount of snowfall being zero does not allow the conclusion of no snow cover present. Additionally, the calculated variable snowfall was dominated by low temperatures and the expected precipitation signal was mainly absent. Further studies will be needed to determine whether this method for calculating days with snowfall is useful or has to be changed.

Radiation

The effects of sunshine duration and radiation on the development of leaf rust are known (de Vallavieille-Pope et al. 2002). The findings from the literature were confirmed by the correlations. Urediniospores are affected by intense solar radiation during transport (Sache 2000), germination, infection, reproduction, and sporulation. As expected, correlations between sunlight hours and leaf rust incidence showed patterns similar to those between disease incidence and mean temperatures over long periods of time. During winter the correlation structures for sunlight duration were contrary to those for mean temperature. This could be explained by the decoupling of radiation and temperature during winter months. Sunny days and high radiation are common during winter weather situations with persistent high-pressure systems, which cause cold air masses to cover Central Europe. Surprisingly, sunshine duration showed no significant correlations regarding the conditions in March and early April. The negative correlated period around day 290 corresponded with the findings of the correlograms for precipitation and findings from literature (Roelfs & Bushnell 1985). More precipitation and less sunshine duration in late August increase the probability of leaf rust spores surviving the crop-free period in summer by exploiting the abundance of volunteer wheat, referred to as the "green bridge".

Wind

Wind speed is often used to explain the introduction of exogenous inoculum into new regions, initiating leaf rust epidemics or strengthening them (Hirst et al. 1967a, b, Sache 2000). Contrary to the findings in literature the correlogram for wind speed identified mainly negative correlations. This indicated wind speed being too high for urediniospores to adhere to leaf surfaces before appressorium development was able to start. But it is unlikely that this effect could hinder the development of leaf rust for a long period of time. Thus, the strongest effect of wind speed on leaf rust incidence detected in the results could be attributed to the accelerated drying of leaf surfaces at higher wind speeds. Under these conditions leaf wetness is lowered below the level required for infection, the germination of leaf rust spores, and the formation of appressoria (Stuckey & Zadoks 1989). According to the results, leaf wetness accelerated the development of leaf rust in late summer, early autumn, at the time of winter wheat sowing, and during spring. But long periods of leaf dryness can result in massive obstruction or even long-term interruption of the developmental cycle of *P. triticina* (de Vallavieille-Pope et al. 1995).

7.1.2 Powdery mildew

Temperature

Powdery mildew is likely to capitalize from warmer temperatures in winter. Mild winters allow more conidia to survive resulting in more initial inoculum at the beginning of spring (Boland et al. 2004). The findings supported this theory as they showed significant positive relationships between minimum temperatures and powdery mildew incidence at the beginning of February until early December. Minimum temperatures seemed to approach the lower limit for powdery mildew development from March to December, because minimum temperatures during the time frame were positively correlated with disease incidence. A similar pattern was shown by the correlogram for freezing days and disease incidence.

The negative correlations between mid-October and late November found in this study were not discussed in literature. No biological process explaining this phenomenon was found. Mean temperature in late autumn exhibits values between 5 and 9°C and is much lower than required for optimal disease development (Bouma 2008). Hence, it is unlikely for higher temperatures to impede the development of powdery mildew in autumn.

Temperature sensitivity of powdery mildew was observed during the three months before the monitoring date and in late August of the preceding year. This effect was also documented by Stephan (1984) and Aust (1981). In consequence, before anthesis and during late summer temperatures were too high for volunteer wheat to develop. Hence, the “green bridge” for conidia was missing.

An interesting difference in patterns was recognized in March and April between correlograms for minimum temperature and disease incidence and maximum temperature and disease incidence. According to the correlograms minimum temperatures seemed to approach the lower limit of powdery mildew development, as indicated by the positive correlations, and maximum temperatures seemed to approach the upper limit of powdery mildew development, as indicated by negative correlations. This indicated an extremely small temperature range for the optimal development of powdery mildew during spring. Stephan (1984) demonstrated that powdery mildews do in fact have a rather small window of optimal temperature for overall development. Moreover, the results contradicted the findings of Te Beest et al. (2008), who did not find maximum temperatures in spring and early summer approaching the upper temperature limit for powdery mildew. According to their data, warmer temperatures supported the development of powdery mildew beginning in spring. This was confirmed by the correlogram for minimum temperature.

However, the results indicated that minimum temperatures in March and April were critical for powdery mildew incidence. The analysis of correlations between disease incidence and the number of days with temperatures between 17 and 23°C supported the observations further. The findings obtained for minimum temperature confirmed the results obtained by Morgounov et al. (2011). The results for March and April presented an interesting analogy to Chester’s findings on March as the “critical month” of leaf rust development (Chester 1946). According to Chester warmer conditions during the critical month can support leaf rust by shortening latency and infection periods and by amplifying the number of generations until anthesis.

The negative influence of very high temperatures on powdery mildew incidence in the weeks before the monitoring date and in late summer goes hand in hand with high radiation periods having a significantly negative impact on disease incidence. This correspond to the findings of Spencer (1978) and Martin et al (1975), who found that high insolation conditions and therefore higher leaf surface temperatures (Te Beest et al. 2008) can hamper germination of powdery mildew conidia.

Precipitation

The correlogram obtained for precipitation sums and powdery mildew incidence displays two patterns. Firstly, precipitation averaged over periods of at least one month had a significantly negative effect on disease incidence during the whole vegetation period and especially in autumn. Secondly, precipitation sums aggregated over the first 20 days before monitoring revealed significant positive correlations with disease incidence.

The first pattern was in agreement with the findings of Spencer (1978) and Boughey (1949), who stated that powdery mildew is more dangerous under drier conditions. In addition, laboratory experiments showed that the conidia of powdery mildew have higher moisture content than for example urediniospores of leaf rust. Thus, precipitation events are not necessarily needed for moisture supply (Yarwood et al. 1954). The second pattern indicated that the additional moisture content is not sufficient at higher temperatures during summer. Precipitation events had to provide additional moisture for infection and germination of conidia. High relative humidity is a well known prerequisite for the developmental processes of powdery mildew (Hassebrauk 1959, MerchánVargas 1984, Friedrich 1994, Prigge et al. 2005).

7.2 Influence of combined meteorological variables on the diseases

The parameter estimates of the logistic regression models confirmed the most important findings of the "window pane" approach for both diseases. Because logistic regression models selected only the most important variables and were constructed under the constraint to avoid overfitting, not all results achieved by the correlation approach were reflected by the model parameters. In addition, some effects detected by the regression analyses were not revealed by the correlograms, because the correlation analyses did not account for effects of variety susceptibility.

7.2.1 Leaf rust

The positive parameter estimates for temperature in April, January, and December supported theories from the literature. Higher temperatures during spring (Chester 1946, Hogg 1969) and winter support the development of leaf rust inoculum. Higher winter temperatures allow a higher number of leaf rust spores to overwinter and build a bigger inoculum source for the coming growth season (Burleigh et al 1969, Eversmeyer & Kramer 1994, 1995, 1996, 1998). Higher spring temperatures allow the surviving inoculum to get an earlier start into the growth period and thus build more generations of the pathogen (Chester 1946). The finding of temperature in late August having a negative impact on LRI may represent the negative effect of higher temperature on the "green bridge", allowing inoculum to survive on volunteers during the summer months (Hassan et al. 1986).

The regression analyses confirmed a supporting effect of moisture on leaf rust development mainly during spring and autumn and during the second half of May on resistant varieties. The findings contradicted those of Jahn et al. (1996), who found out that leaf rust infestation on winter wheat increases under drier future conditions. In addition, the parameter estimates indicated that precipitation could also have a negative effect on leaf rust occurrence during two distinct periods: one in late December and the second one during April. The first period may be addressed to an isolating effect of snow cover, causing temperature under the snow cover to be higher than above. The isolating effect can of course only be present, when temperature is low enough to cause precipitation to be transformed into snowfall. These requirements are met between November and February. The latter period could be attributed to a negative effect of heavy precipitation events in spring washing off leaf rust conidia from the host tissue and thereby reducing the amount of inoculum available to infect the wheat plant (Sache 2000).

The different signs of parameter estimates for wind speed during March and the first half of April resulted out of two concurring processes. On one hand, higher wind speed let wheat leaves dry faster thereby lowering leaf wetness over longer time periods. Leaf wetness is necessary for the formation of appressoria and for the germination of leaf rust spores on the leaf surface (de Vallavieille-Pope et al. 1995). On the other hand, higher wind speed supports the distribution of leaf rust spores over large areas (Hirst et al.

1967a, b) and thus increases the overall incidence in the federal state. The negative impact of wind speed on leaf rust between mid December and mid January could be attributed to wind chill. It describes the effect of wind lowering the temperature above a surface by removing the boundary layer above the surface.

7.2.2 Powdery mildew

The regression models verified the negative influence of mean temperature on powdery mildew incidence. Daamen et al. (1992) determined a negative impact in the Netherlands between April and June. Wiik & Ewaldz (2009) observed a negative correlation during the whole growth period in Sweden. Cao et al. (2012) detected a negative influence in China, especially during growth stages 5 to 10 on the Zadoks scale (Zadoks et al. 1974).
The results of the regression approach demonstrated not only negative impacts of temperature during May and June but impacts depending on the susceptibility of the wheat variety, especially during the two weeks before the disease assessment and during March. The negative impact observed on susceptible varieties and the positive impact on resistant varieties may be connected to the fact that wheat leaves senesce earlier if temperatures are high and precipitation is low in early summer (Aust 1981). A faster senescence of wheat leaves can result in senescence-induced resistance of wheat leaves, which hampers leaf rust development. Aust (1981) showed this behavior for leaf rust, but it may be transferable to powdery mildew, too. The negative impact of temperature during March and early April on PMI on resistant varieties was in agreement with the results of the author mentioned above. But the positive impact on susceptible varieties is contradictory. A possible explanation includes the impact of temperature on the growth of the host plant. At lower temperatures *Gramineae* may produce more young and susceptible tissues, enhancing the susceptibility of the plants to biotrophic pathogens (Evans et al. 1964, Friend 1966, Lindner 1989, Stephan 1984). Unfortunately, the literature results for field studies are hard to compare with the results of this study. Daamen et al. (1992) used a mixture of more and less susceptible varieties, Wiik & Ewaldz (2009) did not reveal any details about the susceptibility of the varieties considered, and Cao et al. (2012) based their calculations on observations on a highly susceptible variety over the course of only three years.
The parameter estimates for the relationships between PMI and precipitation changed signs over the course of the epidemic year. During early summer (two weeks before the disease monitoring) and late August of the previous year precipitation played a very

important role in supplying the spores with the moisture needed for infection of the host tissue. Between these periods, moisture was detrimental to powdery mildew development, though. This is in agreement with studies by Spencer (1978), Boughey (1949), Cao et al. (2012), Aust & von Hoyningen-Huene (1986), Kolesnikov et al. (2009), and Polley & King (1973), who stated that precipitation is negatively correlated with powdery mildew incidence. Cao et al. (2012) revealed that air humidity has a positive influence on spore germination, infection, and production, but a negative effect on spore liberation. Other processes, which influence powdery mildew negatively through high precipitation, are wash-out (Hirst et al. 1967a, b) and wash-off (Merchán Vargas & Kranz 1986). This could be the reason why only few periods with very weak impacts of moisture on powdery mildew incidence and threshold exceeding probability were observed. Another interesting observation was that most parameter estimates of the PMI50 model showed similar signs, compared to the PMI and PMI0 model, only on resistant varieties. Precipitation had a negative influence on PMI50 on susceptible varieties during June and August of the previous year and a positive impact for most periods in between. The explanation for the opposing behavior can be found in Te Beest et al. (2008), who mentioned the opposing effects of rainfall on powdery mildew severity. The results of this study indicated the damaging influence of heavy rainfall during the summer months and the supporting influence of increased humidity after rainfall events during the remaining year, especially being important for powdery mildew incidence to exceed the 50% threshold on susceptible varieties. On resistant varieties and for modeling PMI and PMI0, the damaging effect of precipitation prevailed for most parts of the season and the supporting effect of raised humidity only mattered during summer.

Wind speed has already been identified by Hirst et al. (1967a) as a supporting factor for pathogens in general and by Cao et al. (2012) as a supporting factor for powdery mildew epidemics. This was only reflected by the positive parameter estimates during early May and early February in this study. The opposing effect of wind speed, discussed by Te Beest et al. (2008) for Great Britain, was observed for winter months and late April in this study. Higher wind speed, especially during the early season, promotes faster drying of leaf surfaces, creates a drier environment, and hampers powdery mildew infection. In contrast to Te Beest et al. (2008), who identified the effect to be the most important factor for the occurrence of a damaging epidemic, wind speed was not selected as an important parameter for the PMI50 model.

7.3 Non-climatic influences on disease incidence

7.3.1 Leaf rust

It was slightly surprising that no non-climatic variables, except for doy of monitoring and resistance degree, had a significant influence on LRI. Especially the variables influencing the nutrition and the developmental stage of the host plant, like useable field capacity and day of sowing, were thought to show an impact on LRI (Howard et al. 1994, Dordas 2008). Another interesting result was the negative impact of the monitoring doy on LRI. The results indicated that the later the disease was assessed, the smaller the incidence detected was. This supported the results for the resistance degree, when considering that resistance increases with increasing age of the host plant (Tivoli et al. 2012). The higher the resistance of the variety, the lower the incidence measured was. According to the results of the Kruskal-Wallis and Kolmogorov-Smirnov tests for the resistance degree, two groups of varieties were built as input for the regression procedure. The group including susceptible varieties, consisted of the resistance degrees two to five and the group, including resistant varieties, consisted of degrees six to nine. The groups exhibited large differences regarding their number of observations. Only two groups were built to adapt the variable susceptibility to the binary logistic regression scheme. In addition, both groups were constructed under the precondition of containing an equal amount of observations.

The autocorrelation function of mean LRI time-series presented an influence of LRI of the preceding year on LRI of the current year. Despite the significance of the autocorrelation function at a lag of one year, the correlation was rather weak with $r \sim 0.5$. Another significant autocorrelation emerged at a lag of seven years with $r \sim 0.4$, which, in addition to the whole autocorrelation function, indicated a cyclic behaviour of LRI with a recurrence interval of seven years. One study concerning the cyclic behaviour of leaf rust was found (Yang 1995). But the study dealt with the cycles of leaf rust phenotypes in Canada and detected recurrence for lags of 1, 4, and 10 years. A connection to the results of this study seems unlikely. The only climatic oscillations with recurrence intervals of around seven years are the El Niño-Southern Oscillation (Hanson et al. 1989) and a seven year cycle in European rainfall patterns (Vines 1985).

7.3.2 Powdery mildew

The positive correlations for the day of sowing and emergence and the negative correlation of the monitoring day fit together well concerning the negative impact of the length of the vegetation period. The later the wheat is sown and the earlier anthesis starts, the shorter the vegetation period and the faster wheat plants develop. Thus, fast growing wheat varieties and weather conditions, conducive to a fast wheat development, increased the PMI, as well as a late sowing date. This contradicts the position of Kluge (1990), who revealed that wheat plots with late emerging plants had less PMI during anthesis. As an exception after mild winters, Kluge identified higher PMI during disease assessments in spring (BBCH 30-32) for late sown wheat. The possible cause of the positive relationship between sowing and PMI and the negative relationship between the length of the vegetation periods and PMI is the development of age-related resistance in wheat plants. Early sown plants have more time to accumulate silica in the upper two leaves. As a side effect of an adaptation to microclimatic conditions of the upper two leaves (Aust 1981), wheat plants surveyed for this study may have benefited from the longer growing time and therefore having a higher degree of silification of the upper two leaves by developing an age-related resistance for powdery mildew.

The negative correlation between the usable field capacity of the underlying soil and PMI identified can be interpreted as an indirect relationship. Higher water availability granted by a higher usable field capacity strengthens the growing conditions of wheat. By offering soil bound water during dry phases, water and nutrient availability improves the growth of the wheat plant. Due to the fast growth of the plant new leaves develop faster and infections are “transported downwards” faster on the plant, which lowers powdery mildew incidence on the upper leaves in turn. The effect of a faster growing host on powdery mildew was described for early and late sown wheat in (Graf-Marin 1934, Spencer 1978) and is comparable to the fast growth induced by higher water availability. The speculated negative effect of higher nutrient availability is in agreement with the negative correlation of PMI and potential cation exchange capacity identified. But the results are contradictory to studies attesting nutrients, especially nitrogen, a supporting role for higher PMI (Kluge 1990, Kádár et al. 1999, Dordas 2008).

The analysis showed a significant impact of the preceding crop on PMI. Further analyses were not conducted, because of the strongly differing number of observations between the preceding crops.

For the influence of the susceptibility degree on PMI results similar to those for LRI were achieved. The higher the susceptibility of the wheat variety, the higher the PMI was. Based upon the differences in mean values and the distribution of PMI between susceptibility degrees and under the precondition of groups with nearly equal numbers of observations, two groups with different degrees of resistance to powdery mildew were constructed. Resistance degrees one to four were categorized as resistant and degrees five to nine as susceptible.
Unfortunately, only the variables resistance degree and monitoring doy were available for the whole timeframe 1976 to 2010. All other variables were observed between 1990 and 2010. Hence, only variety resistance, compiled as resistance groups, was included in the logistic regression procedures for both pathogens. In contrast to leaf rust, the mean PMI time-series did not show any periodicity.

7.4 Comparing both diseases

Only few statistical modeling approaches for powdery mildew exist compared to the modeling of leaf rust incidence. The fact can be attributed to the higher importance of leaf rust compared to powdery mildew for most wheat growing areas. The comparison of the results for both pathogens clearly demonstrated fundamental differences between the influences of the climatic and the non-climatic variables. For leaf rust, temperatures in winter, sunshine duration in spring and fall, and precipitation in spring had positive impacts on the incidence and the probability of exceeding different incidence thresholds. Detrimental effects of temperature in spring, early summer, and fall and negative effects of sunshine duration in the two months before the monitoring date were observed for powdery mildew. In spring, the moisture requirements for powdery mildew were nearly the opposite of those for leaf rust. The sunshine requirements were opposed, too.
In this study, 23% of the parameter estimates of the leaf rust models compared to 36% of those of the powdery mildew models showed an interaction with the susceptibility class of the host plant variety. This leads to the conclusion that the relationships between meteorological variables and powdery mildew are more dependent on the susceptibility of the specific variety compared to leaf rust. The feature was already considered in a statistical approach by Daamen et al. (1992). Furthermore, Colhoun (1973) mentioned that the susceptibility of the host to infection could be temperature-dependent. In addition,

the author observed that plant nutrition could affect host susceptibility and relationships between the host and other environmental aspects, such as climatic factors, too.
Besides meteorological influences non-climatic effects were reported to play an important role for both pathogens by the literature. Environmental variables such as susceptibility (Aust 1981), nutritional conditions (Dordas 2008, Lindner 1989, Neumann et al. 2004), variety of the host plant (Li et al. 2012, Tivoli et al. 2012), cultivation measures (Han et al. 2013, Kluge 1990), disease incidence in the previous season (Stephan 1984), and soil properties have a significant impact. The results of this study revealed many differences and single analogies regarding the effect of non-climatic influences on both diseases. Overall, leaf rust proved to be much less affected by non-climatic variables compared to powdery mildew. As expected, both pathogens were supported by a higher susceptibility of the host. Powdery mildew was more affected by agricultural practices and site specific conditions, represented by the soil characteristics. On the contrary, leaf rust showed a relationship with the incidence of the preceding year and signs of a cyclic behavior based on a seven year recurrence interval. In comparison to powdery mildew this result indicated a stronger dependence of leaf rust on the summer survival of urediniospores.

7.5 Climatic changes in Saxony-Anhalt

The annual warming trend projected for the whole state was expected considering that the temperature trend was prescribed in the STARS algorithm. The increase in annual mean temperature and the stronger increase in winter temperature detected by the simulations confirmed the results derived by WETTREG and REMO (Kropp et al. 2009). The magnitude of changes differed between STARS and both models from the literature, because different 30-year periods were compared. 1961 to 1990 with 2041 to 2070 for WETTREG and REMO compared to 1981 to 2010 with 2031 to 2060 for STARS. Despite the differences the 2K-scenario of STARS showing a warming of 1.7°C revealed a warming comparable to the A1B-scenario of WETTREG (1.4°C) and REMO (1.8°C). The regional warming trends calculated for the 3K-scenario presented similarities to the results derived by WETTREG (A2-scenario), projecting a stronger warming in the northwest, and REMO (A2-scenario), projecting a stronger warming in the southeast and a weaker warming in the northern part of the state and the medieval mountains. The seasonal distribution of mean temperature revealed similarities and differences between STARS and both models. Compared to the STARS results in this study both models exhibited a similar increase in winter temperature. In contrast to the stronger increase in summer temperature projected by REMO the results of this study indicated a smaller increase during summer.

Regarding precipitation differences between base and scenario period the results obtained by STARS showed a decrease in annual precipitation sums similar to WETTREG. The results disagreed with REMO, projecting an increase in precipitation sums. The regional precipitation changes based on the STARS 3K-scenario revealed results similar to the A2-scenario of REMO by indicating the strongest decrease to be located in the Harz Mountains. In contrast to STARS and REMO, WETTREG detected an increase in annual precipitation sums for the medieval mountains. The seasonal changes identified in the study mainly confirmed the projections derived by WETTREG and REMO. All models projected a decrease in summer precipitation and an increase in winter precipitation. But only a slight increase in winter precipitation was projected by STARS compared to the other models. The increase in spring and autumn precipitation projected by REMO was not present in the STARS simulations.

A more detailed description and discussion of WETTREG and REMO simulations as well as a comparison with STARS simulations for Saxony-Anhalt can be found in Kropp et al. (2009).

7.6 Future development of leaf rust and powdery mildew in Saxony-Anhalt

7.6.1 Leaf rust

The results of this study confirmed the increasing importance of leaf rust of wheat for agriculture in Germany found in the literature (Jahn et al. 1996, Racca et al. 2012, Bregaglio et al. 2013). In addition, the study verified the hypothesis deducted from calculating disease scenarios based on the logical equations of the "Befallsatlas" (Kluge et al. 1999). With the methods used, it was possible to conduct more detailed analyses on the behavior of the pathogen for varieties with different susceptibility to the particular disease and to discover changes in the distribution of the incidence. The differences between present and future mean probability to exceed the 0% and 30% threshold already showed some differences for the 0K-scenario. This could be attributed to the overdispersion of the model residuals and to the different number of observations analyzed when comparing present and future means. The results of this study revealed that leaf rust incidence will increase on susceptible and resistant varieties. Significant increases were detected on susceptible varieties only for the 3K-scenario, but a marked increase will already occur with an increase of mean German temperature by 2°C. A mean temperature increase of at least 2°C would cause a significant increase in leaf rust incidence on resistant varieties.

But, the cause of the increase in LRI was different on susceptible and resistant varieties. On susceptible varieties ΔLRI30 increased with increasing mean temperature, whereas ΔLRI0 changed only marginally, for all warming scenarios. On resistant varieties ΔLRI0 and ΔLRI30 increased for higher mean temperatures in Saxony-Anhalt and the differences was already significant at a warming trend of 1°C for Germany. Analysis of linear trends for time-series of future leaf rust development supported the results on differences further. Hence, the incidence on susceptible varieties will increase due to a higher frequency of high incidence cases, whereas the incidence on resistant varieties will increase due to a higher frequency of cases with incidence detected. In addition, leaf rust on resistant varieties reacted faster on rising mean temperatures and showed a significant increase in a 1 to 2°C warmer climate, already. In contrast, leaf rust on susceptible varieties needed a 2 to 3°C warmer climate for significant changes to be detected.

The results on spatial patterns of LRI, LRI0, and LRI30 in reaction to a rise in mean temperature showed only small regional differences. The reason was a lack of the models to reproduce the variability of the present data observations. The underestimation of cases with high incidence or probability and overestimation of cases with low incidence or probability led to a smaller range of projections. Despite these shortcomings, some regional differences could be demonstrated by the results.

The importance of leaf rust on susceptible varieties will be subject to a stronger increase in the central parts of Saxony-Anhalt compared to the remaining state. This will be caused due to a stronger increase in temperature projected for this area. The smaller increase in importance in the northern parts of the state and the Harz Mountains can be attributed to the smaller increase in temperature projected for these areas. The changes projected will favor leaf rust on resistant varieties, especially in the central and northwestern parts of the state.

7.6.2 Powdery mildew

Contrary views on future development of powdery mildew in Germany were found in the literature (von Tiedemann 1996, Volk et al. 2010, Racca et al. 2012). The trend and comparison results of this study for PMI, PMI0, and PMI50 on resistant varieties supported the hypothesis that powdery mildew will lose importance in German agriculture. A decrease in importance was also projected by using the equations of the "Befallsatlas" (Kluge et al. 1999). An increase in mean German temperature of 1°C was projected to be sufficient for PMI and PMI0 to decline significantly. The decline for PMI50 was projected to be similarly strong, but significance was only detected for a mean warming of at least 2°C. Hence, an increase of mean German temperature by 1°C would already significantly raise the incidence of powdery mildew by increasing the probability that plots become infected. Assuming an increase of mean temperature by more than 1°C, incidence will become even higher supported by a significant higher probability for plots to exceed the 50% threshold and thus be infected severely. In contrast, findings on susceptible varieties strengthened the insecurity about the future development of the disease. PMI trends and comparisons with present PMI showed a slight and not significant decline in importance under the assumption of rising mean temperature. But, results for PMI0 and PMI50 revealed an increase in observations exceeding the thresholds. The increase in PMI0 on susceptible varieties was still slight compared to the projected changes in PMI0 on resistant varieties, but still significant for an increase in mean temperature of 3°C. The projected increase in PMI50 was higher compared to PMI0 and already significant for an increase in mean temperature of 1°C.

The results on spatial patterns of PMI, PMI0, and PMI50 in reaction to a rise in mean temperature showed only small regional differences. Similar to leaf rust, the models lacked in reproducing the variability of the present data observations. Despite these shortcomings, regional differences could be demonstrated by the results.

7.7 Methods for analyzing weather-disease relationships

7.7.1 Long-term weather and disease data

Long-term data on fungal infestation levels in cereals and site-related weather data can be used to determine the influence of different weather periods on infestation levels empirically. Analyses of long-term data was already conducted by several authors

(Coakley et al. 1988, Coakley 1989, Calvero Jr. et al. 1996, Jahn et al. 1996, Jahn & Freier 2001, Pietravalle et al. 2003, Te Beest et al. 2008, 2009) and granted insight into relationships between weather and disease occurrence under field conditions on different temporal and spatial resolutions. Unfortunately, long-term disease data are scarce (Jeger & Pautasso 2008). This is mainly due to an underestimation of the disease importance, their changing importance over time (Hodson 2011), and the very high financial and time investments required for data collection. Long-term disease monitoring is not only beneficial for empirical analyses but also for the development of better mathematical disease models (Juroszek & von Tiedemann 2013). Simulation models often lack sufficient temporal and/or spatial resolution of monitoring data for proper evaluation (e.g. Klose 1974, Räder 2007). The statewide monitoring system in the former GDR took enormous efforts to monitor plant diseases. Because many of these structures are still existent, long-term disease data on leaf rust and powdery mildew of winter wheat collected from up to 35 monitoring sites for up to 34 years were available for the analysis. This collection of data for both plant pathogens is unique in Germany: The data were compiled in a database at the Federal Research Institute for Cultivated Plants (Julius Kühn-Institute, JKI). The data collection has been supported by a consistent computer-aided data acquisition system for plant disease infestation called ISIP since 2004 (Kleinhenz & Röhrig 2003). In contrast to most studies found in the literature, disease incidence was chosen instead of severity for the analyses. The monitoring of incidence was considered more precise than severity with regard to the method of measurement.

Besides disease monitoring data, a sufficient number of weather stations were needed for a meaningful assignment of the monitoring sites. Daily weather records from the German Weather Service provided a valuable source of weather data for this study. But the reduction of the German Weather Service's observational network in 2009 proved to be detrimental to the allocation of monitoring sites and weather stations. The reduction of weather stations by 50% lowered the spatial resolution of the analyses by increasing the distances between the weather stations and the locations of disease monitoring. However, the replacement of missing data and correction of data showing inhomogeneities by the PIK ensured high quality weather records.

To connect data points measured at different locations the weather dataset was interpolated. Despite more sophisticated interpolation methods available, e.g. Kriging, Triangulation, and Splines, inverse distance weighting was used to calculate Thiessen polygons. The method is fast and easy to perform (Kropp et al. 2009) but can result in sharp contrasts between polygons.

7.7.2 “Window pane” approach

Analyses of daily weather variables provide evidence of important time intervals during the wheat growing period. But the identification of periods of strongest influence is not possible using daily weather data because the explanatory power of correlations between daily weather variables and disease data is very limited and contains many spurious relationships. No evidence was found in the literature that daily weather measured a few months before the monitoring date for a fungal disease could possibly influence disease incidence every year similarly. Hence, meteorological variables, like mean temperature and precipitation, aggregated over many days and the sum of days with favorable or unfavorable conditions occurring in a specific time interval are more valuable when included in the analyses (Burleigh et al. 1972a). Therefore, daily weather data were accumulated on different time scales to gain further insight into disease-weather relationships.

The “Window Pane” algorithm produced reasonable results. The algorithm is a useful tool for investigating disease-weather relationships, because all time periods that could possibly explain variations in disease levels can be evaluated rather than only a few selected intervals. Coakley (1988) and Te Beest et al. (2008) used this method for preliminary variable selection before regression modeling when a large amount of possible explanatory variables had to be processed. As a next step explanatory variables were condensed to those explaining the biggest part of variability of the predictand. Hence, Calvero Jr. et al. (1996), Pietravalle et al. (2003) and Te Beest et al. (2008, 2009) mentioned only the “best” correlations for each variable but provided no overview of the calculated results.

In this study the approach was used to get an overview of the timescales on which meteorological variables influenced leaf rust and powdery mildew incidence in Saxony-Anhalt and to identify the position and length of the most important windows on the developmental timeline of both pathogens. By displaying the results as correlograms the interpretation of correlation structures in dependence of window position and length was simplified and autocorrelations for each meteorological variable and their influence on analyses of relationships with disease incidence were revealed.

The Goldwin correlogram (Goldwin 1982) is an excellent method for obtaining an overview of all significantly correlated time windows. The use of correlograms offered the possibility for presenting not only significance or non-significance, but also the direction of correlation between infestation data and meteorological variables. Over 350,000 correlations were analyzed per disease.

Non-parametric Kendall correlation coefficients were used in the analyses to account for the non-normal distribution of the disease data. By transforming the original data to ranks and calculating the correlation between the ranks of both datasets, Kendall's method allows analyses on relationships between normal distributed and non-normal distributed data. The results demonstrated that the majority of the correlations investigated were significant despite their small correlation coefficient. The values of the correlation coefficient turned out to be small due to different factors introducing noise into the analyses. First, the monitoring data was collected at different locations every year. Second, after connecting disease and weather data, no weather station had a continuous time series of disease incidence. Third, the incidence was measured for wheat plants of strongly varying susceptibility to each disease, respectively. Fourth, other effects introducing noise, e.g. soil parameters, varied over time and place. Despite the multitude of noise parameters potentially limiting correlation coefficients, most of the coefficients were significant because of the large number of observation used.

7.7.3 Regression models

Regression models are a valuable tool to identify relationships between the incidence of important plant pathogens and environmental conditions. Methods used to analyze data on plant disease occurrence often concentrated on analyzing the development of epidemics during the course of an epidemic year (Burleigh et al. 1972a, Daamen 1991, Eversmeyer & Kramer 1996). Only few dealt with the analysis of disease occurrence during the time of peak incidence (Coakley et al. 1988, Daamen et al. 1992, Te Beest et al. 2008, Wiik & Ewaldz 2009). Many of these studies were based on strong assumptions (e.g. normal distribution of disease data) and methods that do not account for data with fixed boundaries at zero and one.

In the present study logistic regression analysis of raw and dichotomized incidence data was used to avoid these problems. Logistic regression has very few limitations regarding input data and can even be applied to data with strongly skewed distributions (Fletcher et al. 2005, Allison 2012) and data confined to a specific interval (Hastie et al. 2009).

Another benefit of using logistic regression is the ability to analyze the influence of variables on the probability of exceeding a predefined threshold by dividing the data into values below and above the threshold. Thresholds of 0% and 30% were used for leaf rust incidence and thresholds of 0% and 50% for powdery mildew incidence. The 30% and 50% thresholds were selected based on the definition of a damaging leaf rust and powdery mildew epidemic by Beer (2005).
To calculate logistic regression models for both diseases only the most important meteorological variables were selected to fit the disease data. Three meteorological variables of those analyzed with the correlation approach were selected as possible predictors to avoid strongly correlated predictors, e.g. mean temperature and sunshine duration, entering the regression procedure. Multicollinearity between predictor variables can severely distort the variable selection and induce bias into the parameter estimation (Harrell Jr. 2010). Correlated predictors may explain similar parts of the variability of the predictand. The importance of meteorological variables can be significantly overestimated in the presence of multicollinearity.
In this study the meteorological variables were deseasonalized and aggregated over 15-day periods to reduce autocorrelation effects within the meteorological time series. Given a mean persistence of large-scale atmospheric circulation patterns over Europe with a minimum of 3 to 6 days (Bárdossy & Caspary 1990, Kysely 2008), autocorrelation effects were reduced by deseasonalization and aggregating the weather data over 15-day intervals. Hence, the weather variables from different intervals could be defined as independent. The multicollinearity remaining in the meteorological data after the adjustments did not affect the predicted values, because the dataset of future climatic conditions contained the same degree of multicollinearity (Harell Jr. 2010).

7.7.4 Variable selection

The MSE is a standard measure for the evaluation of prediction errors (Rawlings et al. 1998). It was used as the variable and model selection statistic for the logistic regression procedure with raw disease data. For the logistic regression models using dichotomized disease data, the f-measure developed by Torgo & Ribeiro (2006) was applied. The f-measure represents an alternative to the widely used misclassification rate. Furthermore, the f-measure is a valuable statistic for variable and model selection, especially when modeling the occurrence of plant diseases. The calculation of the f-measure can be adjusted to the needs of the disease expert by changing β. To increase the importance of

precision false positives can be given more weight, which improves the model's ability to avoid unnecessary spraying of wheat when no disease has occurred. Thus, one aim could be to avoid spraying, which generates unnecessary costs and environmental pollution. The other aim could be to avoid failure to detect the target disease, which would generate higher costs due to yield loss. This aim could be approached by giving recall and false negatives more weight. However, it is impossible to decide which strategy is the best. It depends on the expert's opinion of which failure outweighs the other. By choosing $\beta = 0.5$ this study followed the recommendation of Ribeiro & Torgo (2009) favoring a higher importance of precision compared to recall for numerical prediction tasks. This conservative approach was chosen, because avoiding false negatives was considered more important than predicting all observed positives correctly at all costs.
Both measures were calculated for the training data set to determine the best variable to be included in the model at each step. The same measures were calculated at each step for an independent validation sample to stop the variable selection, when the optimal amount of variables was reached without overfitting the data. This validation strategy, also known as cross-validation, is an often used method (Harrell Jr. 2010) and was implemented in the model procedure as leave-one-out cross-validation.

7.7.5 Model selection and validation

After stopping the variable selection the predictive performance of the resulting model had to be evaluated. Because the validation sample of the inner cross-validation was already used to validate the temporary models during the variable selection for fulfilling the stop criterion another independent sample was needed. Anderssen (2006) found out that models using cross-validation for the model fitting procedure did not give good estimates of the predictive value. This justified the need for a second validation, which was implemented by using a test sample originating from the outer 10-fold cross-validation. MSE and f-measure, calculated for the test sample, were used as measures to estimate the predictive performance of the 10 candidate models and to select the model performing best.
The quality of the final "best" model identified for each pathogen and input data type (raw data and dichotomized data including two different thresholds) was then assessed using all data available, including data used for generating the model. The selected models where then applied to the climate scenario data.

Models for both pathogens based upon raw incidence had high mean RMSE values. Errors for the whole base period and RMSE values of annual and station-wise averages gave a more detailed picture of the quality of both models. The LRI model replicated the overall and annual mean values with small errors. The error for station-wise averages was higher but still allowed for inference about future conditions. The PMI model had similar errors compared to the LRI model, but replicated the annual means with less accuracy. Both models exhibited good performance according to the ROC AUC. Both models underestimated the sample variance demonstrated by the non-constant variance of the residuals with respect to the linear predictor. In addition, the residuals of the PMI model showed a trend, which indicated the logit-link function not being the optimal choice for modeling the data.

The models simulating the probability to exceed 0% incidence for both pathogens showed good performance according to the f-measure. The PMI0 model predicted nearly all observed positive values correctly at a high value of precision. The LRI0 model predicted about half of the observed positives correctly with high precision. The ROC AUC values of both models underlined the good predictive quality. Both models exhibited small errors in predicting the overall probability to exceed 0% incidence during the period 1976 to 2010. But both models had difficulties in simulating mean annual and station-wise probabilities. The lower prediction quality of annual and station-wise averages can be attributed to the weakness of the models reproducing the sample variance. Similar to the models for raw disease data sample variance is underestimated by the model approach.

As supposed, the f-measure of the LRI30 and PMI50 model indicated a lower quality compared to the models for the 0% threshold, because much fewer observations exceeding the thresholds were present in the data and the f-measure weights were adjusted to use a conservative approach for model validation. High values of precision compared to low values of recall for both models supported this hypothesis further. Despite smaller values for the f-measure both models had smaller errors in predicting the annual and station-wise means of threshold exceedance compared to the LRI0 and PMI0 model. The ROC AUC results of both models were more optimistic than the f-measure regarding the predictive accuracy. Plots of residuals versus the linear predictor revealed an underestimation of the sample variance, resulting in less accurate prediction results for the annual and station-wise averages similar to the models for a threshold of 0%.

To explain the cause of the overdispersion detected within the generated models, it has to be taken into account that the logistic regression function can also be interpreted as a generalized linear model with the logit (or log odds) function representing a link function utilizing the binomial distribution. The link function is used to link the responses to the linear predictors. In contrast to a linear model the logistic model does not estimate the variance independently from the mean, but already contains a specification of the relationship between mean and variance through the binomial distribution. If overdispersion is detected for a logistic regression model, the difference between observed and predicted values was larger than assumed by using the binomial distribution (Allison 2012).

Three causes of overdispersion were described in the literature (Allison 2012, Garson 2012): the variance function determined by the distributional assumption underestimated the variance, the sampling was not randomized, or important covariates were missing in the model.

The first cause can be approached by adjusting the covariance matrix introducing a scale parameter. But this only adjusts the test subjects for chi-square-based goodness-of-fit tests, which were not used to assess the model quality in this study. The second cause did not apply to the data used for this study, as the data collection was randomized according to Schwähn & Röder (1982). The third cause can only be approached by including more covariates in the model. As the models generated for this study already included the maximum amount of predictors without overfitting the model, more data has to be collected to justify the integration of a larger amount of predictors into the models.

Hence, it can be concluded that the logistic link function was not the optimal choice for modelling the data. A link function supporting a higher amount of extreme values may lead to better modelling results. In addition, the integration of more non-climatic variables, for example the variables analyzed in this study by a correlation approach, may help to describe the variability more accurately. To include these variables an important pre-condition is the availability of non-climatic data for the whole timeframe of interest in a regular spatial resolution. The inclusion of soil parameters as location characterizing variables recorded for each monitoring spot and the precise recording of the monitoring spot via GPS coordinates is strongly recommended for future data collections of agricultural diseases.

7.7.6 STARS simulation

The STARS model was used, because the calculations of STARS-scenarios are much faster compared to those needed when working with dynamical regional climate models.

Hence a bigger ensemble of future climate scenarios was available. Despite the absence of complex differential equations and large amounts of parameterizations, included in dynamical climate models, validation results (Orlowsky et al. 2008) and the amount of climate impact studies successfully utilizing STARS (Liersch et al. 2013, Lutz et al. 2013) supported the quality of STARS simulations and underlined the usefulness of the model. Nevertheless, the value of STARS as a model to project future climate development has to be questioned. In a recent study Wechsung & Wechsung (2014) revealed that STARS generates predictable outcomes exemplified by the projection of wetter winter and drier summer conditions for Germany. This can be attributed to STARS translating short-term interannual variability between temperature and covariables into long-term climate trends. Thus, climate impact projections, calculated by implementing STARS simulations as input for future climatic conditions, have to be treated as reactions to a selected type of climate change (Bloch et al. 2015).

8 Conclusions

In conclusion, this study demonstrated the importance of long-term pathogen time-series and proposed ways to organize and analyze non-normally distributed data on disease incidence using the examples of leaf rust (*P. triticina*) and powdery mildew (*B. graminis* f.sp. *tritici*) in winter wheat. An effective and easy to use method demonstrated how meteorological observations can be connected with disease information. Moving window correlation approaches presented interesting insight into relationships between meteorological variables and disease incidence on various timescales during the vegetation period. Multivariate logistic regression models identified the most important relationships and quantified them on the basis of a generalized linear regression framework. Impacts of climatic changes on the future incidence of both diseases were quantified by utilizing the generated regression models in combination with climate scenarios derived from a statistical climate model.

Analyzes showed that meteorological variables affected both pathogens very differently. Temperature and precipitation had a mainly positive influence on leaf rust and a negative one on powdery mildew during most parts of the vegetation period. But, to improve the quality of statistical models for both diseases, more extreme probability distributions have to be considered when utilizing a generalized linear regression framework.

The model results indicated that leaf rust incidence in Saxony-Anhalt will increase and incidence of powdery mildew will decrease in the future according to simulations of changing climatic conditions projected for the state. In addition, the study demonstrated that the relationships and changes will be dependent on the varieties used.

This study also demonstrated that the effects of non-climatic factors like soil properties, variety characteristics, and cultivation methods have to be considered as additional effects when modeling plant disease occurrence. In addition, auto-regressive effects and interactions between both diseases may have to be implemented. Therefore, it is concluded that more data on soil-variety-cultivation subgroups and longer time series are needed to construct better models and to develop better scenarios of disease incidence in the future.

A larger database on the occurrence of plant diseases would set the preconditions to comply with the demand for more empirical studies on plant diseases under field conditions (Chakraborty & Newton 2011). Empirical studies are urgently needed to develop options for crop adaptation and disease management under changing climatic conditions. The adaptation of crops and the management of plant diseases are essential preconditions to increase the productivity of agricultural systems in the future in order to adequately meet the nutritional demands of a fast growing world population (Borlaug 1965, 1997, 2007).

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