Response to comments

Paper #: *essd-2019-118*
Title: *Mapping the yields of lignocellulosic bioenergy crops from observations at the global scale*
Journal: *Earth System Science Data*

<u>Reviewer #2:</u>

Comment #1

The authors reported 3,963 observations covering five bioenergy crops in the abstract, however, they only used 161 grid cells to train the RF model. The sample size is too limited to map the spatial distribution of global bioenergy crops (over 60,000 grid cells). The comparison of the derived maps with other modeled maps cannot convince me.

Response #1

We thank the reviewer for the comments and suggestions. Please see the detailed point-by-point responses below. For the sample size, please see **Response #3** for details.

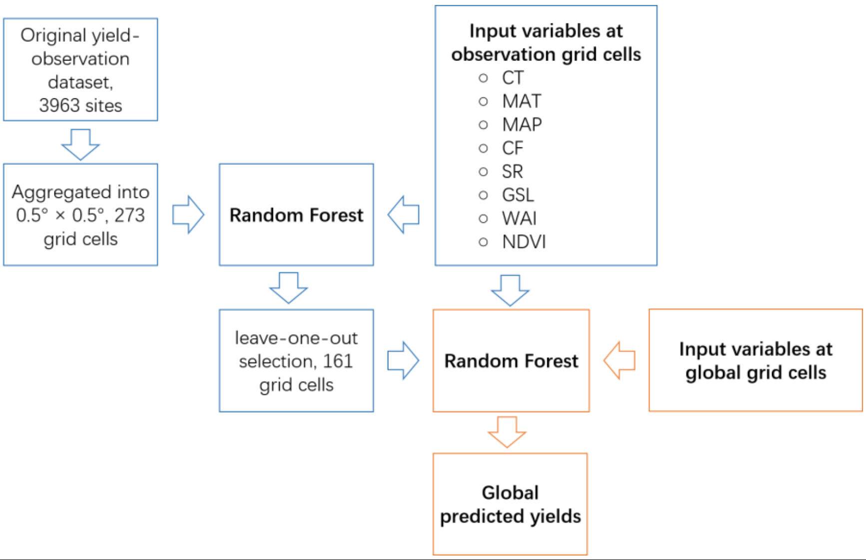
Comment #2

1. There were a bunch of variables included in the RF regressions. I suggested to add a diagram to show how random forest algorithm works in your study.

Response #2

We will add it as suggested (**Fig. R5**).

Fig R5 Workflow of random forest training and predicting in this study. The abbreviations of input variables can be found in Table 1.



Comment #3

2. At the global scale, there are more than 60,000 grids in 0.5◦ × 0.5◦. Here the authors used 161 grid cells for model training, among which you included five types of crop types. I think the training data are not substantial enough to build RF regression models.

Response #3

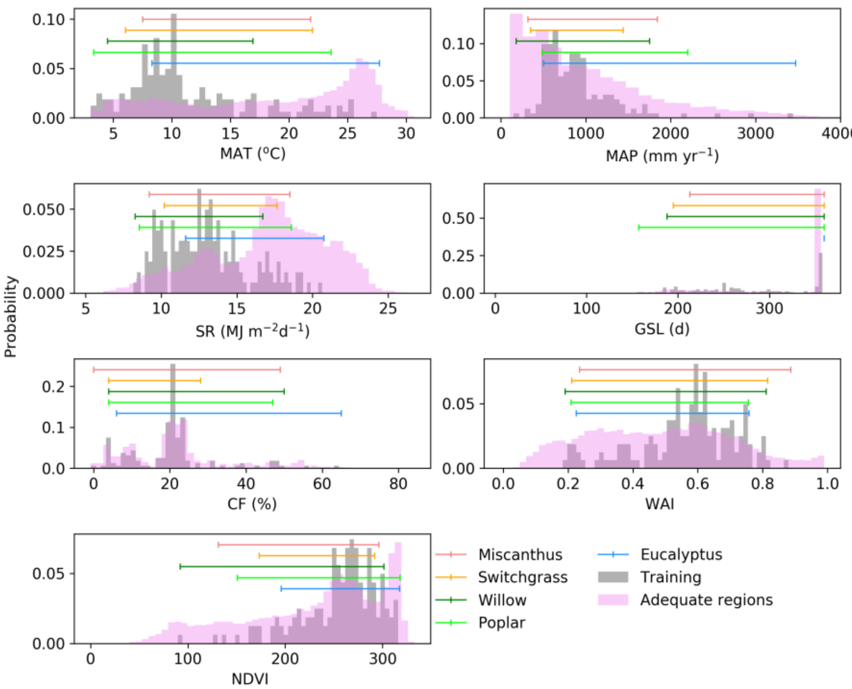
We agree that if we only look at the grid cell number, the training dataset covers about ~0.3% (161 / 60,000) of the global total grid cells. However, the spatial representativeness of the sample is more important when being used to upscale the whole population pattern. As shown in **Fig. S7** (reproduced below as **Fig. R6**), our training sample (gray) covers **most ranges of climate and soil variables** in the regions that we predicted (pink), implying that our training data are representative of the global adequate regions for bioenergy crop growth and thus appropriate for up-scaling (see **L363-373**). In addition to the range, the distributions also match well between the training sample and the prediction region (**Fig. R6**). Although the distributions of shortwave radiation are different, the importance of this variable in the random forest (RF) model is low (7%, **Fig. 2a**).

In addition, to avoid possible biases induced by out-of-range prediction, we only limited our predictions in regions with MAT and MAP above the minimums in the training data (**Section 2.2.3**). Thus, this gives us 33,216 grid cells in the prediction regions (instead of >60,000 globally) and avoids biased predictions in regions that are beyond the capacity of our trained random forest model. We can also add a short discussion on the comparison of the "out-of-range" predictions with IAM maps in the revised manuscript if needed.

At last, we would like to emphasize that we systematically collected all the published bioenergy crop yield observations that we searched in several literature databases (*Li et al. 2018*), so it is impossible to include more grid cells (currently 273 half-degree cells, 161 after selecting, **L157-171**) as there are no more observations available. Using these data, the OOB R^2 that serves as an evaluation of the trained random forest is 0.63, implying the trained RF algorithm is acceptable for prediction.

We will further summarize and discuss these points in the revised manuscript.

Fig. R6 (S7) Distributions of explanatory variables in the training data and in the regions that are adequate for bioenergy crop growth. The ranges of variables for each bioenergy crop type in the training data are also shown as lines with different colors.



Reference:

Li, W., Ciais, P., Makowski, D. and Peng, S.: A global yield dataset for major lignocellulosic bioenergy crops based on field measurements, Sci. Data, 5(180169), 2018.

Comment #4

3. Section 2.3. I appreciate that the authors compared their derived yield maps with the current three IAMs. However, it still cannot convince me since all these are modeled maps rather than the actual yield data. Is it possible to compare your derived yield maps with the existing inventory? Moreover, the authors assumed the derived maps are in 2010 without no temporal changes. To the best of my knowledge, the technology improvement has led to a significant increase of crop yield during the past several decades. Thus, I think it is not appropriate to compare your yield map with the present day's maps. The long-term average covering the time period of your collected observations is better for comparison. Line 198-199: What do you mean 'actual yield maps'? Is it your derived yield map from RF or other? If yes, I do not think you can consider it as an 'actual yield map'.

Response #4

In **Section 2.3**, we compared our random forest derived yield maps with those used in IAMs because our yield maps are observation based and can be used a benchmark for the present-day yield maps used in IAMs. Please see **Response #6** for the comparison with inventory data.

We agree with the reviewer that technology improvement has led to yield increase during the past decades, and thus "the long-term average covering the time period of collected observations" is better for comparison. However, the plantation of bioenergy crops applied in the IAMs is mainly for climate mitigation for removing CO_2 from the atmosphere e.g. through BECCS. This mitigation option has been proposed in most IAMs to keep the future temperature increase below 1.5 or 2 °C (*Rogelj et al., 2018*) but **not yet** implemented in large scales. Therefore, there are very limited (no) existing inventory data like e.g. those reported to the FAO by countries for other crops (see also **Response #6**), and the maps from IAMs start from present day. That is, unfortunately, **no** "long-term average covering the time period of collected observations" is available for comparison.

In addition, the comparison of our derived maps with maps from IAMs could be also justified: 1) the yield maps used in IMAGE and MAgPIE are from the simulated maps from LPJml model. In the model parameterization and calibration for bioenergy crops, LPJml also used available observation data (though a much smaller dataset compared to our dataset) covering the past period (e.g. at least since 1996 in *Beringer et al., 2011;* 1993-2008 in *Heck et al., 2016*). 2) The yield map from GLOBIOM is also based on historical observation data from FAO and other databases between 1984 and 2006 (see details on **L216-223**).

L198-199: Yes, "actual yield maps" is the derived yield map from RF. We call "actual yield maps" because our derived maps are based on observations and represent the yield that can be achieved under current (optimal) technology. We will revise this sentence as "For comparison, we used the present day (2010) actual yield maps (derived from RF).".

Reference:

Beringer, T., Lucht, W. and Schaphoff, S.: Bioenergy production potential of global biomass plantations under environmental and agricultural constraints, GCB Bioenergy, 3(4), 299–312, doi:10.1111/j.1757-1707.2010.01088.x, 2011

Heck, V., Gerten, D., Lucht, W. and Boysen, L. R.: Is extensive terrestrial carbon dioxide removal a "green" form of geoengineering? A global modelling study, Glob. Planet. Change, 137, 123–130, doi:10.1016/j.gloplacha.2015.12.008, 2016

Rogelj, J., Popp, A., Calvin, K. V., Luderer, G., Emmerling, J., Gernaat, D., Fujimori, S., Strefler, J., Hasegawa, T., Marangoni, G., Krey, V., Kriegler, E., Riahi, K., Van Vuuren, D. P., Doelman, J., Drouet, L., Edmonds, J., Fricko, O., Harmsen, M., Havlík, P., Humpenöder, F., Stehfest, E. and Tavoni, M.: Scenarios towards limiting global mean temperature increase below 1.5 °C, Nat. Clim. Chang., doi:10.1038/s41558-018-0091-3, 2018.

Comment #5

4. Figure 3. The spatial distribution of predicted yields seems to highly correlated with MAP. For example, the Amazon basin and Southeast Asia receive a substantial rainfall per year. The spatial

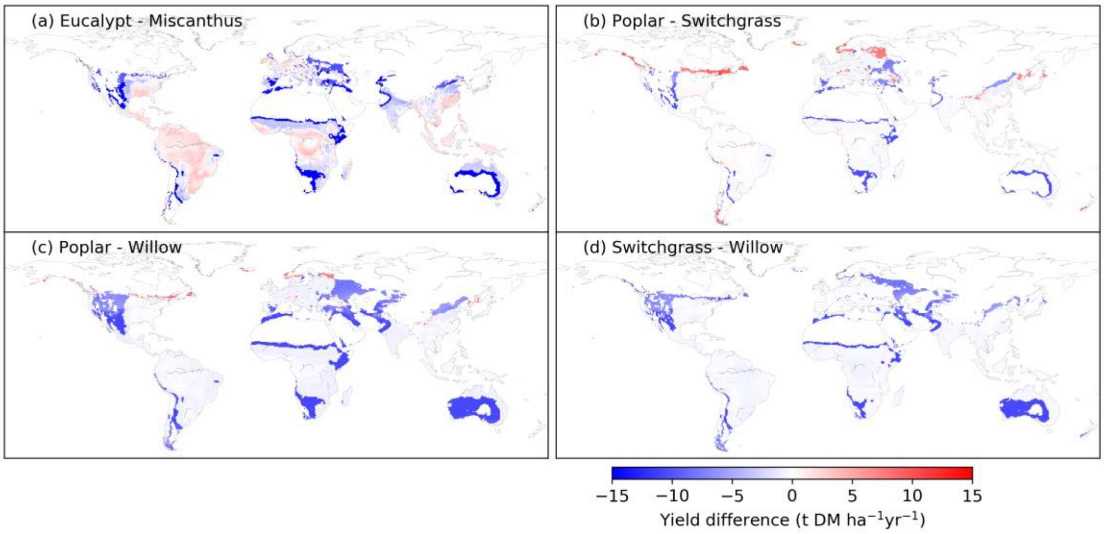
distribution of Eucalypt and Miscanthus are so similar, the same as the remaining three crops. Thus, nothing new surprised me.

Response #5

Yes, MAP as the most important variable in the RF regression is exactly what we obtained from the model training, and thus the predictions largely depend on the spatial patterns of annual rainfall. This is consistent with previous studies that MAP is the main predictor of NPP across spatial gradients (*Knapp et al., 2017*). Although the general spatial patterns look similar, there are still differences caused by other factors than MAP. This could be partly reflected by the different occupying regions from different bioenergy crops in **Fig. 3g**. To address the reviewer's concern on the similarity, we further plotted the map of yield differences between eucalypt and *Miscanthus* and among the other three crops. As shown in **Fig R7**, there are substantial differences between the yields of eucalypt and *Miscanthus*. The higher yields of eucalypt than *Miscanthus* in South America, East US, central Africa and southeast Asia and lower yields in other regions (**Fig. R7a**) can also be reflected by the best crop type in **Fig. 3g**. Because the contribution of crop types (poplar, switchgrass and willow) is low the trained random forest algorithm (CT_poplar, CT_switchgrass and CT_willow in **Fig. 2a**), the predicted yields in the regions where all three crops can grow are controlled by other mutual variables and thus similar. Therefore, the yield differences among these three crops are mainly caused by the different 'adequate' regions for growth (**Fig. S4**) defined by the minimum MAT and MAP in the observation dataset (**L181-190**). For example, willow can survive in regions with lower MAT and MAP, and thus have higher yield that poplar and switchgrass in these regions (**Fig. R7c,d**).

We will add the figure and corresponding discussion in the revised manuscript.

Figure R7 Difference of predicted yields between various bioenergy crop types.



Reference:

Knapp, A. K., Ciais, P., & Smith, M. D. Reconciling inconsistencies in precipitation–productivity relationships: implications for climate change. New Phytologist, 214(1), 41-47, 2017.

Comment #6

5. Figure 5. Did you compare your areas with any existing inventory data? It is better to compare yours with them since the total amount of production is also important.

Response #6

For Miscanthus and switchgrass, there are only small-scale experimental plots in different regions and no large-scale plantation, so, to the best of our knowledge, no region- or country-scale inventory data are available. Most yield data at farm levels were already included in our observation yield dataset (see “Field_type” and “Field_size” in *Table 2* in *Li et al. 2018*).

For poplar, willow and eucalypt, we searched on several literature databases and on Google but only found one *FAO* report by *Del Lungo et al.* (*FAO, 2006*). We collected the mean annual increment (MAI) data for species of *eucalyptus*, *populus* and *salix* for each country (**Table R1**, extracted from **Table 6a** in *FAO, 2006*). The volume unit of MAI was converted to mass unit of yield based on the wood density of different tree types (*Engineering ToolBox, 2004*).

The main difficulty is however lack of spatially explicit data about where are plantations located in national-scale inventory data, preventing an accurate comparison with the RF predicted yields. Still, we derived the yield range in the whole country from the RF predicted yield maps and compared with the yield range from the inventory data (*FAO, 2006*, **Fig. R8**). Most yield ranges from the inventory data overlapped with the ranges from RF maps (e.g. eucalypt and willow in Argentina) although the former is generally lower than the latter (**Fig. R8**). The higher minimum and maximum yields from RF could be caused partly by the exclusion of regions with MAP and MAT below the minimums from the observation dataset (to avoid out-of-range prediction, see details on **L181-190**). Especially, in some large countries, the inventory data may have plantations in some harsh climate and soils (e.g. most eucalypt plantations distribute in drier areas in the South Brazil). However, we must note that it is not a fair comparison without knowing the exact plantation locations in each country.

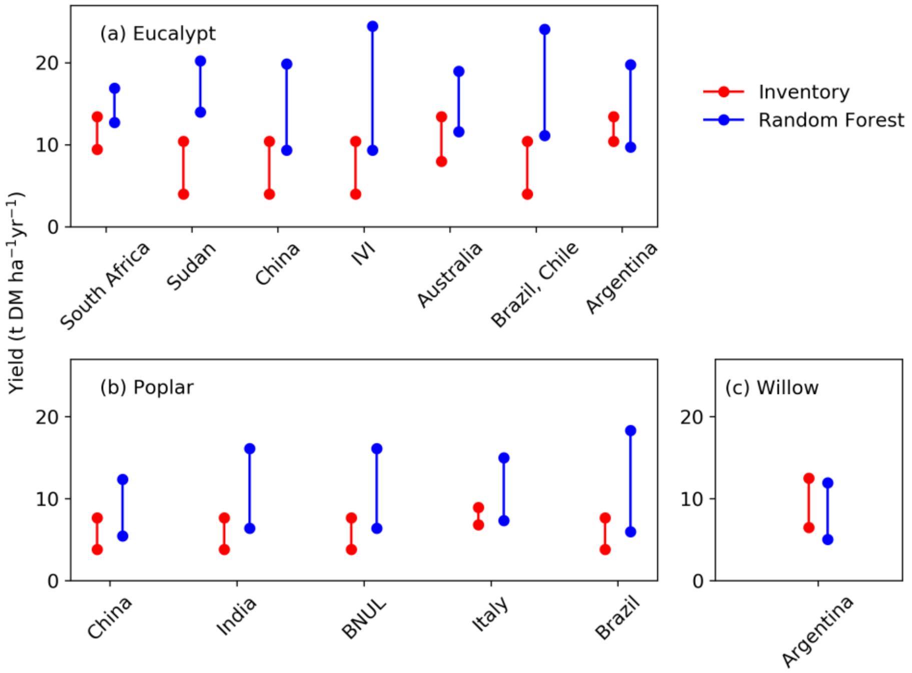
If the reviewer knows some other data sources, we will appreciate if you could let us know and we will add them for comparison.

Table R1 Plantation area and maximum and minimum MAI (mean annual increment) of eucalypt, poplar and willow from inventory data compiled in *FAO 2006*.

Species	Area (1000 ha)	MAI min (m^3/ha/y)	MAI max (m^3/ha/y)	Country
Eucalyptus grandis	335	21	27	South Africa
Eucalyptus nitens	231	19	26	South Africa
Eucalyptus spp.	473	8	21	Sudan
Populus spp.	3220	9	18	China
Eucalyptus spp.	2397	8	21	China
Eucalyptus spp.	4047	8	21	Indonesia, Viet Nam, India
Populus spp.	171	9	18	India
Populus spp.	84	9	18	Belgium, Netherlands, Ukraine, Latvia
Populus hybrids	83	16	21	Italy
Eucalyptus globulus	442	16	25	Australia
Eucalyptus nitens	35	19	26	Australia
Eucalyptus dunnii	18	16	18	Australia
Eucalyptus grandis	18	21	27	Australia
Eucalyptus pilularis	18	18	18	Australia
Eucalyptus regnans	18	18	20	Australia
Eucalyptus spp.	3678	8	21	Brazil, Chile
Eucalyptus grandis	99	21	27	Argentina
Populus spp.	31	9	18	Brazil, Chile
Salix alba	23	13	20	Argentina
Salix babylonica	23	20	25	Argentina

Salix babylonica var. sacramenta	23	20	25	Argentina
Salix hibrids	23	20	25	Argentina

Figure R8 Yield ranges from (limited) inventory data and our random forest maps at country levels. IVI stands for Indonesia, Viet Nam and India; BNUL stands for Belgium, Netherlands, Ukraine and Latvia.



Reference:

Engineering ToolBox. Density of Various Wood Species. [online] Available at: https://www.engineeringtoolbox.com/wood-density-d_40.html [Accessed 15/11/2019]. 2004.

Brown, S. Estimating biomass and biomass change of tropical forests: a primer (Vol. 134). Food & Agriculture Org. 1997.

FAO. Global planted forests thematic study: results and analysis, by A. Del Lungo, J. Ball and J. Carle. Planted Forests and Trees Working Paper 38. Rome (also available at www.fao.org/forestry/site/10368/en). 2006.

Li, W., Ciais, P., Makowski, D. and Peng, S.: A global yield dataset for major lignocellulosic bioenergy crops based on field measurements, Sci. Data, 5(180169), 2018.

Comment #7

6. Figure 2. You listed the variable importance in the trained RF model. It turns out that MAP is the dominant variable. You provide Figure S8 to show the relationship of bioenergy crop yield with temperature. However, MAT is not quite important compared with other variables. Why did not you show the relationship of each crop with dominant variables, such as MAP, GSL, WAI, etc.

Response #7

We only plotted the relationship with MAT because temperature is a target variable of future global warming and we would like to show how the yield will change with temperature increase in the future. We agree that MAP is the dominant variable in the RF, but temperature related variables (GSL and MAT) also contribute significantly. As suggested, we will further add the relationships with the dominant variables (reproduced below).

Figure R9 Relationship of bioenergy crop yield with mean annual precipitation (MAP) across all grid cells that are adequate for bioenergy crop growth.

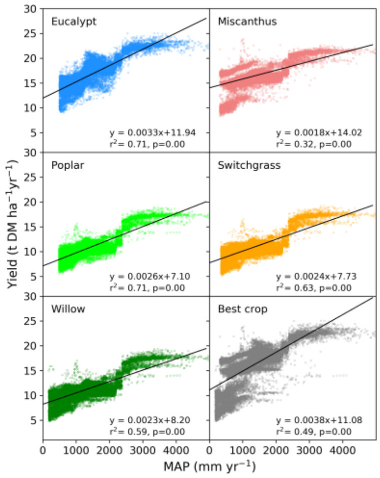


Figure R10 Relationship of bioenergy crop yield with growing season length (GSL) across all grid cells that are adequate for bioenergy crop growth.

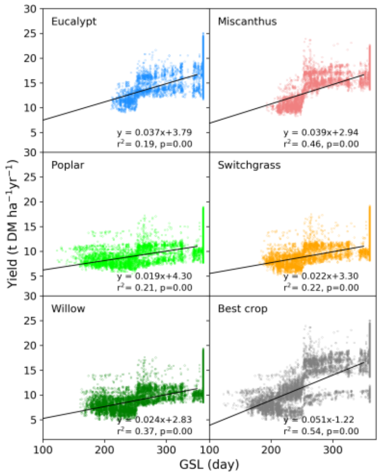


Figure R11 Relationship of bioenergy crop yield with soil water availability index (WAI) across all grid cells that are adequate for bioenergy crop growth.

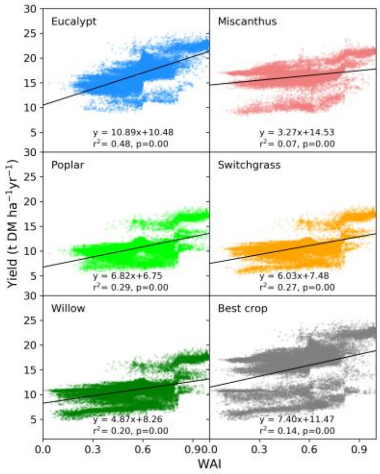


Figure R12 Relationship of bioenergy crop yield with growing season integrated normalized difference vegetation index (NDVI) across all grid cells that are adequate for bioenergy crop growth.

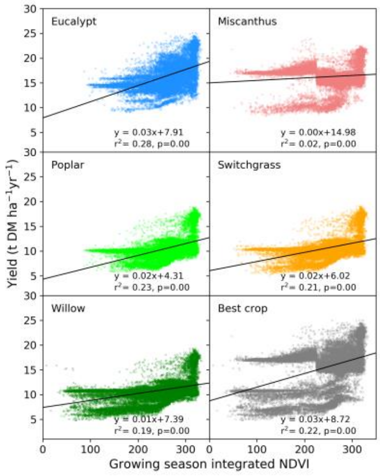


Figure R13 Relationship of bioenergy crop yield with shortwave radiation (SR) across all grid cells that are adequate for bioenergy crop growth.

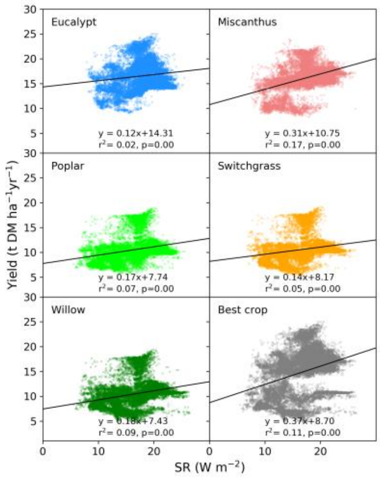
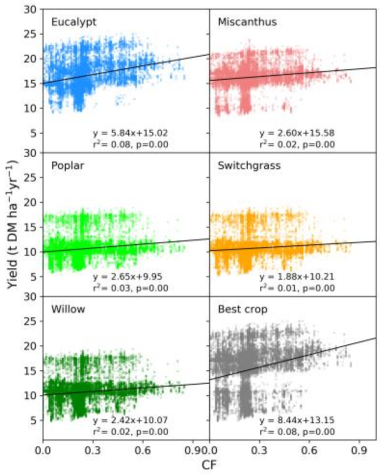


Figure R14 Relationship of bioenergy crop yield with clay fraction (CF) across all grid cells that are adequate for bioenergy crop growth.


Eucalypt
y = 5.84x+15.02
r^2= 0.08, p=0.00
Miscanthus
y = 2.60x+15.58
r^2= 0.02, p=0.00
Poplar
y = 2.65x+9.95
r^2= 0.03, p=0.00
Switchgrass
y = 1.88x+10.21
r^2= 0.01, p=0.00
Willow
y = 2.42x+10.07
r^2= 0.02, p=0.00
Best crop
y = 8.44x+13.15
r^2= 0.08, p=0.00
Yield (t DM $ha^{-1}yr^{-1}$)
CF