AI and Crop Improvement

true

June 2022

Abstract

Lorem ipsum dolor sit amet.

Contents

Example Section

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua

In-text reference to Fig. 1.

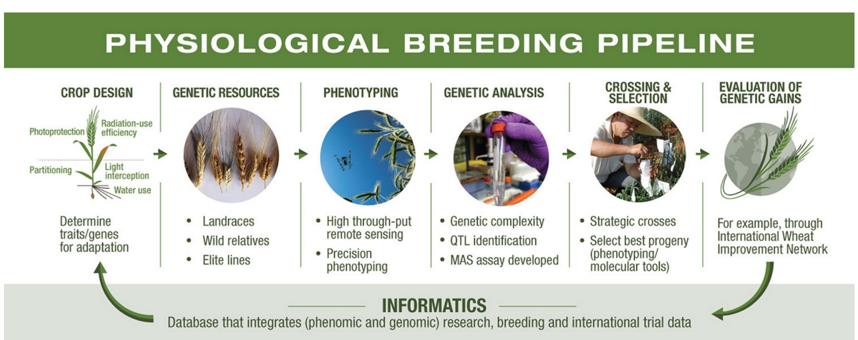

Figure 1: Caption.

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua citation (Duvick 2005). See sec.

Crop Improvement

To achieve a rate of yield increase that keeps pace with the growing world population, new approaches to crop improvement will be required.

Prior Progress

When comparing crop cultivars of a century ago and those of today, considerable differences are often observed. Improvements to yield, plant architecture, and biotic and abiotic resistances, among other traits, have been targeted by breeding and management strategies since the early part of the 20th century. Through the 1930s to 2000s, both breeding and cultural practices contributed considerably to increases in productivity as measured by average yield increases (Duvick 1999; Duvick 2005).

Conventional breeding took advantage of traditional phenotyping methods to inform crossing and selection.

With the increase in genetic technology availability and decrease in cost during the (1980s-2000s), targeted improvements through approaches such as marker assisted selection became feasible. Genetic improvement was seen as the new way forward in contrast to the plateauing gains made from cultural practices. Genetic data became abundant in the next-generation sequencing era. Earlier QTL studies have identified many loci with large contributions to highly heritable traits. Traits with unresolved genetic architecture, result from the contributions of many, small effect loci. QTL studies in such traits require extensive phenotyping and are often not stable across environment.

The "phenotyping bottleneck" issue has driven increased research on high throughput phenotyping (HTP) platforms and spurred in the generation of "big data" in many facets of crop improvement schemes.

Modern Crop Improvement

In recent years focus has returned to approaching crop improvement from all angles. An example of a breeding approach that integrates many different types of data is physiological breeding. Reynolds and Langridge (2016) break physiological breeding into 6 parts - crops design, genetic resource exploration, phenotyping, genetic analysis, hybridization and progeny selection, and genetic gain evaluation via multi-location testing. This framework helps describe the purpose of obtaining genomic, phenomic and enviromic data during the current breeding cycle and why dissection of traits, genetically and physiologically, is important for

AI

In recent years, Artificial intelligence (AI) has been increasingly explored as a means to analyze big data. Within crop improvement in the 2020s, the processes of genotyping, phenotyping, and envirotyping a single population can produce dramatically more data then was cumulatively obtained in the breeding process in previous decades. While bottlenecks of traditional methods have been overcome with higher levels of automation achieved with post-NGS sequencing technologies, HTP, and remote sensing, fully exploiting these data in an efficient manor is difficult with prior approaches. AI is most commonly applied through machine learning which includes such *technologies* as computer vision, neural networks, and deep learning, among others. Machine learning

References

Duvick DN (1999) Heterosis: feeding people and protecting natural resources. Genetics and exploitation of heterosis in crops 19–29

Duvick DN (2005) The Contribution of Breeding to Yield Advances in maize (Zea mays L.). In: Advances in agronomy. Academic Press, pp 83–145

Reynolds M, Langridge P (2016) Physiological breeding. Current Opinion in Plant Biology 31:162–171. https://doi.org/10.1016/j.pbi.2016.04.005