

1 **Mycorrhizal status impacts the genetic architecture of mineral accumulation in field**
2 **grown maize (*Zea mays* ssp. *mays* L.)**

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27

28 **SUMMARY**

29 Arbuscular mycorrhizal fungi (AMF) establish symbioses with major crop species, providing
30 their hosts with greater access to mineral nutrients and promoting tolerance to heavy metal

31 toxicity. There is considerable interest in AMF as biofertilizers and for their potential in
32 breeding for greater nutrient efficiency and stress tolerance. However, it remains a challenge
33 to estimate the nutritional benefits of AMF in the field, in part due to a lack of suitable AMF-
34 free controls. Here we evaluated the impact of AMF on the concentration of 20 elements in
35 the leaves and grain of field grown maize using a custom genetic mapping population in
36 which half of the families carry the AMF-incompatibility mutation *castor*. By comparing
37 AMF-compatible and AMF-incompatible families, we confirmed the benefits of AMF in
38 increasing the concentration of essential mineral nutrients (*e.g.*, P, Zn, and Cu) and reducing
39 the concentration of toxic elements (*e.g.*, Cd and As) in a medium-input subtropical field. We
40 characterised the genetic architecture of element concentration using quantitative trait
41 mapping and identified loci that were specific to AMF-compatible or AMF-incompatible
42 families, consistent with their respective involvement in mycorrhizal or direct nutrient
43 uptake. Patterns of element covariance changed depending on AMF status and could be used
44 to predict variation in mycorrhizal colonisation. We comment on the potential of AMF to
45 drive genotype-specific differences in the host ionome across fields and to impact the
46 alignment of biofortification breeding targets. Our results highlight the benefits of AMF in
47 improving plant access to micronutrients while protecting from heavy metals, and indicate
48 the potential benefits of considering AMF in biofortification programs.

49 **Key words:** arbuscular mycorrhizal fungi (AMF), AMF incompatible mutation, ionome,
50 maize, quantitative trait loci mapping, colonisation, biofortification

51

52 INTRODUCTION

53 Arbuscular mycorrhizal fungi (AMF) are a widely distributed group of soil fungi that form
54 mutualistic associations with more than 80% of terrestrial plant species including the major
55 staple crops (Wang & Qiu, 2006). One of the major benefits of AMF to hosts is enhanced
56 phosphorus (P) acquisition through an extensive root-external hyphal network that accounts
57 for up to 90% of the total P uptake (van der Heijden *et al.*, 2015). Arbuscular mycorrhizal
58 (AM) symbioses also play important roles in promoting the uptake of other macro- and
59 micronutrients such as N, S, Zn, and Cu, and mitigating the toxicity of heavy metals, such as
60 Cd, As, and Pb (Lehmann & Rillig, 2015; Ruytinx *et al.*, 2020). Previous studies have
61 reported that the nutritional benefits of AMF extend to the edible tissues of various crops
62 (Pellegrino & Bedini, 2014; Pepe *et al.*, 2022; Gupta *et al.*, 2022), suggesting the potential for

63 enhanced food quality and biofortification. Given the nutritional benefits provided by AMF,
64 there is a growing interest in breeding for more AMF-effective crops as a contribution to
65 enhanced plant nutrient use efficiency (Cobb *et al.*, 2021; Thirkell *et al.*, 2022). However,
66 although AM symbioses have been shown to be beneficial in many greenhouse studies, there
67 is a lack of support at the field scale due to environmental heterogeneity and the lack of non-
68 mycorrhizal controls (Ryan & Graham, 2018). In addition, the low heritability of AMF
69 colonisation and its inconsistent relationship with plant growth and nutrient content suggest
70 the need to search for more reliable breeding targets for AM fungal benefits (Leiser *et al.*,
71 2016; Feldmann, 2009).

72 Field evaluation of the nutritional benefits of AM symbioses is challenging, as it is
73 difficult to manipulate AM communities without changing other variables. Field inoculation
74 can be complicated by the presence of native fungal communities and is not cost-effective at
75 a large scale in many cropping systems (Ortas, 2012; Salomon *et al.*, 2022). Applying
76 fungicides to experimentally reduce the abundance of native AMF has limited effect and may
77 impact non-target fungal species, disrupting other biotic interactions and complicating the
78 interpretation of the results (Buysens *et al.*, 2015). Other strategies using agricultural
79 management practices to manipulate AM fungal communities, such as plant rotation with
80 non-host species or tillage, are confounded by other factors, such as soil water and nutrient
81 availability (Ryan & Graham, 2018). As a result, reported estimates of host nutritional
82 responses to AMF at the field scale vary widely (Lehmann *et al.*, 2014; Lehmann & Rillig,
83 2015). Comparing AMF-incompatible mutant plants to their AMF-compatible wild-type
84 siblings is an attractive complementary strategy to evaluate the impact of the AM symbiosis
85 under field conditions (Watts-Williams & Cavagnaro, 2015; Bowles *et al.*, 2016; Ryan &
86 Graham, 2018; Ramírez-Flores *et al.*, 2020).

87 Traditionally, studies of plant nutrition focused on different elements in isolation.
88 However, the accumulation of nutrients in plants is strongly influenced by the interactions
89 among elements, through soil chemistry, physiological disruption caused deficiency or
90 toxicity, and crosstalk among plant nutrient signalling pathways (Baxter, 2015). Profiling the
91 ionome, the complete set of mineral nutrients and trace elements in an organism (Lahner *et*
92 *al.*, 2003), provides an opportunity to comprehensively understand element accumulation and
93 patterns of interaction. AMF can improve the content of some nutrient elements, such as P,
94 by direct transportation through fungal networks (Chiu & Paszkowski, 2019). AMF can also

95 impact host nutrient status indirectly by altering root architecture or as a consequence of
96 alleviating primary deficiencies (Ramírez-Flores *et al.*, 2019). Indeed, the concentration of a
97 number of elements can be significantly changed in response to AMF inoculation (Hart &
98 Forsythe, 2012; Ramírez-Flores *et al.*, 2017). It is possible that the acquisition, translocation,
99 and homeostasis of one element may be affected by the capacity of plants to acquire other
100 nutrients directly or indirectly through AMF. The interplay between elements and AMF can
101 be further complicated by soil nutrient availability. As reviewed in a meta-analysis, AMF
102 increased tissue Cu, Mn, Fe and S levels under P deficiency, but not when P was sufficient
103 (Watts-Williams & Cavagnaro, 2014). Given the impact of complex interactions among
104 elements and AM symbiosis, it is informative to consider the ionome as a whole to fully
105 understand the nutritional benefits of AM symbiosis under field conditions.

106 Plant roots can take up nutrients directly from the soil (the *direct* pathway) or acquire
107 them via symbiosis with AMF (the *AMF* pathway; (Smith *et al.*, 2003)). In the case of P,
108 specific members of the PHT1 phosphate transporter family have been identified to be
109 involved in the direct and AMF pathways, their expression and accumulation patterns
110 responding to colonisation by AMF (Bucher, 2007; Chiu & Paszkowski, 2019; Salvioli di
111 Fossalunga & Novero, 2019). For example, MtPT4, OsPT11 and ZmPT6 accumulate
112 predominantly in the periarbuscular membrane surrounding arbuscules in *Medicago*
113 *truncatula*, rice and maize, respectively (Harrison *et al.*, 2002; Sawers *et al.*, 2017;
114 Paszkowski *et al.*, 2002; Willmann *et al.*, 2013; Fabiańska *et al.*, 2020). Conversely,
115 transporters implicated in direct P uptake are repressed in response to AMF (Bucher, 2007;
116 De Vita *et al.*, 2018). Although currently less well defined, analogous direct and AMF
117 pathways appear to also function in N uptake, driven by specific accumulation of distinct
118 ammonium transporters (Hui *et al.*, 2022; Koegel *et al.*, 2013). Further transporter families
119 (for example, the ZIP Zn transporters (Nguyen *et al.*, 2019); or SULTR sulphate transporters
120 (Casieri *et al.*, 2012)) have been reported to show gene-specific patterns of induction or
121 repression during AM symbiosis, suggesting the concept of direct and AMF uptake to extend
122 across the ionome, with the potential for AMF to influence crosstalk during nutrient
123 homeostasis (Xie *et al.*, 2019). The accumulation of nutrient transporter genes involved in
124 direct and AMF pathway can vary among plant genotypes, *e.g.*, phosphate transporter genes
125 in maize (Sawers *et al.*, 2017), indicating that host genetic factors may have a large impact on
126 mycorrhizal-mediated nutrient uptake of plants.

127 Here we evaluated the ionome of a bi-parental maize genetic mapping population in
128 which half the families carry the mutation *castor* and are incompatible with AMF. By
129 comparing AMF-compatible and AMF-incompatible families, we estimated the importance
130 of AMF on the accumulation of 20 elements in the field. We characterised the genetic
131 architecture of host element accumulation in response to AMF and identified genetic regions
132 associated with element concentration variation in AMF-compatible and incompatible
133 families. Furthermore, we tested the capacity of ionome profiles to predict mycorrhizal status
134 and assessed the potential of breeding AMF-effective hosts to achieve biofortification targets.

135

136 **RESULTS**

137 **The *castor* mutation impacted the leaf and grain ionome of field grown plants**

138 To assess the impact of AM symbioses on host mineral element accumulation in the field, we
139 used inductively coupled plasma mass spectrometry (ICP-MS) to evaluate the concentrations
140 of 20 elements in leaf and grain samples from a previously described custom mapping
141 population (see Materials and Methods and (Ramírez-Flores *et al.*, 2020)) grown in a
142 subtropical, medium input, field in central-western Mexico. The population was generated
143 from the cross between W22 (temperate) and CML312 (subtropical) maize inbred lines and
144 contained both AMF-compatible (AMF-C; 75 families) and AMF-incompatible (AMF-I; 66
145 families) families to allow estimation of the overall impact of AMF and the characterization
146 of genetic architecture underlying ionome differences among the families. Among the 20
147 tested elements, 17 in leaves and 9 in grain differed significantly in concentration between
148 AMF-C and AMF-I families, including both essential mineral nutrients and toxic heavy
149 metals (Fig. 1; Table 1). Element response to AMF (*Mycorrhizal Response* - MR; defined
150 here as the percentage increase in AMF-C compared with AMF-I) ranged from -36% to
151 116% in leaves and from -25% to 65% in grain (Fig. 1A). Zn and Cu concentrations showed
152 the highest positive response in both leaves (116% and 71%, respectively) and grain (50%
153 and 65%, respectively). The concentrations of potential toxic elements, such as As (-36%)
154 and Mn (-24%) in leaves, and As (-20%) and Cd (-23%) in the grain, were significantly
155 reduced in AMF-C plants, consistent with previous reports (Lehmann & Rillig, 2015;
156 Ruytinx *et al.*, 2020). We conducted Principal Component (PC) analyses, and AMF-C and
157 AMF-I ionomes were separated by the first PCs in both leaf and grain, which captures AM
158 effect driven by Zn, Cu, and Fe (Supplementary Fig. S1). Although not the most responsive

159 element, leaf P concentration was significantly increased in AMF-C compared to AMF-I
160 families (8.5%). Grain P concentration did not change significantly with AMF status. In our
161 study field, both AMF-C and AMF-I families maintained an average P concentration within a
162 typical critical range (Gagnon *et al.*, 2020), indicating that P limitation was not a major driver
163 of previously reported differences in plant performance (Ramírez-Flores *et al.*, 2020).

164 In addition to impacting individual elements, AM status affected patterns of
165 covariance among elements. AMF-C and AMF-I families were more clearly distinguished by
166 leaves than grain as shown by the magnitude of MR associated with individual elements (Fig.
167 1A). This pattern was supported by significant differences between pairwise correlation
168 matrices for element concentrations in the leaves of AMF-C and AMF-I families ($p < 0.001$;
169 Fig. 1B). For AMF-C and AMF-I leaves (Fig. 1B), 11 of the significant correlations were
170 independent of AM status (*e.g.*, the positive correlations between Sr and Ca, or As and Fe). In
171 contrast, the sign of three correlations changed with AM status, indicating a strong effect of
172 AMF on covariance (*e.g.*, the positive correlation between Zn and the three elements Sr, Ca
173 and Mn in AMF-C became negative in AMF-I). Ten significant correlations were specific to
174 AMF-C (*e.g.*, the positive correlations between K and P) and 10 to AMF-I (*e.g.*, the positive
175 correlation of P and Cu) families. The grain element correlation matrix, unlike that of leaves,
176 was not significantly different between AMF-C and AMF-I families ($p = 0.0596$; Fig. 1B),
177 although only five pairwise correlations were shared across AM status of a total of 11 and 14
178 significant correlations in AMF-C and AMF-I families, respectively (Fig. 1B). We also
179 conducted Factor Analysis to reduce the dimension of element accumulation patterns and
180 extracted the latent variables that share common trends in differentiating AMF-C and AMF-I
181 for downstream analyses (Supplementary Fig. S2). In summary, AM status substantially
182 affected patterns of covariance among elements, with more than half of the significant
183 correlations changing depending on AMF status in leaf and grain.

184

185 **The genetic architecture of element accumulation was impacted by AMF status**

186 Having observed a significant general effect of AMF status on the plant ionome, we
187 proceeded to use Quantitative Trait Loci (QTL) linkage mapping to evaluate genetic
188 differences between W22 and CML312 hosts and AMF \times QTL effects. As discussed
189 previously, we equated AMF-C and AMF-I specific QTL with mycorrhizal *benefit* and
190 *dependence*, respectively (Ramírez-Flores *et al.*, 2020; Sawers *et al.*, 2010). In the context of
191 the ionome, AMF \times QTL effects may also reflect a distinction between AMF and direct plant

192 uptake pathways (Smith *et al.*, 2003). To identify AMF \times QTL effects, we ran a series of
193 QTL models: 1) all families without taking AMF status into account; 2) all families with
194 AMF status as an additive covariate; 3) all families with AMF status as an interactive
195 covariate; 4) AMF-I families alone; 5) AMF-C families alone. Model 2 eliminates the main
196 effect of AMF status, but does not allow for the effect of W22 and CML312 alleles to differ
197 with AMF status (*i.e.*, AMF \times QTL effects are not modelled). AMF \times QTL effects are
198 captured explicitly by model 3, and by comparing the results of models 4 and 5. We
199 considered leaf and grain element concentrations as separate traits in our analysis.

200 Across all models, we detected a total of 33 element QTL, considering QTL for the
201 same element detected in the same genetic bin in different models as the same. When QTL
202 for different elements colocalized to the same bin, we report them as distinct loci, although it
203 is likely they represent a single pleiotropic genetic variant. Similarly, we report QTL detected
204 for leaf and grain data as distinct. QTL were annotated by element, chromosome, genetic bin,
205 and tissue (Fig. 2). Thirteen QTL were detected in the grain and 20 in the leaves. In a single
206 instance (qCd 2.05), a QTL for the same element is co-localised in leaf and grain, presumably
207 representing a single causal locus. Fifteen QTL were detected specifically in AMF-C families
208 but not AMF-I families, and, conversely, 5 QTL were detected in AMF-I but not AMF-C
209 families. Six of these AMF status specific QTL were further supported as examples of AMF
210 \times QTL interaction by Model 3. A further QTL (qAs_{gr}8.09) was identified uniquely by Model
211 3. The AMF \times QTL effects we detected were all *conditional* in nature (*i.e.*, specific to AMF-
212 C or AMF-I families). We did not find evidence of any QTL showing strong, but opposing,
213 allelic effects between AMF-C and AMF-I families (*antagonistic pleiotropy*. See *e.g.*,
214 (Ramírez-Flores *et al.*, 2020)). For the AMF-C specific QTL qCd_{lf/gr}2.05 and qNi_{gr}9.01, the
215 effect was sufficiently strong that they were supported by Models 1 and 2, but not Model 3
216 (*i.e.*, the interactive model did not present marked improvement over the additive model).
217 Globally, the parental allelic effect of detected QTLs varies depending on the element and
218 tissue type (Fig. 2). For example, for QTLs detected in bin 4.08 for leaf in AMF-C families,
219 the genotypes that carry the CML312 allele tend to accumulate less Ca, Fe and As, but more
220 Rb. For qCd_{lf/gr}2.05, the allelic effect is conserved across grain and leaf in the AMF-C
221 families, where the genotypes with W22 allele tend to accumulate less Cd than genotypes
222 with the CML312 allele. In contrast, for qNi_{gr}9.01, the AMF-C with the W22 allele at this
223 QTL tends to accumulate Ni in the grain.

224

225 **Loci with AMF \times QTL effects co-localized with QTL showing G \times E in a previous**
226 **multisite ionome experiment**

227 To obtain more rigorous support for our QTL and assess the potential for AMF to impact
228 ionome variation across environments, we compared our findings to a published maize
229 multisite ionome dataset (Asaro *et al.*, 2016). This previous work presented grain ionome
230 data for a biparental maize mapping population (hereafter, the IBM data), evaluated during
231 the period of 2005 to 2012, in five different US states, although without specific
232 characterization of the soil microbial community. We re-analysed these data to facilitate
233 comparison with our results and considered each location separately to investigate overlap
234 between AMF \times QTL effects in our work and G \times E effects in the published study. In
235 addition to QTL identified for individual elements in the previous section, we also included
236 QTL identified for element interaction patterns, including element ratios and the first five
237 latent variables of Factor Analysis, for comparison. We obtained support for 12 of our QTL
238 from the previous data through common signals associated with the same elements in shared
239 genomic bins (Fig. 3A). Interestingly, 10 of the QTL supported by the IBM grain data were
240 identified by us in leaves. The greater power and resolution of the IBM data set increased
241 confidence in our QTL and allowed a more precise estimation of our genomic location
242 (Supplementary Table S1). Nine of the overlapping QTL were detected preferentially in
243 AMF-C plants in our experiments, suggesting AMF communities to be active in the IBM
244 field sites (Fig. 3B). These common QTL also showed evidence of G \times E interaction in the
245 previous study (Fig. 3B). Although difficult to substantiate without further data, we speculate
246 that variation in the AMF community between field sites contributed to G \times E effects seen in
247 the IBM. For example, strongly supported AMF-C conditional QTL linked to Cd and Ni on
248 chromosomes 2 and 9, respectively, were clearly recovered in IBM data from North Carolina
249 and New York but not detected at all in Missouri (Fig. 3B). Absolute element concentrations
250 indicate that these elements were present in the Missouri environment, although no QTL were
251 detected. Furthermore, the Missouri location lacked signal for an AMF conditional Fe QTL
252 on chromosome 4 that was mildly supported by the other sites, instead showing strong
253 location-specific signals on other chromosomes.

254

255 **Patterns in the ionome were correlated with the extent of arbuscular mycorrhizal**
256 **colonisation**

257 Having observed clear differences between AMF-C and AMF-I families, we proceeded to
258 assess whether ionome variation *within* the AMF-C family was a reflection of differences in

259 the extent of mycorrhizal colonisation. We used microscopy to quantify mycorrhizal hyphae,
260 arbuscules and vesicles from field sampled AMF-C roots in terms of percent root length
261 colonised (as reported previously, AMF-I families were free from root-internal fungal
262 structures (Ramírez-Flores *et al.*, 2020)). We observed appreciable colonisation in field
263 sampled roots (hyphae = 23.6% \pm 2%, arbuscules = 16% \pm 1.4%, and vesicle = 3.4% \pm
264 0.4%), with individual families ranging from 0 to 74.4% in hyphae colonisation (Fig. 4A). To
265 investigate the relationship between the extent of colonisation and the ionome, we used the
266 Boruta feature-reduction method to identify correlations between individual elements and
267 fungal structures. Leaf and grain element concentrations were included simultaneously in a
268 single analysis. The most informative elements were leaf Fe for hyphae, and leaf Fe and Rb
269 for arbuscules (Fig. 4B; Supplementary Fig. S3). Informative elements were used to build
270 Random Forest (RF) models. The trained RF models were used to predict the colonisation
271 phenotypes in the training and whole dataset, and the performance of the models was
272 assessed by estimating the testing (R^2_T) and whole dataset (R^2_{WD}) metrics between the
273 observed and predicted data (Fig. 4C; Supplementary Fig. S3, S4). The best performing
274 model was for hyphae ($R^2_T = 0.11$, $p_T = 0.17$; $R^2_{WD} = 0.29$, $p_{WD} < 0.001$), followed by
275 arbuscules ($R^2_T = 0.03$, $p_T = 0.49$; $R^2_{WD} = 0.44$, $p_{WD} < 0.001$), and vesicles ($R^2_T = 0.041$, $p_T =$
276 0.49 ; $R^2_{WD} = 0.21$; $p_{WD} < 0.001$).

277 Our models indicated a relationship between the abundance of fungal structures and
278 the ionome, suggesting that, for a specific environment, a locally trained model could
279 estimate colonisation from element quantification without the need to directly examine roots.
280 We reasoned that ionome predicted values based on a field-wide model might be less biased
281 at the level of the individual than direct observation, given the difficulties of estimation when
282 sampling from a large, heterogeneously colonised root system (Montero *et al.*, 2019). To
283 explore this idea, we compared the results of QTL mapping using observed or predicted
284 values of colonisation. Using directly observed values we did not detect any significant QTL
285 ($\alpha = 0.1$), which was not too surprising given the small size of our mapping population and
286 the difficulty of estimating the trait values. Using predicted values, however, we could detect
287 QTL linked to abundance of arbuscules (Chr 4. Fig 4D) and hyphae (Chr 4. Supplementary
288 dataset). The arbuscule QTL qArb4.08 co-localized with QTL for leaf Rb and Fe
289 concentration - the two ions contributing to the predictive model. The CML312 allele at
290 qArb4.08 was associated with relatively high levels of leaf Rb, low levels of leaf Fe, and
291 fewer arbuscules; conversely, the W22 allele at qArb4.08 was associated with relatively low
292 levels of Rb, high levels of Fe and greater arbuscule abundance (Fig. 4E). The effects of

293 qFe_{1r}4.08 and qRb_{1r}4.08 QTL were conditional on AM symbiosis and no significant
294 differences were seen between alleles in AMF-I families (Fig. 4E). The conditionality of
295 qFe_{1r}4.08 and qRb_{1r}4.08 is consistent with their capturing an aspect of mycorrhizal function
296 also reflected in arbuscule abundance. We compared direct observation and predicted values
297 of colonisation in their relationship to plant phenological traits and yield components.
298 Consistent with previous reports (*e.g.*, (Sawers *et al.*, 2017)), we did not find any simple
299 correlation between the abundance of root internal fungal structures and yield components.
300 We did observe greater arbuscule abundance to be correlated with accelerated flowering (Fig.
301 4F). Similar to the QTL analysis, this correlation was more significant with the predicted
302 arbuscule values than the direct observations.

303

304 **Mycorrhizal colonisation promoted alignment of biofortification breeding targets**

305 To understand the potential impact of AMF on host evolvability towards biofortification
306 breeding targets, we compared how well AMF-C and AMF-I families align to a trajectory
307 maximising grain Zn and Fe concentrations, the two mineral elements most commonly
308 lacking in human diets (White & Broadley, 2009). We defined a family to be better aligned if
309 the angle between the major axis of the genetic variance-covariance matrices (G-matrix) and
310 the biofortification target vector was smaller (Fig. 5A; (Noble *et al.*, 2019)). By this criterion,
311 AMF-C families are better aligned with the biofortification target than AMF-I (Fig. 5B).
312 Although AMF-I families showed a higher mean grain Fe concentration (27.5 ppm) than
313 AMF-C families (20.5 ppm), the high Fe concentration was negatively associated with grain
314 Zn concentration (Fig. 5A). Whereas, AMF-C showed a significantly higher grain Zn
315 concentration (19.6 ppm) than AMF-I (13.1 ppm), and the association between Zn and Fe is
316 positive, contributing to its better alignment with biofortification targets. This behaviour was
317 reflected in the AMF-C conditional QTL qGF1 2.10 that was associated with grain factor1
318 (GF1) that captured variation in both Zn and Fe (Supplementary Fig. S2). In AMF-C
319 families, plants homozygous for the CML312 allele at qGF1 2.10 had greater concentrations
320 of both Zn and Fe in the grain than plants homozygous for the W22 allele, such that selection
321 for the CML312 allele would align with biofortification targets (Fig. 5C). In AMF-I families
322 qGF1 2.10 had no significant effect on Zn or Fe concentrations.

323

324 **DISCUSSION**

325 We have characterised the impact of AMF on mineral nutrition in field grown maize. Using a
326 custom mapping resource comprising both AMF-C and AMF-I maize families (hereafter,
327 mycorrhizal and non-mycorrhizal), we estimated the effect of AMF on the concentrations of
328 20 elements in the leaves and grain, evaluated the impact of AMF on covariance among
329 elements, and characterised the host genetic architecture of element accumulation with
330 respect to the presence or absence of AMF.

331 Although the benefit of AMF in cultivated fields has been questioned (Ryan &
332 Graham, 2002, 2018), our data suggest that in our trial AMF improved the uptake of essential
333 nutrients in the field-grown maize. The concentrations of Zn and Cu were significantly higher
334 in mycorrhizal maize families than in non-mycorrhizal families, in both leaf and grain,
335 consistent with previous studies (Lehmann *et al.*, 2014; Lehmann & Rillig, 2015). It has been
336 reported that higher grain yield under P fertilisation reduces Zn concentration through a
337 dilution effect (Zhang *et al.*, 2021). Our results showed that mycorrhizal plants maintained
338 greater Zn concentration even though total grain weight per plant was also higher than that of
339 non-mycorrhizal plants (Ramírez-Flores *et al.*, 2020). In parallel with an increase in essential
340 micronutrients, mycorrhizal plants showed a significant reduction in the concentration of
341 potentially toxic elements, including Ni and Cd in grain and As and Mn in leaf and grain,
342 again consistent with previous greenhouse studies (Göhre & Paszkowski, 2006; Lehmann &
343 Rillig, 2015; Neidhardt, 2021). As in the pentavalent form of arsenate (AsO_4^{3-}) is chemically
344 similar to inorganic phosphate (PO_4^{3-}) and the two can compete for transport through the P
345 uptake system (Meharg & Hartley-Whitaker, 2002). AMF have been reported to reduce As
346 uptake by down-regulating transporters involved in the direct P uptake pathway
347 (Christophersen *et al.*, 2009; Li *et al.*, 2018a). We found that a significant correlation
348 between P and As in the leaves of non-colonised plants was no longer significant in
349 mycorrhizal plants, supporting an effect of AMF in changing the As-P relationship. More
350 generally, we found mycorrhizal colonisation altered patterns of covariance among elements,
351 broadly supporting previous greenhouse studies (Gerlach *et al.*, 2015; Ramírez-Flores *et al.*,
352 2017), although some specific patterns differed.

353 Alongside the desirable effects described above, we saw a potentially deleterious
354 reduction in the concentration of the essential micronutrient Fe in both the leaves and grain of
355 mycorrhizal plants. In addition to being essential for plants, Fe deficiency is a widespread
356 problem in human diets making increasing Fe a major goal of biofortification programs
357 (Maqbool & Beshir, 2019). Fe reduction in the shoots of different greenhouse grown

358 mycorrhizal plant species has been reported previously (Tran *et al.*, 2019), although AMF
359 have also been reported to specifically increase Fe concentration in the roots (Watts-Williams
360 & Cavagnaro, 2014), suggesting an impact of AMF on root-shoot translocation (Ibiang *et al.*,
361 2017; Xie *et al.*, 2019). The interpretation of AMF effects on Fe is further complicated by
362 interactions with Zn status (Ibiang *et al.*, 2017). We observed a negative correlation between
363 Zn and Fe in both the leaves and grain of non-mycorrhizal maize families, in line with
364 previously reported antagonism between Zn and Fe nutrition in plant shoots (Ibiang *et al.*,
365 2017). However, this negative relationship between Zn and Fe became positive in the grain of
366 mycorrhizal plants being Zn a major biofortification target (Maqbool & Beshir, 2019). Our
367 analysis of G matrix alignment indicated that although the mean grain Fe concentration was
368 higher in non-mycorrhizal plants, the positive correlation between Zn and Fe in the
369 mycorrhizal plants would promote simultaneous breeding gains towards an increase in the
370 two elements. Although our results were obtained for a biallelic population in a single
371 location, they illustrate a potentially important aspect of the impact of AMF on mineral
372 nutrition beyond increasing or decreasing concentrations in any given genetic background.

373 We identified 20 element QTLs that showed evidence of interaction with AM status.
374 All AMF \times QTL effects were conditional, *i.e.*, these QTL were specific to either mycorrhizal
375 or non-mycorrhizal plants, although limited statistical power may have prevented
376 identification of more complex genetic architectures. Nutrient acquisition by direct plant
377 uptake or via mycorrhizae follows mechanistically and physiologically distinct pathways
378 (Bucher, 2007; Chiu & Paszkowski, 2019). The contributions of the plant and mycorrhizal
379 uptake pathways are not simply additive but can be better thought of as alternative strategies,
380 one or the other dominating under given conditions (Smith *et al.*, 2003). Molecular analyses
381 have supported this view through the identification of diversified families of plant nutrient
382 transporters containing members that play specific roles in direct or mycorrhizal uptake and
383 are regulated accordingly (Casieri *et al.*, 2012; Yang *et al.*, 2012; Koegel *et al.*, 2013; Li *et*
384 *al.*, 2018b; Hui *et al.*, 2022). Our identification of conditional QTL is consistent with
385 variation in such pathway-specific genetic components, the resulting impact being expressed
386 preferentially in mycorrhizal or non-mycorrhizal plants. We would hypothesise that typically
387 the balance between direct and mycorrhizal uptake differs spatially across the root system
388 and temporally over the lifetime of the plant, as well as with respect to host genotype. In
389 addition to delivery of nutrients to the arbuscule, AMF secondarily impacts nutrient uptake
390 through enhancement of root growth and modulation of root development (Ramírez-Flores *et*

391 *al.*, 2019). As such, AM symbiosis has the capacity to both mask or exaggerate variation in
392 direct nutrient uptake among host genotypes, a further potential contribution to AMF \times QTL
393 effects. For example, our study identified an AMF-specific QTL for Cd in leaf and grain
394 ($qCd_{lf/gr}2.05$). This QTL co-localized with a major locus for maize grain Cd accumulation in
395 a previous study that has been identified as encoding a heavy metal transporter (*ZmHMA3*)
396 (Tang *et al.*, 2021; Chen *et al.*, 2022). AMF have been reported to up-regulate the expression
397 of the orthologous transporter gene in rice, and thus promote sequestration of Cd to vacuoles
398 of root cells and reduce the translocation of Cd from roots to shoots (Chen *et al.*, 2019; Zhu *et*
399 *al.*, 2022). AMF may also contribute to Cd tolerance in maize through influencing the
400 function of important host Cd transporters, although our results suggest the efficacy of this
401 protection is contingent on the host genetic background.

402 Root internal colonisation is widely used to characterise the strength of the AMF-host
403 relationship. However, quantifying colonisation typically involves destructive root harvest,
404 staining, and microscopic examination, making it both labour intensive and time consuming.
405 Variation temporally over development and spatially over the root system also make
406 estimation difficult, especially when small, localised samples are collected from the large,
407 and largely inaccessible, root systems of field grown plants. As such, any molecular,
408 metabolic or other indicators that predict colonisation but can be quantified from aerial parts
409 of the plants are of great potential utility (*e.g.*, the foliar blumenols described by Wang *et al.*,
410 2018). Our analysis suggests that components of the leaf and grain ionome have the capacity
411 to predict AM colonisation. Although we anticipate that any model would have to be trained
412 on a per field/year/population basis, and therefore necessitate some direct root observation,
413 there would still be a great saving of time and effort, especially for large scale field studies.
414 Our models explained, in general, significant variation in the whole dataset (R^2_{WD}), but
415 performed poorly when evaluated in the testing dataset (R^2_T), a behaviour consistent with an
416 overfitted model (Ying 2019). This might be the result of a limited dataset consisting of 75
417 mycorrhizal families, which is then divided into a training and testing set, coupled with the
418 possible presence of noise in the colonisation trait values due to the difficulties in their
419 evaluation discussed above. We hypothesise that a larger dataset might ease the overfitting
420 effect and lead to more conservative results; nevertheless, the modelling approaches we have
421 used identify the most informative predictors from a larger potential set and, given the data, it
422 would be straightforward to combine metabolic, ionic or other indicators in a single
423 analysis. Mapping the genetic basis of variation in root colonisation is challenging, and where

424 attempted the most informative markers in a given experiment have only described a small
425 proportion of the total variation (0.82-1.14% in winter wheat (Lehnert *et al.*, 2017), 6.5% in
426 maize (Kaeppeler *et al.*, 2000), 8% in sorghum (Leiser *et al.*, 2016), 7-16% in durum wheat
427 (De Vita *et al.*, 2018) and 4.5-7.1% in soybean (Pawlowski *et al.*, 2020)). To date, perhaps
428 the only clear single gene natural variant effect on colonisation to be characterised is that of
429 the Dongxiang wild rice allele of *OsCERK1* in promoting colonisation with respect to
430 cultivated varieties (Huang *et al.*, 2020). These results reflect low heritability, in part
431 potentially a result of the aforementioned difficulties in accurately estimating colonisation
432 from small root samples. We had more success in identifying QTL using our ionome-
433 predicted colonisation values than direct observations, which explain ~ 32% of the variation
434 in predicted arbuscules and hyphae, indicating that for any given individual estimates based
435 on a field-scale trained ionome model may be more accurate than direct observation of a root
436 sample.

437 The co-localisation of our AMF conditional element QTL and those identified in a far
438 larger study carried out across multiple years and locations (Asaro *et al.*, 2016), albeit
439 without consideration of AMF, strongly supports the signals we observed. Furthermore, our
440 observation of AMF conditionality associated with QTL that showed $G \times E$ in the previous
441 work is consistent with the hypothesis that variation in AMF communities is contributing to
442 $G \times E$ effects. For example, our data indicate that plant genetic variation in the gene *ZmHma3*
443 (Tang *et al.*, 2021; Chen *et al.*, 2022) located at qCd_2.05 will have the greatest impact on
444 plant Cd concentration in the field when the local AMF community is strong. More generally,
445 the AMF contribution to crop $G \times E$ is central to any proposition to breed towards superior
446 AMF interactions. In the absence of a significant contribution of AMF to $G \times E$, an improved
447 local AMF community (however defined or promoted) will benefit all plant varieties equally
448 with no need to consider the plants themselves. If, however, the impact of AMF is conditional
449 of the host genotype (*e.g.*, (Ramírez-Flores *et al.*, 2020)) we cannot suppose that crop
450 varieties selected for yield in, for example, an AMF poor environment, will necessarily obtain
451 the greatest benefit for efforts to improve the AMF community in cultivated fields.

452

453 **MATERIALS AND METHODS**

454 *Plant material and experimental design*

455 AMF-compatible and AMF-incompatible maize F2:3 families were developed from the cross
456 between a stock homozygous for the *castor-2* allele in the W22 background and a subtropical
457 CIMMYT inbred line CML312. The experiment was conducted in the summer of 2019 at the
458 UNISEM experimental station in Ameca, Jalisco, Mexico (20.57, -104.04). The field was
459 fertilised at planting with 250 kg/ha of diammonium phosphate (DAP; 18-46-00 NPK) and
460 again at 40 days after planting with 250 kg/ha of urea (46-00-00, NPK). A total of 73 AMF-C
461 and 64 AMF-I families were planted in 3-row plots in 3 complete blocks. Within blocks,
462 AMF-C and AMF-I families were alternated with the order of the families randomised within
463 each block. Further details of the mapping population and experimental design are presented
464 in (Ramírez-Flores *et al.*, 2020).

465 ***Determination of elemental concentration by inductively coupled plasma mass*** 466 ***spectrometry***

467 Five flag leaves were collected per plot at flowering and oven dried at 70°C for 48 hours.
468 After drying, 10 cm from the tip were taken from each flag leaf and were pooled to obtain
469 one sample per plot. For the grain samples, 4 kernels were selected randomly from 1-3 ears
470 per plot. Element concentration was determined as described previously (Ramírez-Flores *et*
471 *al.*, 2017). Briefly, flag leaves and grain samples were analysed by ICP-MS to determine the
472 concentration of 20 elements. Samples were digested in 2.5 mL concentrated nitric acid (AR
473 Select Grade, VWR) with an added internal standard (20 ppb In, BDH Aristar Plus).
474 Concentration of the elements Al, As, B, Ca, Cd, Co, Cu, Fe, K, Mg, Mn, Mo, Na, Ni, P, Rb,
475 S, Se, Sr and Zn was measured using an Elan 6000 DRC-e mass spectrometer (Perkin-Elmer
476 SCIEX) connected to a PFA microflow nebulizer (Elemental Scientific) and Apex HF
477 desolvator (Elemental Scientific). A control solution was run every tenth sample to correct
478 for machine drift both during a single run and between runs.

479 ***Root sampling and quantification of mycorrhizal colonisation***

480 At the flowering time, one plant per row was excavated in a soil monolith (~15-20 cm from
481 the stalk and 15 cm to 20 cm in depth) using shovels. Gently, the plant was pulled out and
482 shaken to remove as much soil as possible. Twenty root pieces were randomly sampled from
483 a root system and placed in 50mL Falcon Tubes. For the staining, roots were cleared with
484 10% potassium hydroxide and heated in an autoclave cycle of 15-20 minutes at 121°C.
485 Cleared roots were stained with 0.05% trypan blue solution in a mixture of 1:1:1 acetic acid,
486 glycerol and water. To quantify AMF colonisation, 15 stained roots were mounted in a slide.

487 Randomly 135 selected microscope fields were observed, and a modified intersections
488 method was used to determine fungal colonisation (McGonigle et al., 1990).

489 ***Data cleaning and processing***

490 All data preparation and analyses were performed in R 4.0.4 (R Core Team 2022). Data was
491 trimmed to remove outliers per element/tissue using R/ graphics::boxplot default criteria, and
492 were adjusted on a per block basis to a spline fitted model using R/stats::smooth.spline
493 against row number to reduce spatial variation at the subblock scale. Mean differences
494 between element concentrations of AMF-C and AMF-I families in leaves and grain were
495 tested by Wilcoxon test with p-values adjusted based on the number of elements using the
496 FDR adjustment method. To further explore the differences of element accumulation between
497 AMF-C and AMF-I families, mycorrhizal responses (MR) of element accumulation were
498 calculated for each element in leaves and grain using the equation: $MR = ((AMF-C - AMF-$
499 $I)/AMF-I)*100\%$ (Watts-Williams *et al.*, 2013).

500 ***Mixed effects linear models***

501 The ionic data collected was collapsed into a single median value per plot for grain and
502 leaf independently. The dataset contained 450 observations for 66 AMF-I and 75 AMF-C
503 families of the F_{2:3} population in 3 different blocks. For each element, a mixed effects linear
504 model was fitted using the restricted maximum-likelihood method with R/lme4::lmer, such
505 that:

$$506 \quad y_{ijkm} = \mu + B_i + G_j + C_k + \varepsilon_{ijk}$$

507 where the response variable y_{ijkm} is a function of the overall mean (μ), fixed effect of the
508 block (B_i), random effect of genotype (G_j), and a fixed effect of the AMF status (AMF-
509 I/AMF-C; C_k), and the residual. Best linear unbiased prediction (BLUP) values for the
510 genotypic effect (G) were extracted using R/lme4::ranef. We calculated fitted values by
511 adding BLUPs to the grand mean for data visualisation and downstream analyses using
512 natural units. Broad-sense heritability for each continuous trait was estimated based on the
513 linear mixed model results using the *bwardr::Cullis_H2* function according to (Cullis *et al.*,
514 2006).

515 ***Multivariate analyses***

516 Fitted values of element B, Na, Al, Se, and Rb showed low variation in either leaf or grain
517 and were removed in the multivariate analyses. To analyse major sources of variation and
518 visualise the element accumulation patterns between AMF-C and AMF-I in leaf and grain, a
519 PCA was conducted using the `stats::prcomp` function in R. We also calculated the Euclidean
520 distances between centroids of AMF-C and AMF-I families in leaf and grain using the
521 `usedist::dist_to_centroids` function (Bittinger 2020). Factor analysis was performed to reduce
522 the dimension of element accumulation patterns and extract underlying latent variables that
523 share common trends in differentiating AMF-C and AMF-I. Factor analysis was conducted
524 using the `stats::factanal` function, with the ‘varimax’ rotation method. The first five factors
525 for grain and leaf were used in the QTL mapping analysis. Detailed loading and scores from
526 the five factors are included in the supplementary dataset.

527 We calculated pairwise correlations among elements for both AMF-C and AMF-I
528 groups to explore changes in element correlation patterns in response to AMF colonisation.
529 Correlations between elements were performed using `stats::cor` with spearman correlation
530 method. To test whether correlation matrices are equal between AMF-C and AMF-I, Chi-
531 square test was performed using the `decorate::delaneau.test` (Hoffman 2021).

532 Correlations changed in many pairs of elements from AMF-C to AMF-I in our study.
533 We then manually picked pairs of elements that showed large differences in direction or
534 magnitude of correlations between AMF-C and AMF-I families and calculated their ratios
535 and log transformed for further QTL mapping analysis.

536 ***QTL mapping***

537 QTL mapping was performed as described in (Ramírez-Flores *et al.*, 2020) using the `{qtl}`
538 package in R (Broman *et al.*, 2003). As phenotypic inputs, the BLUPs for leaf and grain
539 element concentration, ratios, factor scores were used. For mycorrhizal colonisation
540 phenotypes, the median and logit transformed medians were used. Single-QTL standard
541 interval mapping was run using `scanone` function with Haley-Knott regression model and
542 standard parameters. The genotype at *castor* was treated as a covariate (AMF-C = 1; AMF-C
543 = 0; hereafter AMF) for further modelling. To identify any AMF \times QTL interaction (Broman
544 & Sen, 2009), four models were considered for mapping: separate analysis on AMF-I (H_{0I})
545 and AMF-C (H_{0C}) families, and models considering AMF as an additive (H_a) or interactive
546 (H_f) covariate. The LOD significance threshold was established with a permutation test (1000
547 permutations, $\alpha = 0.1$). Evidence for AMF \times QTL interaction was obtained by comparing H_f

548 and H_a models, where the difference $LOD_i = LOD_f - LOD_a$ was compared to the threshold
549 difference $LOD_{thr_i} = LOD_{thr_f} - LOD_{thr_a}$ for evidence of possible interaction.
550 Individually detected QTLs were combined into a multiple-QTL model on a per phenotype
551 basis. Where evidence was found of $AMF \times QTL$ interaction in the single scan, the
552 interaction was also included in the multiple-QTL model. Multiple-QTL models were
553 evaluated using the *fitqtl* function and non-significant ($\alpha = 0.1$) terms removed according to
554 the drop-one table.

555 ***Random forest modelling of AMF colonisation levels***

556 A machine learning approach was used to explain and predict the relationship between the
557 ionome and the colonisation level of the AMF-C families using the tidymodels framework
558 (Kuhn & Wickham, 2020). To study the ability of the ionic data of different tissues to
559 explain the observed colonisation phenotypes, three models with different potential predictors
560 were considered: *ion-leaf*, considering only the grain ionic variables as predictors; *ion-*
561 *seed*, considering only the leaf ionome variables as predictor; and *ion-everything*,
562 considering both leaf and grain ionome variables and element ratios as predictors. To
563 improve the robustness of the prediction, five different seeds for the random number
564 generator were used (54955149, 100, 22051959, 2500, 161921). The AMF-C subset ($n = 75$)
565 was split into a training and testing set (75% and 25% of the data, respectively) using the
566 different seed numbers, consisting of five different training sets. The resulting training
567 subsets were used to perform a feature selection process using the {Boruta} package for R
568 (Kursa & Rudnicki 2010) in five bootstrap replicates of the training set. The feature was
569 deemed as relevant if it was selected by the algorithm in at least 20 out of 25 of the
570 seed/bootstrap combinations. The models without features that comply with these
571 characteristics were dropped. Selected features were used as predictors for two different tree
572 ensemble machine learning algorithms: Random Forest modelling was conducted using the
573 {ranger} package (Wright & Ziegler, 2017), and Extreme Gradient Boosting was conducted
574 using the {xgboost} package (Chen & Guestrin, 2016). The number of variables to possibly
575 split at each node, minimal node size and the number of trees for each model/seed/algorithm
576 hyperparameters were optimised independently by cross validation ($vfolds = 3$, $repeats = 10$)
577 according to (Kuhn & Silge 2022). The model was finalised with the best combination of
578 hyperparameters and fit with the training set. The trained models were used to predict the
579 values on the training and whole data set, and the average of the prediction of the five

580 different random seeds was considered as the true prediction of the model. The performance
581 of the model was evaluated according to the testing squared r metric.

582 ***Selection trajectory analysis***

583 To understand the impact of AMF colonisation on the genetic architecture of element
584 accumulations and the evolvability to meet future biofortification breeding targets, we
585 applied an evolutionary quantitative genetic approach by quantifying the alignment between
586 genetic variation and the evolutionary trajectory towards maximised biofortification goals.
587 The biofortification goal was defined to obtain maximised grain Zn and Fe as set by
588 HarvestPlus as 38 µg/g dry weight for Zn and 60 µg/g dry weight for Fe (Bouis *et al.*, 2011).
589 We extracted genetic variance-covariance matrices (G-matrix) by fitting Generalised Linear
590 Mixed models using Markov Chain Monte Carlo techniques (MCMCglmm) in R. Briefly, the
591 pedigree information was inverted to obtain an inverse sparse matrix, which was then used in
592 the MCMCglmm model with a non-informative prior. The evolvability of crops to meet
593 biofortification targets were determined as the alignment between the main axes of G-matrix
594 and the biofortification target vector (calculated as differences in multivariate trait means
595 from the breeding targets) as described in (Noble *et al.*, 2019).

596

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603

604 **COMPLETING INTERESTS**

605 The authors declare no completing interests.

606

607 **AUTHOR CONTRIBUTIONS**

608 MRRF and RJHS conceived and designed the experiment. MRRF, SPL, BBG, MAMM, GZ,
609 IB contributed to the sample collection and analysis. ML and SPL conducted the data
610 analyses. ML, SPL, MRRF, and RJHS wrote the original draft. All authors contributed to the
611 reviewing and revising of the manuscript.

612

613 DATA AVAILABILITY

614 Genotype and phenotype data and supplementary dataset are provided on Figshare under the

615 doi's: <https://doi.org/10.6084/m9.figshare.21684947> and

616 <https://doi.org/10.6084/m9.figshare.12869867>.

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854 **Table 1.** Element concentrations (p.p.m) in leaves and grain of mycorrhizal compatible (AMF-C) and incompatible (AMF-I) families. Means
855 and standard deviation (S.D.) were calculated from 75 and 66 genotypes for AMF-C and AMF-I, respectively. The significance of mean
856 differences between two families were tested using the Wilcoxon test with p-values adjusted (FDR adjustment) based on the number of
857 elements. Note: *: p < 0.05; **: p < 0.01; ***: p < 0.001; NS: not significant. Broad sense heritability (H^2) of the whole mapping population was
858 estimated using the *bwardr::Cullis_H2* function for R.
859

Element	Leaf						Grain					
	AMF-C		AMF-I		p	H^2	AMF-C		AMF-I		p	H^2
	Mean	S.D.	Mean	S.D.			Mean	S.D.	Mean	S.D.		
Al	11.17	3.29	11.61	3.33	NS	0.51	0.57	0.16	0.55	0.16	NS	0
As	0.04	0.02	0.07	0.02	***	0.65	0.01	0.002	0.01	0.002	***	0.26
B	18.61	3.66	16.36	4.53	**	0.21	0.54	0.11	0.56	0.12	NS	0
Ca	6279.35	1682.39	7040.19	1653.11	*	0.64	83.57	23.97	90.79	29.70	NS	0.28
Cd	0.03	0.01	0.03	0.01	NS	0.73	0.004	0.002	0.005	0.002	*	0.58
Co	0.06	0.02	0.06	0.02	NS	0.53	0.004	0.001	0.004	0.001	NS	0.13
Cu	5.57	0.94	3.25	0.90	***	0.69	1.71	0.30	1.03	0.37	***	0.4

Fe	75.70	14.32	117.97	31.65	***	0.62	20.52	2.81	27.50	6.25	***	0.2
K	30672.02	3391.24	33142.20	4283.85	**	0.61	5921.39	659.15	6016.12	635.67	NS	0.14
Mg	2826.21	488.60	3237.95	615.78	***	0.71	1813.79	168.99	1849.13	185.64	NS	0.21
Mn	148.62	37.70	196.77	46.80	***	0.55	5.47	1.02	6.15	1.12	***	0.39
Mo	0.40	0.07	0.36	0.06	**	0.31	0.07	0.07	0.05	0.07	NS	0.03
Na	10.26	4.16	8.24	3.15	**	0.1	0.45	0.09	0.49	0.10	NS	0
Ni	0.04	0.01	0.03	0.01	**	0.17	0.03	0.01	0.03	0.01	*	0.46
P	2510.42	242.64	2313.33	322.66	***	0.63	2662.30	281.83	2770.97	348.63	NS	0.14
Rb	7.15	1.28	6.68	1.23	*	0.4	1.74	0.43	1.57	0.44	NS	0
S	3790.03	275.70	3683.31	318.64	*	0.51	1970.28	244.41	2019.22	198.12	NS	0.23
Se	0.02	0.01	0.02	0.00	**	0	0.01	0.003	0.01	0.003	**	0
Sr	27.42	9.06	30.15	7.95	*	0.66	0.42	0.16	0.52	0.18	*	0.32
Zn	40.89	8.67	18.88	8.61	***	0.44	19.58	3.16	13.08	3.46	***	0.25

861 **Figure Legends**

862

863 **Figure 1. Mycorrhizal colonisation affects element concentrations and correlations in**
864 **field grown maize.**

865

866 **Figure 2. The behaviour of element QTL is contingent on AM status.**

867

868 **Figure 3. QTL specific to AMF-C families colocalize with element QTL showing $G \times E$**
869 **in a previously reported multisite evaluation.**

870

871 **Figure 4. The ionome reflects arbuscular mycorrhizal colonisation.**

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873 **Figure 5. Arbuscular mycorrhizal association may facilitate progress towards**
874 **biofortification breeding targets.**

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877 **SUPPORTING INFORMATION**

878 **Table S1.** QTLs detected in common with a published multisite ionome analysis.

879 **Figure S1.** Principal Component Analysis biplots showing element concentration patterns
880 and loadings.

881 **Figure S2.** Loadings showing the contributions of elements to the first five factors of the
882 Factor Analysis of element concentrations in leaf and grain.

883 **Figure S3.** Random Forest (RF) model results for hyphae abundance.

884 **Figure S4.** Random Forest (RF) model results for vesicle abundance.

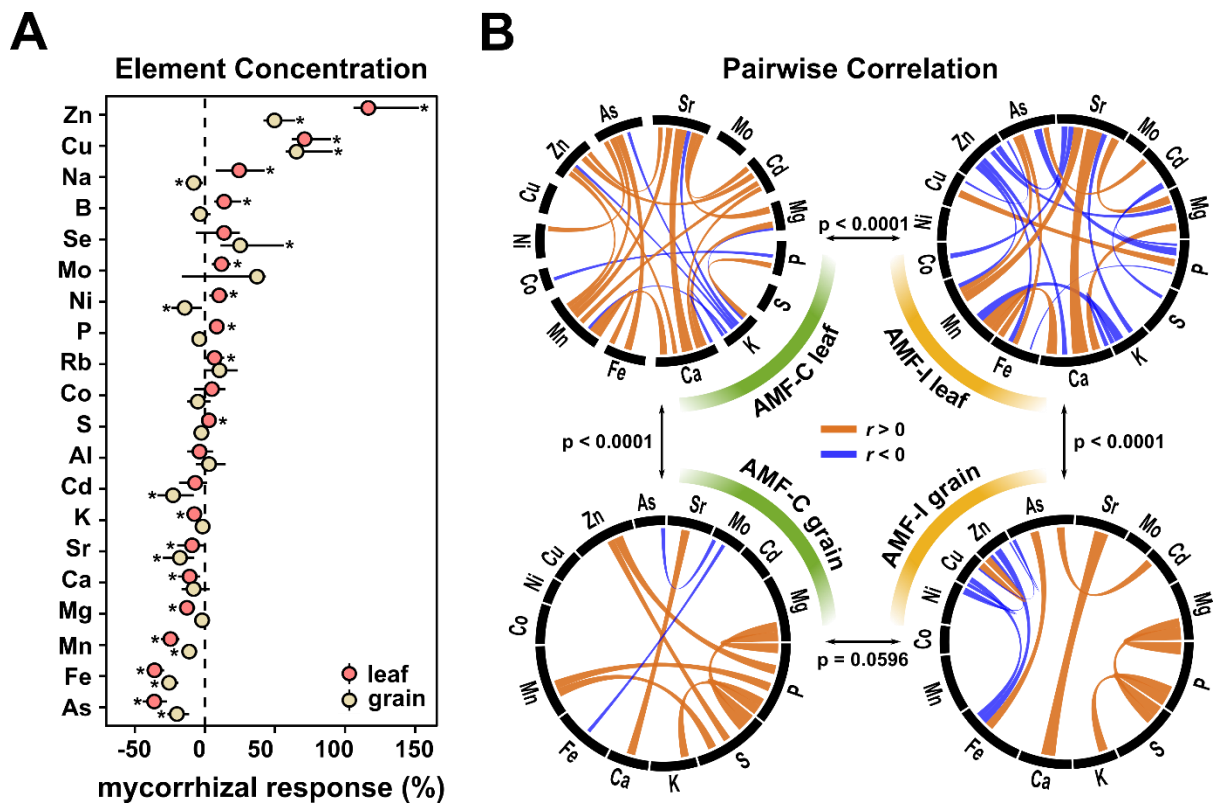
885 **Dataset S1** Genotype and phenotype data and supplementary dataset are provided on

886 Figshare under the doi's: <https://doi.org/10.6084/m9.figshare.21684947> and

887 <https://doi.org/10.6084/m9.figshare.12869867>.

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892 **Figure 1. Mycorrhizal colonisation affects element concentrations and correlations in**

893 **field grown maize.** A) Mycorrhizal responses of element concentration in leaf and grain.

894 Mycorrhizal response of each element was calculated as the mean difference between

895 element concentration in compatible (AMF-C) and incompatible families (AMF-I) divided by

896 AMF-I. Error bars represent 95% confidence intervals. B) Pairwise correlations of element
897 concentration in leaf (upper) and grain (bottom) between AMF-C (left) and AMF-I (right)

898 families. Significant Spearman correlations ($p < 0.05$) shown with positive correlations in

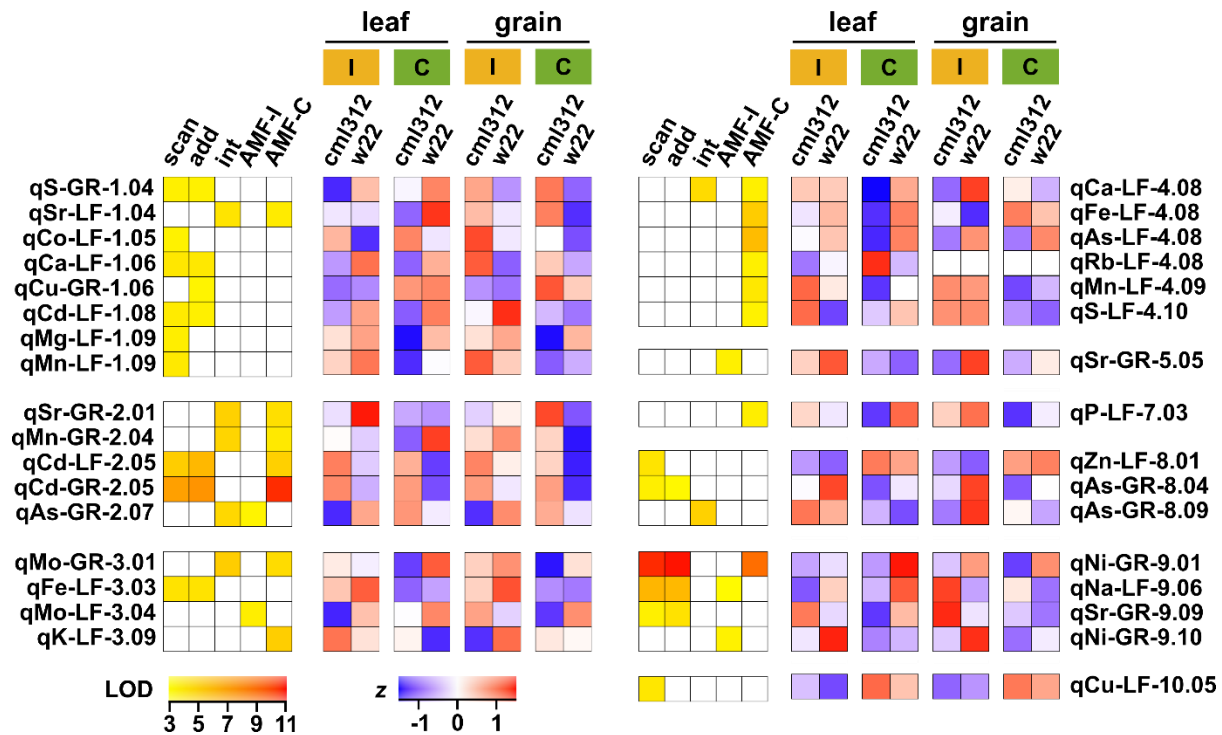
899 orange and negative correlations in blue. The width of links represents the absolute value of

900 correlation coefficients. Differences in correlation matrices were tested using the Chi-square

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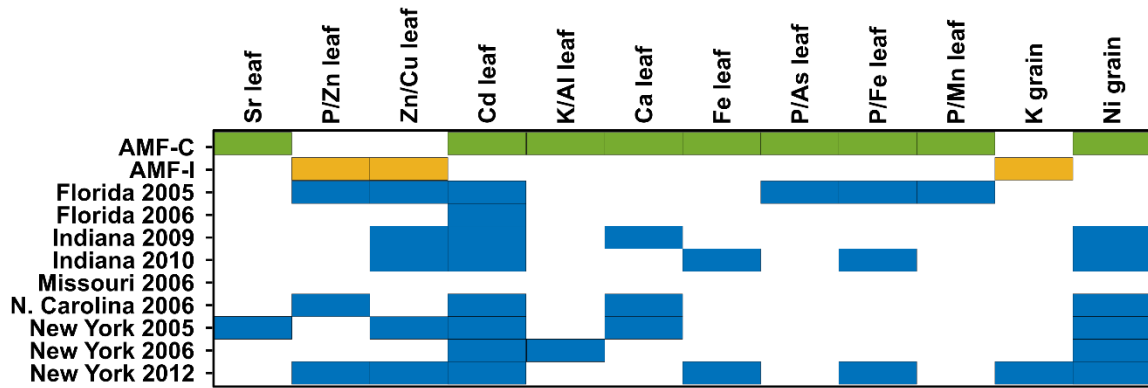
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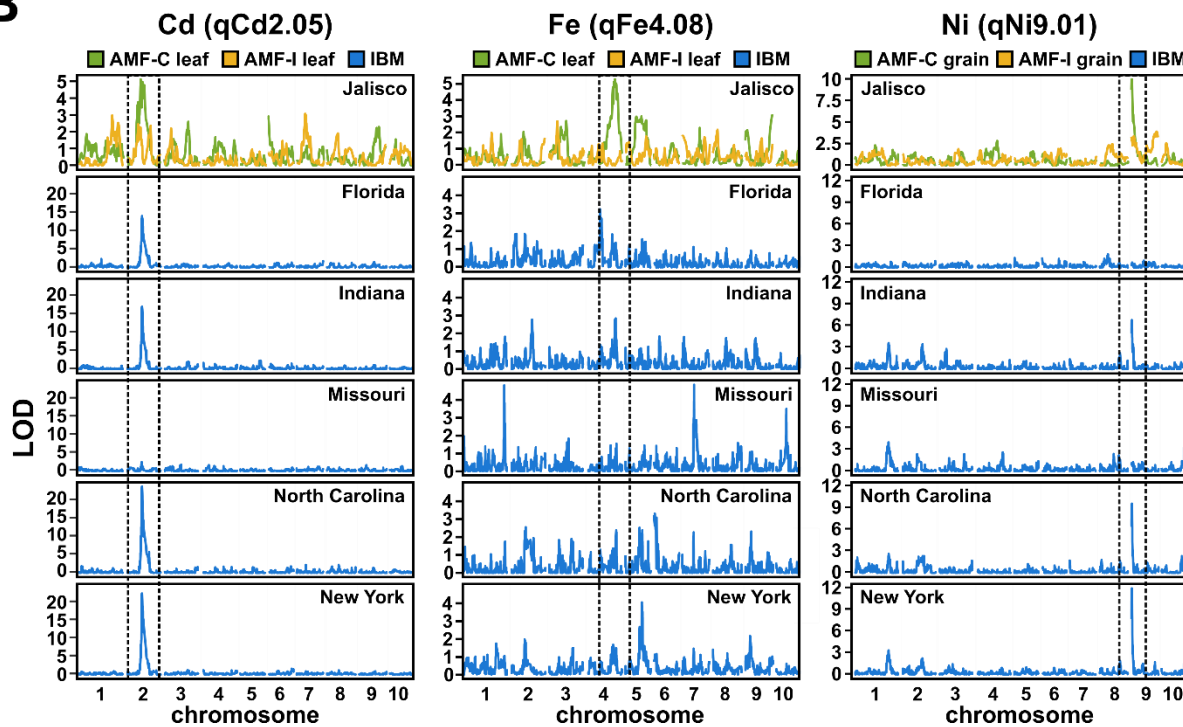
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Figure 2. The behaviour of element QTL is contingent on AM status. QTL support (LOD) and allele effects (standardised z score for W22 or CML312 allele) for significant element QTL. QTL are named for the associated ion, the tissue type (LF for leaf or GR for grain) and the genetic position (chromosome and bin). LOD support is only shown for the models for which the QTL was significant. Models given as *scan* - all families in a single QTL scan; *add* - AMF status as an additive covariate; *int* - AMF status as an interactive covariate; *AMF-I* - separate analysis of AMF-I families; *AMF-C* - separate analysis of AMF-C families. Effect estimates are shown for both leaf and grain, and both AMF-I (I, yellow) and AMF-C (C, green) families irrespective of whether the QTL was significant in any given tissue/AMF status combination. Effects were standardised separately for leaf and grain.

A



B



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920 **Figure 3. QTL specific to AMF-C families co-localize with element QTL showing $G \times E$**

921 **in a previously reported multisite evaluation.** A) Overlap between element QTL identified

922 in the current AMF experiment and evaluation of the Intermated B73·Mo17 (IBM) mapping

923 population across multiple sites and years (Asaro *et al.*, 2016). Coloured boxes indicate a

924 QTL was detected in AMF-C families (green), AMF-I families (yellow) or IBM (blue). B)

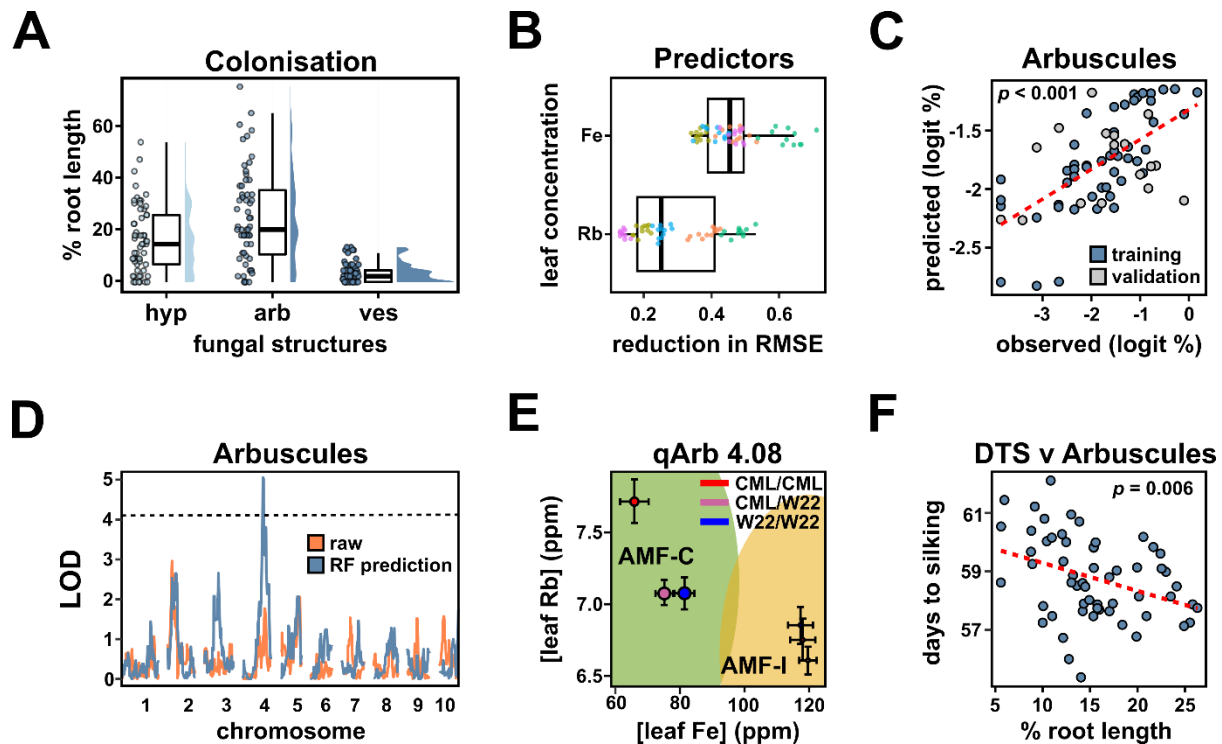
925 Genome wide QTL support (LOD) associated with concentrations of the named elements in

926 the AMF and IBM data. IBM plots were averaged over years when multiple data were

927 available. Dashed vertical lines highlight regions containing the named QTL identified in the

928 AMF-C population.

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932 **Figure 4. The ionome reflects arbuscular mycorrhizal colonisation.** A) Distribution of

933 fungal colonisation across the AMF-C families as percentage root length containing fungal

934 hyphae (hyp), arbuscules (arb) or vesicles (ves). B) Agnostic variable importance for leaf Fe

935 and Rb concentration in the Random Forest (RF) model. The greater the reduction in root

936 mean square error (RMSE) the greater the importance of the variable. C) Correlation between

937 observed and RF model predicted values of logit transformed arbuscule abundance.

938 Observations in the training subset were coloured blue, and data in the validation subset was

939 coloured grey. Validation set $r^2 = 0.041$ ($p = 0.42$); complete set $r^2 = 0.39$ ($p < 0.001$). D)

940 Genome wide QTL support (LOD) support for QTL associated with raw (orange) or

941 predicted (blue) logit transformed arbuscule abundance. The black horizontal line represents

942 the LOD significance threshold ($\alpha = 0.1$) for identifying qArb_4.08. E) Effect of the genotype

943 at qArb_4.08 on leaf Rb and Fe concentration for AMF-C (green) and AMF-I (yellow)

944 families. Colored ellipses contain 90% of the corresponding families. Points show the

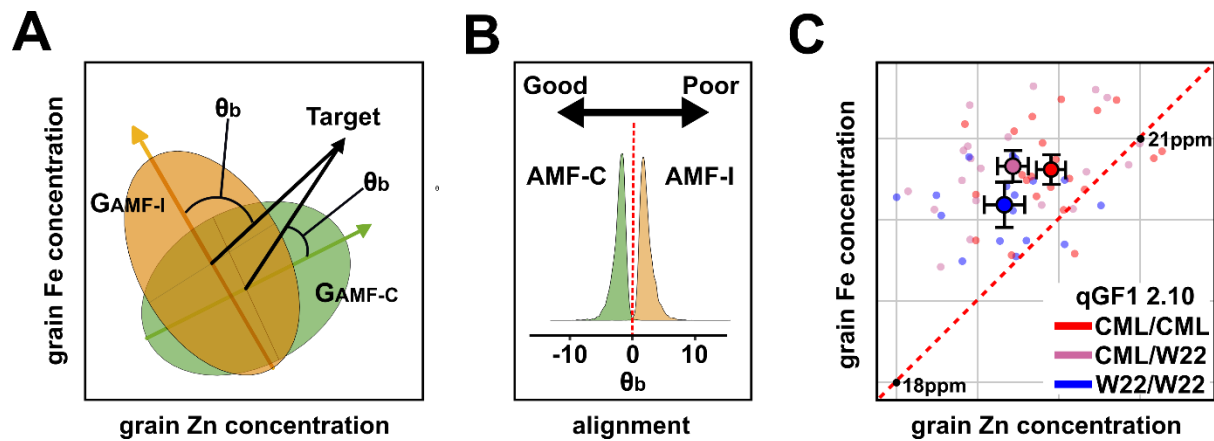
945 average concentration for each genotype, and error bars represent ± 1 standard error. The

946 diameter of the point is proportional to the predicted logit transformed arbuscule abundance.

947 F) Scatterplot of Days to Silking (DTS) and predicted logit transformed arbuscule abundance;

948 a mild negative and significant correlation was observed ($r = -0.36$, $p = 0.006$).

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952 **Figure 5. Arbuscular mycorrhizal association may facilitate progress towards**

953 **biofortification breeding targets.** A) The alignment (θ_b) between the breeding target vector

954 and the major axis of genetic variation in AMF-C (green) and AMF-I families (yellow). B)

955 Distributions showing the effect sizes and corresponding sampling variance of the alignment

956 (θ_b) of AMF-C and AMF-I families from 5000 Monte Carlo simulations. The negative value

957 indicates that the major axis of genetic variation is well aligned with the breeding target,

958 while the positive value indicates a poor alignment. The x-axis is on a transformed scale: -8

959 indicates the alignment is approaching 0° , and 8 indicates the alignment is approaching 90° .

960 C) Effect of the genotype at qGF1_2.1 on grain Zn and Fe concentration in AMF-C families.

961 Large points show the mean concentration ± 1 standard error. Small points show individual

962 families. The red dashed line indicates equivalence of Zn and Fe concentration.

963