Leveraging multi-harvest data for simultaneously selecting high-yield and witches' broom-resistant *Theobroma grandiflorum* hybrids

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Contents

Required packages

```
require(asreml)
require(tidyverse)
require(patchwork)
```

Loading the data

```
data = read.csv("data.csv", header = T, sep=';')
```

Setting the factors

```
data = transform(data,
                 Harvests = factor(Harvests),
                 Plots = factor(Plots),
                 Replicates = factor(Replicates),
                 Hybrids = factor(Hybrids))
```

Linear Mixed Models

Homoscedastic model for Fruit Yield

	Value	Std. Error	Conf. Int.
σ_g^2	14.45	5.56	10.90
σ_p^2	35.08	4.24	8.31
σ_{gh}^2	12.02	1.99	3.90
σ_e^2	71.08	2.47	4.84
r	0.82	NA	NA
H_g^2	0.68	NA	NA

Heteroscedastic model for Fruit Yield

	Value	Std. Error	Conf. Int.
σ_g^2	13.88	4.93	9.67
σ_p^2	26.62	3.23	6.33
σ_{gh}^2	7.92	1.56	3.05
$\sigma_{e_1}^2$	28.98	3.43	6.72
$\sigma_{e_2}^2$	28.41	3.36	6.59
$\sigma_{e_3}^2$	40.46	4.43	8.69
$\sigma_{e_4}^2$	49.32	5.27	10.33
$\sigma_{e_5}^2$	72.59	7.46	14.62
$\sigma_{e_6}^2$	98.50	10.09	19.79
$\sigma_{e_7}^2$	167.26	16.52	32.38
$\sigma_{e_8}^2$	101.13	10.43	20.44
$\sigma_{e_9}^2$	100.17	10.05	19.69
r	0.85	0.85	0.85
$H_{g_1}^2$	0.57	0.57	0.57
$H_{g_2}^2$	0.57	0.57	0.57
$H_{g_3}^2$	0.52	0.52	0.52
$H_{g_4}^2$	0.49	0.49	0.49
$H_{g_5}^2$	0.43	0.43	0.43
$H_{g_6}^2$	0.39	0.39	0.39
$H_{g_7}^2$	0.31	0.31	0.31
$H_{g_8}^2$	0.38	0.38	0.38
$H_{g_9}^2$	0.38	0.38	0.38

Coefficients of determination

```
sig2f = NULL
cgh = NULL
cp = NULL
ce = NULL

for (i in 1:nlevels(data$Harvests)) {
  sig2f[i] = sum(sum.fy2[1:3,1]) + sum.fy2[i+3,1]
  cgh[i] = sum.fy2["Hybrids:Harvests", "component"] / sig2f[i]
  cp[i] = sum.fy2["Plots", "component"] / sig2f[i]
  ce[i] = sum.fy2[i+3,1] / sig2f[i]
}

coef.det = data.frame(
  "Harvests" = levels(data$Harvests),
  "sig2f" = sig2f,
  "chg" = cgh,
```

```
  "cp" = cp,
  "ce" = ce
)
```

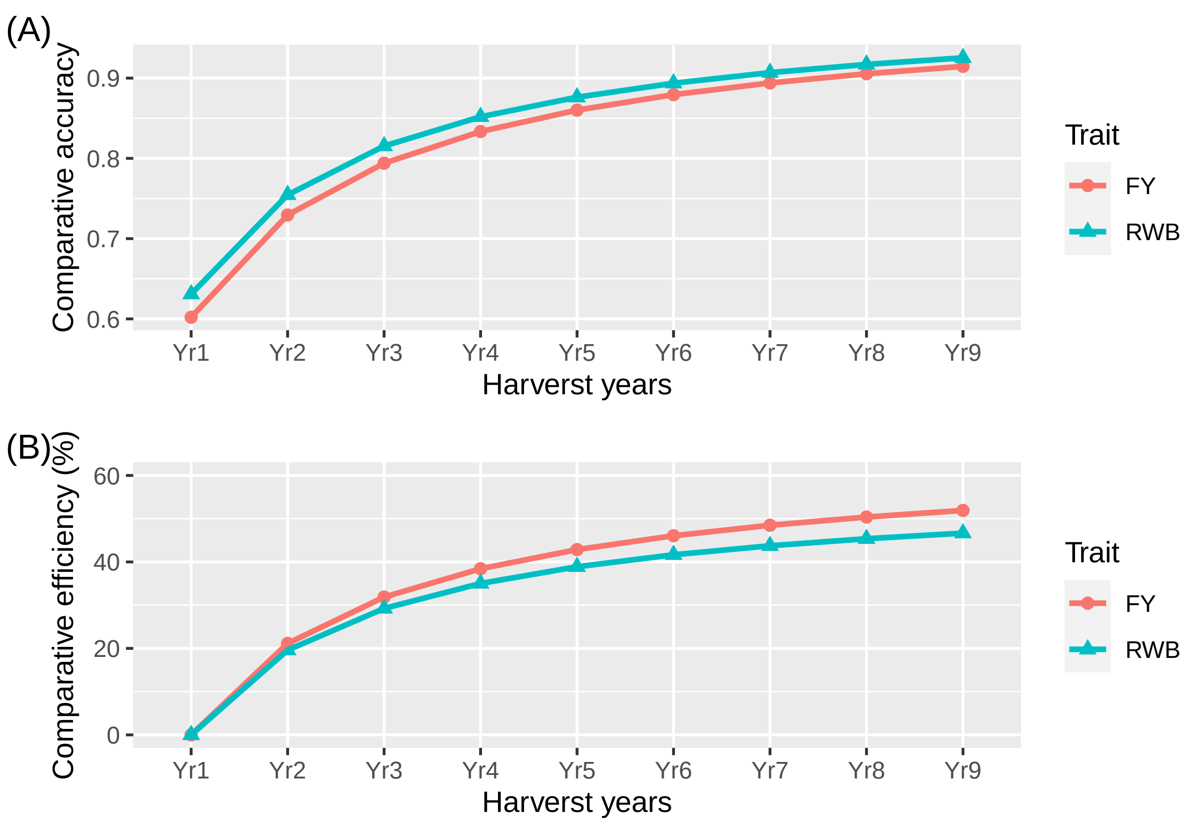
Harvests	σ^2_f	c^2_{gh}	c^2_p	c^2_e
Yr1	77.40	0.10	0.34	0.37
Yr2	76.83	0.10	0.35	0.37
Yr3	88.88	0.09	0.30	0.46
Yr4	97.74	0.08	0.27	0.50
Yr5	121.01	0.07	0.22	0.60
Yr6	146.92	0.05	0.18	0.67
Yr7	215.68	0.04	0.12	0.78
Yr8	149.56	0.05	0.18	0.68
Yr9	148.59	0.05	0.18	0.67

Generalized linear mixed model for witches' broom resistance

Optimum number of harvests

```
rho_fy = NULL
for (i in 1:nlevels(data$Harvests)) {
  rho_fy[i] = sum(sum.fy2["Hybrids","component"],sum.fy2["Plots","component"])/
    sig2f[i]
}

rho_fy = mean(rho_fy) #Fruit yield repeatability

rho_wb = sum(sum.wb["Hybrids","component"],sum.wb["Plots","component"])/
    sum(c(sum.wb[1:3,1],3.29)) #WB resistance repeatability


effh_fy = NULL
acch_fy = NULL
effh_wb = NULL
acch_wb = NULL
for (i in 1:nlevels(data$Harvests)) {
  effh_fy[i] = sqrt(i/(1+(i-1)*rho_fy))
  effh_wb[i] = sqrt(i/(1+(i-1)*rho_wb))
  acch_fy[i] = sqrt((i*rho_fy)/(i*rho_fy+1-rho_fy))
  acch_wb[i] = sqrt((i*rho_wb)/(i*rho_wb+1-rho_wb))
}

a = data.frame(
  "Harvests" = rep(levels(data$Harvests),2),
```

```
  "Trait" = rep(c("FY", "RWB"),each = nlevels(data$Harvests)),
  "Accuracy" = c(acch_fy,acch_wb)
) %>% ggplot()+
  geom_point(aes(x = Harvests, y = Accuracy, color = Trait, shape = Trait),
             size=2)+
  geom_line(aes(x = Harvests, y = Accuracy, color = Trait, group = Trait),
            size=1)+
  labs(y = "Comparative accuracy",x = "Harverst years",tag = "(A)")


b = data.frame(
  "Harvests" = rep(levels(data$Harvests),2),
  "Trait" = rep(c("FY", "RWB"),each = nlevels(data$Harvests)),
  "Efficiency" = c((effh_fy-1)*100,(effh_wb-1)*100)
) %>% ggplot()+
  geom_point(aes(x = Harvests, y = Efficiency, color = Trait, shape = Trait),
             size=2)+
  geom_line(aes(x = Harvests, y = Efficiency, color = Trait, group = Trait),
            size=1)+ ylim(0,60)+
  labs(y = "Comparative efficiency (%)", x = "Harverst years",tag = "(B)")

a/b
```



Selection index

Obtaining the yield persistence

```r
blups.fy = left_join(data.frame(
  'Hybrids' = rep(levels(data$Hybrids),each = nlevels(data$Harvests)),
  'Harvests' = rep(levels(data$Harvests),nlevels(data$Hybrids)),
  'blup' = blups.fy[(nlevels(data$Hybrids)+1):length(blups.fy)]
), data.frame(
  'Hybrids' = levels(data$Hybrids),
  'blup' = blups.fy[1:nlevels(data$Hybrids)]
), by='Hybrids') %>% mutate(
  BLUP = blup.x + blup.y
) %>% select(Hybrids, Harvests, BLUP)


max.fy = blups.fy %>% group_by(Harvests) %>%
  summarise(max = max(BLUP))

num = NULL

for (i in levels(data$Hybrids)) {

  dttes = blups.fy %>% filter(Hybrids == i) %>%
    select(Hybrids,Harvests,BLUP)

  num[i] = 1/sum((dttes$BLUP - max.fy$max)^2)

}

den = sum(num)^2

Per.fy = num/den
Per.fy = rownames_to_column(as.data.frame(Per.fy),'Hybrids')
```

Additive index

```r
blups.fy = blups.fy %>% group_by(Hybrids) %>%
              summarise(BLUP = mean(BLUP))

AI = cbind(Per.fy,blups.fy$BLUP,blups.wb)

colnames(AI)[2:4] = c("PERS.FY","BLUP.FY","BLUP.RWB")

AI = AI %>% mutate(
```

```r
  AI = (BLUP.FY/sqrt(sum.fy2["Hybrids","component"])) -
    (BLUP.RWB/sqrt(sum.wb["Hybrids","component"]))
)
```

Hybrids	PERS.FY	BLUP.FY	BLUP.RWB	AI
H125	2.55	6.94	-0.64	2.39
H165	0.51	5.54	-0.68	2.05
H143	0.09	1.72	-1.17	1.43
H117	0.26	4.50	-0.09	1.28
H137	0.04	-0.76	-1.73	1.23
H140	0.26	4.48	0.05	1.16
H167	0.08	1.68	-0.85	1.15
H124	0.05	-0.37	-1.30	0.98
H129	0.11	2.55	-0.17	0.83
H127	0.08	1.43	-0.43	0.74
H149	0.05	-0.19	-0.89	0.69
H135	0.04	-1.60	-1.31	0.65
H157	0.04	-0.50	-0.89	0.60
H131	0.05	-0.05	-0.50	0.40
H166	0.04	-0.71	-0.65	0.35
H118	0.03	-2.09	-0.94	0.22
H130	0.06	0.39	-0.08	0.17
H132	0.03	-2.18	-0.65	-0.05
H162	0.15	3.46	1.46	-0.28
H169	0.28	4.57	1.86	-0.32
H120	0.12	2.53	1.23	-0.34
H134	0.03	-3.36	-0.65	-0.36
H133	0.03	-3.39	-0.52	-0.48
H136	0.02	-4.03	-0.68	-0.51
H144	0.08	1.39	1.10	-0.54
H163	0.08	1.44	1.38	-0.76
H138	0.05	-0.33	1.10	-1.00
H152	0.04	-1.71	0.91	-1.21
H150	0.04	-1.16	1.30	-1.39
H121	0.04	-1.60	1.29	-1.50
H161	0.06	0.40	1.96	-1.51
H128	0.02	-6.38	-0.20	-1.54
H123	0.01	-7.96	-0.07	-2.08
H126	0.02	-4.67	1.45	-2.46