Combining organic and mineral fertilizers as a climate-smart integrated soil fertility management practice in sub-Saharan Africa: A meta-analysis

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Abstract

Low productivity and climate change require climate-smart agriculture (CSA) for sub-Saharan Africa (SSA), through (i) sustainably increasing crop productivity, (ii) enhancing the resilience of agricultural systems, and (iii) offsetting greenhouse gas emissions. We conducted a meta-analysis on experimental data to evaluate the contributions of combining organic and mineral nitrogen (N) applications to the three pillars of CSA for maize (Zea mays). Linear mixed effect modeling was carried out for; (i) grain productivity and agronomic efficiency of N (AE) inputs, (ii) inter-seasonal yield variability, and (iii) changes in soil organic carbon (SOC) content, while accounting for the quality of organic amendments and total N rates. Results showed that combined application of mineral and organic fertilizers leads to greater responses in productivity and AE as compared to sole applications when more than 100 kg N ha\(^{-1}\) is used with high-quality organic matter. For yield variability and SOC, no significant interactions were found when combining mineral and organic fertilizers. The variability of maize yields in soils amended with high-quality organic matter, except manure, was equal or smaller than for sole mineral fertilizer. Increases of SOC were only significant for organic inputs, and more pronounced for high-quality resources. For example, at a total N rate of 150 kg N ha\(^{-1}\) season\(^{-1}\), combining mineral fertilizer with the highest quality organic resources (50:50) increased AE by 20% and reduced SOC losses by 18% over 7 growing seasons as compared to sole mineral fertilizer. We conclude that combining organic and mineral N fertilizers can have significant positive effects on productivity and AE, but only improves the other two CSA pillars yield variability and SOC depending on organic resource input and quality. The findings of our meta-analysis help to tailor a climate smart integrated soil fertility management in SSA.
Introduction

Management of fertilizer inputs is of key importance for food security in sub-Saharan Africa (SSA), as its rapidly growing and urbanizing population is not being met with a proportionate growth of agricultural production [1]. Smallholder farmers are suffering from nutrient limitations and low nutrient use efficiencies of particularly nitrogen (N) as a consequence of soil degradation [2–5]. The latter arises when the recycling of crop residues and use of mineral and organic fertilizers are insufficient to compensate for harvested nutrients and soil organic matter losses [1, 6]. So far, most increases in food production in SSA have been achieved by agricultural expansion rather than intensification, which comes at the cost of natural lands and ecosystems. Enhancing the productivity and efficiency of food production in SSA by sustainable intensification is therefore crucial to improve its food security [1, 7].

In addition to soil degradation, climate change is further challenging the agriculture-based societies of SSA [8, 9]. Rainfall is becoming increasingly variable and extreme, and most parts of Africa are experiencing more frequent droughts as observed from long-term precipitation and evaporation trends [10]. Yet, the vast majority of staple food production in SSA, such as maize, comes from rainfed agriculture and is thus vulnerable to changing rainfall regimes [11–14]. Maize is the primary staple food of more than 300 million people in SSA and an important source of income for particularly smallholder farmers [5]. Yet, maize productivity in SSA is low and is being exacerbated by climate change [2, 15, 16]. Maize grain yields on average are 58% below the water-limited potential across tropical Africa [17], and are projected to decline by up to 12% by 2050 [15, 18]. Furthermore, agriculture in SSA is dominated by smallholder subsistence farmers, whose adaptive capacity is low and already being compromised by natural resource degradation [13, 15, 18].

Low productivity and climate change impacts require climate-smart agriculture (CSA), through (i) improving food security by sustainably increasing crop productivity, (ii) enhancing the resilience of agricultural systems or adaptive capacity, and (iii) offsetting greenhouse gas emissions [16, 19–21]. The integrated soil fertility management (ISFM) framework could play an important role in achieving sustainable intensification in SSA. It aims to increase crop productivity by maximizing the agronomic efficiency (AE) of fertilizer inputs through the combined application of mineral and organic fertilizers, improved germplasm, and good agronomic practices [1, 22]. A major component of ISFM is the combined application of mineral and organic fertilizers. Research in SSA has shown that the combined application can lead to greater AE of N and crop productivity for maize as compared to separate applications [23–27]. Several reasons have been suggested. First, combining mineral and organic nutrient sources allows smallholder farmers to apply adequate and proportionate amounts of both minor and major nutrients, which is necessary to sustain soil fertility and crop production in the long term [1, 22]. Second, on top of its obvious role for soil fertility, an increased soil organic matter content also improves other soil functions such as soil biological processes and soil moisture regime [22]. This, in turn, improves resilience to droughts. And third, combined application has the potential to generate interactive effects between both resources, as the synchronization of N availability and plant uptake, both in quantity and time, may be improved through decomposition and subsequent N (im)mobilization processes [25, 28, 29]. Since N synchrony depends on N mineralization and immobilization processes, Vanlauwe et al. [28] hypothesized that organic input quality likely affects potential interactive effects. This was confirmed by incubation and field trials, where Gentile et al. [24, 25] found that low-quality organic inputs tend to favor positive interactions when combined with mineral fertilizer, whereas high-quality organic inputs did not. They argued that the rapid mineralization of high-quality organic N combined with mineral N would exceed early crop demand, and hence would contribute to
potential negative interactions. Similarly, high N input rates could exceed crop demand and lead to negative interactions, suggesting that N input rates may also have an effect on interactive effects [23, 29].

Apart from the effect of combined application on productivity and AE, this study further aims to evaluate the effects on the other two pillars of CSA, namely the agricultural system’s resilience and offsetting of greenhouse gas emissions such as CO$_2$. Concerning the resilience of food production systems, yield reliability can be considered as a key indicator as it defines the capacity of the system to remain close to its stable yield equilibrium when exposed to seasonal variation in weather conditions [30]. Since climate change is rendering the latter more variable and extreme, yield variability is expected to increase, and as such will decrease yield reliability [31, 32]. Yet, despite its importance, research addressing maize yield variability or reliability in the context of nutrient trials is scarce. Nevertheless, Bayu et al. [33] found through sorghum trials in Ethiopia that yield stability decreased with the applications of manure combined with higher rates of mineral N, Vanlauwe et al. [34] concluded that combining mineral N with alley-cropping *Senna siamea* in maize-cowpea rotations would outperform the other treatments while achieving an acceptable yield stability, and Fujisaki et al. [35] stated that high organic inputs are needed in the tropics to ensure yield stability and climate change resilience.

Emissions of CO$_2$, on the other hand, can potentially be mitigated by storing atmospheric carbon (C) in soils. Apart from the mitigation potential, raising soil organic carbon (SOC) stocks is also essential for a sustainable soil health and crop productivity [36, 37]. Raising SOC stocks seems, however, to be challenging. Long-term organic and mineral nutrient trials on maize monocropping in SSA consistently reported declining SOC [38–42], but found that treatments with organic inputs were more successful in reducing SOC losses than mineral and no-input treatments [40, 41, 43–45]. A meta-analysis conducted by Chivenge et al. [23] confirmed that mineral fertilizer treatments did not have a significant effect and that organic inputs were necessary to help reduce SOC loss. Whether organic matter inputs contribute to stable soil organic matter or SOC, depends on a number of factors influencing the decomposition and subsequent stabilization processes, such as organic input properties, and soil and climate variables [46–48]. Fujisaki et al. [35] found that organic input quantity and quality were more important predictors than soil and climate properties, though quantity likely has a larger effect than quality according to Gentile et al. [29] and Castellano et al. [49]. In addition, Chivenge et al. [46] and Gentile et al. [50] did not observe quality related long-term differences in SOC stocks.

With climate change adaptation and mitigation of food production systems becoming ever more critical, the need arises for a complete CSA assessment of the ISFM combined application practice. We therefore conducted a meta-analysis of short- and long-term maize nutrient trials across SSA, in order to assess the effect of combined versus sole application of organic and mineral N inputs on (i) maize productivity and AE of N, (ii) maize yield variability, and (iii) on SOC. In parallel, we investigated to what extent these effects were influenced by organic matter quality and total N input rates.

**Materials and methods**

**Data collection**

Relevant peer-reviewed publications were identified through the following key word searches on Google Scholar: ‘combined application’, ‘Sub-Saharan Africa’, ‘maize’, ‘organic’, and ‘mineral’. Studies were selected when providing data on maize grain yields and associated variance for treatments with (i) sole application of mineral N fertilizer (MR), (ii) sole application of unprocessed organic resources (OR), and (iii) combined application of mineral and organic...
resources (ORMR). This first selection process refers to steps one to three of the PRISMA flow chart in Fig 1. A last search was conducted on 9/3/2020, after which no more data were included. After consolidating the data (Cfr. section Data consolidation), the selection of studies was further refined by screening for studies with organic resource type and quality parameters (N, C, polyphenols, lignin content, and C:N ratio), organic and mineral input rates for the productivity and AE analyses, and initial and measured SOC with organic C and N rates for the SOC analyses with C and N inputs, respectively. This second selection round refers to steps four to six of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses
By applying the abovementioned selection criteria, 40 studies were used in total for the productivity and variability analysis, providing 2943 yield data points across 68 sites. Of those 40 studies, 15 provided 488 SOC data points across 21 sites with C rate data, and 17 provided 531 SOC data points across 23 sites with organic N rate data. An overview of the relevant data from the publications selected for each analysis is given in Table 1.

A no-input treatment (control) was not required, but was absent in only two studies, i.e. Mungai et al. [54] and Nziguheba et al. [83]. Studies with fallow rotations were excluded as residual effects were not part of the research questions. When the data were not readily available from tables, they were extracted from graphs using GraphClick [91], or an attempt was made to request the authors for their data. Raw data from publications were obtained from Vanlauwe et al. [92], Franke et al. [93], and the meta-analysis of Chivenge et al. [23], and may have included gray literature data. Unpublished data were obtained from the works of Chivenge et al. [90], Fonte et al. [81], and Mapfumo et al. [89]. For different publications covering the same trial, only the most exhaustive one was considered (e.g. Vanlauwe et al. [34, 92]). The following data were also retrieved from all papers: country and site location (name and GPS coordinates), growing season or year, maize grain yield and variance, type of organic application and cropping system, and mineral fertilizer design.

### Data consolidation

Information from publications was compiled for each individual site within study. A standardized time measure was assigned to all observations, corresponding to the nth growing season of the respective experiment. This could be one or two per year, depending on uni- or bimodal rainfall patterns, respectively. Studies were classified according to their type of organic application or cropping system, i.e. monocrop (with biomass inputs), legume intercrop, and legume rotation. Mineral fertilizer design indicated if phosphorus (P) and potassium (K) are either not applied (fixed), applied as a blanket for all treatments including a control (fixed), or applied proportionally with N (NPK). The study of Akinnifesi et al. [43] concerns three different P rates, so it is used once as an NPK study (3 different MR treatments), and another three times as blanket studies (one for each P rate). Organic resource types included raw residues from crops, biomass from alley crops, legume rotation or intercropping, and animal manure. These were categorized into four quality classes according to the organic data base (ODB) of Palm et al. [47]. High-quality organic classes I and II have a high N content (>2.5%), and low-quality classes III and IV have a low N content (<2.5%). Classes I and III have low lignin contents (<15%), whereas classes II and IV have high lignin contents (>15%) (Table 2). A separate class Manure was created to include variable organic inputs like farm yard manure and compost, analogous to Vanlauwe et al. [94]. When not reported, quality parameters were estimated using average values from the ODB, or otherwise other literature available. Only a few studies addressed organic resources of class IV, and for a limited range of N inputs. As a consequence, class IV was considered too unbalanced throughout the data set and was not used for the yield and AE modeling. It could, however, be included in the SOC modeling with C input as it was balanced across the C input range. The combinations of treatment with the organic classes are hereafter referred to as subtreatments. When organic input rates were reported as tons of biomass added per ha, the organic N and C % input was estimated using the ODB of Palm et al. [47]. No distinction was made for the different experimental designs or maize varieties, nor were different planting stands and densities adjusted for. Yield data were used as they were reported from studies, i.e. as averages from replicated treatments. Standard deviations (SDs) were conservatively derived from the variance components available, for each reported yield estimate if possible. The SOC data of a publication were considered relevant when at least two
Table 1. Overview of the data set used for the YIELD and SOC meta-analyses, with columns for the study’s country-site combination index (id), study (reference), aridity index class (AI class), time span of the study’s experiment (time span), number of yield data (nYield), number of SOC data associated with C and N rates (nSOC C input and nSOC N input, respectively) (*). The site’s aridity index was extracted from the CGIAR-CSI Global-Aridity and Global-PET Database [51].

| id  | reference          | country     | site         | AI class | time span | cropping system | fertilizer design | nYield | nSOC C input | nSOC N input |
|-----|--------------------|-------------|--------------|----------|-----------|-----------------|-------------------|--------|---------------|---------------|
| 9   | Mariki et al. [52] | Tanzania    | Selian arusha| humid    | 2         | monocrop       | fixed             | 10     |               |               |
| 11  | Kihanda et al. [53]| Kenya       | Embu Kihanda | dry sub-humid | 10       | monocrop       | NPK               | 24     | 16            | 16            |
| 12  | Kihanda et al. [53]| Kenya       | Kavutiri     | humid    | 9         | monocrop       | NPK               | 8      | 8             | 8             |
| 21  | Mungai et al. [54] | Kenya       | Njoro Makuru | dry sub-humid | 1        | monocrop       | fixed             | 10     |               |               |
| 22  | Mungai et al. [54] | Kenya       | Piave Makuru | dry sub-humid | 1        | monocrop       | fixed             | 10     |               |               |
| 25  | Murwira et al. [55]| Zimbabwe   | Muchinjike   | dry sub-humid | 1        | monocrop       | fixed             | 12     |               |               |
| 28  | Murwira et al. [55]| Zimbabwe   | Wedza       | dry sub-humid | 1        | monocrop       | fixed             | 12     |               |               |
| 29  | Onyango et al. [56]| Kenya      | Anin Kitale | dry sub-humid | 3        | monocrop       | fixed             | 18     |               |               |
| 30  | Onyango et al. [56]| Kenya      | Cheptya kitale | dry sub-humid | 2        | monocrop       | fixed             | 8      |               |               |
| 31  | Onyango et al. [56]| Kenya      | Chobosta kitale | dry sub-humid | 3        | monocrop       | fixed             | 12     |               |               |
| 32  | Onyango et al. [56]| Kenya      | Matunda Kitale | dry sub-humid | 3        | monocrop       | fixed             | 12     |               |               |
| 33  | Snapp [57]         | Zimbabwe   | Domboshawa RS| dry sub-humid | 1        | rotation       | NPK               | 4      |               |               |
| 34  | Workayehu [58]     | Ethiopia   | Awasa       | dry sub-humid | 3        | monocrop       | fixed             | 54     |               |               |
| 35  | Ikerra et al. [59] | Malawi     | Makoka RS   | humid    | 2         | intercrop      | fixed             | 12     |               |               |
| 36  | Kapkiyai et al. [40]| Kenya     | Kabete RS   | humid    | 19        | monocrop       | NPK               | 4      |               |               |
| 37  | Mugendi et al. [60]| Kenya      | Embu RS     | humid    | 34        | monocrop       | fixed             | 6      | 6             | 6             |
| 40  | Makumba et al. [61]| Malawi     | Makoka RS   | humid    | 2         | monocrop       | fixed             | 12     |               |               |
| 41  | Mugendi et al. in Okalebo et al. [62, 63]| Kenya | Meru | humid | 2 | monocrop | fixed | 28 | |
| 42  | Nandwa [64]        | Kenya      | Kabete      | humid    | 5         | monocrop       | NPK               | 4      |               |               |
| 43  | Gigou and Bredoumy [65]| Ivory Coast | Gagnoa      | humid    | 20        | monocrop       | fixed             | 120    | 30            |               |
| 44  | Iwuafor et al. [66]| Benin      | Derived Savannah | dry sub-humid | 2        | monocrop       | fixed             | 8      |               |               |
| 45  | Iwuafor et al. [66]| Nigeria    | N-Guinea savannah | humid | 2 | monocrop | fixed | 8 | |
| 48  | Nhamo [67]         | Zimbabwe   | Chimombe Mrewa2 | dry sub-humid | 1        | monocrop       | fixed             | 6      |               |               |
| 49  | Nhamo [67]         | Zimbabwe   | Chinonda Mrewa3 | dry sub-humid | 1        | monocrop       | fixed             | 6      |               |               |
| 50  | Nhamo [67]         | Zimbabwe   | Chisunga Mrewa2 | dry sub-humid | 1        | monocrop       | fixed             | 6      |               |               |
| 51  | Nhamo [67]         | Zimbabwe   | Kaitano Mrewa2 | dry sub-humid | 1        | monocrop       | fixed             | 6      |               |               |
| 52  | Nhamo [67]         | Zimbabwe   | Mangena Mrewa2 | dry sub-humid | 1        | monocrop       | fixed             | 6      |               |               |
| 53  | Nhamo [67]         | Zimbabwe   | Manjoro Mrewa2 | dry sub-humid | 1        | monocrop       | fixed             | 6      |               |               |
| 54  | Nhamo [67]         | Zimbabwe   | Mapira Mrewa2 | dry sub-humid | 1        | monocrop       | fixed             | 6      |               |               |

(Continued)
| id | reference                          | country       | site          | AI class          | time span | cropping system | fertilizer design | nYield | nSOC C input | nSOC N input |
|----|-----------------------------------|---------------|---------------|-------------------|-----------|-----------------|-------------------|--------|--------------|--------------|
| 55 | Nhamo [67]                        | Zimbabwe      | Mukudu Mrewa  | dry sub-humid     | 1         | monocrop        | fixed             | 6      |              |              |
| 56 | Nhamo [67]                        | Zimbabwe      | Sunha Mrewa2  | dry sub-humid     | 1         | monocrop        | fixed             | 6      |              |              |
| 57 | Nhamo [67]                        | Zimbabwe      | Zivhu Mrewa   | dry sub-humid     | 1         | monocrop        | fixed             | 6      |              |              |
| 58 | Nziguheba et al. [27]             | Kenya         | Nyabeda       | humid             | 2         | monocrop        | NPK               | 14     |              |              |
| 59 | Uyovbiser and Elemo [68]          | Nigeria       | Samaru RS     | dry sub-humid     | 4         | monocrop        | NPK               | 24     | 16           | 16           |
| 63 | Mucheru-Muna et al. [69]          | Kenya         | Chuka off station | humid       | 4         | monocrop        | fixed             | 40     |              |              |
| 64 | Mucheru-Muna et al. [69]          | Kenya         | Chuka on-farm | humid             | 3         | monocrop        | fixed             | 22     |              |              |
| 65 | Nyanangara et al. [70]            | Zimbabwe      | Domboshawa RS | dry sub-humid     | 3         | monocrop        | fixed             | 18     |              |              |
| 67 | Chilimba et al. in Munthali [71, 72] | Malawi | Bvumbwe       | humid             | 1         | monocrop        | fixed             | 14     |              |              |
| 68 | Chilimba et al. in Munthali [71, 72] | Malawi | Chitedze RS   | dry sub-humid     | 1         | monocrop        | fixed             | 14     |              |              |
| 69 | Delve [73]                        | unknown       | unknown       | humid             | 2         | monocrop        | fixed             | 7      |              |              |
| 70 | Kimani et al. [74]                | Kenya         | Kariti        | humid             | 2         | monocrop        | NPK               | 20     |              |              |
| 71 | Kimani et al. [74]                | Kenya         | Gatunyaga     | semi-arid         | 1         | monocrop        | NPK               | 10     |              |              |
| 72 | Kimetu et al. [75]                | Kenya         | Kabete RS     | humid             | 1         | monocrop        | fixed             | 8      |              |              |
| 73 | Okalebo et al. [76]               | Kenya         | Eldoret       | dry sub-humid     | 4         | monocrop        | fixed             | 18     |              |              |
| 74 | Ayoola and Adeniyan [77]          | Nigeria       | Oniyo         | humid             | 2         | monocrop        | NPK               | 8      |              |              |
| 75 | Ayoola and Adeniyan [77]          | Nigeria       | Moloko-ashipa | humid             | 2         | monocrop        | NPK               | 8      |              |              |
| 77 | Akinnifesi et al. [43]            | Malawi        | Makoka RS     | humid             | 15        | intercrop       | fixed             | 136    | 24           | 24           |
| 78 | Kimani et al. [78]                | Kenya         | Githunguri kiambu | humid       | 1         | monocrop        | fixed             | 8      |              |              |
| 79 | Kimani et al. [78]                | Kenya         | Kariti Maragwa| humid             | 1         | monocrop        | fixed             | 8      |              |              |
| 80 | Kimani et al. [78]                | Kenya         | Mukundiuini   | humid             | 1         | monocrop        | fixed             | 8      |              |              |
| 81 | Mugendi et al. [79]               | Kenya         | Embu RS       | humid             | 22        | monocrop        | fixed             | 108    |              |              |
| 82 | Mugwe et al. [80]                 | Kenya         | Chuka on-farm | humid             | 4         | monocrop        | fixed             | 63     |              |              |
| 82 | Mugwe et al. [80]                 | Kenya         | Chuka on-farm | humid             | 4         | intercrop       | fixed             | 63     |              |              |
| 83 | Mugwe et al. [80]                 | Kenya         | Chuka on-farm | humid             | 4         | monocrop        | fixed             | 33     |              |              |
| 83 | Mugwe et al. [80]                 | Kenya         | Chuka on-farm | humid             | 4         | intercrop       | fixed             | 33     |              |              |
| 84 | Mugwe et al. [80]                 | Kenya         | Kirege school | humid             | 4         | monocrop        | fixed             | 64     |              |              |
| 84 | Mugwe et al. [80]                 | Kenya         | Kirege school | humid             | 4         | intercrop       | fixed             | 64     |              |              |
| 90 | Fonte et al. [81]                 | Ghana         | Kwadaso RS    | humid             | 7         | monocrop        | fixed             | 70     | 22           | 22           |
| 92 | Kimaro et al. [82]                | Tanzania      | Dodoma2       | semi-arid         | 2         | monocrop        | fixed             | 18     |              |              |
| 93 | Nziguheba et al. [83]             | Nigeria       | Samaru Zaria  | dry sub-humid     | 10        | monocrop        | fixed             | 90     |              |              |
| 94 | Nziguheba et al. [83]             | Benin         | Sekou         | humid             | 10        | monocrop        | fixed             | 90     | 18           | 18           |
| 94 | Nziguheba et al. [83]             | Benin         | Sekou         | humid             | 10        | intercrop       | fixed             | 6      | 6            |              |
| 95 | Shisanya et al. [84]              | Kenya         | Kirege        | humid             | 5         | monocrop        | NPK               | 52     | 12           | 14           |
| 96 | Anyanzwa et al. [85]              | Kenya         | Teso          | humid             | 2         | monocrop        | fixed             | 16     | 8            | 8            |

(Continued)
measurements over time were reported, so that responses could be calculated by subtracting the initial SOC from the SOC at a given time during or after the experiment (dSOC). Finally, soil and climate data were not sufficiently reported and therefore not included in the analysis. See Table 1 for a complete overview of the data.

Table 2. List of organic resource types and associated quality classes, with columns for the respective number of studies (nReferences), number of yield data (nYield), and number of SOC data with C and N rates different from zero (nSOC C input and N input, respectively).

| type                           | class | nReferences | nYield | nSOC C input | nSOC N input |
|-------------------------------|-------|-------------|--------|--------------|--------------|
| *Crotalaria juncea* (Sun hemp) | I     | 3           | 74     | 10           | 10           |
| *Crotalaria ochroleuca*       | I     | 2           | 23     |              |              |
| *Gliricidia sepium*           | I     | 3           | 84     | 24           | 24           |
| *Glycine max* (Soybean)       | I     | 1           | 6      |              |              |
| *Parkia biglobosa* (Locust bean) | I     | 1           | 9      | 6            | 6            |
| *Tithonia diversifolia*       | I     | 11          | 316    | 50           | 50           |
| *Azadirachta indica* (Neem tree) | II    | 2           | 89     | 14           | 14           |
| *Calliandra calothyrsus*      | II    | 10          | 365    | 51           | 51           |
| *Leucaena leucocephala*       | II    | 7           | 135    | 20           | 20           |
| *Macuna pruriens*             | II    | 4           | 57     | 6            | 6            |
| *Senna siamea* (Cassia tree)  | II    | 3           | 106    | 16           | 16           |
| *Arachis hypogaea* (Groundnut) | III   | 1           | 2      |              |              |
| Coffee                        | III   | 1           | 48     |              |              |
| Maize residue                 | III   | 7           | 307    | 52           | 55           |
| *Triticum aestivum* (Wheat)   | III   | 1           | 6      |              |              |
| Sawdust                       | IV    | 2           |        | 45           | 45           |
| Compost                       | Manure | 4           | 88     | 2            | 17           |
| Farm yard manure              | Manure | 22          | 579    | 81           | 89           |

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Statistical analysis

All statistical computing and graphic design for this paper was carried out in R [95](version 3.6.1). Yield data were modeled using the multivariate meta-analytical mixed effects function \textit{rma.mv} of the \textit{Metafor} package, which takes the sampling variances into account [96]. The advantage is that this function allows to account for yield variation and covariance among treatments, thereby avoiding biased estimates, overestimating variances, and increasing chances of finding false significant effects [97, 98]. For the SOC data, on the other hand, the reporting of sampling variances was too scarce, hence the \textit{lmer} function of the \textit{lme4} package was used [99]. As opposed to \textit{rma.mv}, the \textit{lmer} function assumes sampling variances are not exactly known. The first is thus essentially a special case of the latter [96]. Absolute yield and SOC values are used for analysis instead of effect sizes. As such, the model can account for variation in yields and SOC of control treatments and their covariance with MR, OR and MROR.

Yield analysis. The linear mixed effect model for the yield analysis (YIELD) was composed of the square root transformed absolute yield as the outcome variable, together with fixed and random effect terms. Residual and QQ plots revealed no significant issues for linearity and normality, but that a square root transformation was necessary to improve homoscedasticity. The choice of fixed effects, also called predictors or moderators, is hypothesis-based and expresses the particular interest in each of their level’s effect on productivity and variability. Maximum likelihood tests were used to compare models with and without fixed effects, in order to evaluate their contribution to the model. Random effects, on the other hand, are chosen based on their significant contribution to explained variance, while aiming for the most parsimonious model. Their contribution’s significance was evaluated using restricted maximum likelihood tests. As such, fixed effects were included in the model for the following variables: mineral N input rates, organic N input rates of each organic class, the interactions between them, the quadratic term of each rate, and also their quadratic terms. Furthermore, fixed effects were included for cropping system and mineral fertilizer design to correct for differences in overall mean yield. As for the random effect structure, random intercepts were included for study, individual observations, site, and time nested within site (hereafter referred to as time). In order to also account for the correlated random effects of the different treatments within site and within time, treatment is included in the random structure as random slopes for the random intercepts site and time. The random terms allow the model to account for their inherent differences and non-independences.

In this study, interactive effects are defined as the difference in yield response when applied in combination, versus the sum of the yields when applied solely as OR and MR. They are quantified according to Eq 1 [28]:

\[
\text{IE} = Y_{\text{ORMR}} - Y_{\text{control}} - (Y_{\text{MR}} - Y_{\text{control}}) - (Y_{\text{OR}} - Y_{\text{control}}) \tag{1}
\]

where IE means the interactive effect and \(Y_{\text{control}}, Y_{\text{MR}}, Y_{\text{OR}}, \) and \(Y_{\text{ORMR}}\) are the mean yield estimates of the respective Control, MR, OR, and ORMR treatments. A positive interaction is thus observed when the combined application (with 50% OR and 50% MR) yields more than the sum of the sole applications. This means that a yield response curve of ORMR with a positive interaction would sit above the ORMR dashed line (b) as illustrated in Fig 2 below.

The coefficients of the YIELD model were used to predict yield estimates and construct mean yield response and AE curves by total N input rate. Predictions were done for total N input rates for which there were actual yield observations, but up until a maximal total N input rate of 200 kg N ha\(^{-1}\), after which inputs are considered not sensible anymore. These predictions were also done for a fixed mineral fertilizer design and separately for each organic class and ORMR treatments with three different organic N proportions, i.e. 25, 50, and 75% (Cfr.
The AE was computed in accordance to Vanlauwe et al. [94], i.e. by taking the differences in predicted maize grain yields of MR, OR and ORMR from the Control (kg ha\(^{-1}\)), and dividing these by the amount of N applied (kg kg\(^{-1}\)).

The random variance, as modeled by the YIELD model’s random structure, can be used as an estimation of yield variability for each treatment across time. The interest of this paper, however, does not reside in the variability of each treatment, but in the variability of each sub-treatment instead. Fitting random slopes for subtreatments was not possible, because covariances would have needed to be estimated between subtreatments that do not make sense or for which no data are available. As an alternative, the subtreatment variances were extracted from the random structure of models that were run for subsets of each organic quality class separately.

The YIELD model and individual organic class models therefore provided yield variance and covariance estimations across time. These were then used to compute variance responses using Eq 2:

\[
\text{var}_{\text{response}} = \text{var}_{\text{treatment}} + \text{var}_{\text{control}} - 2 \times \text{covar}_{\text{treatment, control}}
\]

with \(\text{var}\) and \(\text{covar}\) being the variance and covariance, respectively. The responses were subsequently divided by the mean predicted yields from the YIELD model to obtain relative variance responses. Note that since the data were modeled using a square root transformation, the variance responses are in fact SD responses in t ha\(^{-1}\) for the original data.

**SOC analysis.** Two separate linear mixed effect models were designed to model dSOC, one with organic N rates as predictors (N-SOC model) and one with organic C rates (C-SOC model). Stocks of SOC could not be modeled due to a lack of reported soil bulk densities. For the N-SOC model, fixed effects were included for organic N rates of different quality classes, mineral N rate, the quadratic terms and interactive terms of both. For the C-SOC model, fixed effects were included for organic C rates of different quality classes, mineral N rate, and
interactive terms of both. Fitting quadratic terms was not possible. Both models also included fixed effects for initial SOC and mineral fertilizing design for model fitting purposes in analogy with the YIELD model. Cropping system was not relevant, as all SOC reporting studies were monocropping with biomass application. Both models have the same random intercepts for site and time. Residual and QQ plots confirmed that there were no significant violations of linearity, normality, and homoscedasticity and hence no transformations were needed.

The outputs of the N-SOC and C-SOC models are used to predict dSOC across cumulative N and organic C input rates (t ha$^{-1}$) for which data are available, at a data set average initial SOC of 1.8% and for a fixed mineral fertilizer design. For the N-SOC graph these dSOC are plotted separately for each organic class and ORMR with different proportions of organic N input, while for the C-SOC graphs these are plotted for each treatment and organic class at a cumulative mineral N input of 750 kg ha$^{-1}$.

Publication bias and sensitivity analyses. Publication bias was assessed by funnel plot symmetry, which was statistically tested by adding the sampling variance as a moderator in the model as a way of extending Egger’s test to complex models [100, 101]. While the funnel plot looked slightly asymmetric, the Egger’s test confirmed it was significantly symmetric ($p < 0.05$), therefore suggesting the absence of publication bias. A sensitivity analysis was carried out for the YIELD model, by re-fitting the model without the most influential studies. Based on the diagonal values of the Hat matrix, four studies (469 or 17% of total data points) were identified as relatively most influential, while five studies (1478 or 52% of total data points) were identified based on their Cook’s distances [100]. Removing these study sets did not change the overall trends and conclusions for the yield analysis, with the exception of organic class II and to a greater extent III that were substantially underrepresented in the smallest Cook’s distance subset. The current YIELD model was therefore considered to be sufficiently robust. The SOC model was fitted with a considerably smaller amount of data, and was therefore considered more sensitive to influential studies. In fact, two out of the 15 studies provided long-term data accounting for almost 50% of the total amount of data. Leaving them out did impact the models and consequent findings considerably. However, long-term data on SOC in SSA are scarce, yet could provide valuable insights [102]. We therefore nevertheless consider that including the available long-term data is justified and can contribute to the research questions of this paper, despite their relatively large influence on the results.

**Results**

**Overview original data**

The frequency distribution of yield data across total N rates gives an indication of the amount of data available by N rate, as shown by the density graph of Fig 3. The total N input rate for the MR treatments ranged from 20 to 175 kg N ha$^{-1}$, for OR from 10 to 524 kg N ha$^{-1}$, and for ORMR from 45 to 645 kg N ha$^{-1}$. The graph suggests a potential bias towards higher yields for ORMR treatments compared to MR and OR, and to a lesser extent MR compared to OR. This implies that N rate is a necessary covariate in the meta-analysis.

Fig 4 shows the average and variation of yields for the different treatments, across all publications and study sites, and for each individually. The graph reveals that on average ORMR treatments tend to represent higher yield averages, followed by MR and OR, respectively. The control treatments represent, as expected, the lowest averages.

With the reported yield data, one can calculate the AE across total N input and by treatment and organic class (Fig 5). From these calculations it is observed that the AE decreases in value as well as in variability with increasing N input. Differences between organic qualities seem to confirm this, as classes with a low N content tend to be more variable and lead to both higher
and lower AE values than classes with high N content. This illustrates the importance of analyzing organic quality class and N rate with mixed effect models, where the variance between those classes in relation to N rate can be taken into account.

**Modeled yields and agronomic efficiency**

The YIELD model results (S1 Table) show significant positive effects for input rates of each of the organic quality classes and mineral N, meaning that their mean maize grain yields are estimated to be significantly greater than the control treatment. The model output also revealed a significant interaction between organic and mineral N rates for all organic classes ($P < 0.05$), meaning that the effect of organic inputs in the combined ORMR treatment depends on the estimated effect of mineral N, and vice versa. Intercropping as a cropping system has a significant yield decline as opposed to monocrop with biomass inputs, whereas rotation is not significantly different from the latter. Mineral fertilizing design does not have a significant effect on yields. The relationship of model predicted yields and their derived AE with total N rate is visualized in Figs 6 and 7, respectively.

Predicted yields increase with increasing total N rate, but only up to a certain point, which depends on treatment and organic quality. The combined application ORMR consistently leads to greater yields than OR across the whole range of total N inputs. Compared to MR, however, its relative effect depends on total N input, organic class, and its proportion of organic N. Below total N rates of 100-125 kg N ha$^{-1}$, the ORMR of all organic classes with 25%
organic N have similar yields to that of MR. With higher organic N proportions, the predicted ORMR yields tend to gravitate towards the lower yield predictions of OR. These reduced responses get more pronounced in the order of class I, II, Manure, and in particular class III. For the latter class, OR and ORMR with organic N proportions greater than 50% exhibit culminating and decreasing ORMR responses within the observed range of input rates. On the other hand, with total N rates exceeding 100-125 kg total N ha\(^{-1}\), the MR response curve flattens, while those of OR and ORMR (except for organic class III) do not. As a result, ORMR will outperform MR at a certain N rate, depending again on organic class and proportion. The 25% organic ORMR of classes I and II outperform MR earlier than classes III and Manure. For ORMR with higher organic proportions, one needs higher N rates to outperform MR. For organic class III, however, only the 25% organic ORMR eventually outperforms MR within the 0-200 kg total N input range.

Fig 4. (left) Overview of reported maize grain yield (t ha\(^{-1}\)) data, averaged by publication, site, and treatment, and ranked following increasing ORMR yields. Error bars represent the ± 1.96 \(\mu\) mean standard error on that average. The overall yield average by treatment and across publications and sites is labeled as ‘summary measure’ at the bottom of the graph. (top right) Distribution of maize grain yield (t ha\(^{-1}\)) values by treatment.

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Apart from OR class III, all subtreatments have a similar decreasing AE with increasing total N input, i.e. the decrease is fastest for MR, slowest for OR and intermediate for ORMR. The inclinations of the latter AE curves increase with more mineral N, and decrease with higher proportions of organic N. Class III is the exception as it is the only organic class with a rapidly declining AE for OR as well as for ORMR, and thus similar to MR. The AE of the ORMR treatments always outperforms those of OR, but only outperform that of MR depending on N rate, organic class, and its organic N proportion. The MR treatment has the highest AE for a N rate below 100 kg ha\(^{-1}\), but above that MR will gradually be outperformed by classes I, II, and Manure. With higher organic N proportions of ORMR, the AE curves get flatter, but also start lower, and therefore outperform MR only at higher total N inputs. So, while AE of MR was the highest at low N rates, it declined the most rapidly with increasing N inputs, whereas the AE of OR treatments were the lowest at low N rates, but did not decrease substantially with increasing N inputs. By analogy, the same was observed for ORMR with low and high organic proportions, respectively.

**Modeled yield variability**

The YIELD and individual organic class models report yield variances, which allow a calculation of yield SD responses relative to predicted yields (Fig 8). The graph indicates that variability of organic input treatments increases with decreasing quality, so in the order of class I, II, Manure, and III. Yield variability for the MR treatment is estimated to be higher than OR class I and II, but lower than OR class Manure and III. Combining the OR treatments with MR, seems to increase the variability of the highest organic quality class I, and decrease the variability of the lowest organic quality class III, without considerable effect on classes II and Manure.

**Modeled SOC**

The N-SOC and C-SOC models reveal variances across site being 4.5 and 3.5 times bigger, respectively, than across time, and residual variances smaller than 0.03% (S2 and S3 Tables).
Both models also show that neither of the mineral N and organic input interactions are significant, nor are those of mineral N rate and mineral fertilizer design. The N-SOC model estimated that cumulative N rates from all organic quality classes have a significant increasing effect on SOC, but with diminishing responses as seen from the negative quadratic coefficients. These estimates are, however, relatively larger for the low-quality classes III and especially IV. The C-SOC model on the other hand, estimated significant SOC increases for C rates from all classes except for IV, but with relatively greater estimates for high-quality classes. The estimates decrease following the order of class Manure, I, II, III, and IV that was not significant. The initial SOC had a significant negative effect on SOC change, meaning that sites with higher initial SOC on average experience more SOC loss. The predicted dSOC according to N or C inputs are visualized in Figs 9 and 10, respectively.
The N-SOC model predictions of dSOC indicate that the OR treatments have increasingly positive effects on dSOC with increasing N rates, the extent of the effect depending on organic input quality. The positive effects of OR are most pronounced for the high-quality classes I and Manure, followed by decreasing responses from classes II, III, and IV, respectively. The graphs confirm visually that the effect of mineral N is not significant, and nor is its interaction with organic inputs, since the positive effect of ORMR on dSOC seems to be directly related to the organic proportion of ORMR. The C-SOC model predictions of dSOC confirm the model output (Fig 10). On the one hand, organic C inputs from high-quality organic resources have a greater positive effect on dSOC than the low-quality resources, while on the other hand, the effect of mineral N seems negligible and its interaction with organic inputs absent.

Fig 7. The agronomic efficiency (AE, in kg kgN^{-1}) was plotted for the available total N rate, within a range of 0-200 (kg ha^{-1}), applied as mineral or organic fertilizer, separately for each organic class and for ORMR with three different organic N input proportions.

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Discussion

The ISFM practice of combined organic and mineral fertilizer application has been found to address the three CSA pillars, but to different extents. These extents depend on input rates and organic resource quality, which determine the combined application effect relative to the sole organic and mineral applications. Our analyses showed that ORMR treatments lead to positive interactions, and to AEs and yields that can outperform those of MR treatments. In fact, the ORMR AE curves are a direct evidence of these positive interactions, as the combination of organic and mineral N resources gives higher yields than the individual resources, and at high N rates. These findings are not entirely lining up with the meta-analysis of Chivenge et al. [23]. Like other studies, they revealed potentially greater yield responses for the combined application treatments [24–27], but could not find evidence for improved AE as predominantly negative interactive effects were observed between the two resources. They found that the AE for OR and ORMR treatments were similar and both lower than the AE of MR treatments, and suggested that potential interactive effects might have been masked with reduced AE due to relatively high total N rates of ORMR. We suspect that the different modeling approach of the current analysis, with in particular the emphasis on N rate effects, might have allowed us to identify positive interactions where Chivenge et al. [23] found none or negative ones. Indeed, including N rates as predictors in the model revealed the importance of looking in detail at N rate for productivity and AE differences between treatments (Figs 6 and 7). In contrast to Chivenge et al. [23], the meta-analysis of Vanlauwe et al. [94] observed that combining mineral N with manure or compost resulted in the highest AE. In our analysis, this observation is more nuanced, as it is true for high total N rates only.

The observed ORMR interactions and their effect on AE and yield, relative to the OR and MR treatments, were affected by both N rate and organic resource quality. The diminishing
Fig 9. The output of the N-SOC model is used to predict changes in soil organic carbon from its initial values (dSOC) across the cumulative total N input rates (t ha\(^{-1}\)), applied as mineral or organic fertilizer and for which data are available, but limited to five cumulative t N ha\(^{-1}\). They are plotted at a database average initial SOC of 1.8% and separately for each organic class and ORMR with different proportions of organic N content. The root mean square error (RMSE, in %) is given for the different predicted dSOCs from treatments with the respective organic classes.

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yield increases across N rates, as a result of declining AEs across N rates, were apparent for all treatments and hence support earlier findings that the AE decreases with N rate for the organic treatments [23] and MR [94]. The relatively fast AE decline of MR could be explained by an oversupply of N that is exceeding crop uptake, while the more stable AE of organic treatments could be attributed to other soil health benefits than nutrient supply only [103, 104]. The large initial AE of MR and ORMR with low organic N, are likely due to the high plant availability of N when given in its mineral form, which will be lower in applications with higher organic proportions due to possible immobilization [105]. Hence, in our analysis, the ORMR treatments seem to reflect benefits from both sole OR and MR treatments; while their mineral N ensures a relatively high AE, their organic properties contribute to a more stable AE across N input rate.

An important role was observed for organic resource quality on treatment and interaction effects, confirming what has been postulated [28, 47] and observed in previous studies. Our findings agree with those of Chivenge et al. [23], who found greater yield responses for OR and ORMR treatments with high-quality organic resources as opposed to low quality resources. However, our results are not in line with Vanlauwe et al. [94], who found that only OR class II treatments showed significantly higher AE compared to MR treatments, and are in direct contrast with Gentile et al. [24, 25], who found that ORMR treatments with low-quality organic resources tend to favor positive interactions as opposed to high-quality resources. According to the modeled predictions, increasing inputs of low-quality organic resources, such as class III, does not increase yields per se. In fact, low-quality organic resources would increase yields at low rates, but have a detrimental effect at high rates. This can be explained by the fact that low-quality organic resources have a relatively high C:N ratio, which at high input rates can lead to N immobilization in the soil [23, 24]. The immobilization of N consequently lowers the N availability for plants and so affects the yields negatively. The same explanation can also be used for the interpretation of the organic quality effect on AE. Increasing the rate

![Fig 10. The output of the C-SOC model is used to predict changes in soil organic carbon from its initial values (dSOC) across cumulative organic carbon input rates. These are then plotted for each treatment and organic class, and at an initial SOC of 1.8% and cumulative mineral N input of 750 kg ha⁻¹. The 750 kg ha⁻¹ was based on an annual mineral N application of 75 kg during a time frame of 10 years. The root mean square error (RMSE, in %) is given for the dSOC predictions of the different subtreatments.](https://doi.org/10.1371/journal.pone.0239552.g010)
of low-quality organic resources of class III, likely increases the N-immobilization and would cause the observed sharp declines in AE. However, one would then assume that the N-immobilization of OR class III can be alleviated by mixing it with mineral N, i.e. ORMR class III. While we observed evidence for a slight positive interaction, we would have expected a stronger response based on the given explanation. From our observations, it seems that N immobilization is a more important factor than the potentially enhanced organic N mineralization if high-quality organic resources are combined with mineral N. The latter has been argued by Gentile et al. [24, 25] stating that the excessive amounts of N so supplied would exceed early crop demand, and contribute to negative interactions. In addition, Chivenge et al. [23] suggested that while N immobilization might suppress yields on the short term, this would not necessarily be the case in the long-run due to potential residual effects. However, despite the fact that the meta-analysis included both short- and long-term studies, no evidence was found for the latter.

Many factors like pests and diseases, weeds, and different management practices are involved in causing yield variability over time [106]. Since these factors are assumed to be controlled for in the experiments included in the meta-analysis, we are in fact only considering variability due to meteorological differences between seasons and potential residual effects of treatments. Meteorological differences could be buffered to some extent with soil organic matter build-up, e.g. by improving the soil’s water holding capacity [107]. Mineral N on the contrary, has more short-lived effects and potentially even facilitates the degradation of soil organic matter [108]. The long-term trials of Vanlauwe et al. [34] did not show any evidence of the latter, as they observed reduced variability for the ORMR treatments. The suggested rationale was that ORMR has sufficient N from mineral N inputs, while it’s organic matter could buffer some of the reduced moisture effects. In this regard we would have expected a lower variability for the OR and ORMR treatments compared to MR. However, our results did not confirm facilitated organic matter degradation by mineral N, nor did they suggest a decreased variability for ORMR compared to OR. Mineral N was not observed to affect the variability of OR treatments when the two resources were combined. Comparing the variability of OR with that of MR indicates that organic resource quality plays a role. The variability of OR was only lower than that of MR for high-quality organic resources of class I and II. Organic class Manure was an exception, as together with the low-quality class III they were estimated to have more variable yields than MR. Chivenge et al. [23] suggested that this organic quality influence could be explained by the greater residual effects observed for high-quality organic resources, whether applied as OR or ORMR. Both our meta-analyses thus challenge the general consensus that a slow decomposition associated with low-quality organic resources would lead to stronger residual effects over time.

Our results confirm observations by Chivenge et al. [23], that SOC can be significantly raised only by adding organic resources to the soil, and that the SOC responses increase with increasing organic N and C input. Mineral N had no significant effect on SOC and conversely there was no interaction with organic inputs. Applying mineral N is expected to enhance root growth and contribute to SOC if the added N can be taken up by the plants, otherwise excess N might facilitate the degradation of soil organic matter with loss of SOC as a result [109]. This could imply an initial increase and consequent decrease of SOC under MR, as was observed by Gentile [109] and Chivenge et al. [23]. The same observation could perhaps be made for the N-SOC model predicted SOC, although the MR response was not significant. The effect of MR on long-term soil organic matter stabilization can be either negative [41] or neutral [38, 42, 50], but generally seems to be complex [108, 109]. The study treatments included in this analysis reported or were assumed to have their above ground crop residues removed after harvest. This implies that an increase of biomass due to an improved soil fertility
could only have benefited SOC through the roots [110]. In a situation where crop residues return completely to the soil, MR (and even Control) treatments are expected to show more positive SOC responses [111].

The effects of organic N and C rate on SOC responses were to a large extent determined by the quality of the organic resource. From the cumulative N input graphs (Fig 9), increasingly steeper response curves were observed for decreasing organic resource quality. The reason is likely that for a certain amount of organic N added, more C will be added by low-quality classes with a relatively high C:N ratio, such as class III and IV. However, for an unbiased view regarding C input, the cumulative C input graphs (Fig 10) show clearly that high-quality organic classes with a relatively high N content and low C:N ratio achieved higher SOC responses than low-quality organic inputs with a high C:N ratio, such as class IV whose responses were not significant. These results are supporting Cotrufo et al. [112] and Castellano et al. [49] who argued that low-quality organic input does not contribute more to soil organic matter (SOM) due to its slower decomposition and consequent accumulation in the soil. Instead, proportionally more SOM would be formed from high-quality organic matter, because a faster decomposition results in more initial microbial biomass, which is increasingly shown to be the largest contributor to stable SOM [112, 113]. Gentile et al. [50], however, found that organic quality did not affect the stabilization of SOC in the long term, and argued that all organic matter would eventually get decomposed and passed through the microbial pool. Perhaps, the reason why this was not observed in the current analysis, is that there were not enough long-term studies included in the analysis that could potentially confirm the arguments of Gentile et al. [50].

We have seen that compared to the sole applications, the combination application has a significant positive effect on maize yield productivity and AE of applied N, which is more pronounced at higher N rates. For yield variability, but especially for SOC, the difference of the combined with the sole organic application was marginal. One can therefore not state that the ISFM combined application decreased yield variability or increased SOC compared to the sole organic and mineral N applications. It has been shown, however, that while the ISFM combined application may not outperform the sole applications on individual CSA pillars, the practice is necessary to simultaneously and optimally address all three pillars. First, mineral N proved to be necessary to achieve the highest productivity and AE for N rates < 100 kg N ha⁻¹. This is important since the global average in 2013 was only 74 kg N ha⁻¹, but it is particularly relevant in the context of smallholder farming in SSA, where mineral N use is even lower yet most yield production increase is needed [114, 115]. Within this N input range, the AE of total applied N would decrease when mineral N is combined with organic inputs, but this is limited when high-quality resources are used. Second, when considering the other two aspects of CSA, we observe that high quality organic inputs become necessary to achieve the lowest yield variability and greatest SOC increase, independent if in combination with mineral N. In summary, the findings of this paper therefore suggest that mineral N is necessary for the best low-input productivity, while high quality organics are necessary for achieving the lowest variability (class I or II) and highest SOC response (class I, II, or Manure). Combining the mineral and organic resources is therefore a way to achieve a win-win-win situation, where productivity, variability, and SOC are all three improved and optimized. For high-input scenarios, the case of combined application is even stronger, as it will outperform the mineral N fertilizer application effects on productivity.

In this paper, organic resources were classified into different organic quality classes, according to their quality parameters N, lignin and polyphenol contents as proposed by Palm et al. [47]. A separate class Manure was made for organic resources like farm yard manure, green manure and compost, whose contents are variable and thus their quality unknown. Yet, based
on N content and productivity and AE response similarities, classes I, II, and Manure, were grouped as high-quality organic resources throughout the analyses. Classes III and IV were consequently grouped as low-quality organic resources. This high-vs-low quality subdivision proved to be relevant, as the effects between high- and low-quality resources on productivity and AE were considerably more distinctive than those within the quality groups. This implies that N content was the main factor contributing to differences in organic resource quality, and confirms that the effect of polyphenol content on productivity and AE is minimal [23]. The high-low quality distinction is less clear for yield variability, due to the relatively high variability under class Manure treatments. For SOC, the distinction is also less pronounced, because the relatively high phenol content of class II compared to class I seemed to have reduced its SOC response. Nevertheless, high-quality organic resources clearly outperform low-quality resources, which challenges the concept of enhanced SOC biochemical stabilization due to the recalcitrance of lignin and polyphenols [47, 50].

An inherent limitation for meta-analyses is the presence of research and publication bias [116]. In this paper, research bias has been addressed by taking variance components as weighting factors in the models run with the rma.mv function. Publication bias has been mitigated to an extent by including non-published data, but has also been tested for and evaluated through sensitivity analyses. Another set of limitations to the current meta-analysis are the data constraints that result from the selection criteria. Apart from the main selection criteria such as the specific treatments with maize cropping in SSA, a number of other data variables were often missing because they were either not recorded or simply not reported. Hence, we encourage further research publications to provide yield data for individual seasons instead of averages, variance components of these yield data, input quality parameters, but most importantly organic N rate estimations. The lack of organic N rates alone was accountable for the exclusion of a substantial amount of otherwise useful yield data. For intercropping and rotation systems, especially, the estimation of organic N inputs is challenging, and results in an underrepresentation of these cropping systems in the final data set. Furthermore, it is clear that the majority of studies missed the opportunity to report potential differences in soil characteristics between start and end of experiments, and hence could not be used for the SOC analysis for instance. Similarly, organic quality class IV, and to some extent class III, was underrepresented in the collected literature, and consequently could not take part in the yield analyses. Lastly, we emphasize the need for long-term trials, specifically on weathered soils in the tropics, in order to allow the assessment of treatment effects on yield and SOC over time.

Conclusion

Meta-analyzing 40 short- and long-term maize nutrient trials across SSA, revealed that compared to sole organic (OR) and mineral N (MR) applications the combined application (ORMR) does have a significant positive effect on maize grain yield productivity and AE of N, albeit more pronounced at higher N rates and for high-quality organic resources. For yield variability and SOC, however, the combined effect is negligible and treatment effects are mainly determined by the organic resource rate and quality. The N rate and organic resource quality were found to play an important role overall, such that compared to low-quality organic resources, increasing amounts of high-quality resources allow for (i) an increased productivity and AE, (ii) a less rapidly declining AE with N rate, (iii) a decreased yield variability, and (iv) an increased SOC.

While the ISFM combined application may not unequivocally outperform the sole applications on individual CSA pillars, the practice has been found to be appropriate for simultaneously and optimally addressing all three pillars and hence can be considered climate-smart.
This paper provides evidence for the need of managing both mineral and organic resources in a holistic and integrated approach, such as aspired by the ISFM framework.

**Supporting information**

**S1 Table. Output from the YIELD model.** Run by the `rma.mv` function of the Metafor package in R [117]. (PDF)

**S2 Table. Output from the N-SOC model.** Run by the `lmer` function of the lme4 package in R [99]. Modeled estimates are presented for dSOC, along with p-values for significance [118] and 95% confidence intervals. Extracted and formatted with the stargazer package [119]. (PDF)

**S3 Table. Output from the C-SOC model.** Run by the `lmer` function of the lme4 package in R [99]. Modeled estimates are presented for dSOC, along with p-values for significance [118] and 95% confidence intervals. Extracted and formatted with the stargazer package [119]. (PDF)

**S4 Table. PRISMA checklist.** (PDF)

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References

1. Vanlauwe B, Descheemaeker K, Giller KE, Huisings J, Merckx R, Nziguheba G, et al. Integrated soil fertility management in sub-Saharan Africa: unravelling local adaptation. SOIL Discuss. 2014; 1(1):1239–1286. https://doi.org/10.5194/soild-1-1239-2014

2. Cairns JE, Hellin J, Sonder K, Araus JL, MacRobert JF, Thierfelder C, et al. Adapting maize production to climate change in sub-Saharan Africa. Food Secur. 2013; 5(3):345–360. https://doi.org/10.1007/s12571-013-0256-x

3. Cobo JG, Dercon G, Cadisch G. Nutrient balances in African land use systems across different spatial scales: A review of approaches, challenges and progress. Agric Ecosyst Environ. 2010; 136(1-2):1–15. https://doi.org/10.1016/j.agee.2009.11.006

4. Tully K, Sullivan C, Weil R, Sanchez P. The State of soil degradation in sub-Saharan Africa: Baselines, trajectories, and solutions. Sustain. 2015; 7(6):6523–6552. https://doi.org/10.3390/su7066523

5. Shiferaw B, Prasanna BM, Hellin J, Bänziger M. Crops that feed the world 6. Past successes and future challenges to the role played by maize in global food security. Food Secur. 2011; 3:307–327. https://doi.org/10.1007/s12571-011-0140-5

6. Zingore S, Mutegi J, Agesa B, Tamene L, Kihara J. Soil Degradation in sub-Saharan Africa and Crop Production Options for Soil Rehabilitation. Better Crop. 2015; 99(1):24–26.

7. Jayne TS, Snapp S, Place F, Sitho N. Sustainable agricultural intensification in an era of rural transformation in Africa. Glob Food Sec. 2019; 20(January):105–113. https://doi.org/10.1016/j.gfs.2019.01.008

8. Zougmore RB, Partey ST, Ouédraogo M, Torquebiau E, Campbell BM. Facing climate variability in sub-Saharan Africa: analysis of climate-smart agriculture opportunities to manage climate-related risks. Cah Agric. 2018; 27(3):34001. https://doi.org/10.1051/cagri/2018019

9. Galadzill A, Tingju Z, Katrin R, Tol RSJ, Ringler C. Economically wise impacts of climate change on agriculture in Sub-Saharan Africa. Ecol Econ. 2013; 93:150–165. https://doi.org/10.1016/j.ecolecon.2013.05.006

10. Greve P, Orlowsky B, Mueller B, Sheffield J, Reichstein M, Seneviratne SI. Global assessment of trends in wetting and drying over land. Nat Geosci. 2014; 7(10):716–721. https://doi.org/10.1038/ngeo2247

11. Blanc E. The Impact of Climate Change on Crop Yields in Sub-Saharan Africa. Am J Clim Chang. 2012; 1(1):1–13.

12. Rockström J, Karlberg L, Wani S, Barron J, Hatibu N, Oweis T. Managing water in rainfed agriculture. The need for a paradigm shift. Agric Water Manag. 2010; 97(4):543–550. https://doi.org/10.1016/j.agwat.2009.09.009

13. Cooper PJM, Dimes J, Rao KPC, Shapiro B, Shiferaw B, Twomlo S. Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? Agric Ecosys Environ. 2008; 126:24–35. https://doi.org/10.1016/j.agee.2008.01.007

14. IPCC. Climate Change 2007: Synthesis Report. United Nations; 2007.

15. Tesfaye K, Gbegbelegbe S, Cairns JE, Shiferaw B, Prasanna BM, Sonder K, et al. Maize systems under climate change in sub-Saharan Africa: Potential impacts on production and food security. Int J Clim Chang Strateg Manag. 2015; 7(3):247–271. https://doi.org/10.1108/IJCCSM-01-2014-0005

16. Lipper L, Thornton P, Campbell BM, Baedeker T, Braimoh A, Bwalya M, et al. Climate-smart agriculture for food security. Nat Clim Chang. 2014; 4(12):1068–1072. https://doi.org/10.1038/nclimate2437

17. Hillocks RJ. Addressing the yield gap in Sub-Saharan Africa. Outlook Agric. 2014; 43(2):85–90. https://doi.org/10.5367/oa.2014.0163

18. Jones PG, Thornton PK. The potential impacts of climate change on maize production in Africa and Latin America in 2055. Glob Environ Chang. 2003; 13(1):51–59. https://doi.org/10.1016/S0959-3780(02)00090-0

19. Campbell BM, Thornton P, Zougmore R, Van Asten PJA, Lipper L. Sustainable intensification: What is its role in climate smart agriculture? Curr Opin Environ Sustain. 2014; 8:39–43. https://doi.org/10.1016/j.cosust.2014.07.002

20. FAO. Climate-Smart Agriculture Sourcebook. Food and Agriculture Organization; 2013. Available from: http://www.fao.org/docrep/018/i3325e/i3325e00.htm.

21. Harvey CA, Chacon M, Donatti CI, Garen E, Hannah L, Andrade A, et al. Climate-Smart Landscapes: Opportunities and Challenges for Integrating Adaptation and Mitigation in Tropical Agriculture. Conserv Lett. 2013; 7(2):77–90.
22. Sanginga N, Woomer PL. Integrated Soil Fertility Management in Africa: Principles, Practices, and Developmental Process. Tropical Soil Biology and Fertility Institute of the International Centre for Tropical Agriculture; 2009. Available from: https://books.google.be/books?id=VTX1uHS7jAC.

23. Chivenge P, Vanlauwe B, Six J. Does the combined application of organic and mineral nutrient sources influence maize productivity? A meta-analysis. Plant Soil. 2011; 342(1-2):1–30. https://doi.org/10.1007/s11104-010-0626-5

24. Gentile R, Vanlauwe B, Chivenge P, Six J. Interactive effects from combining fertilizer and organic residue inputs on nitrogen transformations. Soil Biol Biochem. 2008; 40(9):2375–2384. https://doi.org/10.1016/j.soilbio.2008.05.018

25. Gentile R, Vanlauwe B, van Kessel C, Six J. Managing N availability and losses by combining fertilizer-N with different quality residues in Kenya. Agric Ecosyst Environ. 2009; 131(3-4):308–314. https://doi.org/10.1016/j.agee.2009.02.003

26. Mafongoya PL, Bationo A, Kihara J, Waswa BS. Appropriate technologies to replenish soil fertility in southern Africa. Nutr Cycl Agroecosystems. 2006; 76(2-3):76–137.

27. Nziguheba G, Merckx R, Palm CA, Mutuo P. Combining Tithonia diversifolia and fertilizers for maize production in a phosphorus deficient soil in Kenya. Agrofor Syst. 2002; 55(3):165–174. https://doi.org/10.1023/A:1020540411245

28. Vanlauwe B, Aihou K, Aman S, Iwuafor ENO, Tossah BK, Diels J, et al. Maize yield as affected by organic inputs and urea in the West African moist savanna. Agron J. 2001; 93(6):1191–1199. https://doi.org/10.2134/agronj2001.1191

29. Gentile R, Vanlauwe B, Kavoo A, Chivenge P, Six J. Residue quality and N fertilizer do not influence aggregate stabilization of C and N in two tropical soils with contrasting texture. Nutr Cycl Agroecosystems. 2010; 88(1):121–131. https://doi.org/10.1007/s10705-008-9216-9

30. Rufino MC, Tittonell P, Reidsmad L, Lopez-Ridaura S, Hengsdijk H, Giller KE, et al. Network analysis of the combined application of organic and mineral nutrient sources influence maize productivity? A meta-analysis. Plant Soil. 2011; 342(1-2):1–30. https://doi.org/10.1007/s11104-010-0626-5

31. Lak R. Soil carbon sequestration impacts on global climate change and food security. Science (80-). 2004; 304(5677):1623–1627. https://doi.org/10.1126/science.1097396 PMID: 15192216

32. Lak R. Beyond Copenhagen: mitigating climate change and achieving food security through soil carbon sequestration. Food Secur. 2010; 2(2):169–177. https://doi.org/10.1007/s12571-010-0060-9

33. Diels J, Vanlauwe B, Meersch MKVD, Sanginga N, Merckx R. Long-term soil organic carbon dynamics in a subhumid tropical climate: C data in mixed C 3 / C 4 cropping and modeling with ROTHC. Soil Biol Biochem. 2004; 36(11):1739–1750. https://doi.org/10.1016/j.soilbio.2004.04.031

34. Mucheru-Muna M, Mugendi D, Pypers P, Mugwe J, Kung’u J, Vanlauwe B, et al. Enhancing Maize Productivity and Profitability Using Organic Inputs and Mineral Fertilizer in Central Kenya Small-Hold Farms. Exp Agric. 2014; 50(2):250–269. https://doi.org/10.1017/S0014479713000525

35. Kapkiyai JJ, Karanja NK, Qureshi JN, Smithson PC, Woomer PL. Soil organic matter and nutrient dynamics in a Kenyan nitisol under long. Soil Biol Biochem. 1999; 31(13):1773–1782. https://doi.org/10.1016/S0038-0717(99)00088-7
41. Kibunja CN, Mwaura FB, Mugendi DN, Gicheru PT, Wamuongo JW, Batiino A. Lessons learned from Long-term Soil Fertility Management Experiments in Africa. In: Batiano A, Waswa B, Kihara J, Adolwa I, Vanlauwe B, Saidou K, editors. Lessons Learn. from Long-term Soil Fertil. Manag. Exp. Africa. Dordrecht: Springer; 2012. p. 59–84. Available from: http://link.springer.com/10.1007/978-94-007-2938-4.

42. Sommer R, Paul BK, Mukalama J, Kihara J. Reducing losses but failing to sequester carbon in soils—the case of Conservation Agriculture and Integrated Soil Fertility Management in the humid tropical agro-ecosystem of Western Kenya. Agric Ecosyst Environ. 2018; 254:82–91. https://doi.org/10.1016/j.agee.2017.11.004

43. Akinfunlesi FK, Makumba W, Sileshi G, Ajayi OC, Mweta D. Synergistic effect of inorganic N and P fertilizers and organic inputs from Gliricidia sepium on productivity of intercropped maize in Southern Malawi. Plant Soil. 2007; 294(1-2):203–217. https://doi.org/10.1007/s11104-007-9247-z

44. Ayuke FO, Brussaard L, Vanlauwe B, Six J, Lelei DK, Kibunja CN, et al. Soil fertility management: Impacts on soil macrofauna, soil aggregation and soil organic matter allocation. Appl Soil Ecol. 2011; 48(1):53–62. https://doi.org/10.1016/j.apsoil.2011.02.001

45. Bedada W, Karltn E, Lemenih M, Tola M. Long-term addition of compost and NP fertilizer increases crop yield and improves soil quality in experiments on smallholder farms. Agric Ecosyst Environ. 2014; 195(1 October 2014):193–201. https://doi.org/10.1016/j.agee.2014.06.017

46. Chivengé P. Exploring mechanisms by which organic and mineral nutrient sources regulate nutrient cycling [Master of philosophy thesis]. University of California, Davis, USA; 2008. Available from: https://search.proquest.com/openview/27722a52a4a5c5f31ca089f6319e3cc/1?pq-origsite=gscholar&cbl=18750&diss=y.

47. Palm CA, Gachengo CN, Delve RJ, Cadisch G, Giller KE. Organic inputs for soil fertility management in tropical agroecosystems: Application of an organic resource database. Agric Ecosyst Environ. 2001; 83:27–42. https://doi.org/10.1016/S0167-8809(00)00267-X

48. Mafongoya PL, Giller KE, Palm CA. Decomposition and nitrogen release patterns of tree prunings and litter. In: Nair PKR, Latt CR, editors. Dir. Trop. Agrofor. Res. For. Sci. 53rd ed. Dordrecht: Springer; 1998. p. 77–97.

49. Castellano MJ, Mueller KE, Oik DC, Sawyer JE, Six J. Integrating plant litter quality, soil organic matter stabilization, and the carbon saturation concept. Glob Chang Biol. 2015; 21(9):3200–3208. https://doi.org/10.1111/gcb.12982 PMID: 25990618

50. Gentile R, Vanlauwe B, Chivengé P, Six J. Trade-offs between the short- and long-term effects of residue quality on soil C and N dynamics. Plant Soil. 2011; 338(1-2):159–169. https://doi.org/10.1007/s11104-010-0360-z

51. Trabucco A, Zomer RJ. Global Aridity Index (Global-Aridity) and Global Potential Evapo-Transpiration (Global-PET) Geospatial Database; 2009.

52. Mariki W, Akonaay H, Mugedi L. The effects of crop residue (stover) on yield, soil structure and soil fertility. In: Ransom J, Palmer AFE, Zambezi BT, Murumna ZO, Waddington SR, Pixely KV, et al., editors. Maize Product. Gains Through Res. Technol. Dissem. proceeding ed. Arusha: International Maize and Wheat Improvement Center (CIMMYT); 1996. p. 200–201.

53. Kihanda FM. The role of farmyard manure in improving maize production in the sub-humid highlands of central Kenya [Master of philosophy thesis]. University of Reading, UK; 1997.

54. Mungai NW, Kamau AW, Macharia CN. The effect of organic and inorganic phosphorus, and time of split application of nitrogen on maize in Kenya. In: Maize Prod. Technol. Futur. Challenges Oppor. Proc. sixth East. South. Africa Reg. maize Conf. 21-25 Sep 1998. Addis Abeba, Ethiopia: CIMMYT; 1998. p. 242–246.

55. Munwira HK, Agwira FT, Chikow R, Waddington SR. An evaluation of the agronomic effectiveness of low rates of cattle manure and combinations of inorganic N in Zimbabwe. In: Waddington S, Munwira H, Kumwenda J, Hikwa D, Tagwira F, editors. Soil Fertil. Res. Maize-based Syst. Malawi Zimbabwe. Proc. Soil Fertil. Network. Results Plan. Table+++1. Harare; 1998. p. 179–182.

56. Onyango RMA, Mwangi TK, Kiyia WW, Kamidi MK. Maintaining maize productivity by combining organic and inorganic fertilizers in small holder farms within the Kitale region. In: Maize Prod. Technol. Futur. Challenges Oppor. Proc. sixth East. South. Africa Reg. Maize Conf. Addis Ababa: CIMMYT; 1998. p. 242–246.

57. Snapp SS, Mafongoya PL, Waddington S. Organic matter technologies for integrated nutrient management in smallholder cropping systems of southern Africa. Agric Ecosyst Environ. 1998; 71(1-3):185–200. https://doi.org/10.1016/S0167-8809(98)00140-6

58. Workayehu T, Kena K. Residual effects of coffee husk/pulp on grain yield of maize. In: Maize Prod. Technol. Futur. Challenges Oppor. Proc. sixth East. South. Africa Reg. Maize Confer- ence. Addis Ababa: International Maize and Wheat Improvement Center (CIMMYT); 1998. p. 271–273. Available
Combining organic and mineral fertilizers as a climate-smart integrated soil fertility management practice

59. Ikerra ST, Maghembe JA, Smithson PC, Buresh RJ. Soil nitrogen dynamics and relationships with maize yields in a glicicida—maize intercrop in Malawi. Plant Soil. 1999; 211(2):155–164. https://doi.org/10.1023/A:1004636501488

60. Mugendi DN, Nair PK, Mugwe R, O’neill JN, Woomer PL. Colliand ra and Leucaena alley cropped with maize production. Part 1: Soil fertility changes and maize productivity in the Sub-humid highlands of Kenya. Agrofor Syst. 1999; 46(1):39–50.

61. Makumba WHI, Akinnifes FK, Kwasiga FR. Above and belowground performance Glicridium sepium/ Maize mixed cropping in Makoka, Malawi. In: Kwasiga F, Ayuk E, Agumya A, editors. Proc. 14th South. African Reg. Rev. Plan. Work. Harare; 2001. p. 72–79.

62. Mugendi D, Mucheru M, Kungu J, Otor S, Micheni A, Mugwe J. Soil fertility improvement strategies for increased food production in the central highlands of Kenya. In: African Crop Sci. Conf. Proc. 5; 2001. p. 897–904.

63. Okalebo JR, Othieno CO, Woomer PL, Karanja NK, Semoka JRM, Bekunda MA, et al. Available technologies to replenish soil fertility in East Africa. In: Batiano A, Waswa B, Kihara J, Kimetu J, editors. Adv. Integr. Soil Fertil. Manag. Sub-Saharan Africa Challenges Oppor. Dordrecht: Springer; 2007. p. 45–62. Available from: https://link.springer.com/chapter/10.1007/978-1-4020-5760-1_3#citeas.

64. Nandwa SM. Soil organic carbon (SOC) management for sustainable productivity of cropping and agro-forestry systems in Eastern and Southern Africa. Nutr Cycl Agroecosystems. 2001; 61(1-2):143–158. https://doi.org/10.1023/A:1013386710419

65. Gigou J, Bredoumy SK. Yield trends, soil nitrogen and organic matter content during 20 years of continuous maize cultivation. In: Vanlauwe B, Diels J, Sangina N, Merckx R, editors. Integr. Plant Nutr. Manag. Sub-Saharan Africa From Concept to Pract. CABI Publishing; 2002. p. 199–208. Available from: https://books.google.be/books?hl=nl&lr=&id=0eP_0c-MjNEC&oi=fnd&pg=PA199&dq=Gigou+and+Bredoumy&q=2002+Gigou+and+Bredoumy&ots=ZEKA8yMhF9&sig=Zk2PP1-gvZLdhirpnjhhkUGEeGo#v=onepage&q=2002GigouandBredoumy&f=false.

66. Iwuafor ENO, Alhau K, Jaryum JS, Vanlauwe B, Diels J, Sanginda N, et al. On-farm evaluation of the contributions of sole and mixed applications of organic matter and urea to maize grain production in the savannah. In: Vanlauwe B, Diels J, Sanginda N, Merckx R, editors. Integr. Plant Nutr. Manag. Sub-Saharan Africa From Concept to Pract. CABI Publishing; 2002. p. 185–197.

67. Nhamo N. An evaluation of the efficacy of organic and inorganic fertilizer combinations in supplying nitrogen to crops [Master of Philosophy thesis]. University of Zimbabwe; 2002.

68. Uyovisere EO, Elema KA. Effect of foliages of locust bean (Parkia biglobosa) and neem (Azadirachta indica) on soil fertility and productivity of early maize in savanna Alfisols. Nutr Cycl Agroecosystems. 2002; 62(2):115–122. https://doi.org/10.1023/A:1015590823039

69. Mucheru-Muna M, Mugendi D, Kangai R, Mugwe J, Micheni A. Organic Resources for Soil Fertility Management in Eastern Kenya. In: Savala CEN, Omare MN, Woomer PL, editors. Org. Resour. Manage. Kenya Perspect. Guidel. Nairobi: FORMAT; 2003. p. 26–33.

70. Nyamangara J, Piha MI, Gillier K. Effect of combined cattle manure and mineral nitrogen on maize N uptake and grain yield. African Crop Sci J. 2003; 11(4):289–300.

71. Chilimba ADC, Sakala WD, Kabambwe VH. The effects of different organic fertilizers and their interactions with inorganic fertilizers on maize yields; 2004.

72. Munthali M. Integrated Soil Fertility Management Technologies: A Counteract to Existing Milestone in Obtaining Achievable Economical Crop Yields in Cultivated Lands of Poor Smallholder Farmers in Malawi. In: Adv. Integr. Soil Fertil. Manag. Sub-Saharan Africa Challenges Oppor. Dordrecht: Springer; 2007. p. 531–536. Available from: http://dx.doi.org/10.1007/978-1-4020-5760-1_50.

73. Delve RJ, Probert ME. Modelling nutrient management in tropical cropping systems. In: Delve RJ, Probert ME, editors. ACIAR Proc. vol. 114. Canberra,: Australian Centre for International Agricultural Research (ACIAR); 2004. p. 138. Available from: https://cgspace.cgiar.org/bitstream/handle/10568/56579/n ut_mgt_full_text.pdf?sequence=1.

74. Kimani SK, Lekasi JK. Managing manures throughout their production cycle enhances their usefulness as fertilizers: A review. In: Batiano A, editor. Manag. Nutr. Crops to Sustain Soil Fertil. Sub-Saharan Africa. Nairobi: Academy of Science Publishers; 2004. p. 187–198. Available from: https://books.google.be/books?hl=nl&lr=&id=ML9-fWEZFS8C&oi=fnd&pg=PA187&dq=Managing+manures+throughout+their+production+cycle+enhances+their+usefulness+as+fertilizers&ots=UEbyzb4&sig=BXlG5HstNpDAnn1tQwP0KJ7b6Y#v=onepage&q=Managing%20manures%20throughout%2020.

75. Kimetu JM, Mugendi DN, Palm CA, Mutuo PK, Gachengo CN, Batiano A, et al. Nitrogen fertilizer equivalences of organics of differing quality and optimum combination with inorganic nitrogen source
in Central Kenya. Nutr Cycl Agroecosystems. 2004; 68(2):127–135. https://doi.org/10.1023/B:FRES.0000019043.33580.a6

76. Okalebo JR, Palm CA, Lekasi JK, Nandwa SM, Othieno CO, Waqwa M, et al. Use of organic and inorganic resources to increase maize yields in some Kenyan infertile soils: A five year experience. In: Batiano A, editor. Manag. Nutr. Cycles to Sustain Soil Fert. Sub-Saharan Africa. Nairobi: Academy of Science Publishers; 2004. p. 359–372. Available from: https://books.google.be/books?hl=nl&lr=&id=mFL9-4WEZFB&dg=nd&pg=PA359&dq=Use+of+organic+and+inorganic+resources+to+increase+maize+yields+in+some+Kenyan+infertile+soils&ots=UEbyz2LIs&sig=denaGQoMQW6A9uhNzLbBpge6U!#v=onepage&q=Use%20of%20organic%20and%20inorganic.

77. Ayoola OT, Adeniyan ON. Influence of poultry manure and NPK fertilizer on yield and yield components of crops under different cropping systems in south west Nigeria. African J Biotechnol. 2006; 5 (15):1386–1392.

78. Kimani SK, Esilaba aO, Odera MM, Kimenyi L, Vanlauwe B, Batiano A. Effects of organic and mineral sources of nutrients on maize yields in three districts of central Kenya. In: Batiano A, Waswa B, Kihara J, Kimetu J, editors. Adv. Integr. Soil Fertil. Manag. Sub-Saharan Africa Challenges Oppor. Dordrecht: Springer; 2007. p. 353–357. Available from: https://link.springer.com/chapter/10.1007/978-1-4020-5760-1_32#citeas

79. Mugendi D, Mucheru-Muna M, Mugwe J, Kung’u J, Batiano A. Improving food production using best bet soil fertility technologies in the Central Highlands of Kenya. In: Batiano A, Waswa B, Kihara J, Kimetu J, editors. Adv. Integr. Soil Fertil. Manag. Sub-Saharan Africa Challenges Oppor. 1996. Dordrecht: Springer; 2007. p. 345–351.

80. Mugwe J, Mugendi D, Kungu J. Effect of plant biomass, manure and inorganic fertilizer on maize yield in the Central highlands of Kenya. African Crop Sci J. 2007; 15(3):111–126.

81. Fonte SJ, Yeboah E, Ofori P, Quansah GW, Vanlauwe B, Six J. Fertilizer and Residue Quality Effects on Organic Matter Stabilization in Soil Aggregates. Soil Sci Soc Am J. 2009; 73(3):961. https://doi.org/10.2136/sssaj2008.0204

82. Kimaro AA, Timmer VR, Chamsama SAO, Ngaga YN, Kimaro DA. Competition between maize and pigeonpea in semi-arid Tanzania: Effect on yields and nutrition of crops. Agric Ecosyst Environ. 2009; 134(1-2):115–125. https://doi.org/10.1016/j.agee.2009.06.002

83. Niziguheba G, Tossah BK, Diels J, Franke AC, Aihou K, Iwuafor ENO, et al. Assessment of nutrient deficiencies in maize in nutrient omission trials and long-term field experiments in the West African Savannah. Plant Soil. 2009; 314(1-2):143–157. https://doi.org/10.1007/s11104-008-9714-1

84. Shisanya CA, Mucheru MW, Mugendi DN, Kung’u JB. Effect of organic and inorganic nutrient sources on soil mineral nitrogen and maize yields in central highlands of Kenya. Soil Tillage Res. 2009; 103 (2):239–246. https://doi.org/10.1016/j.still.2008.05.016

85. Anyanwza H, Okalebo JR, Othieno CO, Batiano A, Waswa BS, Kihara J. Effects of conservation tillage, crop residue and cropping systems on changes in soil organic matter and maize-legume production: A case study in Teso District. Nutr Cycl Agroecosystems. 2010; 88(1):39–47. https://doi.org/10.1007/s10705-009-9210-2

86. Mutegi EM, Kung’u JB, Muna M, Pieter P, Mugendi DN. Complementary effects of organic and mineral fertilizers on maize production in the smallholder farms of Meru South District, Kenya. Agric Sci. 2012; 03(02):221–229.

87. Detchinli KS, Sogbedji JM. Yield performance and economic return of maize as affected by nutrient management strategies on Ferralsols in Coastal Western Africa. Eur Sci J. 2015; 11(27):312–324.

88. Tovihoudji PG, Ire`nikatche ´ Akponikp Background of Science Publishers; 2004. p. 359–372. Available from: https://books.google.be/books?hl=nl&lr=&id=mFL9-4WEZFB&dg=nd&pg=PA359&dq=Use+of+organic+and+inorganic+resources+to+increase+maize+yields+in+some+Kenyan+infertile+soils&ots=UEbyz2LIs&sig=denaGQoMQW6A9uhNzLbBpge6U!#v=onepage&q=Use%20of%20organic%20and%20inorganic.

89. Mapfumo P, Mtambanengwe F, Vanlauwe B. Organic matter quality and management effects on enrichment of soil organic matter fractions in contrasting soils in Zimbabwe. Plant Soil. 2007; 296(1-2):137–150. https://doi.org/10.1007/s11104-007-9304-7

90. Chivenge P, Vanlauwe B, Gentile R, Wangchhi H, Mugendi D, van Kessel C, et al. Organic and mineral input management to enhance crop productivity in central Kenya. Agron J. 2009; 101(5):1266–1275. https://doi.org/10.2134/agronj2008.0188x

91. Arizona-software. GraphClick; 2008. Available from: http://www.arizona-software.ch.

92. Vanlauwe B, Diels J, Sanginda N, Mercx R. Long-term integrated soil fertility management in South-western Nigeria: Crop performance and impact on the soil fertility status. Plant Soil. 2005; 273(1-2):337–354. https://doi.org/10.1007/s11104-005-0194-2
93. Franke AC, Laberge G, Oyewole BD, Schulz S. A comparison between legume technologies and fallow, and their effects on maize and soil traits, in two distinct environments of the West African savannah. Nutr Cycl Agroecosystems. 2008; 82(2):117–135. https://doi.org/10.1007/s10705-008-9174-2

94. Vanlauwe B, Kihara J, Chivenge P, Pypers P, Coe R, Six J. Agronomic use efficiency of N fertilizer in maize-based systems in sub-Saharan Africa within the context of integrated soil fertility management. Plant Soil. 2011; 339(1):35–50. https://doi.org/10.1007/s11104-010-0462-7

95. R Core Team (version 3 6 1). R: A language and environment for statistical computing.; 2018. Available from: https://www.r-project.org/.

96. Viechtbauer W. A Comparison of the rma() and the lm(), lme(), and lmer() Functions; 2019. Available from: http://www.metafor-project.org/doku.php/tips:rma_vs_lm_lme_lmer.

97. Aloe AM, Shisler SM, Norris BD, Nickerson AB, Rinker TW. A multivariate meta-analysis of student misbehavior and teacher burnout. Educ Res Rev. 2014; 12:30–44. https://doi.org/10.1016/j.edurev.2014.05.003

98. Mavridis D, Salanti G. A practical introduction to multivariate meta-analysis. Stat Methods Med Res. 2011; 22(2):133–158. https://doi.org/10.1177/0962280211432219 PMID: 22275379

99. Bates D, Maechler M, Bolker B, Walker S. Fitting Linear Mixed-Effects Models Using lme4 (version 1.1-21). J Stat Softw. 2015; 67(1):1–48. https://doi.org/10.18637/jss.v067.i01

100. Viechtbauer W, Cheung MWL. Outlier and influence diagnostics for meta-analysis. Res Synth Methods. 2010; 1(2):112–125. https://doi.org/10.1002/jrsm.11 PMID: 20613777

101. Egger M, Davey Smith G, Schneider M, Minder C. Bias in meta-analysis detected by a simple, graphical test. BMJ. 1997; 315(7108):629–34. https://doi.org/10.1136/bmj.315.7108.629 PMID: 9310563

102. Triberti L, Nasti A, Giordani G, Comellini F, Baldoni G, Toderi G. Can mineral and organic fertilization help sequestrate carbon dioxide in cropland? Eur J Agron. 2008; 29(1):13–20. https://doi.org/10.1016/j.eja.2008.01.003

103. Heerink N. Soil fertility decline and economic policy reform in Sub-Saharan Africa. Land use policy. 2005; 22(1):67–74. https://doi.org/10.1016/j.landusepol.2003.08.002

104. Lal R. Digging deeper: A holistic perspective of factors affecting soil organic carbon sequestration in agroecosystems. Glob Chang Biol. 2018; 24(8):3285–3301. https://doi.org/10.1111/gcb.14054 PMID: 29341449

105. Mohanty S, Nayak AK, Kumar A, Tripathi R, Shahid M, Bhattacharyya P, et al. Carbon and nitrogen mineralization kinetics in soil of rice-rice system under long term application of chemical fertilizers and farmyard manure. Eur J Soil Biol. 2013; 58:119–121. https://doi.org/10.1016/j.ejsobi.2013.08.016

106. Frieler K, Schäuberger B, Arnett A, Balkovič J, Elliott J, Folberth C, et al. Understanding the weather signal in national crop-yield variability Earth’s Future. Earth’s Futur. 2017; 5:605–616. https://doi.org/10.1002/2016EF000525 PMID: 27078564

107. Paustian K, Lehmann J, Ogle S, Reay D, Robertson GP, Smith P. Climate-smart soils. Nature. 2016; 532(7597):49–57. https://doi.org/10.1038/nature17174 PMID: 27078564

108. Khan SA, Mulvaney RL, Ellsworth TR, Boast CW. The Myth of Nitrogen Fertilization for Soil Carbon Sequestration. Environ Qual. 2007; 36:1821–1832. https://doi.org/10.2134/jeq2007.0099 PMID: 17965385

109. Gentile RM, Vanlauwe B, Six J. Integrated Soil Fertility Management: Aggregate carbon and nitrogen stabilization in differently textured tropical soils. Soil Biol Biochem. 2013; 67:124–132. https://doi.org/10.1016/j.soilbio.2013.08.016

110. Karhu K, Gardensäis AI, Heikkinen J, Vanhala P, Tuomi M, Liski J. Impacts of organic amendments on carbon stocks of an agricultural soil—Comparison of model-simulations to measurements. Geoderma. 2012; 189-190:606–616. https://doi.org/10.1016/j.geoderma.2012.06.007 PMID: 31301684

111. Börjesson G, Bolinder MA, Kirchmann H, Kätterer T. Organic carbon stocks in topsoil and subsoil in long-term ley and cereal monoculture rotations. Biol Fertil Soils. 2018; 54(4):549–558. https://doi.org/10.1007/s00374-018-1281-x

112. Cotrufo MF, Wallenstein MD, Boot CM, Denef K, Paul E. The Microbial Efficiency-Matrix Stabilization (MEMS) framework integrates plant litter decomposition with soil organic matter stabilization. Do labile plant inputs form stable soil organic matter? Glob Chang Biol. 2013; 19(4):988–995. https://doi.org/10.1111/gcb.12113 PMID: 23504877

113. Knicker H. Soil organic N—An under-rated player for C sequestration in soils? Soil Biol Biochem. 2011; 43(6):1116–1129. https://doi.org/10.1016/j.soilbio.2011.02.020

114. Lu CC, Tian H. Global nitrogen and phosphorus fertilizer use for agriculture production in the past half century: shifted hot spots and nutrient imbalance. Earth Syst Sci Data. 2017; 9:181. https://doi.org/10.5194/essd-9-181-2017
115. Pasley HR, Camberato JJ, Cairns JE, Zaman-Allah M, Das B, Vyn TJ. Nitrogen rate impacts on tropical maize nitrogen use efficiency and soil nitrogen depletion in eastern and southern Africa. Nutr Cycl Agroecosystems. 2020; 116(3):397–408. https://doi.org/10.1007/s10705-020-10049-x PMID: 32765186

116. Borenstein M, Hedges LV, Higgins JPT, Rothstein HR. Publication bias. In: Introd. to Meta-Analysis. John Wiley & Sons, Ltd.; 2009. p. 277–292.

117. Viechtbauer W. Conducting Meta-Analyses in R with the metafor Package (version 2.1-0). J Stat Softw. 2010; 36(3):1–48. https://doi.org/10.18637/jss.v036.i03

118. Kuznetsova A, Brockhoff PB, Christensen RHB. lmerTest Package: Tests in Linear Mixed Effects Models. J Stat Softw. 2017; 82(13):1–26. https://doi.org/10.18637/jss.v082.i13

119. Hlavac M. Stargazer: Well-Formatted Regression and Summary Statistics Tables; 2018. Available from: https://cran.r-project.org/package=stargazer.