

Diego Jarquin

List of Publications by Year in descending order

Source: <https://exaly.com/author-pdf/4836472/publications.pdf>

Version: 2024-02-01

52
papers

3,428
citations

304743

22
h-index

175258

52
g-index

55
all docs

55
docs citations

55
times ranked

2934
citing authors

#	ARTICLE	IF	CITATIONS
1	Genomic Selection in Plant Breeding: Methods, Models, and Perspectives. Trends in Plant Science, 2017, 22, 961-975.	8.8	1,004
2	A reaction norm model for genomic selection using high-dimensional genomic and environmental data. Theoretical and Applied Genetics, 2014, 127, 595-607.	3.6	439
3	Genotyping by sequencing for genomic prediction in a soybean breeding population. BMC Genomics, 2014, 15, 740.	2.8	191
4	A Population Structure and Genome-Wide Association Analysis on the USDA Soybean Germplasm Collection. Plant Genome, 2015, 8, eplantgenome2015.04.0024.	2.8	174
5	Genomic Prediction of Gene Bank Wheat Landraces. G3: Genes, Genomes, Genetics, 2016, 6, 1819-1834.	1.8	159
6	Increasing Genomic-Enabled Prediction Accuracy by Modeling Genotype \times Environment Interactions in Kansas Wheat. Plant Genome, 2017, 10, plantgenome2016.12.0130.	2.8	107
7	A chickpea genetic variation map based on the sequencing of 3,366 genomes. Nature, 2021, 599, 622-627.	27.8	106
8	The effect of artificial selection on phenotypic plasticity in maize. Nature Communications, 2017, 8, 1348.	12.8	105
9	Genomic-Enabled Prediction in Maize Using Kernel Models with Genotype \times Environment Interaction. G3: Genes, Genomes, Genetics, 2017, 7, 1995-2014.	1.8	92
10	Prospects of Genomic Prediction in the USDA Soybean Germplasm Collection: Historical Data Creates Robust Models for Enhancing Selection of Accessions. G3: Genes, Genomes, Genetics, 2016, 6, 2329-2341.	1.8	90
11	Deep Kernel and Deep Learning for Genome-Based Prediction of Single Traits in Multienvironment Breeding Trials. Frontiers in Genetics, 2019, 10, 1168.	2.3	77
12	Genome-Wide Analysis of Grain Yield Stability and Environmental Interactions in a Multiparental Soybean Population. G3: Genes, Genomes, Genetics, 2018, 8, 519-529.	1.8	75
13	Genomic Selection in Preliminary Yield Trials in a Winter Wheat Breeding Program. G3: Genes, Genomes, Genetics, 2018, 8, 2735-2747.	1.8	74
14	Genomic Prediction Enhanced Sparse Testing for Multi-environment Trials. G3: Genes, Genomes, Genetics, 2020, 10, 2725-2739.	1.8	68
15	Genomic-enabled prediction models using multi-environment trials to estimate the effect of genotype \times environment interaction on prediction accuracy in chickpea. Scientific Reports, 2018, 8, 11701.	3.3	61
16	Genomic Prediction with Pedigree and Genotype \times Environment Interaction in Spring Wheat Grown in South and West Asia, North Africa, and Mexico. G3: Genes, Genomes, Genetics, 2017, 7, 481-495.	1.8	56
17	Utility of Climatic Information via Combining Ability Models to Improve Genomic Prediction for Yield Within the Genomes to Fields Maize Project. Frontiers in Genetics, 2020, 11, 592769.	2.3	44
18	A Genomic Selection Index Applied to Simulated and Real Data. G3: Genes, Genomes, Genetics, 2015, 5, 2155-2164.	1.8	42

#	ARTICLE	IF	CITATIONS
19	Bayesian Estimation of the Additive Main Effects and Multiplicative Interaction Model. <i>Crop Science</i> , 2011, 51, 1458-1469.	1.8	39
20	Genome-wide Association Mapping of Qualitatively Inherited Traits in a Germplasm Collection. <i>Plant Genome</i> , 2017, 10, plantgenome2016.06.0054.	2.8	37
21	Genomic-enabled Prediction Accuracies Increased by Modeling Genotype \times Environment Interaction in Durum Wheat. <i>Plant Genome</i> , 2018, 11, 170112.	2.8	31
22	Genome-based trait prediction in multi-environment breeding trials in groundnut. <i>Theoretical and Applied Genetics</i> , 2020, 133, 3101-3117.	3.6	29
23	A General Bayesian Estimation Method of Linear \times Bilinear Models Applied to Plant Breeding Trials With Genotype \times Environment Interaction. <i>Journal of Agricultural, Biological, and Environmental Statistics</i> , 2012, 17, 15-37.	1.4	24
24	Enhancing Hybrid Prediction in Pearl Millet Using Genomic and/or Multi-Environment Phenotypic Information of Inbreds. <i>Frontiers in Genetics</i> , 2019, 10, 1294.	2.3	23
25	Relative utility of agronomic, phenological, and morphological traits for assessing genotype \times environment interaction in maize inbreds. <i>Crop Science</i> , 2020, 60, 62-81.	1.8	21
26	Pedigree-Based Prediction Models with Genotype \times Environment Interaction in Multienvironment Trials of CIMMYT Wheat. <i>Crop Science</i> , 2017, 57, 1865-1880.	1.8	19
27	Increasing Predictive Ability by Modeling Interactions between Environments, Genotype and Canopy Coverage Image Data for Soybeans. <i>Agronomy</i> , 2018, 8, 51.	3.0	17
28	A Hierarchical Bayesian Estimation Model for Multienvironment Plant Breeding Trials in Successive Years. <i>Crop Science</i> , 2016, 56, 2260-2276.	1.8	16
29	Genome-enabled prediction for sparse testing in multi-environmental wheat trials. <i>Plant Genome</i> , 2021, 14, e20151.	2.8	15
30	Joint Use of Genome, Pedigree, and Their Interaction with Environment for Predicting the Performance of Wheat Lines in New Environments. <i>G3: Genes, Genomes, Genetics</i> , 2019, 9, 2925-2934.	1.8	13
31	Genomic Predictions for Common Bunt, FHB, Stripe Rust, Leaf Rust, and Leaf Spotting Resistance in Spring Wheat. <i>Genes</i> , 2022, 13, 565.	2.4	13
32	Genome and Environment-Based Prediction Models and Methods of Complex Traits Incorporating Genotype \times Environment Interaction. <i>Methods in Molecular Biology</i> , 2022, 2467, 245-283.	0.9	13
33	Interaction between FTO rs9939609 and the Native American-origin ABCA1 rs9282541 affects BMI in the admixed Mexican population. <i>BMC Medical Genetics</i> , 2017, 18, 46.	2.1	12
34	Response Surface Analysis of Genomic Prediction Accuracy Values Using Quality Control Covariates in Soybean. <i>Evolutionary Bioinformatics</i> , 2019, 15, 117693431983130.	1.2	12
35	An Assessment of the Factors Influencing the Prediction Accuracy of Genomic Prediction Models Across Multiple Environments. <i>Frontiers in Genetics</i> , 2021, 12, 689319.	2.3	12
36	Comparison of array- and sequencing-based markers for genome-wide association mapping and genomic prediction in spring wheat. <i>Crop Science</i> , 2020, 60, 211-225.	1.8	11

#	ARTICLE	IF	CITATIONS
37	Modeling spatial trends and enhancing genetic selection: An approach to soybean seed composition breeding. <i>Crop Science</i> , 2021, 61, 976-988.	1.8	11
38	Genomic Prediction Using Canopy Coverage Image and Genotypic Information in Soybean via a Hybrid Model. <i>Evolutionary Bioinformatics</i> , 2019, 15, 117693431984002.	1.2	10
39	Genome-Wide Association Mapping and Genomic Prediction of Anther Extrusion in CIMMYT Hybrid Wheat Breeding Program via Modeling Pedigree, Genomic Relationship, and Interaction With the Environment. <i>Frontiers in Genetics</i> , 2020, 11, 586687.	2.3	10
40	Genome-based prediction of agronomic traits in spring wheat under conventional and organic management systems. <i>Theoretical and Applied Genetics</i> , 2021, 135, 537.	3.6	10
41	Coupling day length data and genomic prediction tools for predicting time-related traits under complex scenarios. <i>Scientific Reports</i> , 2020, 10, 13382.	3.3	9
42	Use of family structure information in interaction with environments for leveraging genomic prediction models. <i>Crop Journal</i> , 2020, 8, 843-854.	5.2	8
43	Variance heterogeneity genome-wide mapping for cadmium in bread wheat reveals novel genomic loci and epistatic interactions. <i>Plant Genome</i> , 2020, 13, e20011.	2.8	8
44	Differentiate Soybean Response to Off-Target Dicamba Damage Based on UAV Imagery and Machine Learning. <i>Remote Sensing</i> , 2022, 14, 1618.	4.0	8
45	Genome-Wide Association and Gene Co-expression Network Analyses Reveal Complex Genetics of Resistance to Gossâ€™s Wilt of Maize. <i>G3: Genes, Genomes, Genetics</i> , 2019, 9, 3139-3152.	1.8	6
46	Prediction Strategies for Leveraging Information of Associated Traits under Single- and Multi-Trait Approaches in Soybeans. <i>Agriculture (Switzerland)</i> , 2020, 10, 308.	3.1	5
47	Development of a Genomic Prediction Pipeline for Maintaining Comparable Sample Sizes in Training and Testing Sets across Prediction Schemes Accounting for the Genotype-by-Environment Interaction. <i>Agriculture (Switzerland)</i> , 2021, 11, 932.	3.1	5
48	Climate and genetic data enhancement using deep learning analytics to improve maize yield predictability. <i>Journal of Experimental Botany</i> , 2022, 73, 5336-5354.	4.8	5
49	The use of high-throughput phenotyping in genomic selection context. <i>Crop Breeding and Applied Biotechnology</i> , 2021, 21, .	0.4	4
50	Genomic Prediction Accuracy of Stripe Rust in Six Spring Wheat Populations by Modeling Genotype by Environment Interaction. <i>Plants</i> , 2022, 11, 1736.	3.5	3
51	IBFIELDBOOK, AN INTEGRATED BREEDING FIELD BOOK FOR PLANT BREEDING. <i>Revista Fitotecnia Mexicana</i> , 2013, 36, 201.	0.1	2
52	Enhancing Genomic Prediction Models for Forecasting Days to Maturity in Soybean Genotypes Using Site-Specific and Cumulative Photoperiod Data. <i>Agriculture (Switzerland)</i> , 2022, 12, 545.	3.1	1