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EXPLORING LONG-TERM VARIETY PERFORMANCE TRIALS TO IMPROVE GENOTYPE, MANAGEMENT, AND ENVIRONMENT RECOMMENDATIONS: A CASE-STUDY FOR WINTER WHEAT

Lucas Berger Munaro
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TÍTULO DA DISSERTAÇÃO: EXPLORING LONG-TERM VARIETY PERFORMANCE TRIALS TO IMPROVE GENOTYPE, MANAGEMENT, AND ENVIRONMENT RECOMMENDATIONS: A CASE-STUDY FOR WINTER WHEAT

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DADOS CURRICULARES DO AUTOR

LUCAS BERGER MUNARO – filho de Roseli Berger Munaro e Avelino Munaro, nascido em 26 de julho de 1991 em Realeza e criado em Santa Izabel do Oeste, ambos no sudoeste do estado do Paraná. Formado Técnico em Agropecuária em 2008 pela Escola Agrotécnica Federal do Concórdia. Ingressou no curso de Agronomia na Universidade Tecnológica Federal do Paraná - UTFPR, câmpus Pato Branco em 2009. Como aluno de graduação estagiou no grupo de melhoramento genético de trigo (2009-2013) sob orientação do Prof. Dr. Giovani Benin, foi bolsista do Programa de Educação Tutorial – PET (2009-2011), monitor da disciplina de mecanização agrícola (2011-2012), bolsista PIBITI (2012-2013) e realizou estágio curricular obrigatório no programa de melhoramento de soja da Fundação MT em Rondonópolis/MT (2013-2014). Obteve o título de Engenheiro Agrônomo em abril de 2014, trabalhou como Melhorista Jr no programa de melhoramento de soja para a região sul do Brasil na Nidera Sementes Ltda. (2014). Trabalhou como Engenheiro Agrônomo na Coamo Agroindustrial Cooperativa prestando assistência técnica a produtores rurais nos municípios de Reserva/PR e Toledo/PR (2015-2018). Em março de 2018 ingressou no curso de Mestrado de Pós-graduação em Agronomia (Genética e Melhoramento de Plantas) da Universidade Estadual Paulista – Faculdade de Ciências Agrárias e Veterinárias de Jaboticabal (UNESP/FCAV) sob orientação da Profa. Dra. Sandra Helena Unêda-Trevisoli. Foi bolsista CNPq de março a julho de 2018, trabalhou como “Assistant Scientist” na “Kansas State University” em Manhattan, KS, EUA sob supervisão do Prof. Dr. Romulo Pisa Lollato, onde desenvolveu o projeto de pesquisa de mestrado e participou de outros projetos de pesquisa e publicações (agosto de 2018 a dezembro de 2019).

Dedicatória

Dedico este trabalho a minha família, que sempre me apoiou e me incentivou durante todas as etapas da minha formação

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SUMMARY

EXPLORING LONG-TERM VARIETY PERFORMANCE TRIALS TO IMPROVE GENOTYPE, MANAGEMENT, AND ENVIRONMENT RECOMMENDATIONS: A CASE-STUDY FOR WINTER WHEAT

ABSTRACT - The complex and interactive effects of genotype (G), environment (E), and management (M) can be a barrier to the development of sound agronomic recommendations. We hypothesize that long-term variety performance trials (VPT) can be used to understand these effects and improve regional recommendations. Our objective was to explore long-term VPT data to improve management and variety-selection recommendations using winter wheat (*Triticum aestivum* L.) in the U.S. central Great Plains as a case-study. Data of grain yield, variety, and trial management were collected from 748 wheat VPT conducted in the states of Colorado, Kansas, and Oklahoma over nineteen harvest years (2000-2018) and 92 locations, resulting in 97,996 yield observations. Using 30-yr cumulative annual precipitation and growing degree-days, we partitioned the study region into 11 contiguous sub-regions, which we refer to as growing adaptation regions (GAR). We used variance component analysis, gradient boosted trees, and conditional inference trees to explore the management and variety trait effects within each GAR. For the variety trait analysis, the VPT dataset was reduced to account for varieties for which 17 agronomic traits and 11 disease/insect reaction ratings were available (65,264 yield observations). GAR accounted for 46% of the total variation in grain yield, M for 32%, residuals (including interactions) for 13%, year for 7%, and G for 2%. Conditional inference trees identified interactions among management practices and their effects on yield within each GAR. For instance, water regime was the most important practice influencing wheat yield in the semi-arid western portion of the study region, followed by sowing date and fungicide. In dryland trials, there was typically an interaction between fungicide, sowing date, and tillage system, depending on GAR. Other management practices (e.g. dual-purpose management, crop rotation, and tillage practice) also significantly affected yield, depending on GAR. The main variety trait associated with increased yields depended on region and management combination. For instance, drought tolerance was the most important trait in dryland trials while stripe rust tolerance was more relevant in irrigated trials in the semi-arid region. In this research, we demonstrated an approach that uses widely available long-term VPT data to improve management and variety selection recommendations and can be used in other regions and crops for which long-term VPT data are available.

Keywords: conditional inference trees, exploratory analysis, *Triticum aestivum* L., long-term data, management practices

EXPLORANDO ENSAIOS DE LONGA DURAÇÃO DE PERFORMANCE DE VARIEDADES PARA MELHORAR AS RECOMENDAÇÕES DE GENÓTIPO, MANEJO E AMBIENTE: UM ESTUDO DE CASO PARA O TRIGO DE INVERNO

RESUMO – Os complexos efeitos de genótipo, ambiente e manejo podem ser uma barreira para o desenvolvimento de recomendações agronômicas sólidas. Nossa hipótese é que dados de longa duração de ensaios de performance de variedades (VPT) podem ser utilizados para entender esses efeitos e melhorar as recomendações regionais. Nosso objetivo foi explorar dados de longa duração de VPT para melhorar as recomendações de manejo e seleção de variedades utilizando trigo de inverno (*Triticum aestivum* L.) na região central das grandes planícies dos Estados Unidos da América como um estudo de caso. Dados de rendimento de grãos, variedades e manejo dos ensaios foram coletados de 748 VPT de trigo conduzidos nos estados do Colorado, Kansas e Oklahoma durante dezenove anos (2000-2018) e 92 locais, resultando em 97.996 observações de rendimento. Utilizando dados de 30 anos de precipitação anual acumulada e graus-dia, nós dividimos a região de estudo em 11 sub-regiões contíguas, as quais nos referimos como regiões de adaptação de cultivo (GAR). Nós utilizamos "variance componente analysis", "gradiante boosted trees" e "conditional inference trees" para explorar os efeitos de manejo e características das variedades em cada GAR. Para a análise das características das variedades o conjunto de dados de VPT foi reduzido para considerar as variedades cuja informação referente a 17 características agronômicas e 11 reações a doença/inseto estava disponível (65.264 observações de rendimento). GAR representou por 46% da variação total no rendimento de grãos, manejo por 32%, resíduo (incluindo interações) por 13%, ano por 7% e genótipo por 2%. "Conditional inference trees" identificaram a presença de interação entre práticas de manejo e seus efeitos no rendimento de grãos em cada GAR. Por exemplo, regime hídrico foi a prática mais importante influenciando o rendimento de grãos de trigo na porção oeste e semiárida da região de estudo, seguido por data de semeadura e fungicida. Em ensaios de sequeiro, normalmente há uma interação entre aplicação de fungicida, data de semeadura e sistema de preparo do solo, dependendo da GAR. Outras práticas de manejo (e.g. manejo de duplo propósito, rotação de culturas e práticas de preparo do solo) também afetaram significativamente o rendimento de grãos, dependendo da GAR. A principal característica varietal associada a maiores rendimento de grãos foi dependente da combinação de região e manejo. Por exemplo, tolerância a seca foi a característica mais importante em ensaios de sequeiro, enquanto tolerância a ferrugem estriada foi mais relevante em ensaios irrigados na região semiárida. Nesta pesquisa demonstramos uma abordagem que utiliza dados de longa duração de VPT, amplamente disponíveis, para melhorar recomendações de manejo e de seleção de variedades e pode ser utilizado em outras regiões ou culturas para as quais dados de VPT são disponíveis.

Palavras-chave: "conditional inference trees", análise exploratória, *Triticum aestivum* L., dados de longa duração, práticas de manejo

1. INTRODUCTION

A significant increase in crop production is needed to meet the increasing demand of the world's population for food and fiber in the coming decades (Bodirsky et al., 2015; Godfray et al., 2010). Expansion of existing cropland is not sustainable and has limited potential due to its negative environmental and social impacts (Conijn et al., 2018; Ramankutty et al., 2002); thus, crop yield needs to increase on existing cropland (Fischer et al., 2014; Foley et al., 2005; Tilman et al., 2002). This scenario is worsened by the decreasing rates of yield improvement of major crops in recent decades (Cassman, 1999; Cassman et al., 2003; Lin and Huybers, 2012), which, in combination with adoption of conservative management practices, causes yield stagnation in many important cereal growing regions of the world (Grassini et al., 2013). Within this context, improvements in management practices can play a crucial role in increasing crop yields (van Ittersum et al., 2013).

A common approach to identify best management practices and their interaction with the environment is to conduct controlled experiments in which different practices are imposed on a crop (Andrade et al., 2019; Grassini et al., 2015a). While well-conducted randomized controlled experiments might meet the assumptions that enable causal inference between management practices and crop yield (Jaenisch et al., 2019; Lollato et al., 2019b, 2013), the high cost of establishing new experiments may be impracticable to evaluate the performance of multiple management practices in several environments (van Ittersum et al., 2013). Potential alternatives to this approach are to explore management and yield data collected from actual production fields, such as yield contests (Lollato et al., 2018; Long et al., 2017; Villamil et al., 2012), progressive producers (van Rees et al., 2014), and representative producers (Grassini et al., 2015a; Rattalino Edreira et al., 2017); or to utilize existing datasets from long-term experiments (Hinds et al., 2016; Kaur et al., 2017; Lollato et al., 2019a; Prasad et al., 2017; Schwalbert et al., 2018) or variety performance trials (VPT) (Mourtzinis et al., 2019; Wójcik-Gront, 2018).

Variety performance trials are frequently conducted by local research and extension institutions to improve recommendations for variety selection for most cultivated species. The results of VPT are typically published in extension bulletins comparing varieties in specific environments (e.g., site-years) that are mostly of local relevance and usually lack depth (multi-year) and breadth (multi-environment) (e.g., Johnson et al., 2018; Lingenfelser et al., 2019, 2018b, 2018a; Marburger et al., 2018). While information from localized VPT is important to guide growers' decisions, we propose that VPT data are currently underutilized. A few published examples extracting more value from VPT data include distilling genotype by environment interactions over a long time-period for wheat in the U.S. Great Plains (Graybosch, 2017; Peterson, 1992); determining optimal soybean (*Glycine max* L.) sowing dates across the U.S. (Mourtzinis et al., 2019); exploring the yield penalty from the dual-purpose (i.e., grazing plus grain) wheat system (Edwards et al., 2011); underpinning variables influencing yield of winter wheat in Poland (Wójcik-Gront, 2018); evaluating the effects of warming temperature on wheat and sorghum (*Sorghum bicolor*) in the U.S. (Tack et al., 2017a, 2017b, 2015); and predicting the influence of genetic gain, weather, and diseases on winter wheat yield across Kansas (Barkley et al., 2014; Holman et al., 2011). These examples demonstrate the potential of existing VPT datasets to help explore variety traits (e.g., maturity, disease tolerance, etc.), management practices (e.g., sowing date, water regime, etc.), and their interaction.

Exploring VPT datasets to determine best management practices, however, might provide unique challenges due to their structure and nature. For instance, crop husbandry might be different in each trial; thus, the evaluation of differences in management practices could potentially be confounded with site-year due to their nested structure (e.g., as opposed to controlled replicated treatments). In this paper, we used winter wheat VPT data from the U.S. central Great Plains as a case study to demonstrate how modern statistical tools can help explore VPT data and improve current management recommendations. Our objectives were to explore long-term VPT data to: i) quantify the effects of region, year, genotype, and management practices on crop yield variability; ii) identify management practices associated with improved grain yield to enhance management recommendations; and iii) identify agronomic traits of different genotypes consistently associated with increased grain yield within the main management effect to improve variety selection recommendations.

2. REVIEW OF LITERATURE

2.1. Wheat production overview

Wheat is the second most widely grown crop in the world. In 2017, wheat was the crop with the largest harvested area in the world with a total of 219 million hectares (FAO, 2019). During 2017, average total wheat production in the world was approximately 772 million metric tons, ranking third among production crops behind sugarcane (1,842 million metric tons) and maize (1,135 million metric tons) (FAO, 2019). China was the largest producer of wheat, with 134 million metric tons (i.e. 17% of global production), followed by India with 99 million metric tons (13%), Russia with 86 million metric tons (11%), and United States with 47 million metric tons (6%) (FAO, 2019).

The United States produces six classes of wheat in different parts of the country: hard red winter, hard red spring, soft red winter, soft white, hard white, and durum (*Triticum durum* Desf.). In 2019, the United States produced 53 million metric tons from a harvested area of 15 million hectares and an average yield of 3.5 Mg ha^{-1} across all wheat classes (USDA-NASS, 2019). Hard red winter wheat had the largest production among all the wheat classes, adding to 22.7 million metric tons. This wheat class is primarily grown in Texas, Oklahoma, Kansas, Nebraska, Montana, and Colorado. Total soft red winter wheat production was 6.5 million metric tons, with the crop primarily grown in Ohio, Kentucky, and Michigan; total soft white winter wheat production was 5.8 million metric tons, primarily produced in Washington and; total spring wheat production was 16.3 million metric tons, primarily cultivated in North and South Dakota, and Minnesota; and durum wheat, which is primarily grown in North Dakota and Montana, totaled 1.6 million metric tons (USDA-NASS, 2019).

The central portion of the U.S. Great Plains (i.e., Colorado, Kansas, and Oklahoma) accounted for 25% of the total U.S. wheat production and represented 30% of the U.S. wheat harvested area in during the period of 2000 to 2018 (USDA-NASS, 2019). The average grain yield for each of these states, comprising the same period, ranged from 1.1 Mg ha^{-1} in Oklahoma on the year 2014 to 3.8 Mg ha^{-1} in Kansas on the year 2016.

2.2. Effects driving wheat grain yield

Grain yield result from both manageable and unmanageable factors. For example, environmental constraints such as temperature, light intensity (radiation efficiency), precipitation total and distribution, soil type, texture and water holding capacity establish a gap on nonirrigated yield potential (Jaenisch, 2017). Manageable factors, on the other hand, are crucial in ensuring current yields are economically close to their yield potential for a particular growing season at a given location. These include fertilizer management (placement, type, timing, and rate), variety selection, sowing date, seeding rate, control of diseases, weeds, insects, and irrigation management. (Jaenisch, 2017).

2.2.1 Environmental

Yield potential is defined as the yield achieved by an adapted cultivar when grown under non-limiting water and nutrient conditions with all biotic stresses properly managed (van Ittersum et al., 2013). Provided non-limiting water conditions, the theoretical yield potential of a crop can be estimated as the product of total intercepted solar radiation, radiation-use efficiency, and the ratio between grain yield and crop aboveground biomass at physiological maturity (i.e. harvest index) (Hay and Porter, 2006). Following this approach, Sinclair (2013) estimated the theoretical yield potential of wheat as 12.9 Mg $ha^{−1}$. However, in rainfed agricultural systems, yield potential is often decreased due to inadequate total water supply and/or seasonal water distribution (Lobell et al., 2009, Lollato et al., 2017). Therefore, the degree of water limitation needs to be taken into account when determining a crop’s yield potential in rainfed environments, also referred to as water-limited potential yield (Connor et al., 2011).

Recent analysis of historical wheat yields in the U.S. Great Plain indicated that average farm yield have been nearly stagnant for the last 30-yr with state-level yields never surpassing 3 Mg ha^{-1} and county-level yields ranging from 0.2 to 3.6 Mg ha^{-1} (Patrignani et al., 2014). These yield levels are well below maximum yields reported from well-managed field trials across the region along the years, which ranged from 6.8 to 9.3 Mg ha^{-1} (Lingenfelser et al., 2016; Lollato and Edwards, 2015; Musick et al., 1994).

Lollato et al., (2017) studied the effects of weather variables to assess the meteorological drivers of wheat productivity in the U.S. southern Great Plains. The authors identified differences on latitudinal or longitudinal gradients in meteorological variables, depending on the phase of crop development and the meteorological variable evaluated. The results indicated that highest wheat yield was achieved in locations with plentiful precipitation and high average minimum temperature during the growing season, abundant cumulative radiation, abundant plant available water at sowing and low cumulative evapotranspiration during the sowing – anthesis interval. On the other hand, wheat grain yield was negatively correlated with average maximum temperature during the anthesis – physiological maturity interval (Lollato et. al., 2017).

Water is generally the most limiting resource to crop productivity in modern rainfed agriculture (Connor et al., 2011). In the U.S. southern Great Plains, cumulative precipitation accounted for the largest proportion of the variation in simulated rainfed wheat water-limited yield (Lollato et al., 2017). Similarly, Barkley et al. (2014) evaluated the effects of weather on wheat yield across Kansas using historical data from variety performance tests and suggested that rainfall distribution is often the most limiting factor for wheat productivity. Holman et al. (2011) also highlighted the importance of growing season precipitation for wheat yields in western Kansas. In Oklahoma, Patrignani et al. (2014) demonstrated that wheat yields are limited by water supply when growing season precipitation is less than approximately 400 mm, a value beyond which wheat yields become limited factors other than precipitation total. Consequently, the effect of precipitation on the grain yield depend on the region and it is a more important factor in the west and west-central portion of the U.S. southern Great Plains (Lollato et al., .2017)

Increased temperatures during the reproductive stages of wheat, on the other hand, can hasten wheat senescence and decrease kernel weight and grain yield (Asseng et al., 2011; Fischer, 2007). The negative association of wheat yield to temperature during the reproductive stages have been documented for different regions in the U.S. Great Plains western Kansas (Holman et al., 2011; Lollato et al., 2017).

2.2.2. Management practices

Improved agronomic management and crop genetics resulted in high rates of yearly yield gain for wheat between 1960 and 1980 (Bell et al., 1995; Brancourt-Hulmel et al., 2003). After approximately 1980, yield gains decreased and yield stagnation has been reported for several important regions such as the U.S. southern Great Plains (Patrignani et al., 2014), the North China Plain (Wu et al., 2006), France (Brisson et al., 2010), the Netherlands, the United Kingdom, and India (Grassini et al., 2013). In high-yielding wheat regions, yield stagnation might result from regional yield approaching 70 to 80% of the yield potential (Grassini et al., 2013), resulting in a small yield gap, which is the difference between average regional yield and the yield limited only by moisture regime in rainfed regions (i.e., water-limited yield; Lobell et al., 2009). Meanwhile, yield stagnation in lower wheat-yielding regions might result from low input and risk aversion (Connor et al., 2011). As a consequence, the opportunity to decrease yield gap through improved agronomic management exists (Hochman et al., 2017). Increasing wheat production in water-limited regions through agronomic management can help meet future food demand while minimizing expansion of the current agricultural land, especially as the genetic yield potential for wheat fails to enhance at historical rates (Cassman, 1999).

However, with few exceptions (e.g., Jaenisch et al., 2019), most of the manageable agronomic practices in the U.S. southern Great Plains were explored in low- and average-yielding systems, ranging between 2 and 4 Mg ha^{-1} (Edwards et al., 2011; Schroder et al., 2011; Bushong et al., 2012; Lollato et al., 2013). Holman et al. (2011) suggested a 1.2 Mg ha^{-1} increase in wheat yield due to supplementary irrigation when evaluating 56 years of VPT data in western Kansas. These yield gains likely resulted from the high influence of precipitation on the long-term dryland wheat yields in this semi-arid region (i.e., water supply accounting for as much as 83% of variability in water-limited yield; Lollato et al., 2017).

The identification of the optimum sowing date presents a potential to increase regional grain yield because of the expected quadratic response to sowing date due to different yield-reducing factors (Sacks et al., 2010). Early sowing might limit yield due to i) increased exposure to insect pests (Schmid et al., 2019) that might transmit viral diseases (Wibberley, 1989; Wiersma et al., 2006); ii) decreased germination due to high soil temperatures (Smith, 1995); and iii) excessive fall growth and non-productive water and N consumption (Herwaarden et al., 1998). Yield-limiting factors for late sown winter wheat include i) a decreased fall tillering potential (Dahlke et al., 1993) requiring increased seeding rates (Staggenborg et al., 2003); ii) insufficient root growth in the fall, increasing the chances of water deficit and winterkill (Hammon et al., 1999); and iii) insufficient time for full vernalization (Wiersma et al., 2006).

Several previous studies reported positively association between fungicide application and grain yield (e.g., from controlled replicated experiments [Jaenisch et al., 2019], yield contests in Kansas [Lollato et al., 2018], and field experiments in Oklahoma [Edwards et al., 2012; Puppala et al., 1998]). Jaenisch et al., (2019) attributed the greater grain yield due to foliar fungicide because of the severe stripe rust infestations experienced. Under optimum conditions, greater than 60% of photosynthates translocated to developing wheat grains are produced by the upper canopy during grain fill; thus, fungicide application protected the green leaf area and allowed for photosynthate production and translocation (Rawson et al., 1983). Foliar fungicide applications typically decrease wheat yield losses in susceptible wheat varieties in the presence of disease pressure (Thompson et al., 2014, Lollato et al., 2019b), with yield losses greater than 20% from the absence of fungicide (Edwards et al., 2012) or as much as 1 Mg ha^{-1} in yield-contest fields (Lollato et al., 2018), both in the U.S. Great Plains.

No till system presents a low frequency of adoption in the U.S. Great Plains (Lollato et al., 2018), it may be a consequence of the lack of yield increase (Patrignani et al., 2012) and the occasional yield decrease (Decker et al., 2009) measured in wheat grown under no till, especially in wetter seasons (Giller et al., 2015) or in the subhumid region of the Great Plains (Patrignani et al., 2012). However, wheat yields have been shown to benefit from (Amato et al., 2013; Pittelkow et al., 2015; Toliver et al., 2012) and have greater stability (Giller et al., 2015) due to no till in semiarid regions. The benefits of no till in may have resulted from improved soil physical characteristics (Six et al., 2002; Hobbs et al., 2008; Lollato et al., 2012), as the latter likely contributes to yield stagnation in the region (Patrignani et al., 2014). Crop rotation is another important component of no-tillage systems, benefitting the crop by breaking weed and disease cycles (Bushong et al., 2012). The southern portion of the studied subhumid region is highly characterized by continuous wheat production (i.e., lack of crop rotation), perhaps supporting the decreased adoption of no-tillage practices in this region (Patrignani et al., 2012). Although winter wheat–fallow rotation has historically been the predominant cropping system in the semiarid region of the Great Plains (Stone and Schlegel, 2010), rotations with two crops in 3 yr are more profitable (Kaan et al., 2002), and no till has been suggested as a strategy to conserve soil moisture (Farahani et al., 1998). Combined, these factors might help explain the greater adoption of no till and crop rotation in the semiarid region.

Tillage practices and previous crop were significant factors in the analysis of producer-reported yields in the region (Lollato et al., 2018). Increased yields from no-till might result from a greater yield stability (Giller et al., 2015) or greater soil moisture conservation (Farahani et al., 1998) of wheat grown under no-till in semi-arid regions. Meanwhile, studies in Oklahoma suggested a yield penalty to continuous no-till wheat fields (i.e., fields that lack crop rotation; Decker et al., 2009). Continuous wheat cropping might partially justify the negative association of no-till and wheat yields, as well as the low rate of adoption of no-till in the southern portion of the study region (Patrignani et al., 2012). The benefits of no-tillage practices to semi-arid regions in which crop rotations are adopted is otherwise well reported (Amato et al., 2013; Pittelkow et al., 2015; Toliver et al., 2012).

2.2.3. Genotypic traits

The U.S. Great Plains experienced a series of stripe rust epidemics during the last 19 years (Chen et al., 2010, 2002; DeWolf, 2018; Jaenisch et al., 2019; Lollato et al., 2018), with production losses due to the disease ranging from 3 to 10.6% depending on state in a given year (Chen, 2007) and as great as 15.4% in Kansas in 2015 (Hollandbeck et al., 2016). Selecting varieties with inherent disease resistance is the most effective and economical way to control stripe rust (Chen, 2014, 2005), although evolution of the stripe rust pathogen (Wan et al., 2016) can render certain varieties susceptible and decrease their commercial life (Perronne et al., 2017).

Likewise, Holman et al. (2011) suggested the need to improve wheat variety drought tolerance to increase wheat yields in western Kansas. The physiological mechanisms conferring drought tolerance to different wheat varieties are genotype-specific and might be different depending on wheat growing region. Field and greenhouse studies in the U.S. Great Plains suggested that the increased grain yield of more drought-adapted cultivars resulted from greater water use and greater biomass production under drought stress when compared to less drought-tolerant cultivars (Reddy et al., 2014; Xue et al., 2014). Additionally, genotypic differences exist for root traits in winter wheat genotypes grown in the study region (Awad et al., 2018) and other areas (Aziz et al., 2017), which might help confer drought tolerance to winter wheat (Sciarresi et al., 2019).

Acidic soils are a growing concern for wheat production in the central region of the U.S. Great Plains (Johnson et al., 1997; Lollato et al., 2013). Previous studies suggested that varieties more tolerant to low soil pH usually outperform susceptible ones in acidic soil conditions (Johnson et al., 1997; Kariuki et al., 2007; Lollato et al., 2019b). Thus, considerable efforts have been made for breeding acidic soil tolerant cultivars in the region (Bona et al., 1994; Carver et al., 1988; Tang et al., 2002; Zhou et al., 2007).

2.3. Data mining

The development of information technology has generated large amount of databases and huge data in various areas, consequently the term “Big Data” is appearing in many contexts. It ranges from meteorology, genomics, complex physics simulations, biological and environmental research, finance and business to healthcare (Sowmya and Suneetha, 2017). Creating a need to develop technologies and tools to find, transform, analyze and visualize data in order to make it consumable for effective decision making and to use it intelligently (Liao et al., 2012; Sowmya and Suneetha, 2017). Consequently, data mining techniques has become an increasingly important research area (Fayyad et al., 1996; Liao et a., 2012; Sowmya and Suneetha, 2017). Data mining allows a search, for valuable information, in large volumes of data (Weiss and Indurkhya, 1998; Liao et al., 2012; Sowmya and Suneetha, 2017). Data mining is a five-step process: i) identifying the source information; ii) picking the data points that need to be analyzed; iii) extracting the relevant information from the data; iv) identifying and reporting the results; and v) interpreting and reporting the results (Brown, 2014).

Data mining methods can be generally divided into two categories, the first category is the use of statistical models. Its greatest contribution to data mining is in evaluating hypotheses, evaluating the results, and applying the results. Some popular statistical techniques employed include probability distributions, correlation, regression, cluster analysis, and discriminant analysis (Chen et al., 2000). The second category of methods applied in data mining is a branch of leading-edge artificial intelligence called machine learning. It suggests using a training set of data from which the data mining system learns and finds the parameters for its models. Such an approach is also called inductive reasoning, which involves deriving rules by studying a large number of samples in the database (Chen et al., 2000).

3. MATERIAL AND METHODS

3.1. Study-region

The U.S. central Great Plains is part of the largest contiguous area of low-precipitation winter wheat production in the world (Fischer et al., 2014). Together, the states included in this study (i.e., Colorado, Kansas, and Oklahoma) accounted for 25% of the total U.S. wheat production and represented 30% of the U.S. wheat harvested area during the study period (i.e., 2000-2018) (USDA-NASS, 2019). This region shows a diverse gradient in climatic conditions. Elevation ranges from more than 1,500 m in the west to less than 300 m in the east. Average cumulative precipitation from winter wheat sowing to maturity ranges from ~200 mm in the west to ~800 mm in the east, while potential evapotranspiration (Allen et al., 1998) during the same period follows the opposite gradient and ranges from ~800 mm in the west to ~600 mm in the east (Lollato et al., 2017). There are also latitudinal and longitudinal gradients in mean temperature and cumulative incident solar radiation during the winter wheat growing season (Lollato et al., 2017).

3.2. Regional subdivision into growing adaptation regions (GAR)

The aforementioned gradients in meteorological variables naturally result in gradients in management practices and differences in varieties tested in each location in the study-region. For instance, sowing date increases from ca. day of year (DOY) 265 to 290 (Sep. 22nd to Oct. 17th) from north to south, and from ca. 260 to 296 (Sep. 17th to Oct. 23rd) from west to east (Fig. 1). Likewise, varieties bred in drought-prone environments (e.g., Colorado, western Kansas, and Texas panhandle) tend to populate the VPT conducted in the western portion of the study region while eastern Kansas- and Oklahoma-bred varieties tend to populate the VPT conducted in the central portion of the region (data not shown). To account for differences in climate, management variables, and varieties that resulted from each trial's geographical location, we developed a climate zonation scheme within which the remaining analyses were performed.

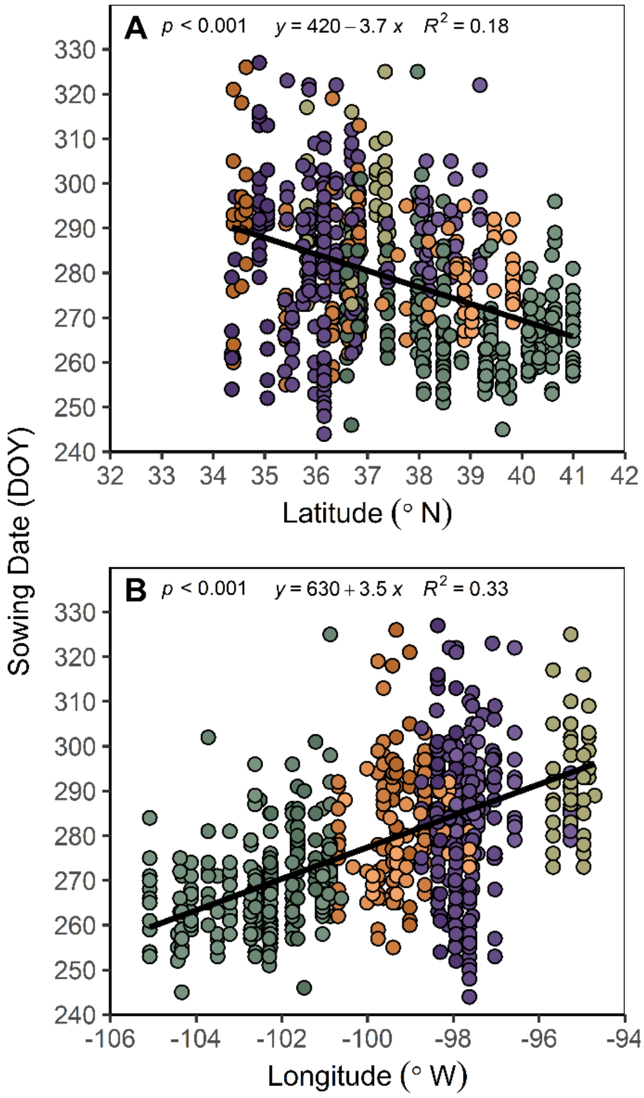

Fig. 1. Sowing dates in the U.S. southern Great Plains according to the (A) latitude and (B) longitude range. The colors of the circles correspond to the color of the respective growing adaptation region (GAR) color.

The climate zonation scheme was based on annual accumulation of wheat-specific growing degree-days (GDD, considering 0 ºC as the base temperature;

Gallagher, 1979) and cumulative annual precipitation using data derived from 53 weather stations located throughout the region (inset in Fig. 2) that accounted for 30 consecutive years of daily weather data (1986-2015). The GDD range was divided into five classes averaging 460 ºC and precipitation was divided into four classes of 200 mm, resulting in 11 distinct zones for which grain yield data were available (Fig. 2). Both surfaces (i.e., continuous maps of GDD and precipitation) were created using the Empirical Bayesian Kriging tool in ArcGIS (Krivoruchko, 2012). Hereafter, we will refer to these zones as growing adaptation regions (GAR).

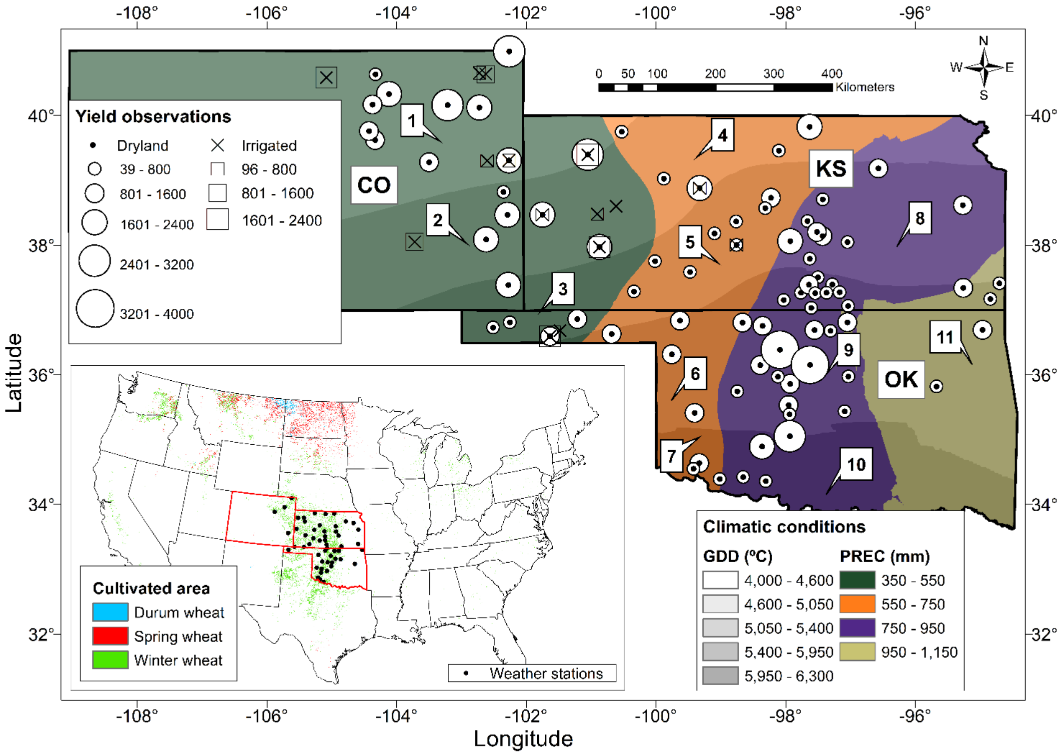

Fig. 2. Map of Colorado (CO), Kansas (KS), and Oklahoma (OK) showing the eleven growing adaptation regions (GAR) (number in the white box), dryland VPT (solid circles), irrigated VPT ("X") and their respective number of yield observations (dimension of circles for dryland and squares for irrigated) used in this study. The colors represent the four cumulative yearly precipitation (PREC) levels and the shade intensities represent the five annual growing degree-days (GDD) intervals. Bottom inset: raster represents the wheat cultivated area in 2017 (USDA-NASS, 2017), location of the three states within the continental USA (red highlight), and location of the weather stations (black solid circles).

3.3. Database description

3.3.1. Crop management

Grain yield data were collected from hard winter wheat VPT conducted in the three aforementioned states over nineteen harvest years (2000-2018). The initial dataset included 92 locations and 738 genotypes, comprising both commercial varieties and elite experimental lines, and resulted in a dataset of 97,996 observations (Fig. 2 and Table 1). We retrieved all available information about the management of each individual trial, including: i) sowing date in DOY; ii) water regime, comprising dryland or irrigated trials; iii) presence or absence of foliar fungicide applied at the heading stages of crop development; iv) presence or absence of “intensive management”, which comprised of two foliar fungicide applications (e.g., at jointing and at heading) plus an additional 45 kg N ha^{-1} to the base fertility used in the standard trials; v) trial purpose described as grain-only or dual-purpose (i.e., grazing during fall and winter followed by grain harvest); vi) tillage system (conventional or no-till); and vii) previous crop, comprised of alfalfa (*Medicago sativa*), canola (*Brassica napus*), maize (*Zea mays*), fallow, sunflower (*Helianthus annuus*), wheat, or others. Other management variables such as fertilization practices were not uniformly reported and thus these data were not evaluated. The dataset did not include experiments that failed due to winterkill, hail damage, wheat streak mosaic virus, or other disasters. Additionally, grain yield observations from trials yielding less than 0.3 Mg ha^{-1} were removed from the final analysis. Experiments included in this study were conducted in both farmer’s fields and research stations.

Table 1. Summary of winter wheat grain yield data derived from variety performance trials for each evaluated growing adaptation region (GAR). The number of years with trials (Y), number of test locations (L), number of year-location combinations (Y-L), number of genotypes tested (G), total number of grain yield (GY) measurements and management practices evaluated ("X") are shown.

GAR	Y	L	Y-L	G	GY	Management practices evaluated						
	(n)	(n)	(n)	(n)	(n)	Sowing date	Water regime	Fungicide	Intensive management	Trial purpose	Tillage system	Previous crop
All	19	92	748	738	97996	X	X	X	X	X	X	X
1	19	15	166	516	24905	X	X	X	-	-	-	-
2	19	8	76	521	11963	X	X	X	-	-	-	-
3	19	6	52	446	7028	X	X	-	-	X	-	-
4	17	5	38	270	5669	X	X	X	-	-	-	X
5	12	8	22	211	3879	X	X	X	X	-	-	X
6	18	5	68	168	6030	X	-	X	-	X	X	-
7	17	3	25	154	2426	X	-	-	-	X	X	-
8	16	9	58	225	6750	X	-	X	X	-	-	X
9	19	24	165	255	20047	X	-	X	X	X	X	-
10	17	4	34	163	5564	X	-	X	X	X	X	-
11	19	5	44	188	3735	X	-	X	-	-	-	X

3.3.2. Genotypic traits

For each released variety entered in the VPT, we collected agronomic traits and disease/insect reaction characteristics reported yearly in extension reports (Ehmke, 2018, 2017, 2016, 2015; Watson, 2014, 2013, 2012, 2011, 2010, 2009, 2008, 2007, 2006, 2005, 2004, 2003, 2002, 2000). We compiled information on 17 agronomic traits per variety and divided each trait into three categorical levels (Table 2A). If an individual variety was scored for agronomic traits in several consecutive years, only the most recent scores were used. Likewise, we collected information on each variety's reaction to eleven diseases or insect pests and divided in five scores ranging from 1 (susceptible) to 5 (resistant) (Table 2B). For *Fusarium graminearum* (head blight), resistance ratings ranged from extremely susceptible (1) to intermediate (5) due to a lack of truly resistant varieties. For disease/insect resistance ratings, scores were retrieved after each individual growing season as the reaction of an individual variety might change from one year to another (Kolmer, 1996; Wan et al., 2016). Elite experimental lines were also evaluated in the VPT, and agronomic or disease ratings were not available for this subset. After excluding yield observations from experimental lines that were not released, the resulting dataset comprised of 65,264 yield observations from 194 commercial wheat varieties. These included 60,340 yield observations for hard red winter wheat varieties, and 4,924 yield observations for hard white winter wheat varieties. We checked for potential differences in grain yield between both classes by first selecting only trials that had at least one white variety (n = 36,825 for red vs. 4,924 for white), and second comparing their yields, which were similar (3.6 vs. 3.5 Mg ha^{-1} for red vs. white).

Table 2. (A) Agronomic traits and their respective levels, and (B) disease/insect reaction information collected from each individual variety.

(A)

Abbreviation	Trait	Levels		
AST	Acid soil tolerance	susceptible (s)	intermediate (i)	tolerant (t)
CL	Coleoptile length	short (s)	intermediate (i)	long (l)
DT	Drought tolerance	poor (p)	intermediate (i)	good (g)
ESG	Early spring greenup	early (e)	intermediate (i)	late (l)
FGCP	Fall ground cover potential	poor (p)	intermediate (i)	good (g)
FGH	Fall growth habit	prostrate (p)	intermediate (i)	up (u)
FGP	Fall grazing potential	poor (p)	intermediate (i)	good (g)
FHS	First hollow stem	early (e)	intermediate (i)	late (l)
PH	Plant height	short (s)	intermediate (i)	tall (t)
HD	Heading date	early (e)	intermediate (i)	late (l)
SS	Seed size tendency	small (s)	intermediate (i)	large (l)
SHR	Shattering reputation	poor (p)	intermediate (i)	good (g)
ST	Spouting tolerance	poor (p)	intermediate (i)	good (g)
STS	Straw strength	poor (p)	intermediate (i)	good (g)
TW	Test weight	low (l)	intermediate (i)	good (g)
TT	Tillering tendency	poor (p)	intermediate (i)	good (g)
WH	Winterhardiness	poor (p)	intermediate (i)	good (g)

(B)

Abbreviation	Disease/insect	Abbreviation	Disease/insect
BYDV	Barley yellow dwarf virus	YR	Stripe rust (*Puccinia striiformis*)
SBWMV	Soil-borne mosaic virus	PM	Powdery mildew (*Blumeria graminis*)
WSMV	Wheat streak mosaic virus	SLB	Septoria leaf blotch (*Mycosphaerella graminicola*)
HF	Hessian fly (*Mayetiola destructor*)	TS	Tan spot (*Pyrenophora tritici-repentis*)
LR	Leaf rust (*Puccinia triticina*)	SCB	Head blight (*Fusarium graminearum*)
SR	Stem rust (*Puccinia graminis*)		

To evaluate the G effect from multiple trials, we transformed the response variable (yield) by centering (subtracting the mean) and scaling (dividing by the standard deviation) each trial (Cheadle et al., 2003; Ishii et al., 2000; Lê Cao et al., 2014):

$$z_{ij} = \frac{x_{ij} - x_{.j}}{\sigma_j} \quad [1]$$

where, z_{ij} is the Z-score of the ith observation $(i = 1, \dots, n)$ from the jth trial $(j = 1, \dots, n)$, x_{ij} is the individual grain yield measurement, x_j is the trial mean grain yield, and σ_j is the trial standard deviation. The Z-score fitted a standard normal distribution with a mean of zero and standard deviation of one (Clark-Carter, 2014) (Fig. 3).

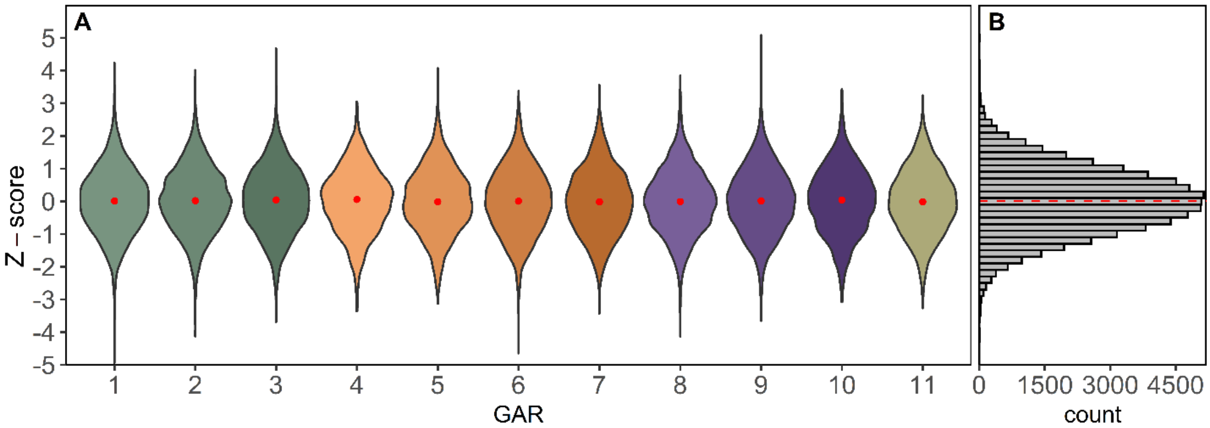

Fig. 3. Violin plot of Z-score for each growing adaptation region (GAR). (A) Within the violin plot, the red dot represents the mean and the filled area with the respective GAR color represents the data distribution. (B) Histogram of all data, the dashed line represents the global mean.

3.4. Statistical analysis

3.4.1. Data dispersion and variance component analyses

We used exploratory data analysis tools (i.e., violin plot and histograms) to demonstrate the range of variation associated with sowing date, grain yield, and Z-score. We also calculated the frequencies of adoption of management practices to illustrate the range of variation across the entire dataset and by GAR. To quantify how much of the total variability in grain yield was accounted for by GAR, year, genotype, and management practice, we performed a variance component analyses (e.g. random effects associated with yield) with linear mixed-effects models through the “lme4” package in R software (Bates et al., 2015). This analysis was performed both across the entire dataset using genotype as a random effect, and across the smaller dataset (n = 65,264) using traits of each genotype (e.g., disease and insect resistances and agronomic traits) as random effects. In these analyses, only effects that had less than 25% of missing data were considered.

3.4.2. Effects of management practices and genotypic traits on grain yield

First, we calculated the relative variable influence of each management practice on yield within each GAR using the machine learning algorithm gradient boosted trees (De’ath, 2007) implemented using “gbm” package in R software (Greenwell et al., 2019). Second, we evaluated potential interactions of management practices on wheat yield within each GAR using conditional inference trees through the “partykit” package in R software (Hothorn and Zeileis, 2015). To explore genotype × management interactions in the variety trait analysis, we forced the conditional inference tree to first split the data based on the main management practice impacting wheat yields within each GAR. We then investigated the association of variety traits with wheat yield within the GAR × management combination using conditional inference trees. For instance, if water regime was the main management practice affecting wheat yield in a particular GAR, the next step was to evaluate variety traits associated with wheat yield for trials conducted under irrigated versus dryland conditions separately within the corresponding GAR. Both gradient boosted trees and conditional inference trees were subjected to appropriate sensitivity analyses and the model with the highest R^2 was selected and used for inference.

Gradient boosted trees: In a single regression tree, the relative influence of a variable is quantified by the sum of squared improvements at all splits determined by the variable (Breiman et al., 1984). Gradient boosted trees are grown sequentially and each tree is grown using information from previously grown trees; and in these models, the relative influence of each variable is averaged over the collection of trees (De'ath, 2007). To optimize the predictive accuracy of the model, we tested a combination of 81 hyperparameters and applied it to 5,000 trees. The hyperparameters tested were learning rate (0.01, 0.1, and 0.3), depth of trees (1, 3, and 5), minimum number of observations allowed in the trees' terminal nodes (5, 10, and 15%), subsampling (0.65, 0.8, and 1), all in a training rate of 80% of the observations. The best combination of hyperparameters, as well as the optimum number of trees, were selected based on the minimum root mean square error (RMSE).

Conditional inference trees: these trees can handle categorical and continuous explanatory variables, model complex interactions, deal with missing data, and are robust to outliers, multicollinearity, and heteroscedasticity (De'ath, 2007; Tittonell et al., 2008). Conditional inference trees estimate a relationship among several variables by binary recursive partitioning in a conditional inference framework without bias or overfitting issues (Hothorn et al., 2006). We used the stop criterion based on alpha = 0.05. As a sensitivity test, we started all analyses requiring a minimum of 20% of the total observations to create an intermediate node and 10% of the total observations to create a terminal node, with no restrictions to tree depth. We then allowed intermediate nodes to range from 10 to 40% of total observations and terminal nodes to range from 5 to 10% of the total observations, ensuring that each terminal node was comprised of at least two trials. A more complex model was only selected when it improved R^2 at least 5% from the original model.

3.4.2. Determination of optimum sowing date

Boundary function provides a framework to quantify the highest attainable unit of a given measured output as function of the availability of a particular resource.

French and Schultz (1984) first demonstrated this framework to quantify the maximum attainable wheat yield per unit of seasonal water supply in Australia. Afterwards, different authors validated this approach for wheat (Lollato et al., 2017; Passioura and Angus, 2010; Patrignani et al., 2014; Sadras and Angus, 2006) and other crops (Grassini et al., 2015b, 2011, 2009). Boundary functions were also used to quantify how different crop husbandry practices affect crop yield potential (Hajjarpoor et al., 2018; Huang et al., 2008; Lollato et al., 2018; Tasistro, 2012).

Within this context, we fitted a smooth and convex shape-restriction to relate wheat yield potential (i.e., 99th percentile) with sowing date within each GAR. We used the constrained generalized additive model of through the “cgam” package in R software (Liao and Meyer, 2019).

4. RESULTS

4.1. Management practices adopted in the different VPT

Sowing date ranged from DOY 244 to 327 (Sep. 1st to Nov. 23rd, Fig. 4) across the entire study region and was earlier (DOY 266 to 281; Sep. 23rd to Oct. 8th) in the northwest (GAR 1, 2, 3, 4, 5, and 6) and later (DOY 283 to 293; Oct. 10th to Oct. 20th) in the southeast region (GAR 7, 8, 9, 10, and 11). Most of the VPT were conducted under dryland conditions, except for trials in the semi-arid, western regions (GAR 1 to 5); where 7-31% of the trials were irrigated (Table 3). Fungicide was applied around heading in 10% of the studied trials and, within GAR, frequency of fungicide adoption ranged from 0% (GAR 3 and 7) to 34% (GAR 10) (Table 3). Only 2% of the trials were intensively managed and these were located in four GAR (i.e., 5, 8, 9, and 10). Within these GAR, the frequency of intensive management trials ranged from 2-17%. Dual-purpose trials represented 6% of the total observations, and occurred in the GAR 3, 6, 7, 9, and 10. The number of trials conducted under dual-purpose ranged from 2-20% within these GAR (Table 3). Tillage practices were not reported in several trials and only met the criteria for variable inclusion (i.e., less than 25% missing data) in four GAR (i.e., 6, 7, 9, and 10). Previous crop was only reported in 54% of the trials and within GAR, its reporting varied between 19-100% in GAR 4, 5, 8, and 11. A 14-month fallow period was the most common previous crop in GAR 4 (69%) and GAR 8 (40%), and the second most common rotation (37%) and similar to sorghum (39%) in GAR 5.

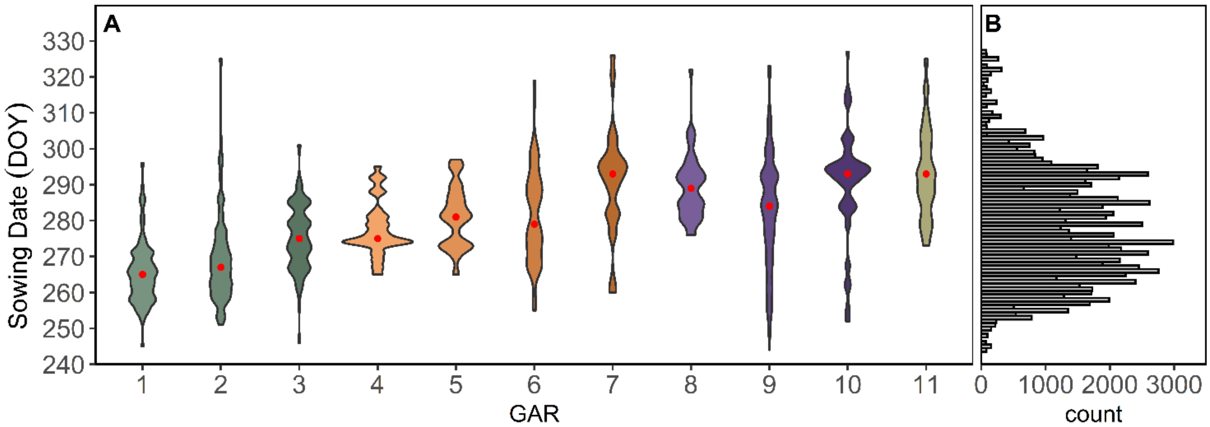

Fig. 4. Violin plot of sowing date in day of year (DOY) for each growing adaptation region (GAR). (A) Within each violin plot, the red dot represents the mean and the filled area with the respective GAR color represents the data distribution. (B) Histogram of all sowing date data, with each bar corresponding to one DOY.

Table 3. Management practices frequencies of adoption and missing values for each growing adaptation region (GAR).

Agronomic practice		GAR											
		All	1	2	3	4	5	6	7	8	9	10	11
		(%)											
Sowing date	*na*[a]	11	22	9	7	4	6	5	13	11	13	4	9
Water regime	Irrigated	12	22	30	31	7	8	-	-	-	-	-	-
	Dryland	88	78	70	69	93	92	100	100	100	100	100	100
	na	-	-	-	-	-	-	-	-	-	-	-	-
Fungicide	Fungicide	10	7	8	-	2	19	2	-	17	20	34	2
	No fungicide	90	93	92	100	98	81	98	100	83	80	66	98
	na	-	-	-	-	-	-	-	-	-	-	-	-
Intensive management	Intensive	2	-	-	-	-	12	-	-	6	2	17	-
	Standard	98	100	100	100	100	88	100	100	94	98	83	100
	na	-	-	-	-	-	-	-	-	-	-	-	-
Trial purpose	Dual	6	-	-	2	-	-	15	2	-	20	15	-
	Grain only	94	100	100	98	100	100	85	98	100	80	85	100
	na	-	-	-	-	-	-	-	-	-	-	-	-
Tillage system	Conventional	30	-	-	37	-	0	77	88	-	77	61	36
	No till	9	-	-	35	-	4	23	12	3	9	39	8
	na	61	100	100	29	100	96	-	-	97	14	-	56
Previous crop	Alfalfa	-	-	-	-	-	-	-	-	-	1	3	-
	Canola	2	1	-	-	-	-	-	4	7	4	12	4
	Maize	4	-	12	1	5	8	-	-	-	1	-	51
	Fallow	22	15	38	36	69	37	17	17	40	5	-	2
	Sorghum	3	-	-	4	15	39	-	-	5	2	-	4
	Soybean	3	-	2	2	-	-	-	-	27	1	5	16
	Wheat	16	2	1	4	10	14	36	38	6	45	14	9
	Others	2	-	1	-	-	-	-	-	2	-	38	-
	na	46	81	46	53	-	3	47	40	13	41	29	14

[a] missing values

4.2. Yield variation and dispersion among and within GAR

Average winter wheat yield was ca. 3.4 Mg ha^{-1} and ranged from ca. 2.5 Mg ha^{-1} in GAR 6 and 7 to ca. 4.0 Mg ha^{-1} in GAR 4 and 5 (Fig. 5). Within GAR, grain yield ranged from ca. 0.3 – 11.0 Mg ha^{-1} in GAR 1, to ca. 0.3 – 5.0 Mg ha^{-1} GAR 7. Across the entire dataset, GAR was the most important factor accounting for overall wheat yield variability and accounted for 46% of the total variance (Table 4A). Management practices accounted for 32% of the yield variability, residuals (including unmodelled interactions) accounted for 13%, year accounted for 7%, and genotype accounted for 2% (Table 4A). Although GAR was the main effect driving wheat yield, substantial variation in yield remained after the trials were separated by GAR (Fig. 5). Within GAR, management practices were the most important effect explaining wheat yield variation (44 – 77%), followed by year (13 – 37%), residual (3 – 21%), and genotype (1 – 8%) (Table 4A). The exception was GAR 1, where the residuals accounted for 19% and year accounted for 13%. The variance component analysis for the second dataset using genotype traits as random effect (instead of genotype) resulted in similar proportion of yield variability accounted for by each evaluated random effect (Table 4B).

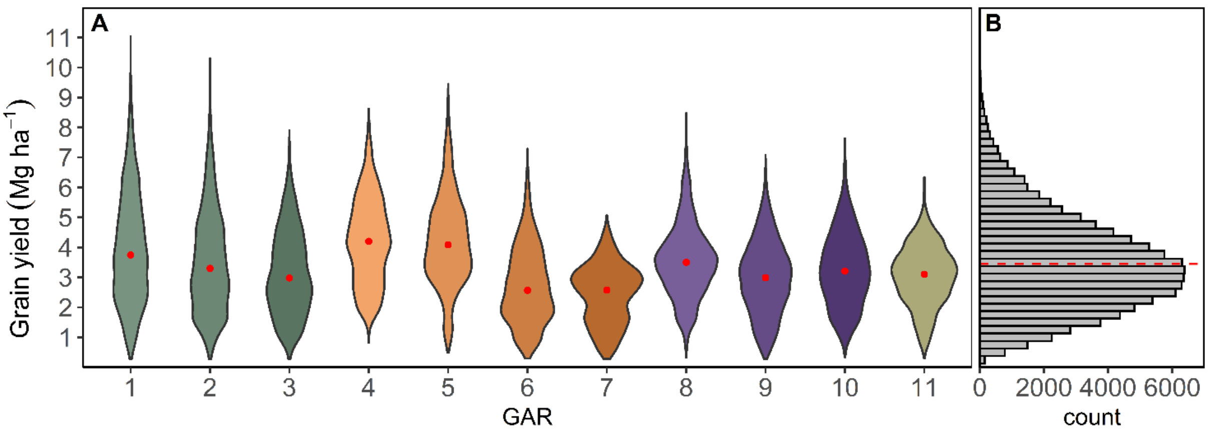

Fig. 5. Violin plot of grain yield (Mg ha^{-1}) for each growing adaptation region (GAR). (A) Within the violin plot, the red dot represents the mean and the filled area with the respective GAR color represents the data distribution. (B) Histogram of all yield data, with the dashed line representing the global mean.

Table 4. Variance component analysis of the individual effects of growing adaptation region (GAR), management practices, year, genotype, agronomic traits, disease reaction, and residual on the grain yield variance across and within GAR for both datasets with (A) 97,996 and (B) 65,264 yield observations for which variety traits were available.

Source of variation	GAR											
	All	1	2	3	4	5	6	7	8	9	10	11
(A)	Variance (%)											
GAR	46	-	-	-	-	-	-	-	-	-	-	-
Management practices[a]	32	66	57	62	63	53	66	58	77	44	61	70
Year	7	13	23	28	30	37	30	31	17	27	22	21
Genotype	2	2	3	1	2	2	1	3	1	8	3	4
Residuals[d]	13	19	17	9	5	8	3	8	5	21	14	5
(B)	Variance (%)											
GAR	46	-	-	-	-	-	-	-	-	-	-	-
Management practices[a]	32	66	63	69	79	52	64	62	69	38	44	78
Year	7	16	24	22	7	37	33	30	26	29	7	14
Agronomic traits[b]	4	1	2	1	2	3	1	2	1	13	26	1
Diseases/insects reaction[c]	1	1	2	2	4	2	1	2	2	3	17	1
Residuals	11	16	10	6	8	6	1	5	3	16	7	5

[a] sum of the individual management practice effects; [b] sum of the individual agronomic trait effects; [c] sum of the individual disease reaction effects; [d] including unmodelled interactions

4.3. Effects of management practices on winter wheat grain yield

Boosted trees identified the relative importance of each important management practices influencing wheat grain yield within each GAR (Fig. 6). For example, water regime was the most important variable in the GAR 1, with a relative importance of 56.9%; sowing date was the second (39.1%), and lastly foliar fungicide (4.0%). Water regime also was the most important variable in the GAR 2 and 3. Sowing date was the most important variable in all other GAR, with relative importance ranging from 50.0 to 99.8%. The exception was GAR 9 where tillage system was the most important variable influencing yield. The relative importance of other variables varied among GAR. Foliar fungicide, for example, was applied in nine of the eleven GAR and its importance ranged from 0 to 18.1%. Previous crop and tillage system, in the GAR for which data was available, had relative importance of as much as 32.1 and 46.4% (Fig. 6).

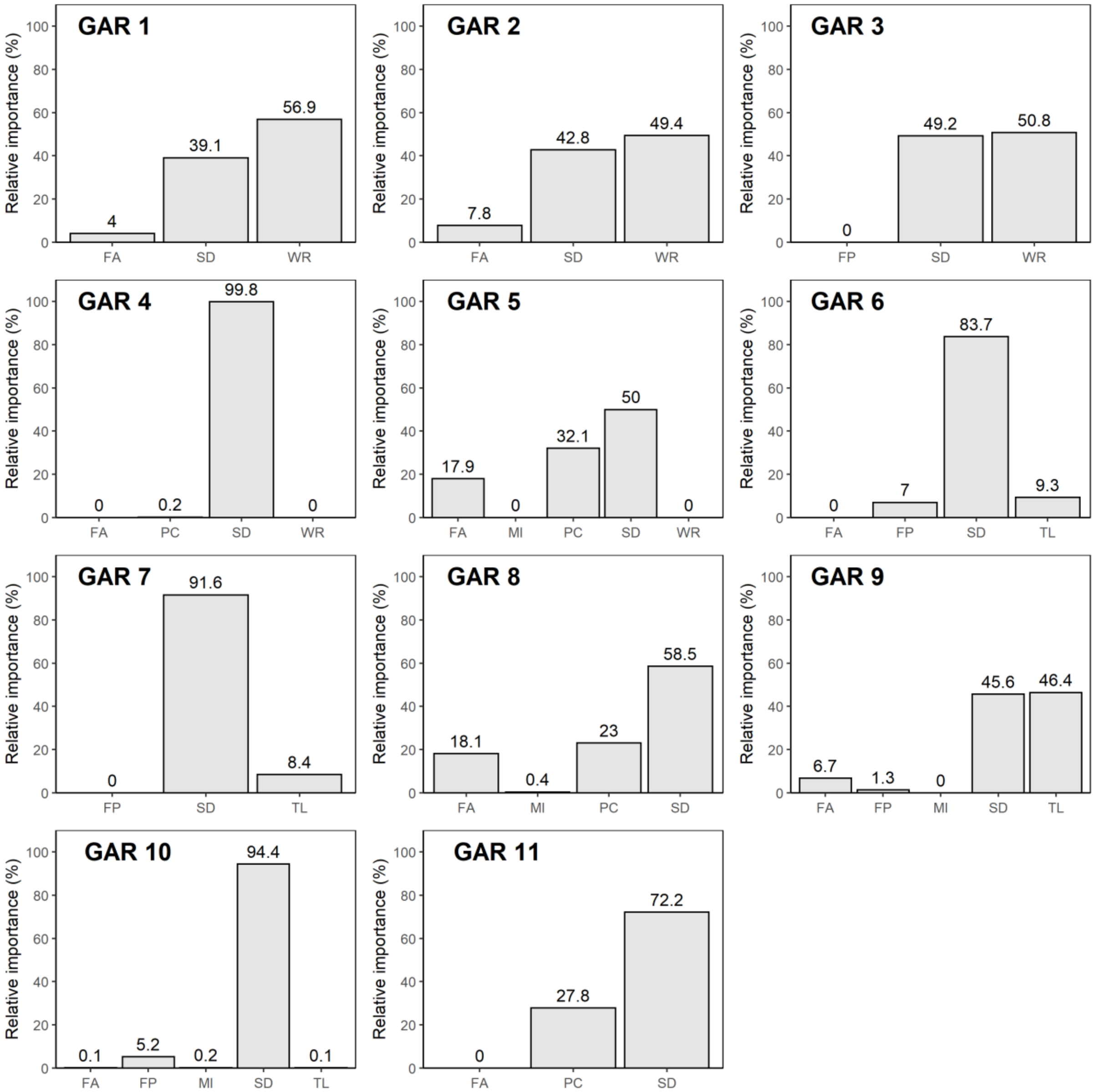

Fig. 6. Analysis of the relative importance of each evaluated management practice on grain yield within each growing adaptation region (GAR). FA, fungicide application; SD, sowing date; WR, water regime; FP, final purpose of the trial; PC, previous crop; MI, management intensity; TL, tillage system.

The conditional inference trees fit to data from each GAR are shown in Fig. 7 to 17. Similar to Mourtzinis et al. (2018), these analyses illustrated interactions among management practices within and between GAR. For example, in the western, semi-arid portion of the study region (GAR 1, 2, and 3), the water regime was the most important variable influencing wheat yield (Figs. 6, 7, and 8). Using GAR 1 as an example, irrigated trials sown between DOY 267 and 296 (Sep. 24th to Oct. 23rd) yielded 6.0 Mg ha^{-1}, which is 7% greater than the average yield in irrigated trials sown between DOY 253 and 266 (Sep. 10th to 23rd) (Fig. 7). In dryland trials in the GAR 1, foliar fungicide resulted in the highest yields (ca. 5.0 Mg ha^{-1}) and, in the absence of foliar fungicide application, sowing after Sep. 17th (DOY 260) was associated with higher yield (3.5 Mg ha^{-1}) compared to earlier sowing dates (2.8 – 3.1 Mg ha^{-1}). The three variables of the explanatory model (water regime, foliar fungicide, and sowing date) captured 36% of total yield variability within GAR 1 (R^2 = 0.36) (Fig. 7).

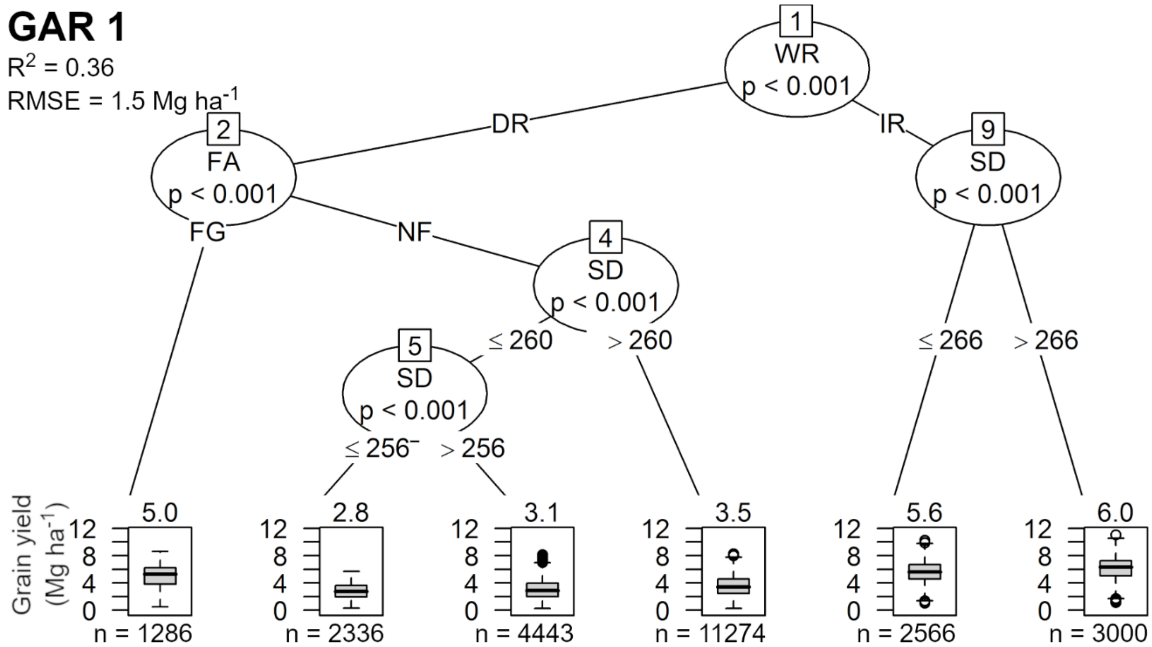

Fig. 7. Conditional inference tree for grain yield in the growing adaptation region (GAR) 1 (shown in Fig. 2) as affected by water regime (WR), fungicide application (FA), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. DR, dryland; IR, irrigated; FG, fungicide; NF, no fungicide.

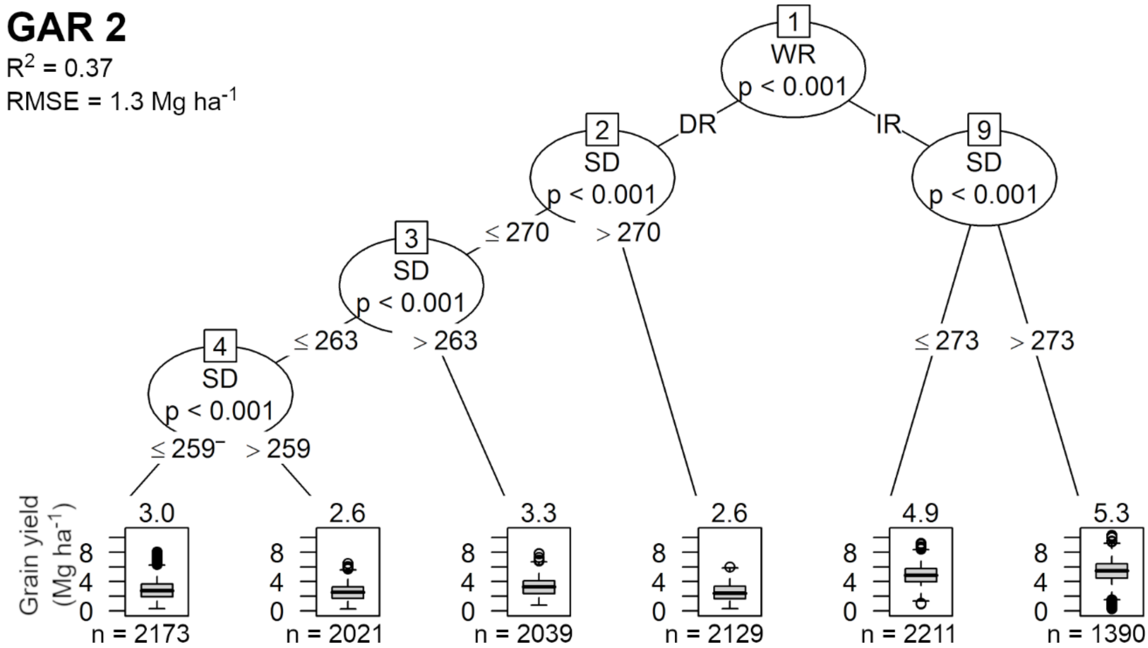

Fig. 8. Conditional inference tree for grain yield in the growing adaptation region (GAR) 2 (shown in Fig. 2) as affected by water regime (WR), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. DR, dryland; IR, irrigated.

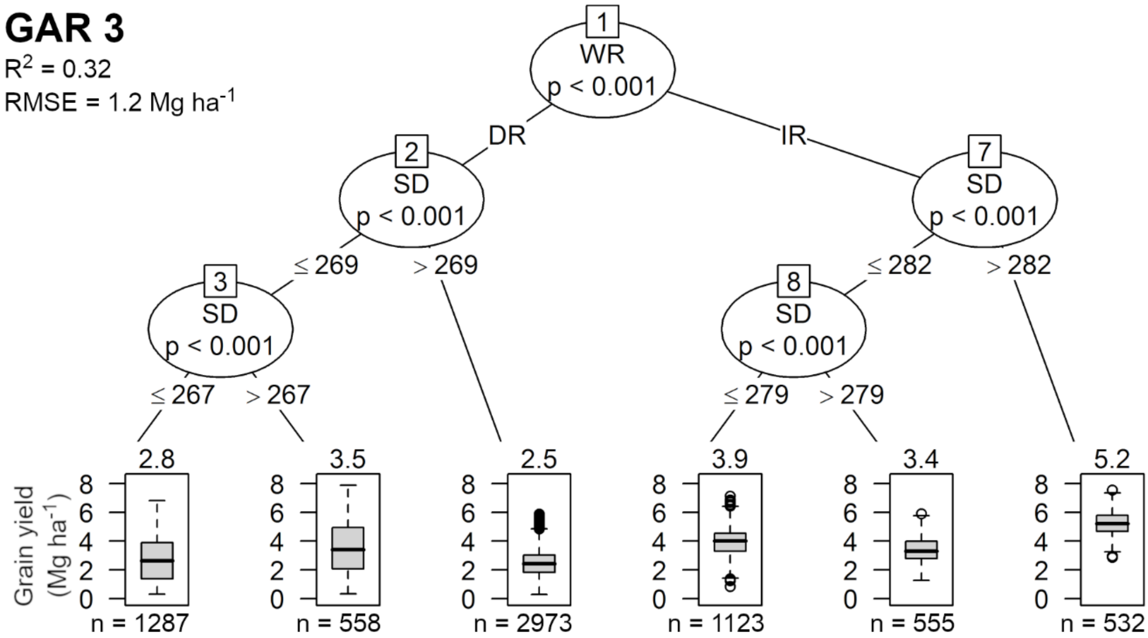

Fig. 9. Conditional inference tree for grain yield in the growing adaptation region (GAR) 3 (shown in Fig. 2) as affected by water regime (WR), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. DR, dryland; IR, irrigated.

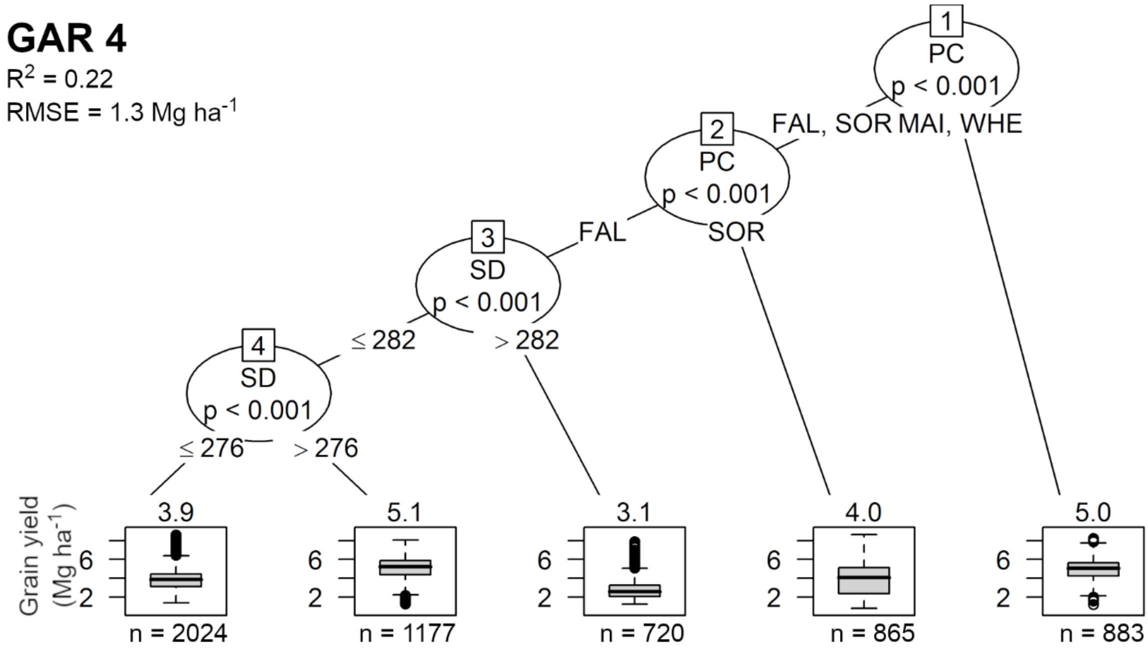

Fig. 10. Conditional inference tree for grain yield in the growing adaptation region (GAR) 4 (shown in Fig. 2) as affected by previous crop (PC), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. FAL, fallow; SOR, sorghum; MAI, maize; WHE, wheat.

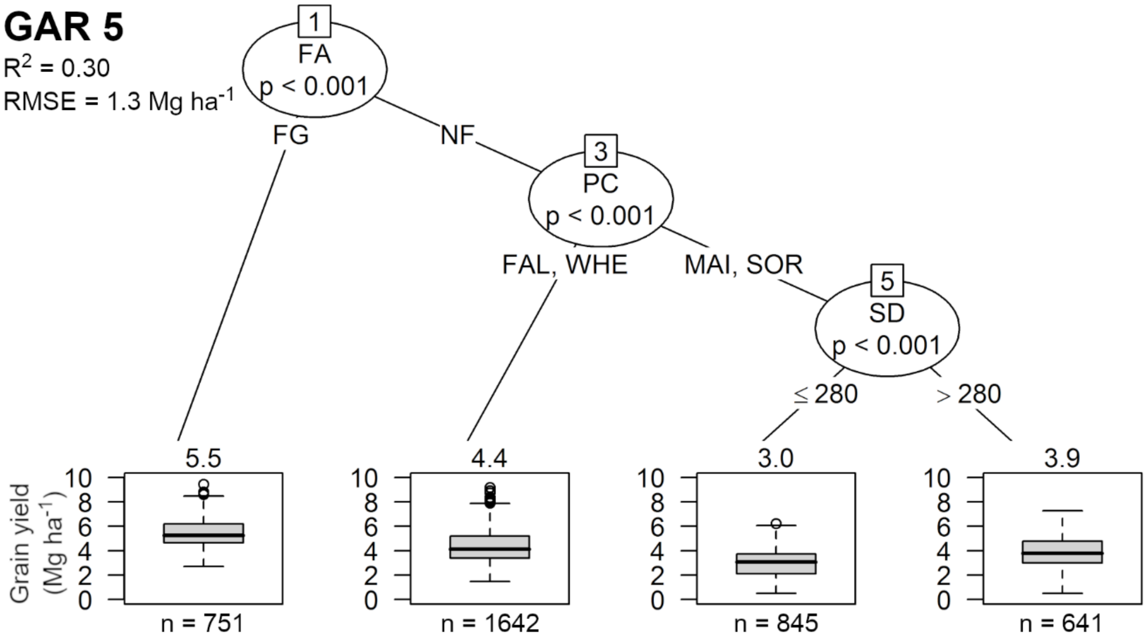

Fig. 11. Conditional inference tree for grain yield in the growing adaptation region (GAR) 5 (shown in Fig. 2) as affected by fungicide application (FA), previous crop (PC), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. FG, fungicide; NF, no fungicide; FAL, fallow; WHE, wheat; MAI, maize; SOR, sorghum.

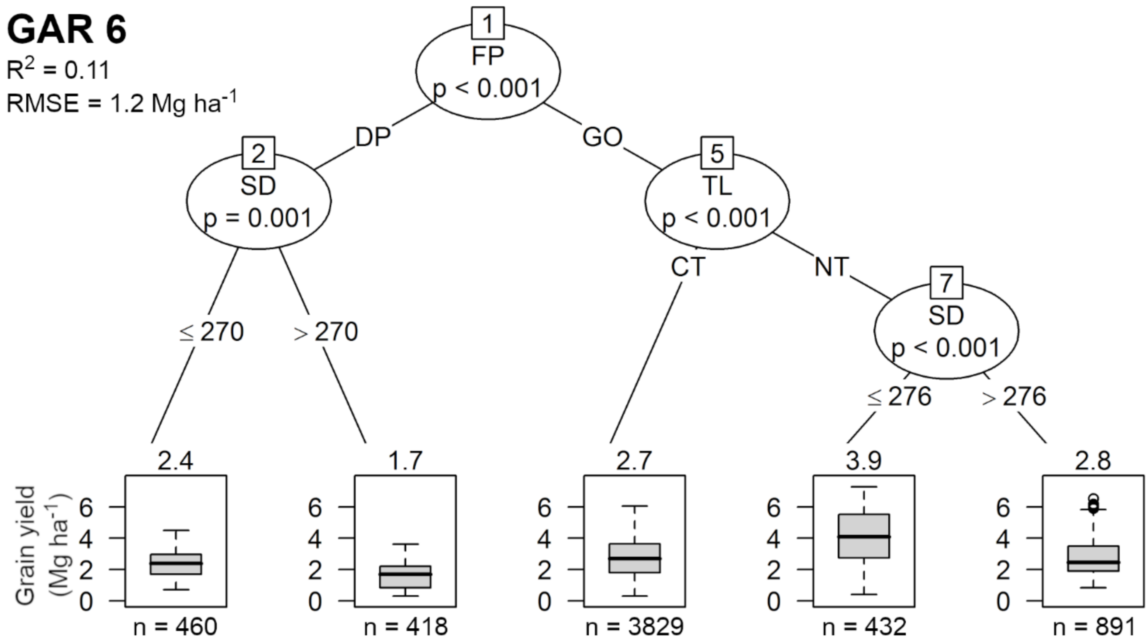

Fig. 12. Conditional inference tree for grain yield in the growing adaptation region (GAR) 6 (shown in Fig. 2) as affected by final purpose of the trial (FP), sowing date (SD), and tillage system (TL). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. DP, dual-purpose; GO, grain-purpose; CT, conventional till; NT, no-till.

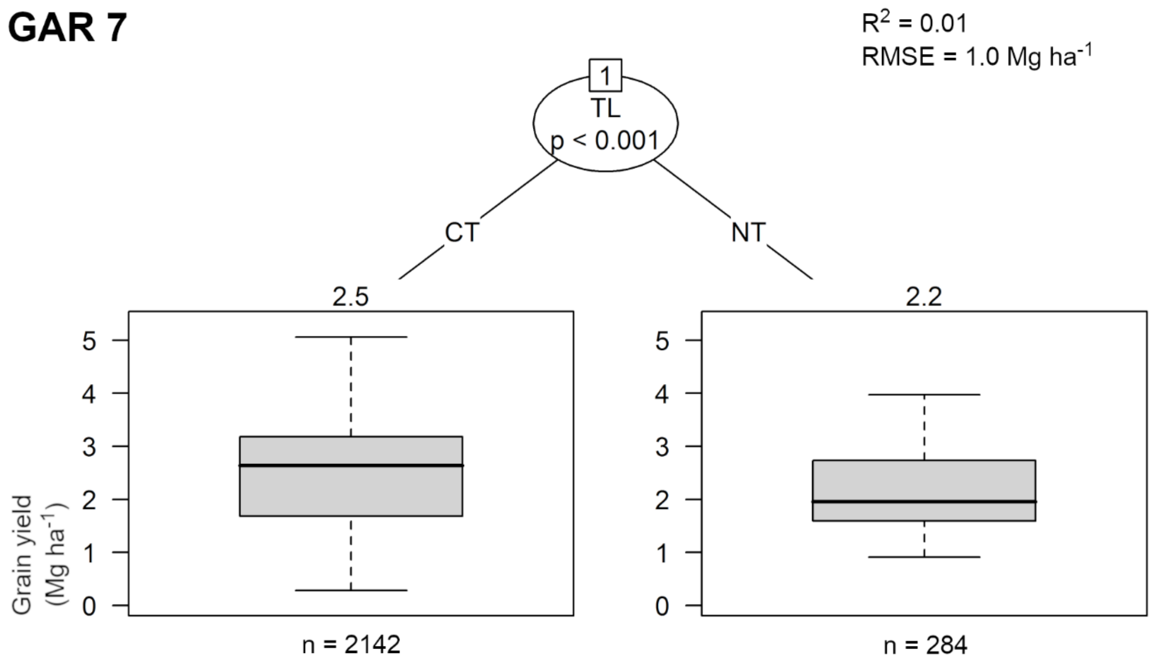

Fig. 13. Conditional inference tree for grain yield in the growing adaptation region (GAR) 7 (shown in Fig. 2) as affected by tillage system (TL). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. CT, conventional till; NT, no-till.

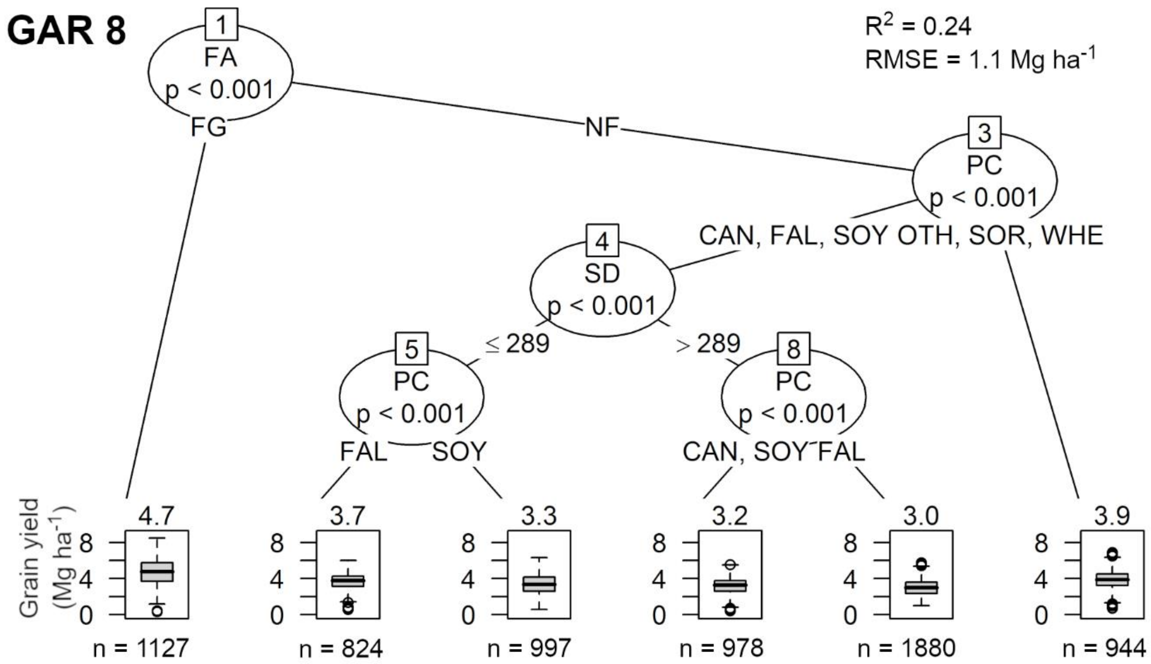

Fig. 14. Conditional inference tree for grain yield in the growing adaptation region (GAR) 8 (shown in Fig. 2) as affected by fungicide application (FA), previous crop (PC), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. FG, fungicide; NF, no fungicide; CAN, canola; FAL, fallow; SOY, soybean; OTH, others; SOR, sorghum; WHE.

The GAR 9 has a dry subhumid climate and provides a contrasting environment for evaluation of the effects of management practices on wheat yield as those described in GAR 1. In GAR 9, the use of fungicide was the most important variable affecting wheat yield (Fig. 15). Trials in which foliar fungicide was applied yielded ca. 4.1 Mg ha^{-1}, which is 28% greater than the average yield attained under the best suite of management practices without fungicide application (c.a., 3.2 Mg ha^{-1}, attained in grain-only trials sown between DOY 279 and 286 or Oct. 6th to 13th). Dual-purpose (grazing plus grain) management decreased grain yield to an average of ca. 2.4 Mg ha^{-1} compared to grain-only trials (2.6 – 3.2 Mg ha^{-1}). In GAR 9, management practices explained 20% of total yield variability within the GAR (Fig. 15). Besides the previous detailed GAR 1 and 9, foliar fungicide was an important effect influencing wheat yield in the GAR 5 (Fig. 11), 8 (Fig. 14), and 10 (Fig. 16). Sowing date significantly influenced yield in nine out of the eleven GAR established. Due to its importance across the majority of the GAR, we expanded the sowing date analysis using boundary function.

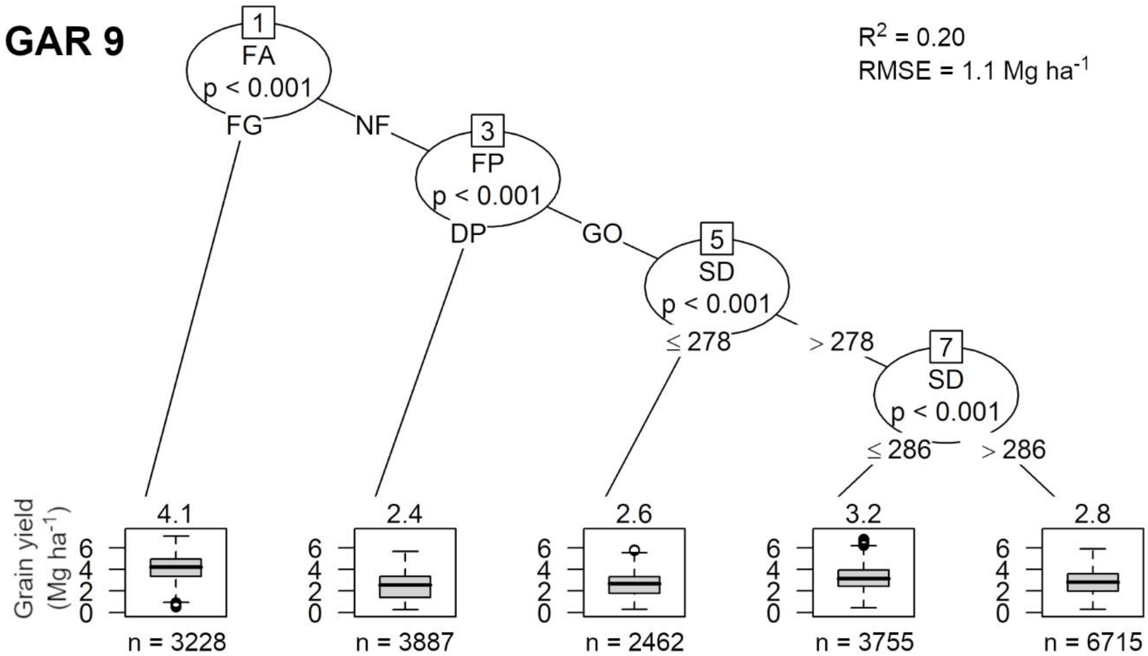

Fig. 15. Conditional inference tree for grain yield in the growing adaptation region (GAR) 9 (shown in Fig. 2) as affected by fungicide application (FA), final purpose of the trial (FP), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. FG, fungicide; NF, no fungicide; DP, dual-purpose; GO, grain-purpose.

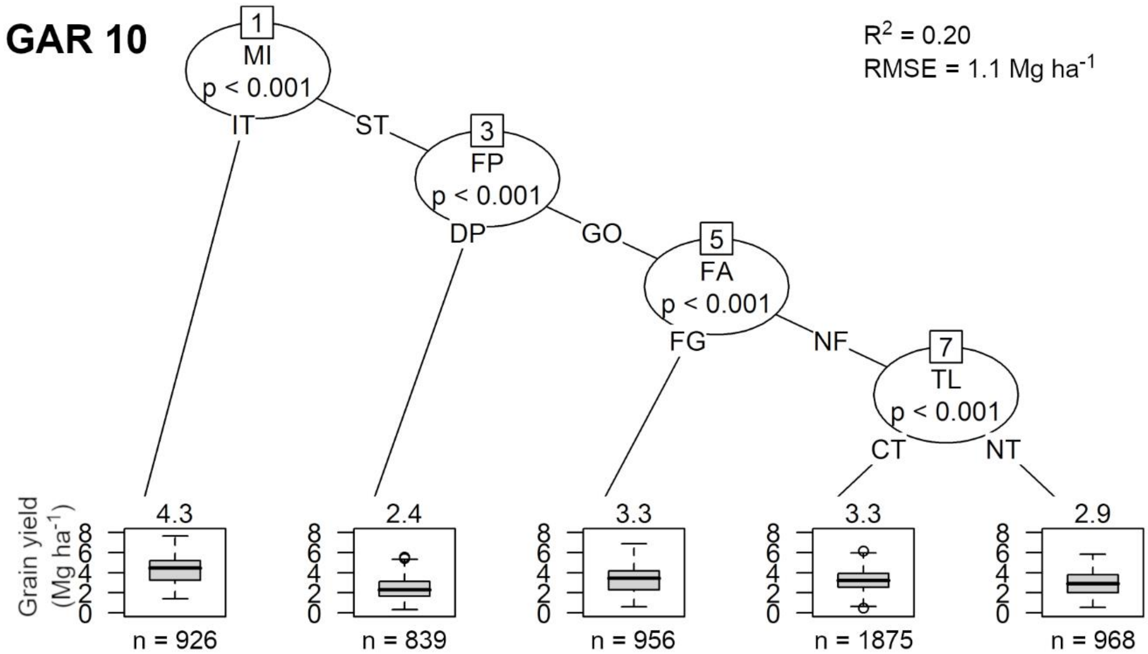

Fig. 16. Conditional inference tree for grain yield in the growing adaptation region (GAR) 10 (shown in Fig. 2) as affected by management intensity (MI), final purpose of the trial (FP), fungicide application (FA), and tillage system (TL). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. IT, intensive management; ST, standard; DP, dual-purpose; GO, grain-purpose; FG, fungicide; NF, no fungicide; CT, conventional till; NT, no-till.

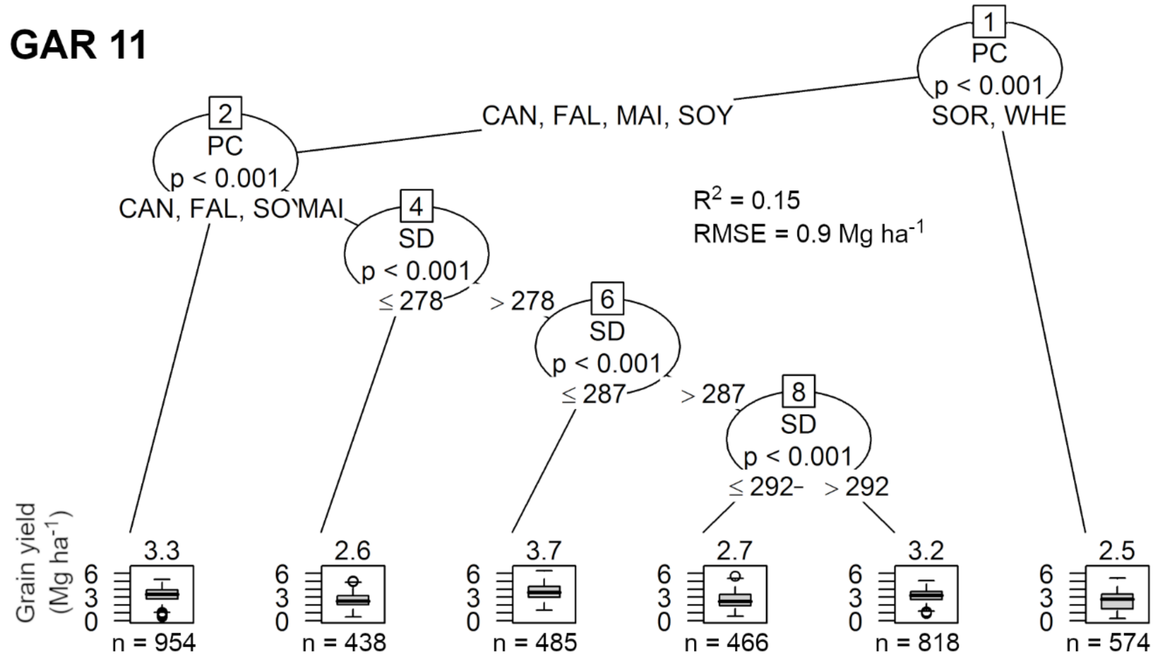

Fig. 17. Conditional inference tree for grain yield in the growing adaptation region (GAR) 11 (shown in Fig. 2) as affected by previous crop (PC), and sowing date (SD). The number in the small boxes indicate the sequence of the split with respective split significance (p) in the circle. Boxplots show data distribution in each terminal node. The average grain yield (shown on top of each boxplot), number of observations (n), and model fit statistics (R^2 and root mean square error, RMSE) are shown. CAN, canola; FAL, fallow; MAI, maize; SOY, soybean; SOR, sorghum; WHE, wheat.

We identified the optimum sowing date and the average daily loss of early and late sowing dates on grain yield (Table 5). The optimum sowing date ranged from day of the year 263 to 296 (i.e., Sep. 20th to Oct. 23th). Overall the average daily loss in yield were greater in early sown trials compared to late sown trials and ranged from 1-314 kg ha^{-1} d^{-1} for earlier sowing dates and from 8-93 kg ha^{-1} d^{-1} to late sowing dates. (Table 5). Other management practices influencing yield were previous crop, trial purpose, tillage system, and intensive management. The significance of the different management practices and their interactions depended on GAR.

Table 5. Summary of the boundary functions for grain yield for the growing adaptation regions (GAR) as affected by the sowing dates.

GAR	Optimum		Early sown		Late sown	
	Sowing date	Grain yield	Sowing date	Average daily loss	Sowing date	Average daily loss
	(DOY)	(kg ha^{-1})	(DOY)	(kg ha^{-1} d^{-1})	(DOY)	(kg ha^{-1} d^{-1})
Dryland						
1	266	6495	245	199	286	93
2	263	4911	251	139	325	40
3	269	4713	261	217	301	32
4	271	6904	265	314	295	44
5	272	6450	265	301	297	12
6	277	4648	255	81	319	34
7	276	3642	260	1	326	8
8	283	5845	276	198	322	83
9	284	4793	244	84	323	42
10	296	4803	252	44	327	46
11	283	4680	273	13	325	31
Irrigated						
1	278	8323	253	45	296	16
2	272	7050	260	175	302	11
3	290	6116	246	28	290	0

4.4. Association of genotype traits with winter wheat grain yield

Identifying variety traits associated with higher wheat yields within the combination of GAR by the first management practice split required 22 conditional inference trees (Appendix A). The variety traits per se captured between 1 to 20% of total Z-score variability (i.e., R^2) within the GAR's most important management practice. Reaction to stripe rust was the variety characteristic with higher frequency of significant effect on Z-score, as it was significant in 16 of the 22 trees (Fig. 18). Other variety traits often associated with Z-score were coleoptile length, winterhardiness, plant height, straw strength, acid soil tolerance, drought tolerance, and heading date (significant in five to eight out of the 22 trees) (Fig. 18). While these traits were often related to wheat yield, the specific traits of importance were specific to each GAR and depended on the first split in the trees for management practices, reflecting genotype × management interactions.

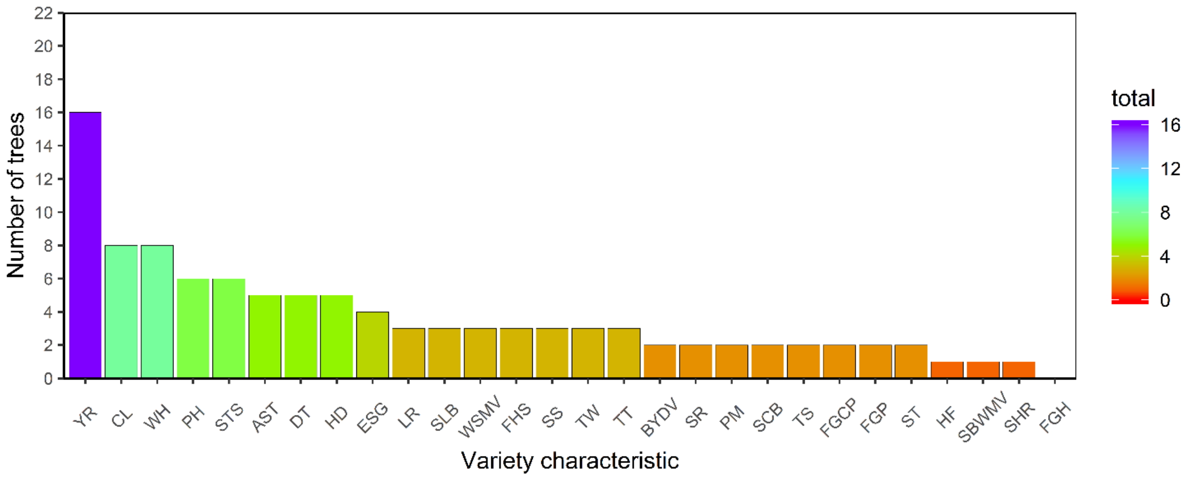

Fig. 18. Frequency of significance of each variety characteristic in the conditional inference trees across all 22 models built resulting from the combination of 11 growing adaptation regions (GAR) and the first management practice split. YR, Stripe rust (*Puccinia striiformis*); CL, Coleoptile length; WH, Winterhardiness; PH, Plant height; STS, Straw strength; AST, Acid soil tolerance; DT, Drought tolerance; HD, Heading date; ESG, Early spring greenup; LR, Leaf rust (*Puccinia triticina*); SLB, Septoria leaf blotch (*Mycosphaerella graminicola*); WSMV, Wheat streak mosaic virus; FHS, First hollow stem; SS, Seed size tendency; TW, Test weight; TT, Tillering tendency; BYDV, Barley yellow dwarf virus; SR, Stem rust (*Puccinia graminis*); PM, Powdery mildew (*Blumeria graminis*); SCB, Head blight (*Fusarium graminearum*); TS, Tan spot (*Pyrenophora tritici-repentis*); FGCP, Fall ground cover potential; FGP, Fall grazing potential; ST, Spouting tolerance; HF, Hessian fly (*Mayetiola destructor*); SBWMV, Soil-borne mosaic virus; SHR, Shattering reputation; FGH, Fall growth habit.

Similarly to the management practices analysis, we will describe GAR 1 as an example for the semi-arid wheat growing region and GAR 9 as an example for the subhumid wheat growing region (Table 6), while results for the remaining regions are shown in Appendix A. In GAR 1, the genotype trait analyses were performed separately for dryland and irrigated trials. In dryland trials, drought tolerance was the most important variable and, on average, varieties with good drought tolerance, long or short coleoptile, and intermediate time for first hollow stem presented the highest Z-score (Z

= 0.11) (Table 6). Meanwhile, varieties with intermediate or poor drought tolerance and intermediate to susceptible reaction to stripe rust resulted in the lowest Z-score (Z = -0.19).

Table 6. Summary of conditional inference trees for Z-score for the growing adaptation regions (GAR) 1 and 9 and its corresponding main management practice effect, as affected by the genotype traits. The Z-score and number of observations (n) of each terminal node, as well as fit statistics (R^2 and root mean square error, RMSE) are shown.

GAR (main effect)	Node 1	Node 2	Node 3	Node 4	Z-score	n	R^2	RMSE (score)
1 (DR)[a]	DT (g)	CL (i)			-0.05	1937	0.01	0.98
		CL (l, s)	FHS (e, l)		0.08	1744		
			FHS (i)		0.11	1722		
	DT (i, p)	YR ≤ 3			-0.19	1360		
		YR > 3			0.04	2204		
1 (IR)	YR ≤ 3	ESG (e, i)	SS (i, s)		-0.14	581	0.04	0.97
			SS (l)		-0.03	380		
		ESG (l)			-0.16	516		
	YR > 3	CL (i, l)	STS (g)	YR ≤ 4	0.21	466		
				YR > 4	0.45	303		
			STS (i, p)		-0.03	394		
		CL (s)			-0.08	371		
9 (FG)	DT (g)	AST (i, s)			0.29	486	0.05	0.97
		AST (t)	PH (i)		0.09	479		
			PH (s, t)		0.14	280		
	DT (i, p)	WH (g, i)	YR ≤ 4		-0.10	465		
			YR > 4		0.19	295		
		WH (p)			-0.30	572		
9 (NF)	YR ≤ 2	FGP (g, i)			-0.26	1802	0.04	0.97
		FGP (p)			-0.18	1565		
	YR > 2	BYDV ≤ 2	WH (g)		0.14	1919		
			WH (i, p)	WSMV ≤ 2	-0.14	2080		
				WSMV > 2	0.04	1789		
		BYDV > 2	WH (g, i)		0.32	1966		
			WH (p)		0.10	2136		

[a] AST, acid soil tolerance (s, susceptible; i, intermediate; t, tolerant); BYDV, barley yellow dwarf virus; CL, coleoptile length (s, short; i, intermediate; l, long); DR, dryland; DT, drought tolerance (p, poor; i, intermediate; g, good); ESG, early spring greenup (e, early; i, intermediate; l, late); FG, fungicide; FGP, fall grazing potential (p, poor; i, intermediate; g, good); FHS, first hollow stem (e, early; i, intermediate; l, late); IR, irrigated; NF, no-fungicide; PH, plant height (s, short; i, intermediate; t, tall); SS, seed size tendency (s, small; i, intermediate; l, large); STS, straw strength (p, poor; i, intermediate; g, good); WH, winterhardiness (p, poor; i, intermediate; g, good); WSMV, wheat streak mosaic virus; YR, stripe rust (*Puccinia striiformis*).

On the other hand, genetic resistance to stripe rust was the most important variable in irrigated trials in GAR 1. Varieties resistant to stripe rust, with intermediate or long coleoptile and good straw strength resulted in the highest Z-score (Z = 0.45); while varieties with an intermediate reaction or susceptibility to stripe rust with late early-season growth resulted in the lowest Z-score (Z = -0.16). In GAR 9 (subhumid wheat growing region), drought tolerance was the most important factor influencing yield in trials in which foliar fungicide was applied, as varieties with good drought tolerance and intermediate or susceptible reaction to acid soils showed higher Z-score

(Z = 0.29) (Table 6). Meanwhile, in trials without foliar fungicide, the highest Z-score was obtained by varieties with intermediate to resistant reaction to stripe rust and barley yellow dwarf virus, and with intermediate or good winterhardiness (Z = 0.32).

5. DISCUSSION

5.1. Division of large agricultural regions into smaller homogenous domains

Subdivision of large geographies into smaller and uniform domains is usually performed in agricultural research spanning large regions (Graybosch, 2017; Peterson, 1992; Rattalino Edreira et al., 2018; van Wart et al., 2013). An appropriate extrapolation domain should be small enough to minimize variation in climate and management practices within the domain, and large enough to minimize data collection requirements (van Wart et al., 2013). The GAR scheme we created accomplished these characteristics, as it minimized the variation in climate and management practices within each domain. While the GAR scheme captured broad-scale spatial autocorrelation well (Hefley et al., 2017), we acknowledge that sowing dates still vary slightly within GAR due to within-GAR weather variability. While local-scale autocorrelation could still, to some extent, influence our results, there were no significant longitudinal or latitudinal trends in sowing date in nine and seven of the eleven GAR, respectively (data not shown). In addition, the R^2 for longitudinal and latitudinal trends in sowing date within GAR were low (i.e., 0.00-0.12 and 0.01-0.22, respectively), reinforcing that the local-scale autocorrelation effect should be minimal.

The GAR scheme is similar to the climate zone (CZ) scheme (van Wart et al., 2013). However, the CZ scheme considers three categorical variables (i.e., growing degree-days, temperature seasonality, and annual aridity index) and uses data for the entire continental U.S. rather than weather data from stations strictly located within the study region. Other authors expanded on the CZ to also consider the root zone plant-available water holding capacity [i.e., the Technology Extrapolation Domains (TED), Rattalino Edreira et al., 2018]. While the TED scheme could improve the analysis of agronomic data by considering soil characteristics (Rattalino Edreira et al., 2018), the extremely variable nature of the soils in the southern and central Great Plains would result in a large number of domains and, consequently, reduce the number of observations within each domain and the power of the analysis (data not shown). An alternative method to a meteorological determination of agricultural domains is the use of yield ranking from wheat breeding lines across locations (Graybosch, 2017; Peterson, 1992). Typically, this regional characterization results in larger domains as those produced by GAR, CZ, or TED, which would not effectively account for the differences in management practices in our study (e.g., sowing date, Appendix A).

5.2. Genotype effect on grain yield variability

The genotype effect accounted for a relatively low proportion of the total grain yield variability, which is similar to other published results evaluating released wheat cultivars. For instance, Friesen et al. (2016) evaluated spring wheat cultivars across Manitoba (Canada) over 10 years and reported that the genotype and all its interactions accounted for less than 10% of the yield variance. The authors suggested the low genotype effect may be explained by the cultivar development/registration trials and the strict scrutiny to commercialization (i.e., only well adapted cultivars with good performance record are released). Additionally, cultivars entered in the VPT are typically well adapted to the region, artificially minimizing the overall genotypic effect on yield variability. Several other studies using performance data from wheat registration process in different countries suggested a relatively low explanatory power from the genotype effect [i.e., 6 to 35% in Brazil (Munaro et al., 2014; Woyann et al., 2019); 0 to 8% in Australia (Cullis et al., 2000); 0 to 33% in Canada (Finlay et al., 2007); and 1.3% in Iran (Mohammadi et al., 2010)]. These results do not undermine the relevance of breeding programs; instead, they suggest that the contribution of the genotype effect to the total variance on wheat grain yield is dependent on the variability remaining of the genotypes tested in the variety performance trials after the selection and release process. Our results also highlight the need for local breeding efforts due to the diversity of weather conditions and disease/insect problems, as the explanatory power of genotype traits increased within the GAR × management practice combination.

5.3. Effects of management practices on wheat grain yield

Management practices accounted for the highest yield variability within GAR, suggesting that improved agronomy has the potential to increase regional wheat yield and contribute to food security. Water regime, sowing date, and foliar fungicides were among the management practices more consistently associated with wheat yields, depending on the domain evaluated. Irrigation increased wheat grain yield in 52-76% in the western, semi-arid portion of the studied region. Likewise, Holman et al. (2011) suggested a 1.2 Mg ha^{-1} increase in wheat yield due to supplementary irrigation when evaluating 56 years of VPT data in western Kansas. These yield gains likely resulted from the high influence of precipitation on the long-term dryland wheat yields in this semi-arid region (i.e., water supply accounting for as much as 83% of variability in water-limited yield; Lollato et al., 2017). Sowing date also consistently influenced grain yield and the quadratic yield response to sowing date is due to different yield-reducing factors (Sacks et al., 2010). Early sowing might limit yield due to i) increased exposure to insect pests (Schmid et al., 2019) that might transmit viral diseases (Wibberley, 1989; Wiersma et al., 2006); ii) decreased germination due to high soil temperatures (Smith, 1995); and iii) excessive fall growth and non-productive water and N consumption (Herwaarden et al., 1998). Yield-limiting factors for late sown winter wheat include i) a decreased fall tillering potential (Dahlke et al., 1993) requiring increased seeding rates (Staggenborg et al., 2003); ii) insufficient root growth in the fall, increasing the chances of water deficit and winterkill (Hammon et al., 1999); and iii) insufficient time for full vernalization (Wiersma et al., 2006). Foliar fungicide applied around heading was an important practice positively associated with yield, similar to previous reports from controlled replicated experiments (Jaenisch et al., 2019), yield contests in Kansas (Lollato et al., 2018), and field experiments in Oklahoma (Edwards et al., 2012; Puppala et al., 1998).

Tillage practices and previous crop also had high relative importance influencing wheat yields when the data were available. Tillage practices and previous crop were also significant factors in the analysis of producer-reported yields in the region (Lollato et al., 2018). No-till was associated with increased yields in the west-central region (GAR 6) and reduced wheat yields in the southern portion of the studied region (GAR 7 and 10). Increased yields in GAR 6 from no-till might result from a greater yield stability (Giller et al., 2015) or greater soil moisture conservation (Farahani et al., 1998) of wheat grown under no-till in semi-arid regions. Meanwhile, studies in Oklahoma suggested a yield penalty to continuous no-till wheat fields (i.e., fields that lack crop rotation; Decker et al., 2009), typically adopted in the trials in GAR 7 and 10. Continuous wheat cropping might partially justify the negative association of no-till and wheat yields, as well as the low rate of adoption of no-till in the southern portion of the study region (Patrignani et al., 2012). The benefits of no-tillage practices to semi-arid regions in which crop rotations are adopted is otherwise well reported (Amato et al., 2013; Pittelkow et al., 2015; Toliver et al., 2012). Other results, although more restricted geographically, were also in agreement with the literature. For example, dual-purpose management typically reduced wheat yield in as much as 27% in our study. Similar yield penalties from grazing the winter wheat crop were reported in the region (Edwards et al., 2011).

5.4. Genotype traits to improve wheat variety selection

Genetic resistance to stripe rust was the characteristic most often positively related to wheat yields. The U.S. central Great Plains experienced a series of stripe rust epidemics during the studied years (Chen et al., 2010, 2002; DeWolf, 2018; Jaenisch et al., 2019; Lollato et al., 2018), with production losses due to the disease ranging from 3 to 10.6% depending on state in a given year (Chen, 2007) and as great as 15.4% in Kansas in 2015 (Hollandbeck et al., 2016). Selecting varieties with inherent disease resistance is the most effective and economical way to control stripe rust (Chen, 2014, 2005), although evolution of the stripe rust pathogen (Wan et al., 2016) can render certain varieties susceptible and decrease their commercial life (Perronne et al., 2017). In the case of the appearance of new virulent races, foliar fungicides are effective to control stripe rust when applied in the right stage of development (Chen, 2014; Cruppe et al., 2017; Edwards et al., 2012). Evidence suggests, though, that wheat yield response to foliar fungicides is not restricted to susceptible cultivars (Edwards et al., 2012).

Varieties with good drought tolerance also showed a positive association with higher Z-scores and its significance depended on the region and management practices. This finding is in agreement with previous simulation studies suggesting that water supply was the variable accounting for the greatest proportion of the wheat yield potential under dryland conditions in the western portion of the U.S. central Great Plains (Lollato et al., 2017). Likewise, Holman et al. (2011) suggested the need to improve wheat variety drought tolerance to increase wheat yields in western Kansas. The physiological mechanisms conferring drought tolerance to different wheat varieties are genotype-specific and might be different depending on wheat growing region. Field and greenhouse studies in the U.S. Great Plains suggested that the increased grain yield of more drought-adapted cultivars resulted from greater water use and greater biomass production under drought stress when compared to less drought-tolerant cultivars (Reddy et al., 2014; Xue et al., 2014). Additionally, genotypic differences exist for root traits in winter wheat genotypes grown in the study region (Awad et al., 2018) and other areas (Aziz et al., 2017), which might help confer drought tolerance to winter wheat (Sciarresi et al., 2019).

Acidic soils are a growing concern for wheat production in the central region of the U.S. Great Plains (Johnson et al., 1997; Lollato et al., 2013). Previous studies suggested that varieties more tolerant to low soil pH usually outperform susceptible ones in acidic soil conditions (Johnson et al., 1997; Kariuki et al., 2007; Lollato et al., 2019b). Thus, considerable efforts have been made for breeding acidic soil tolerant cultivars in the region (Bona et al., 1994; Carver et al., 1988; Tang et al., 2002; Zhou et al., 2007). However, our results suggested that tolerant varieties presented lower Z-scores than intermediate and susceptible varieties. To better understand these results, we evaluated the soil pH values from GAR by management combinations where tolerance to acidic soils was significant. Soil pH values were only available for a subset of trials and varied from 6.0 to 7.3 (GAR 7), from 4.7 to 7.1 (GAR 9), and from 5.6 to 8.0 (GAR 10). Lollato et al. (2019b) identified wheat yield reduction when soil pH was lower than 4.8 for tolerant varieties and 5.8 for sensitive varieties (with similar thresholds identified by Kariuki et al., 2007). This suggests that, with few exceptions, the soil pH levels in the test locations were not low enough to cause injury in more susceptible varieties. While our data suggest that acidic-tolerant varieties have lower yield when soil pH is non-limiting, it does not allow inference as to whether this is a consequence of lower genetic yield gain when breeding for aluminum tolerance (which was not evidenced by Johnson et al., 1997) or whether the subset of varieties tolerant to acidic soils evaluated simply had poorer performance than the susceptible ones.

6. CONCLUSIONS

The approach we followed is generic enough that could benefit other crops and growing regions for which VPT are conducted. These results can help guide growers in better managing their crop and selecting varieties with appropriate characteristics for a given environment × management scenario, as well as help drive plant breeding programs on important genotypic traits for selection. While our analysis highlighted the importance of regional breeding programs releasing adapted varieties, most strikingly was the importance of management practices affecting wheat yield. These results support investment prioritization in both regional breeding programs (to continue releasing adapted cultivars with important traits of interest) and agronomic research and outreach (which proved to be a crucial portion of increasing yields in this study). Due to the nature of these datasets and analyses, results obtained here show associations between management practices or genotype traits with grain yield and do not allow derivation of cause-effect relationships. However, these results can help guide future and more specific controlled experiments testing cause-effect relationships among the different practices.

7. REFERENCES

Allen RG, Pereira LS, Raes D, Smith M (1998) **Crop evapotranspiration: guidelines for computing crop water requirements - FAO Irrigation and Drainage Paper No. 56**, FAO, Rome, Italy. 300p.

Amato G, Ruisi P, Frenda AS, Di Miceli G, Saia S, Plaia A, Giambalvo D (2013) Long-term tillage and crop sequence effects on wheat grain yield and quality. **Agronomy Journal** 105:1317-1327. https://doi.org/10.2134/agronj2013.0019

Andrade JF, Rattalino Edreira JI, Mourtzinis S, Conley SP, Ciampitti IA, Dunphy JE, Gaska JM, Glewen K, Holshouser DL, Kandel HJ, Kyveryga P, Lee CD, Licht MA, Lindsey LE, McClure MA, Naeve S, Nafziger ED, Orlowski JM, Ross J, Staton MJ, Thompson L, Specht JE, Grassini P (2019) Assessing the influence of row spacing on soybean yield using experimental and producer survey data. **Field Crops Research** 230:98-106. https://doi.org/10.1016/j.fcr.2018.10.014

Asseng S, Foster I, Turner NC (2011) The impact of temperature variability on wheat yields. **Global Change Biology** 17:997-1012. https://doi.org/10.1111/j.1365-2486.2010.02262.x

Awad W, Byrne PF, Reid SD, Comas LH, Haley SD (2018) Great Plains winter wheat varies for root length and diameter under drought stress. **Agronomy Journal** 110:226-235. https://doi.org/10.2134/agronj2017.07.0377

Aziz MM, Palta JA, Siddique KHM, Sadras VO (2017) Five decades of selection for yield reduced root length density and increased nitrogen uptake per unit root length in Australian wheat varieties. **Plant Soil** 413:181-192. https://doi.org/10.1007/s11104-016-3059-y

Barkley A, Tack J, Nalley LL, Bergtold J, Bowden R, Fritz A (2014) Weather, disease, and wheat breeding effects on Kansas wheat varietal yields, 1985 to 2011. **Agronomy Journal** 106:227-235. https://doi.org/10.2134/agronj2013.0388

Bates D, Mächler M, Zurich E, Bolker BM, Walker SC (2015) Fitting linear mixed-effects models using lme4. **Journal of Statistical Software** 67:1. https://doi.org/10.18637/jss.v067.i01

Bell MA, Fischer RA, Byerlee D, Sayre K (1995) Genetic and agronomic contributions to yield gains: A case study for wheat. **Field Crops Research** 44:55-65. https://doi.org/10.1016/0378-4290(95)00049-6

Bodirsky BL, Rolinski S, Biewald A, Weindl I, Popp A, Lotze-Campen H (2015) Global food demand scenarios for the 21st century. **PLOS ONE** 10:e0139201. https://doi.org/10.1371/journal.pone.0139201

Bona L, Carver BF, Wright RJ, Baligar VC (1994) Aluminum tolerance of segregating wheat populations in acidic soil and nutrient solutions. **Communications in Soil Science and Plant Analysis** 25:327-339. https://doi.org/10.1080/00103629409369040

Brancourt-Hulmel M, Doussinault G, Lecomte C, Bérard P, Le Buanec B, Trottet M (2003) Genetic improvement of agronomic traits of winter wheat cultivars released in France from 1946 to 1992. **Crop Science** 43:37-45. https://doi.org/10.2135/cropsci2003.3700

Brisson N, Gate P, Gouache D, Charmet G, Oury FX, Huard F (2010) Why are wheat yields stagnating in Europe? A comprehensive data analysis for France. **Field Crops Research** 119:201-212. https://doi.org/10.1016/j.fcr.2010.07.012

Brown M (2014) 5 steps to start data mining. **Computer Science**. Available at: < http://scitechconnect.elsevier.com/5-steps-start-data-mining/>. Access on: 23 January 2020.

Bushong JA, Griffith AP, Peeper TF, Epplin FM (2012) Continuous winter wheat versus a winter canola– winter wheat rotation. **Agronomy Journal** 104:324-330. https://doi.org/10.2134/agronj2011.0244

Carver BF, Inskeep WP, Wilson NP, Westerman RL (1988) Seedling tolerance to aluminum toxicity in hard red winter wheat germplasm. **Crop Science** 28:463-467. https://doi.org/10.2135/cropsci1988.0011183X002800030006x

Cassman KG (1999) Ecological intensification of cereal production systems: Yield potential, soil quality, and precision agriculture. **Proceedings of the National Academy of Sciences of the United States of America** 96:5952-5959. https://doi.org/10.1073/pnas.96.11.5952

Cassman KG, Dobermann A, Walters DT, Yang H (2003) Meeting cereal demand while protecting natural resources and improving environmental quality. **Annual Review of Environment and Resources** 28:315-358. https://doi.org/10.1146/annurev.energy.28.040202.122858

Cheadle C, Vawter MP, Freed WJ, Becker KG (2003) Analysis of microarray data using Z score transformation. **The Journal of Molecular Diagnostics** 5:73-81. https://doi.org/10.1016/S1525-1578(10)60455-2

Chen L, Sakaguchi T, Frolick MN (2000) Data Mining Methods, Applications, and Tools. **Information Systems Management** 17:65-70. https://doi.org/10.1201/1078/43190.17.1.20000101/31216.9

Chen X, Moore M, Milus EA, Long DL, Line RF, Marshall D, Jackson L (2002) Wheat stripe rust epidemics and races of *Puccinia striiformis* f. sp. *tritici* in the United States in 2000. **Plant Disease** 86:39-46. https://doi.org/10.1094/PDIS.2002.86.1.39

Chen X, Penman L, Anmin W, Cheng P (2010) Virulence races of *Puccinia striiformis* f. sp. *tritici* in 2006 and 2007 and development of wheat stripe rust and distributions, dynamics, and evolutionary relationships of races from 2000 to 2007 in the United States. **Canadian Journal of Plant Pathology** 32:315-333. https://doi.org/10.1080/07060661.2010.499271

Chen X (2014) Integration of cultivar resistance and fungicide application for control of wheat stripe rust. **Canadian Journal of Plant Pathology** 36:311-326. https://doi.org/10.1080/07060661.2014.924560

Chen X (2007) Challenges and solutions for stripe rust control in the United States. **Australian Journal of Agricultural Research** 58:648-655. https://doi.org/10.1071/AR07045

Chen X (2005) Epidemiology and control of stripe rust [*Puccinia striiformis* f. sp. *tritici*] on wheat. **Canadian Journal of Plant Pathology** 27:314-337. https://doi.org/10.1080/07060660509507230

Clark-Carter D (2014) Z scores, in: **Wiley StatsRef: Statistics Reference Online.** John Wiley & Sons, Ltd, Chichester, UK. https://doi.org/10.1002/9781118445112.stat06236

Conijn JG, Bindraban PS, Schröder JJ, Jongschaap ERR (2018) Can our global food system meet food demand within planetary boundaries? **Agriculture, Ecosystems & Environment** 251:244-256. https://doi.org/10.1016/j.agee.2017.06.001

Connor DJ, Loomis RS, Cassman KG (2011) **Crop Ecology: Productivity and Management in Agricultural Systems.** Cambridge Univ. Press, Cambridge, UK.

Cruppe G, Edwards JT, Lollato RP (2017) In-season canopy reflectance can aid fungicide and late-season nitrogen decisions on winter wheat. **Agronomy Journal** 109:2072-2086. https://doi.org/10.2134/agronj2016.12.0720

Cullis BR, Smith A, Hunt C, Gilmour A (2000) An examination of the efficiency of Australian crop variety evaluation programmes. **The Journal of Agricultural Science** 135:213-222. https://doi.org/10.1017/S0021859699008163

Dahlke BJ, Oplinger ES, Gaska JM, Martinka MJ (1993) Influence of planting date and seeding rate on winter wheat grain yield and yield components. **Journal of Production Agriculture** 6:408-414. https://doi.org/10.2134/jpa1993.0408

De'ath G (2007) Boosted trees for ecological modeling and prediction. **Ecology** 88:243-251. https://doi.org/https://doi.org/10.1890/0012-9658(2007)88[243:BTFEMA]2.0.CO;2

Decker JE, Epplin FM, Morley DL, Peeper TF (2009) Economics of five wheat production systems with no-till and conventional tillage. **Agronomy Journal** 101:364-372. https://doi.org/10.2134/agronj2008.0159

DeWolf E (2018) **Wheat stripe rust.** Kansas State University Agricultural Experiment Station and Cooperative Extension Service, EP-167, Manhattan, KS. Available at: <https://cottonwood.k-state.edu/crops-livestock/ag_articles/stacy_ag_articles/Wheat_Sripe_Rust.pdf>. Access on: 13 August 2019.

Edwards JT, Carver BF, Horn GW, Payton ME (2011) Impact of dual-purpose management on wheat grain yield. **Crop Science** 51:2181-2185. https://doi.org/10.2135/cropsci2011.01.0043

Edwards JT, Hunger RM, Payton ME (2012) Agronomic and economic response of hard red winter wheat to foliar fungicide in the Southern Plains. **Crop Management** 11:1. https://doi.org/10.1094/CM-2012-0730-01-RS

Ehmke L (2018) **Wheat varieties for Kansas and the Great Plains, 2019: your best choices.** 34 Star Publishing, Healy, KS.

Ehmke L (2017) **Wheat varieties for Kansas and the Great Plains, 2018: your best choices.** 34 Star Publishing, Healy, KS.

Ehmke L (2016) **Wheat varieties for Kansas and the Great Plains, 2017: your best choices.** 34 Star Publishing, Healy, KS.

Ehmke L (2015) **Wheat varieties for Kansas and the Great Plains, 2016: your best choices.** 34 Star Publishing, Healy, KS.

FAO (2019) **FAOSTAT 2019: FAO Statistical Databases.** Available at: <http://www.fao.org/faostat/en/#data>. Access on: 24 October 2019.

Farahani HJ, Peterson GA, Westfall DG, Sherrod LA, Ahuja LR (1998) Soil water storage in dryland cropping systems: The significance of cropping intensification. **Soil Science Society of America Journal** 62:984-991. https://doi.org/10.2136/sssaj1998.03615995006200040020x

Fayyad U, Djorgovski SG, Weir N (1996). Automating the analysis and cataloging of sky surveys. In.: Fayyad U, Piatetsky-Shapiro G, Smyth P, Uthurusamy R (Eds.) **Advances in Knowledge Discovery and Data Mining**. Cambridge, MA: MIT Press, p. 471-494.

Finlay GJ, Bullock PR, Sapirstein HD, Naeem HA, Hussain A, Angadi SV, DePauw RM (2007) Genotypic and environmental variation in grain, flour, dough and bread-making characteristics of western Canadian spring wheat. **Canadian Journal of Plant Science** 87:679-690. https://doi.org/10.4141/P06-150

Fischer RA (2007) Understanding the physiological basis of yield potential in wheat. **Journal of Agricultural Science** 145:99-113. https://doi.org/10.1017/S0021859607006843

Fischer T, Byerlee D, Edmeades G (2014) **Crop yields and global food security: Will yield increase continue to feed the world?** Australian Centre for International Agricultural Research. ACIAR Monographs, Canberra.

Foley JA, DeFries R, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ, Monfreda C, Patz JA, Prentice IC, Ramankutty N, Snyder PK (2005) Global consequences of land use. **Science** 309:570-574. https://doi.org/10.1126/science.1111772

French R, Schultz J (1984) Water use efficiency of wheat in a Mediterranean-type environment. I. The relation between yield, water use and climate. **Australian Journal of Agricultural Research** 35:743-764. https://doi.org/10.1071/AR9840743

Friesen LF, Brûlé-Babel AL, Crow GH, Rothenburger PA (2016) Mixed model and stability analysis of spring wheat genotype yield evaluation data from Manitoba, Canada. **Canadian Journal of Plant Science** 96:305-320. https://doi.org/10.1139/cjps-2015-0252

Gallagher J (1979) Field studies of cereal leaf growth: I. Initiation and expansion in relation to temperature and ontogeny. **Journal of Experimental Botany** 30:625-636.

Giller KE, Andersson JA, Corbeels M, Kirkegaard J, Mortensen D, Erenstein O, Vanlauwe B (2015) Beyond conservation agriculture. **Frontiers in Plant Science** 6:870. https://doi.org/10.3389/fpls.2015.00870

Godfray HCJ, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, Pretty J, Robinson S, Thomas SM, Toulmin C (2010) Food security: the challenge of feeding 9 billion people. **Science** 327:812-818. https://doi.org/10.1126/science.1185383

Grassini P, Eskridge KM, Cassman KG (2013) Distinguishing between yield advances and yield plateaus in historical crop production trends. **Nature Communications** 4:2918. https://doi.org/10.1038/ncomms3918

Grassini P, Thorburn J, Burr C, Cassman KG (2011) High-yield irrigated maize in the Western U.S. Corn Belt: I. On-farm yield, yield potential, and impact of agronomic practices. **Field Crops Research** 120:142-150. https://doi.org/10.1016/j.fcr.2010.09.012

Grassini P, Torrion JA, Yang HS, Rees J, Andersen D, Cassman KG, Specht JE (2015a) Soybean yield gaps and water productivity in the western U.S. Corn Belt. **Field Crops Research** 179:150-163. https://doi.org/10.1016/j.fcr.2015.04.015

Grassini P, van Bussel LGJ, Van Wart J, Wolf J, Claessens L, Yang H, Boogaard H, de Groot H, van Ittersum MK, Cassman KG (2015b) How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. **Field Crops Research** 177:49-63. https://doi.org/10.1016/j.fcr.2015.03.004

Grassini P, Yang H, Cassman KG (2009) Limits to maize productivity in western Corn-Belt: A simulation analysis for fully irrigated and rainfed conditions. **Agricultural and Forest Meteorology** 149:1254-1265. https://doi.org/10.1016/j.agrformet.2009.02.012

Graybosch RA (2017) Similarities among test sites based on the performance of advanced breeding lines in the Great Plains hard winter wheat region. **Crop Science** 57:1447-1454. https://doi.org/10.2135/cropsci2016.08.0708

Greenwell B, Boehmke B, Cunningham J, Developers GBM (2019) **gbm: Generalized boosted regression models.** Available at: <https://cran.r-project.org/web/packages/gbm/gbm.pdf>. Access on: 13 August 2019.

Hajjarpoor A, Soltani A, Zeinali E, Kashiri H, Aynehband A, Vadez V (2018) Using boundary line analysis to assess the on-farm crop yield gap of wheat. **Field Crops Research** 225:64-73. https://doi.org/10.1016/j.fcr.2018.06.003

Hammon RW, Sanford DV, Stack MW, Berrada A, Peairs F (1999) **Dryland winter wheat planting date and Russian wheat aphid studies in southwestern Colorado, 1990-1998**. Fort Collins, CO. Available at: <https://mountainscholar.org/handle/10217/39297?show=full>. Access on: 13 August 2019.

Hay R, Porter J (2006) **The Physiology of Crop Yield**. 2nd ed. Blackwell Publishing, Oxford, UK.

Hefley TJ, Broms KM, Brost BM, Buderman FE, Kay SL, Scharf HR, Tipton JR, Williams PJ, Hooten MB (2017) The basis function approach for modeling autocorrelation in ecological data. **Ecology** 98:632-646. https://doi.org/10.1002/ecy.1674

Herwaarden AF, van Farquhar GD, Angus JF, Richards RA, Howe GN (1998) “Haying-off”, the negative grain yield response of dryland wheat to nitrogen fertiliser. I. Biomass, grain yield, and water use. **Australian Journal of Agricultural Research** 49:1067-1082. https://doi.org/10.1071/A97039

Hinds M, Ciampitti IA, Assefa Y, Jeschke M, Vara Prasad PV, Bhalla G, Carter P, Schon R, Paszkiewicz S (2016) Yield responses to planting density for US modern corn hybrids: A synthesis-analysis. **Crop Science** 56:2802-2817. https://doi.org/10.2135/cropsci2016.04.0215

Hobbs PR, Sayre K, Gupta R (2008) The role of conservation agriculture in sustainable agriculture. **Philosophical Transactions of the Royal Society B: Biological Sciences** 363:543-555. https://doi.org/10.1098/rstb.2007.2169

Hochman Z, Gobbert D, Horan H (2017) Climate trends account for stalled wheat yields in Australia since 1990. **Global Change Biology** 23:2071-2081. https://doi.org/10.1111/gcb.13604

Hollandbeck GF, DeWolf E, Todd T, Bockus WW (2016) **Kansas wheat disease loss estimates.** Kansas cooperative plant disease survey report preliminary 2016. Available at: <https://www.agriculture.ks.gov/docs/default-source/pp-disease-reports-2012/kansas-wheat-yield-loss-report-2016.pdf?sfvrsn=0>. Access on: 13 August 2019.

Holman JD, Schlegel AJ, Thompson CR, Lingenfelser JE (2011) Influence of precipitation, temperature, and 56 years on winter wheat yields in western Kansas. **Crop Management** 10:1. https://doi.org/10.1094/CM-2011-1229-01-RS

Hothorn T, Hornik K, Zeileis A (2006) Unbiased recursive partitioning: A conditional inference framework. **Journal of Computational and Graphical Statistics** 15:651-674. https://doi.org/10.1198/106186006X133933

Hothorn, T., Zeileis, A., 2015. partykit: A Modular Toolkit for Recursive Partytioning in R. JMLR. 16, 3905-3909.

Huang X, Wang L, Yang L, Kravchenko AN (2008) Management effects on relationships of crop yields with topography represented by wetness index and precipitation. **Agronomy Journal** 100:1463-1471. https://doi.org/10.2134/agronj2007.0325

Ishii K, Sasaki M, Matsui M, Sakamoto S, Yamaji S, Hayashi N, Mori T, Kitagaki H, Hirono N, Mori E (2000) A diagnostic method for suspected Alzheimer's disease using $H_2{}^{15}O$ positron emission tomography perfusion Z score. **Neuroradiology** 42:787-794. https://doi.org/10.1007/s002340000404

Jaenisch BR (2017) **Plant population and fungicide economically reduce winter wheat yield gap in Kansas.** 127 p. Thesis (Master of Science) – Kansas State University, Manhattan, KS, US.

Jaenisch BR, de Oliveira Silva A, DeWolf E, Ruiz-Diaz DA, Lollato RP (2019) Plant population and fungicide economically reduced winter wheat yield gap in Kansas. **Agronomy Journal** 111:650-665. https://doi.org/10.2134/agronj2018.03.0223

Johnson J, Haley S, Jones S, Asfeld E, Meyer R, Trujillo W, Kaan D, Roesch K, Spring J, Larson J, Vigil M, Pettinger B, Gaines T, Westra E, Shelton C (2018) **Making better decisions - 2018 Colorado winter wheat variety performance trials.** Fort Collins, CO. Available at: <https://webdoc.agsci.colostate.edu/csucrops/reports/winterwheat/wheatreport_2019_WFD.pdf>. Access on: 13 August 2019.

Johnson JP, Carver BF, Baligar VC (1997) Productivity in Great Plains acid soils of wheat genotypes selected for aluminium tolerance. **Plant Soil** 188:101-106. https://doi.org/10.1023/A:1004268325067

Kaan DA, O’Brien DM, Burgener PA, Peterson GA, Westfall DG (2002) **An economic evaluation of alternative crop rotations compared to wheat-fallow in Northeastern Colorado**. Colorado State University Agricultural Experiment Station, TB02-1, Fort Collins. Available at: < https://webdoc.agsci.colostate.edu/aes/AES/pubs/pdf/tb02-1.pdf>. Access on: 6 November 2019.

Kariuki SK, Zhang H, Schroder JL, Edwards J, Payton M, Carver BF, Raun WR, Krenzer EG (2007) Hard red winter wheat cultivar responses to a pH and aluminum concentration gradient. **Agronomy Journal** 99:88-98. https://doi.org/10.2134/agronj2006.0128

Kaur G, Thelen KD, Nafziger ED, Ross WJ, Mourtzinis S, Lofton J, Lindsey LE, Niekamp J, Wiebold WJ, Kandel H, Vonk J, Holshouser D, Staton M, Roozeboom KL, Naeve SL, Conley SP, Orlowski JM, Lee CD, Casteel SN, Wortmann C, Shapiro CA (2017) Soybean response to nitrogen application across the United States: A synthesis-analysis. **Field Crops Research** 215:74-82. https://doi.org/10.1016/j.fcr.2017.09.035

Kolmer JA (1996) Genetics of resistance to wheat leaf rust. **Annual Review of Phytopathology** 34:435-455. https://doi.org/10.1146/annurev.phyto.34.1.435

Krivoruchko K (2012) **Empirical Bayesian Kriging Implemented in ArcGIS Geostatistical Analyst.** Available at: <https://www.esri.com/news/arcuser/1012/empirical-byesian-kriging.html>. Access on: 15 October 2019.

Lê Cao K-A, Rohart F, McHugh L, Korn O, Wells CA (2014) YuGene: A simple approach to scale gene expression data derived from different platforms for integrated analyses. **Genomics** 103:239-251. https://doi.org/10.1016/j.ygeno.2014.03.001

Liao S, Chu P, Hsiao P (2012) Data mining techniques and applications – A decade review from 2000 to 2011. **Expert Systems with Applications** 39:11303-11311. https://doi.org/10.1016/j.eswa.2012.02.063

Liao X, Meyer MC (2019) cgam: An R package for the constrained generalized additive model. **Journal of Statistical Software** 89:5. https://doi.org/10.18637/jss.v089.i05

Lin M, Huybers P (2012) Reckoning wheat yield trends. **Environmental Research Letters** 7:024016. https://doi.org/10.1088/1748-9326/7/2/024016

Lingenfelser J, Bockus B, DeWolf E, Fritz A, Lollato RP, Miller R, Whitworth J, Adee E, Cramer G, Esser A, Kimball J, Larson M, Evans P, Mengarelli L, Schlegel A, Seaman C, Zhang G, Chen M, Chen R, King A, Knopf J, Bonhert C (2016). **Kansas Performance Tests with Winter Wheat Varieties**. Kansas State University Agricultural Experiment Station and Cooperative Extension Service, SRP-1108. Manhattan, KS. Available at: <https://www.ksre.k-state.edu/historicpublications/pubs/SRP1108.pdf>. Access on: 5 Novembro 2019.

Lingenfelser J, Ciampitti I, Jardine D, Knapp M, Davis H, Whitworth J, Adee E, Esser A, Kimball J, Aiken R, Foster AJ, Martin R, Mengarelli L, Ostmeyer T, Sassenrath G, Sower N, Schlegel A (2018a) **2018 Kansas performance tests with corn hybrids.** Kansas State University Agricultural Experiment Station and Cooperative Extension Service, SRP-1145, Manhattan, KS. Available at: <https://www.bookstore.ksre.ksu.edu/pubs/SRP1145.pdf>. Access on: 13 August 2019.

Lingenfelser J, Davis H, DeWolf E, Fritz AK, Knapp M, Lollato RP, Regan R, Whitworth J (2018b) **2018 Kansas performance tests with winter wheat varieties**. Kansas State University Agricultural Experiment Station and Cooperative Extension Service, SRP-1143, Manhattan, KS. Available at: <https://www.bookstore.ksre.ksu.edu/pubs/SRP1143.pdf>. Access on: 13 August 2019.

Lingenfelser J, Schapaugh W, Hessel R, Aiken R, Coltrain J, Martin R, Mengarelli L, Sassenrath G, Adee E, Esser A, Kimball J, Egbert V, Rezac L, Roberds D, Short C (2019) **2018 Kansas performance tests with soybean varieties.** Kansas State University Agricultural Experiment Station and Cooperative Extension Service, SRP-1146, Manhattan, KS. Available at: <https://www.bookstore.ksre.ksu.edu/pubs/SRP1146.pdf>. Access on: 13 August 2019.

Lobell DB, Cassman KG, Field CB (2009) Crop yield gaps: their importance, magnitudes, and causes. **Annual Review of Environment and Resources** 34:179-204. https://doi.org/10.1146/annurev.environ.041008.093740

Lollato RP, Edwards JT (2015) Maximum attainable winter wheat yield and resource use efficiency in the southern Great Plains. **Crop Science** 55:2863-2876. https://doi:10.2135/cropsci2015.04.0215

Lollato RP, Edwards JT, Ochsner TE (2017) Meteorological limits to winter wheat productivity in the U.S. southern Great Plains. **Field Crops Research** 203:212-226. https://doi.org/10.1016/j.fcr.2016.12.014

Lollato RP, Edwards JT, Zhang H (2013) Effect of alternative soil acidity amelioration strategies on soil pH distribution and wheat agronomic response. **Soil Science Society of America Journal** 77:1831-1841. https://doi.org/10.2136/sssaj2013.04.0129

Lollato RP, Figueiredo BM, Dhillon JS, Arnall DB, Raun WR (2019a) Wheat grain yield and grain-nitrogen relationships as affected by N, P, and K fertilization: A synthesis of long-term experiments. **Field Crops Research** 236:42-57. https://doi.org/10.1016/j.fcr.2019.03.005

Lollato RP, Lollato MA, Edwards JT (2012) Soil organic carbon replenishment through long-term no-till on a Brazilian family farm. **Journal of Soil and Water Conservation** 67:74A-76A. https://doi.org/10.2489/jswc.67.3.74A

Lollato RP, Ochsner TE, Arnall DB, Griffin TW, Edwards JT (2019b) From field experiments to regional forecasts: Upscaling wheat grain and forage yield response to acidic soils. **Agronomy Journal** 111:287-302. https://doi.org/10.2134/agronj2018.03.0206

Lollato RP, Ruiz Diaz DA, DeWolf E, Knapp M, Peterson DE, Fritz AK (2018) Agronomic practices for reducing wheat yield gaps: A quantitative appraisal of progressive producers. **Crop Science** 59:333-350. https://doi.org/10.2135/cropsci2018.04.0249

Long NV, Assefa Y, Schwalbert R, Ciampitti IA (2017) Maize yield and planting date relationship: A synthesis-analysis for US high-yielding contest-winner and field research data. **Frontiers in Plant Science** 8:1-9. https://doi.org/10.3389/fpls.2017.02106

Marburger D, Calhoun R, Carver B, Hunger B, Watson B, Gillespie C (2018) **Oklahoma Small Grains Variety Performance Tests 2017-2018.** OSU Cooperative Extension Service Current Reports, CR-2141 and CR-2143, Stillwater, OK. Available at: <http://wheat.okstate.edu/2017-18-wheat-variety-trial-documents/2017-18-variety-testing/2017-2018-oklahoma-small-grains-variety-performance-tests-full-report>. Access on: 13 August 2019.

Mohammadi R, Haghparast R, Amri A, Ceccarelli S (2010) Yield stability of rainfed durum wheat and GGE biplot analysis of multi-environment trials. **Crop and Pasture Science** 61:92-101. https://doi.org/10.1071/CP09151

Mourtzinis S, Kyveryga PM, Mueller DS, Rattalino Edreira JI, Naeve SL, Staton MJ, Conley SP, Casteel SN, Nafziger ED, Kandel HJ, Licht MA, Grassini P, Roth AC, Stanley J, Ciampitti IA, Lindsey LE (2018) Sifting and winnowing: Analysis of farmer field data for soybean in the US North-Central region. **Field Crops Research** 221:130-141. https://doi.org/10.1016/j.fcr.2018.02.024

Mourtzinis S, Specht JE, Conley SP (2019) Defining optimal soybean sowing dates across the US. **Scientific Reports** 9:2800. https://doi.org/10.1038/s41598-019-38971-3

Munaro LB, Benin G, Marchioro VS, de Assis Franco F, Silva RR, da Silva CL, Beche E (2014) Brazilian spring wheat homogeneous adaptation regions can be dissected in major mega-environments. **Crop Science** 54:1374-1383. https://doi.org/10.2135/cropsci2013.06.0365

Musick JT, Jones OR, Stewart BA, Dusek DA (1994) Water-yield relationships for irrigated and dryland wheat in the US Southern Plains. **Agronomy Journal** 86:980-986. https://doi:10.2134/agronj1994.00021962008600060010x

Passioura JB, Angus JF (2010) Improving productivity of crops in water-limited environments. **Advances in Agronomy** 106:37-75. https://doi.org/10.1016/S0065-2113(10)06002-5

Patrignani A, Godsey CB, Ochsner TE, Edwards JT (2012) Soil water dynamics of conventional and no-till wheat in the southern Great Plains. **Soil Science Society of America Journal** 76:1768-1775. https://doi.org/10.2136/sssaj2012.0082

Patrignani A, Lollato RP, Ochsner TE, Godsey CB, Edwards JT (2014) Yield gap and production gap of rainfed winter wheat in the southern Great Plains. **Agronomy Journal** 106:1329-1339. https://doi.org/10.2134/agronj14.0011

Perronne R, Diguet S, Vallavieille-Pope C de, Leconte M, Enjalbert J (2017) A framework to characterize the commercial life cycle of crop varieties: Application to the case study of the influence of yellow rust epidemics on French bread wheat varieties. **Field Crops Research** 209:159-167. https://doi.org/10.1016/j.fcr.2017.05.008

Peterson JC (1992) Similarities among test sites based on cultivar performance in the hard red winter wheat region. **Crop Science** 32:907-912. https://doi.org/10.2135/cropsci1992.0011183X003200040014x

Pittelkow CM, Linquist BA, Lundy ME, Liang X, van Groenigen KJ, Lee J, van Gestel N, Six J, Venterea RT, van Kessel C (2015) When does no-till yield more? A global meta-analysis. **Field Crops Research** 183:156-168. https://doi.org/10.1016/j.fcr.2015.07.020

Prasad PVV, Ciampitti IA, Bradley P, Wright Y, Stamm M, Assefa Y, Young S, Foster C (2017) Major management factors determining spring and winter canola yield in North America. **Crop Science** 58:1-16. https://doi.org/10.2135/cropsci2017.02.0079

Puppala V, Herrman TJ, Bockus WW, Loughin TM (1998) Quality response of twelve hard red winter wheat cultivars to foliar disease across four locations in central Kansas. **Cereal Chemistry** 75:94-99. https://doi.org/10.1094/CCHEM.1998.75.1.94

Ramankutty N, Foley JA, Norman J, McSweeney K (2002) The global distribution of cultivable lands: Current patterns and sensitivity to possible climate change. **Global Ecology and Biogeography** 11:377-392. https://doi.org/10.1046/j.1466-822x.2002.00294.x

Rattalino Edreira JI, Cassman KG, Hochman Z, van Ittersum MK, van Bussel L, Claessens L, Grassini P (2018) Beyond the plot: Technology extrapolation domains for scaling out agronomic science. **Environmental Research Letters** 13:054027. https://doi.org/10.1088/1748-9326/aac092

Rattalino Edreira JI, Mourtzinis S, Conley SP, Roth AC, Ciampitti IA, Licht MA, Kandel H, Kyveryga PM, Lindsey LE, Mueller DS, Naeve SL, Nafziger E, Specht JE, Stanley J, Staton MJ, Grassini P (2017) Assessing causes of yield gaps in agricultural areas with diversity in climate and soils. **Agricultural and Forest Meteorology** 247:170-180. https://doi.org/10.1016/j.agrformet.2017.07.010

Rawson HM, Hindmarsh JH, Fischer RA, Stockman YM (1983) Changes in leaf photosynthesis with plant ontogeny and relationships with yield per ear in wheat cultivars and 120 progeny. **Functional Plant Biology** 10:503–514. https://doi.org/10.1071/PP9830503

Reddy SK, Liu S, Rudd JC, Xue Q, Payton P, Finlayson SA, Mahan J, Akhunova A, Holalu SV, Lu N (2014) Physiology and transcriptomics of water-deficit stress responses in wheat cultivars TAM 111 and TAM 112. **Journal of Plant Physiology** 171:1289-1298. https://doi.org/10.1016/j.jplph.2014.05.005

Sacks WJ, Deryng D, Foley JA, Ramankutty N (2010) Crop planting dates: an analysis of global patterns. **Global Ecology and Biogeography** 19:607-620. https://doi.org/10.1111/j.1466-8238.2010.00551.x

Sadras VO, Angus JF (2006) Benchmarking water-use efficiency of rainfed wheat in dry environments. **Australian Journal of Agricultural Research** 57:847-856.

Schmid RB, Hefley T, Lollato R, McCornack BP (2019) Landscape effects on Hessian fly, *Mayetiola destructor* (Diptera: Cecidomyiidae), distribution within six Kansas commercial wheat fields. **Agriculture, Ecosystems & Environment** 274:52-61. https://doi.org/10.1016/j.agee.2018.12.018

Schroder JL, Zhang H, Girma K, Raun WR, Penn CJ, Payton ME (2011) Soil acidification from long-term use of nitrogen fertilizers on winter wheat. **Soil Science Society of America Journal** 75:957-964. https://doi:10.2136/sssaj2010.0187

Schwalbert R, Amado TJC, Horbe TAN, Stefanello LO, Assefa Y, Prasad PVV, Rice CW, Ciampitti IA (2018) Corn yield response to plant density and nitrogen: Spatial models and yield distribution. **Agronomy Journal** 110:970-982. https://doi.org/10.2134/agronj2017.07.0425

Sciarresi C, Patrignani A, Soltani A, Sinclair TR, Lollato RP (2019) Plant traits to increase winter wheat yield in semiarid and subhumid environments. **Agronomy Journal** 111:1728-1740. https://doi.org/10.2134/agronj2018.12.0766

Sinclair TR (2013) Transpiration: moving from semi-empirical approaches to first principles. In: Fleisher, D. (Ed.), **Symposium—Improving Tools to Assess Climate Change Effects on Crop Response: Modeling Approaches and Applications: I.** ASA, CSSA, and SSSA. Tampa, FL, Available at: <https://dl.sciencesocieties.org/publications/meetings/2013am/11501>. Access on: 5 November 2019.

Six J, Feller C, Denef K, Ogle SM, de Moraes Sa JC, Albrecht A (2002) Soil organic matter, biota and aggregation in temperate and tropical soils: Effects of no-tillage. **Agronomie** 22:755-775. https://doi.org/10.1051/agro:2002043

Smith CW, (1995) **Crop production: Evolution, history, and technology.** John Wiley and Sons Inc., New York.

Sowmya R, Suneetha KR (2017) Data mining with big data. **11th International Conference on Intelligent Systems and Control (ISCO)**. https://doi.org/10.1109/isco.2017.7855990

Staggenborg SA, Whitney DA, Fjell DL, Shroyer JP (2003) Seeding and nitrogen rates required to optimize winter wheat yields following grain sorghum and soybean. **Agronomy Journal** 95:253-259. https://doi.org/10.2134/agronj2003.2530

Stone LR, Schlegel AJ (2010) Tillage and crop rotation phase effects on soil physical properties in the west-central Great Plains. **Agronomy Journal** 102:483-491. https://doi.org/10.2134/agronj2009.0123

Tack J, Barkley A, Hendricks N (2017a) Irrigation offsets wheat yield reductions from warming temperatures. **Environmental Research Letters** 12:114027. https://doi.org/10.1088/1748-9326/aa8d27

Tack J, Barkley A, Nalley LL (2015) Effect of warming temperatures on US wheat yields. **Proceedings of the National Academy of Sciences of the United States of America** 112:6931-6936. https://doi.org/10.1073/pnas.1415181112

Tack J, Lingenfelser J, Jagadish SVK (2017b) Disaggregating sorghum yield reductions under warming scenarios exposes narrow genetic diversity in US breeding programs. **Proceedings of the National Academy of Sciences of the United States of America** 114:9296-9301. https://doi.org/10.1073/pnas.1706383114

Tang Y, Garvin DF, Kochian LV, Sorrells ME, Carver BF (2002) Physiological genetics of aluminum tolerance in the wheat cultivar Atlas 66. **Crop Science** 42:1541-1546. https://doi.org/10.2135/cropsci2002.1541

Tasistro A, (2012) Use of boundary lines in field diagnosis and research for Mexican farmers. **Better Crops** 96:11-13.

Thompson NM, Epplin FM, Edwards JT, Hunger RM (2014) Economics of foliar fungicides for hard red winter wheat in the USA southern Great Plains. **Crop Protection** 59:1-6. https://doi.org/10.1016/j.cropro.2014.01.009

Tilman D, Cassman KG, Matson PA, Naylor R, Polasky S (2002) Agricultural sustainability and intensive production practices. **Nature** 418:671-677. https://doi.org/10.1038/nature01014

Tittonell P, Shepherd KD, Vanlauwe B, Giller KE (2008) Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western Kenya-An application of classification and regression tree analysis. **Agriculture, Ecosystems & Environment** 123:137-150. https://doi.org/10.1016/j.agee.2007.05.005

Toliver DK, Larson JA, Roberts RK, English BC, De La Torre Ugarte DG, West TO (2012) Effects of no-till on yields as influenced by crop and environmental factors. **Agronomy Journal** 104:530-541. https://doi.org/10.2134/agronj2011.0291

USDA-NASS, 2019. **United States Department of Agriculture - National Agricultural Statistics Service.** Available at: <https://www.nass.usda.gov/Quick_Stats/Lite/index.php>. Access on: 5 November 2019.

USDA-NASS, 2017. **2017 Cropland data layer - United States Department of Agriculture - National Agricultural Statistics Service.** Available at: <https://www.nass.usda.gov/Research_and_Science/Cropland/Release/index.php>. Access on: 15 October 2018.

van Ittersum MK, Cassman KG, Grassini P, Wolf J, Tittonell P, Hochman Z (2013) Yield gap analysis with local to global relevance - A review. **Field Crops Research** 143:4-17. https://doi.org/10.1016/j.fcr.2012.09.009

van Rees H, McClelland T, Hochman Z, Carberry P, Hunt J, Huth N, Holzworth D (2014) Leading farmers in south east Australia have closed the exploitable wheat yield gap: Prospects for further improvement. **Field Crops Research** 164:1-11. https://doi.org/10.1016/j.fcr.2014.04.018

van Wart J, van Bussel LGJ, Wolf J, Licker R, Grassini P, Nelson A, Boogaard H, Gerber J, Mueller ND, Claessens L, van Ittersum MK, Cassman KG (2013) Use of agro-climatic zones to upscale simulated crop yield potential. **Field Crops Research** 143:44-55. https://doi.org/10.1016/j.fcr.2012.11.023

Villamil MB, Davis VM, Nafziger ED (2012) Estimating factor contributions to soybean yield from farm field data. **Agronomy Journal** 104:881-887. https://doi.org/10.2134/agronj2012.0018n

Wan A, Chen X, Yuen J (2016) Races of *Puccinia striiformis* f. sp. *tritici* in the United States in 2011 and 2012 and comparison with races in 2010. **Plant Disease** 100:966-975. https://doi.org/10.1094/PDIS-10-15-1122-RE

Watson S (2014) **Wheat varieties for Kansas and the Great Plains, 2015: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2013) **Wheat varieties for Kansas and the Great Plains, 2014: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2012) **Wheat varieties for Kansas and the Great Plains, 2013: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2011) **Wheat varieties for Kansas and the Great Plains, 2012: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2010) **Wheat varieties for Kansas and the Great Plains, 2011: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2009) **Wheat varieties for Kansas and the Great Plains, 2010: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2008) **Wheat varieties for Kansas and the Great Plains, 2009: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2007) **Wheat varieties for Kansas and the Great Plains, 2008: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2006) **Wheat varieties for Kansas and the Great Plains, 2007: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2005) **Wheat varieties for Kansas and the Great Plains, 2006: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2004) **Wheat varieties for Kansas and the Great Plains, 2005: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2003) **Wheat varieties for Kansas and the Great Plains, 2004: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2002) **Wheat varieties for Kansas and the Great Plains, 2003: your best choices.** Lone Tree Publishing, Topeka, KS.

Watson S (2000) **Wheat varieties for Kansas and the Great Plains, 2001: your best choices.** Lone Tree Publishing, Topeka, KS.

Weiss SH, Indurkhya N (1998). **Predictive Data Mining: A Practical Guide**. San Francisco, CA: Morgan Kaufmann Publishers.

Wibberley EJ (1989) **Cereal husbandry.** Farming Press Brooks, Ipswich.

Wiersma JJ, Durgan BR, Hollingsworth C, MacRae IV, Rehm G (2006) **Winter wheat in Minnesota.** University of Minnesota, Extension Service. Available at: <https://conservancy.umn.edu/handle/11299/191680>. Access on: 13 August 2019.

Wójcik-Gront E (2018) Variables influencing yield-scaled global warming potential and yield of winter wheat production. **Field Crops Research** 227:19-29. https://doi.org/10.1016/j.fcr.2018.07.015

Woyann LG, Zdziarski AD, Zanella R, Rosa AC, de Castro RL, Caierão E, Toigo MDC, Storck L, Wu J, Benin G (2019) Genetic gain over 30 years of spring wheat breeding in Brazil. **Crop Science** 59:2036:2015. https://doi.org/10.2135/cropsci2019.02.0136

Wu D, Yu Q, Lu C, Hengsdijk H (2006) Quantifying production potentials of winter wheat in the North China Plain. **European Journal of Agronomy** 24:226-235. https://doi.org/10.1016/j.eja.2005.06.001

Xue Q, Rudd JC, Liu S, Jessup KE, Devkota RN, Mahan J (2014) Yield determination and water-use efficiency of wheat under water-limited conditions in the U.S. southern High Plains. **Crop Science** 54:34-47. https://doi.org/10.2135/cropsci2013.02.0108

Zhou L-L, Bai G-H, Ma H-X, Carver BF (2007) Quantitative trait loci for aluminum resistance in wheat. **Molecular Breeding** 19:153-161. https://doi.org/10.1007/s11032-006-9054-x

APPENDICE

Appendix A. Summary of the conditional inference trees

Table A1. Summary of conditional inference trees for Z-score by growing adaptation region (GAR) and its corresponding main management effect, as affected by the genotype traits. The Z-score, number of observations (n) and R^2 are shown.

GAR (main effect)	Node 1	Node 2	Node 3	Node 4	Node 5	Z-score	*n*	R^2
1 (DR)[a]	DT (g)	CL (i)				-0.05	1937	0.01
		CL (l, s)	FHS (e, l)			0.08	1744	
			FHS (i)			0.11	1722	
	DT (i, p)	YR ≤ 3				-0.19	1360	
		YR > 3				0.04	2204	
1 (IR)	YR ≤ 3	ESG (e, i)	SS (i, s)			-0.14	581	0.04
			SS (l)			-0.03	380	
		ESG (l)				-0.16	516	
	YR > 3	CL (i, l)	STS (g)	YR ≤ 4		0.21	466	
				YR > 4		0.45	303	
			STS (i, p)			-0.03	394	
		CL (s)				-0.08	371	
2 (DR)	FHS (e)	AST (i, t)				-0.21	594	0.02
		AST (s)				0.04	782	
	FHS (i, l)	YR ≤ 3	TS ≤ 2			0.06	1002	
			TS > 2			-0.11	635	
		YR > 3	SLB ≤ 2			0.16	686	
			SLB > 2			0.16	914	
2 (IR)	WH (g, i)	CL (i, s)	TW (g)	YR ≤ 3		0.00	400	0.05
				YR > 3		0.24	335	
			TW (i, l)			-0.14	362	
		CL (l)	YR ≤ 3			0.11	275	
			YR > 3			0.43	242	
	WH (p)	TS ≤ 2				0.10	265	
		TS > 2				-0.27	425	
3 (DR)	CL (i, s)	TW (g)	STS (g, i)	HF ≤ 1		0.03	410	0.03
				HF > 1		-0.11	336	
			STS (p)			0.20	316	
		TW (i, l)	SHR (g)			-0.11	427	
			SHR (i, p)			-0.22	371	
	CL (l)	PM ≤ 3				0.09	579	
		PM > 3				0.24	473	
3 (IR)	YR ≤ 2	SLB ≤ 2				-0.03	215	0.04
		SLB > 2				-0.32	272	
	YR > 2	TT (g, p)	ST (g)			-0.06	338	
			ST (i, p)			0.12	343	
		TT (i)	BYDV ≤ 2			0.16	231	
			BYDV > 2			0.37	219	
4 (FAL, SOR)	YR ≤ 2	TT (g)				-0.17	763	0.05
		TT (i, p)				-0.38	426	
	YR > 2	YR ≤ 4	TT (g, p)			0.11	859	
			TT (i)			-0.05	715	
		YR > 4	PH (i)			0.48	376	
			PH (s, t)			0.10	632	
4 (MAI, WHE)	WH (g, i)	PM ≤ 3	YR ≤ 2			-0.36	63	0.07
			YR > 2	WH (g)		0.20	130	
				WH (i)		-0.33	81	
		PM > 3	HD (e)			0.04	95	
			HD (i, l)			0.17	62	
	WH (p)					0.33	114	

Continue

GAR (main effect)	Node 1	Node 2	Node 3	Node 4	Node 5	Z-score	*n*	R^2
5 (FG)	YR ≤ 1					-0.63	86	0.13
	YR > 1	STS (g)	CL (i, s)	SR ≤ 4		0.04	115	
				SR > 4		0.43	143	
			CL (l)			-0.03	110	
		STS (i, p)	BYDV ≤ 2			-0.46	76	
			BYDV > 2			0.08	79	
5 (NF)	YR ≤ 1					-0.29	307	0.05
	YR > 1	HD (e)	WH (g)			-0.21	275	
			WH (i, p)			-0.01	365	
		HD (i, l)	YR ≤ 4	FGP (g)		-0.19	255	
				FGP (i, p)		0.13	526	
			YR > 4			0.31	488	
6 (DP)	CL (i, l)	DT (g, i)	SCB ≤ 2			0.30	194	0.06
			SCB > 2			0.13	241	
		DT (p)				-0.12	141	
	CL (s)					-0.35	156	
6 (GO)	PH (i, s)	DT (g)	LR ≤ 2			-0.09	718	0.04
			LR > 2			0.19	477	
		DT (i, p)	STS (g)			-0.28	806	
			STS (i, p)			-0.09	727	
	PH (t)	YR ≤ 4				0.13	867	
		YR > 4				0.36	457	
7 (CT)	YR ≤ 2a	AST (i, t)				-0.51	220	0.09
		AST (s)				-0.05	239	
	YR > 2	WSMV ≤ 2	ESG (e, i)	WH (g, i)		-0.04	190	
				WH (p)		-0.15	312	
			ESG (l)			0.20	272	
		WSMV > 2	YR ≤ 4			0.02	230	
			YR > 4			0.54	222	
7 (NT)	ESG (e, l)	CL (i, s)	SBWMV ≤ 4			-0.05	39	0.14
			SBWMV > 4			0.43	74	
		CL (l)				-0.36	51	
	ESG (i)	FGCP (g)				-0.13	44	
		FGCP (i, p)				-0.65	28	
8 (FG)	HD (e)	TT (g)	ESG (e)			-0.30	140	0.06
			ESG (i, l)			-0.20	121	
		TT (i)				0.05	147	
	HD (i, l)	ST (g, p)	SR ≤ 4			0.24	134	
			SR > 4			-0.17	99	
		ST (i)	YR ≤ 4			0.37	152	
			YR > 4			0.06	95	
8 (NF)	LR ≤ 1					-0.26	650	0.04
	LR > 1	YR ≤ 1				-0.27	437	
		YR > 1	SLB ≤ 2	HD (e)		-0.01	514	
				HD (i, l)		-0.05	515	
			SLB > 2	PH (i, t)	DT (g, i)	0.27	925	
					DT (p)	0.11	469	
				PH (s)		-0.03	637	
9 (FG)	DT (g)	AST (i, s)				0.29	486	0.05
		AST (t)	PH (i)			0.09	479	
			PH (s, t)			0.14	280	
	DT (i, p)	WH (g, i)	YR ≤ 4			-0.10	465	
			YR > 4			0.19	295	
		WH (p)				-0.30	572	
9 (NF)	YR ≤ 2	FGP (g, i)				-0.26	1802	0.04
		FGP (p)				-0.18	1565	
	YR > 2	BYDV ≤ 2	WH (g)			0.14	1919	
			WH (i, p)	WSMV ≤ 2		-0.14	2080	
				WSMV > 2		0.04	1789	
		BYDV > 2	WH (g, i)			0.32	1966	
			WH (p)			0.10	2136	
10 (IT)	HD (e, i)	STS (g)	WH (g)			0.41	156	0.10
			WH (i, p)	HD (e)		0.29	114	
				HD (i)		-0.07	68	
		STS (i, p)	SS (i, s)			-0.28	114	
			SS (l)			0.16	89	
	HD (l)	AST (i, s)				-0.03	82	
		AST (t)				-0.59	71	

Continue

GAR (main effect)	Node 1	Node 2	Node 3	Node 4	Node 5	Z-score	*n*	R^2
10 (ST)	YR ≤ 2					-0.22	942	0.03
	YR > 2	FGCP (g, p)	PH (i, s)	FHS (e, l)		-0.07	900	
				FHS (i)		0.01	456	
			PH (t)			0.23	543	
		FGCP (i)				0.24	686	
11 (CAN, FAL, MAI, SOY)	WSMV ≤ 2	WH (g, i)	SS (i, s)			0.03	459	0.03
			SS (l)			0.28	377	
		WH (p)				-0.07	576	
	WSMV > 2	LR ≤ 2				-0.27	409	
		LR > 2				0.02	295	
11 (SOR, WHE)	TW (g)	SCB ≤ 2	CL (i, l)			-0.19	78	0.20
			CL (s)			-0.75	61	
		SCB > 2				-0.15	85	
	TW (i, l)	PH (i)				0.00	81	
		PH (s, t)	STS (g, p)			0.79	47	
			STS (i)			0.32	48	

[a] AST, acid soil tolerance (s, susceptible; i, intermediate; t, tolerant); BYDV, barley yellow dwarf virus; CAN, canola; CL, coleoptile length (s, short; i, intermediate; l, long); CT, conventional till; DP, dual-purpose; DR, dryland; DT, drought tolerance (p, poor; i, intermediate; g, good); ESG, early spring greenup (e, early; i, intermediate; l, late); FAL, fallow; FAL, fallow; FG, fungicide; FGCP, fall ground cover potential (p, poor; i, intermediate; g, good); FGH, fall growth habit (p, prostrate; i, intermediate; u, up); FGP, fall grazing potential (p, poor; i, intermediate; g, good); FHS, first hollow stem (e, early; i, intermediate; l, late); GO, grain-only; HD, heading date (e, early; i, intermediate; l, late); HF, hessian fly (*Mayetiola destructor*); IR, irrigated; IT, intensive management; LR, leaf rust (*Puccinia triticina*); MAI, maize; MAI, maize; NF, no-fungicide; NT, no-till; PH, plant height (s, short; i, intermediate; t, tall); PM, powdery mildew (*Blumeria graminis*); SBWMV, soil-borne mosaic virus; SCB, head scab blight (*Fusarium graminearum*); SHR, shattering reputation (p, poor; i, intermediate; g, good); SLB, septoria leaf blotch (*Mycosphaerella graminicola*); SOR, sorghum; SOR, sorghum; SOY, soybean; SR, stem rust (*Puccinia graminis*); SS, seed size tendency (s, small; i, intermediate; l, large); ST, spouting tolerance (p, poor; i, intermediate; g, good); ST, standard management; STS, straw strength (p, poor; i, intermediate; g, good); TS, tan spot (*Pyrenophora tritici-repentis*); TT, tillering tendency (p, poor; i, intermediate; g, good); TW, test weight (l, low; i, intermediate; g, good); WH, winterhardiness (p, poor; i, intermediate; g, good); WHE, wheat; WHE, wheat; WSMV, wheat streak mosaic virus; YR, stripe rust (*Puccinia striiformis*).