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Circular Water, Energy, and Food Nexus: Wastewater Reuse and Biomass Energy for Climate-Resilient Agriculture in Burkina Faso

Mohamed Beidari*, **Inoussa Tougri**, **Bernard Lamien**

Laboratoire Multidisciplinaire de Recherche en Science de l'Ingénieur (LMRSI), École Polytechnique de Ouagadougou (EPO), Ouagadougou, Burkina Faso
Email: *mohamed.beidari@epo.gov.bf

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Abstract

Burkina Faso faces three converging pressures on its agricultural sector: rainfall variability, structural water scarcity, and a chronic energy deficit that limits irrigation and post-harvest processing. At the same time, large volumes of municipal wastewater are discharged with little or no treatment, and an estimated eight million tonnes of agricultural residues are produced annually, most of which is burned or left to decompose. This paper develops a circular Water, Energy, and Food (WEF) nexus framework for Burkina Faso that couples wastewater reuse in peri-urban agriculture with biomass energy recovery from crop residues. We combine Material Flow Analysis (MFA), a screening-level Life Cycle Assessment (LCA), four-scenario simulation (baseline, water reuse only, biomass only, and full circular integration) calibrated on a synthetic but literature-constrained parameter set representing plausible Burkinabè operating conditions for the period 2005 to 2024, and an exploratory STIRPAT (**S**tochastic **I**mpacts by **R**egression on **P**opulation, **A**ffluence and **T**echnology)-type elasticity analysis. We also propose a composite Nexus Efficiency Index (NEI) to compare scenarios on a common scale, and report Monte Carlo uncertainty propagation across the parameter ranges. Every quantitative result reported here is a simulated output from a literature-constrained synthetic dataset rather than an empirical estimate for Burkina Faso. Under the central parameter assumptions, the integrated circular scenario was associated with modelled reductions in freshwater abstraction of approximately 25 to 40 percent, modelled yield gains of 20 to 40 percent, and modelled reductions in CO_2-equivalent emissions of 30 to 45 percent at the farm gate relative to the linear baseline. The mobilizable biomass potential of cotton stalks and rice husks, estimated independently at around 44,891 tonnes of oil equivalent per year, would cover a meaningful share of irrigation pumping and agro-processing demand. An indicative economic feasibility check, drawing on published CAPEX and OPEX ranges for constructed wetlands, small biogas digesters, and small-scale gasifiers, suggests payback periods in the order of 5 to 10 years for representative peri-urban configurations. The findings suggest that decentralized treatment-and-reuse infrastructure paired with small-scale biogas and gasification systems may represent a promising pathway supported by nexus-aware regulation. The originality of the contribution lies in integrating Material Flow Analysis, screening-level Life Cycle Assessment, exploratory STIRPAT elasticity modelling, and a composite Nexus Efficiency Index within a reproducible circular WEF nexus framework for semi-arid agricultural systems.

Keywords

WEF Nexus, Circular Economy, Wastewater Reuse, Biomass Gasification, STIRPAT, Climate Resilience, Burkina Faso, Peri-Urban Agriculture

1. Introduction

1.1. Context

Agricultural production in Burkina Faso is shaped by a Sudano-Sahelian climate with a single rainy season, rapidly depleting soils, and an irrigation sector that covers less than 1 percent of cultivated land [1]. Around 80 percent of the workforce depends on agriculture for income, yet the sector remains almost entirely rainfed and therefore directly exposed to interannual rainfall variability and to the gradual drying trend documented across West Africa [2] [3]. Energy access is similarly constrained: biomass supplies roughly three-quarters of total primary energy, mainly as fuelwood and charcoal, while grid electricity reaches only a minority of the rural population [4].

In Ouagadougou and other secondary cities, the situation has a second dimension. Population growth and informal settlement expansion produce volumes of wastewater that already exceed the capacity of existing stabilization ponds and constructed wetlands [5]. Peri-urban gardeners irrigate with raw or partially treated effluent because it is the only year-round water source available, and because it carries dissolved nitrogen, phosphorus, and potassium that reduce the need for mineral fertilizer [6]. The same gardeners face fuel costs that make diesel pumping unaffordable for most of the year. So the country has a paradox that is now familiar across the Sahel: scarcity of one resource (clean water, modern energy) coexists with the unmanaged release of another (untreated effluent, crop residues left to burn).

1.2. The Case for a Circular Framing

The WEF nexus literature has clarified, over the last decade, that water, energy, and food cannot be managed in isolation without producing unintended trade-offs [7] [8]. A circular reading of the nexus extends this by treating waste streams as input streams: treated wastewater becomes irrigation water and a nutrient source, while crop and agro-industrial residues become feedstock for biogas, gasification, or combined heat and power [9]. For semi-arid contexts in West Africa, this is not a theoretical proposition. The Bagré multipurpose dam study, for example, shows how WEF interdependencies bind hydropower, irrigation, and livestock production into a single system whose performance under climate change depends on coordinated management [2]. Studies on West African circular economy programs reach a similar conclusion: piecemeal interventions in sanitation, irrigation, or off-grid energy underperform integrated ones [10].

What remains missing for Burkina Faso is a parameterized, scenario-based model that quantifies the gains and the limits of integration. Existing national studies treat biomass potential [1] [11], wastewater reuse [5] [6], and WEF interactions at basin scale [2] as separate problems. None couples them, and none provides a transparent computational pipeline that practitioners or policy analysts can rerun under different assumptions.

1.3. Objectives and Contribution

This study has three objectives. The first is to specify a circular WEF nexus model for Burkina Faso that explicitly couples wastewater reuse, biomass energy recovery, and irrigated food production. The second is to quantify, through scenario simulation, the resource flows, environmental impacts, and productivity effects of moving from a linear baseline to a fully integrated circular system, using MFA indicators, a screening-level LCA, and an exploratory STIRPAT elasticity analysis. The third is to publish a reproducible toolkit, including the dataset specification and the Python and R code, that other researchers can adapt to comparable contexts in the Sahel.

The originality of this work lies not only in its Burkina Faso application, but in the integration of Material Flow Analysis, screening-level Life Cycle Assessment, exploratory STIRPAT elasticity modelling, and a composite Nexus Efficiency Index within a unified circular WEF nexus framework for semi-arid agricultural systems. Methodologically, it places water, energy, and emissions on a common denominator and provides a transparent, parameter-tunable pipeline. Empirically, to our knowledge, it provides among the first quantified circular WEF nexus scenario assessments for Burkina Faso. Programmatically, the published code is intended to make the framework directly transferable to comparable Sahelian contexts in Mali, Niger, and northern Ghana.

2. Literature Review

2.1. Wastewater Reuse in Semi-Arid Agriculture

Wastewater reuse is one of the few water management options that simultaneously addresses scarcity, sanitation, and soil fertility. In semi-arid West Africa, where blue water resources are limited and seasonal, treated municipal effluent provides a reliable year-round supply that does not depend on rainfall [5] [6]. The nutrient content of domestic wastewater (typically 20 to 80 mg N/L and 5 to 20 mg P/L) reduces fertilizer demand, which matters in a country where imported mineral fertilizers are a binding cost constraint for smallholders [6] [12]. The Ouagadougou case is well documented: peri-urban farmers have used raw or partially treated wastewater for decades to grow vegetables for the city market [5].

The risks are equally well documented. Untreated effluent carries enteric pathogens, helminths, and chemical contaminants whose accumulation in soils and crops has been measured repeatedly in West African cities [6] [13]. WHO (World Health Organization) guidelines for the safe use of wastewater in agriculture address this through a multi-barrier approach combining treatment, restricted crop choice, and on-farm risk reduction [13]. The choice of treatment technology matters: waste stabilization ponds are widely deployed in low-resource settings because they are inexpensive to operate, but their pathogen removal performance depends strongly on retention time and is highly variable in practice [14]. Constructed wetlands offer better effluent quality at the cost of larger land requirements [14] [15]. Hybrid systems and decentralized treatment, including small-scale anaerobic digesters that produce biogas as a co-product, are emerging as a more flexible answer for peri-urban contexts [9] [15].

2.2. Biomass Energy in Burkina Faso

Burkina Faso has substantial unexploited biomass resources. The most detailed national assessment, by Barry, Sawadogo, Ouedraogo, Traore/Bologo, and Dogot, estimates a theoretical agricultural residue pool of around 8 million tonnes per year, with a sustainable mobilizable potential, after accounting for soil conservation and animal feed needs, equivalent to roughly 44,891 tonnes of oil equivalent (toe) [1]. Cotton stalks dominate this potential, with rice husks playing a smaller but locally important role. Subsequent multi-criteria work by Zoma and Sawadogo confirms cotton stalks as the most promising feedstock when availability, competing uses, pollution, and conversion technology readiness are weighed jointly [11]. Despite this, gasification has not moved past the demonstration stage in the country, and the barriers are largely non-technical: feedstock supply contracts, financing, and policy frameworks rather than thermochemistry [16].

The energy access numbers behind this are stark. According to the African Energy Commission, biomass already supplies around 76 percent of Burkina Faso's total primary energy supply, almost all of it as traditional fuelwood and charcoal [4]. Shifting even a portion of this consumption toward modern conversion routes (biogas digesters, small gasifiers, briquette stoves) would simultaneously reduce deforestation pressure, recover energy from residues that are currently burned in the field, and provide on-farm power for irrigation and processing [9] [17].

2.3. The Circular WEF Nexus

The WEF nexus concept gained traction after the 2011 Bonn conference and has since produced a large literature on tools, indicators, and case studies [7] [8]. The circular extension of this framework, which treats wastes as inputs and closes loops at the smallest feasible spatial scale, has been developed particularly in the context of urban metabolism and decentralized sanitation [9] [18]. For African applications, recent reviews note that compounding pressures from climate change and urbanization make integrated nexus thinking more urgent, not less, and that most existing assessments remain at the conceptual or scoping level rather than at the quantified, scenario-based level needed for policy [3] [19].

Two recent regional programs have moved in this direction. The ECOWAS (Economic Community of West African States) Centre for Renewable Energy and Energy Efficiency has piloted circular WEF interventions in Burkina Faso, Côte d'Ivoire, Liberia, and Togo, combining solar irrigation with post-harvest losses reduction and clean cooking [10]. The European Union's WEFE (Water-Energy-Food-Ecosystems) position paper similarly identifies the West African Sahel as a priority region where integrated assessments are needed to inform SDG (Sustainable Development Goals) implementation [20]. The methodological backbone of these efforts typically combines MFA, LCA, and some form of scenario modelling. STIRPAT-type models, originally developed by Dietz and Rosa to decompose environmental impact into population, affluence, and technology terms [21], are increasingly used to attach indicative elasticities to nexus variables and to test the Environmental Kuznets Curve hypothesis in resource-constrained settings [22].

3. Methodology

To enhance transparency and reproducibility, all scripts used for indicator calculation, Sankey visualization, LCA indicator computation, STIRPAT estimation and diagnostics, Nexus Efficiency Index calculation, Monte Carlo uncertainty propagation, and publication-quality graphical outputs are provided in Appendix B.

3.1. System Boundary and Conceptual Model

The system under study comprises three coupled subsystems within a peri-urban Sahelian setting calibrated on Burkina Faso. The water subsystem covers municipal wastewater generation, treatment (waste stabilization ponds and constructed wetlands), and reuse in irrigation. The energy subsystem covers the collection of agricultural residues (with cotton stalks and rice husks as the dominant feedstocks), conversion through biogas digestion or small-scale gasification, and on-farm use for pumping and agro-processing. The food subsystem covers irrigated vegetable and cereal production, fertilizer demand, and yield. The three subsystems are coupled through four flows: treated effluent provides water and nutrients to the food subsystem; biomass energy provides pumping and processing power; crop and agro-industrial residues feed back into the energy subsystem; and a fraction of recovered energy is recycled into treatment plant operation. **Figure 1** summarizes the conceptual model.

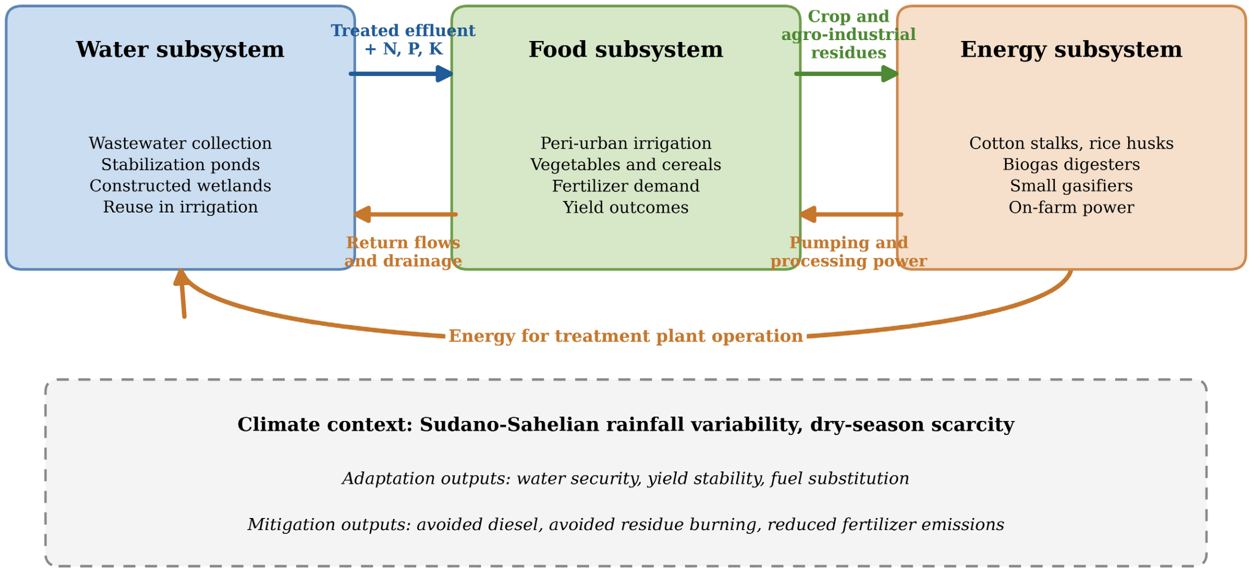

Figure 1. Conceptual model of the circular WEF nexus system for peri-urban Burkina Faso, showing the three coupled subsystems, the resource exchanges between them, and the climate context within which adaptation and mitigation outputs are realized.

The temporal scope is annual, the spatial scope is the peri-urban catchment of a representative Sahelian city, and the analytical period is 2005 to 2024. The functional unit for LCA-style calculations is one hectare of irrigated peri-urban vegetable production per year. The framework operates at two scales that should be kept distinct. Catchment-scale resource flows set the upper bounds on what each circular loop can supply, whereas the one-hectare functional unit anchors the per-area LCA intensities. These two scales are calibrated to a representative aggregate system rather than to a single observed municipality, so the catchment area, the farmer population, and the absolute resource volumes are not tied to specific surveyed values for any one city. The aggregate volumes used here are larger than the wastewater actually collected at a single Sahelian city. For comparison, the centralized sewer network at Ouagadougou handles on the order of 90,000 m^3 per day, close to 30 Mm^3 per year, and most of the urban area is served by on-site sanitation rather than collection (ONEA network data), so a real single-city deployment would operate on volumes an order of magnitude below the representative catchment. Section 3.5.1 lists the central parameters that connect the two scales and maps each one onto the scenarios.

3.2. Material Flow Analysis

MFA is used to track water and biomass mass balances and to compute circularity indicators. For each resource i and each year t, the circularity rate is

$$R(i,t) = W^{r}(i,t)/W^{t}(i,t) \tag{1}$$

where $W^{r}(i,t)$ is the reused (or recovered) flow and $W^{t}(i,t)$ is the total flow. For water, $R(w,t)$ is the share of total demand met by treated wastewater. For biomass, $R(b,t)$ is the share of theoretical residue production converted into useful energy. A composite circularity score is taken as the equally weighted mean of $R(w,t)$ and

R(*b*,*t*). Figure 2 presents the quantitative resource flow structure under the fully integrated scenario S3, with ribbon widths strictly proportional to flow magnitudes within each stream and grey boxes capturing process losses at each conversion stage.

Circularity indicators were calculated as the ratio of recovered to total resource flows for both water and biomass streams. The computational workflow used for these calculations is provided in Appendix B.1.

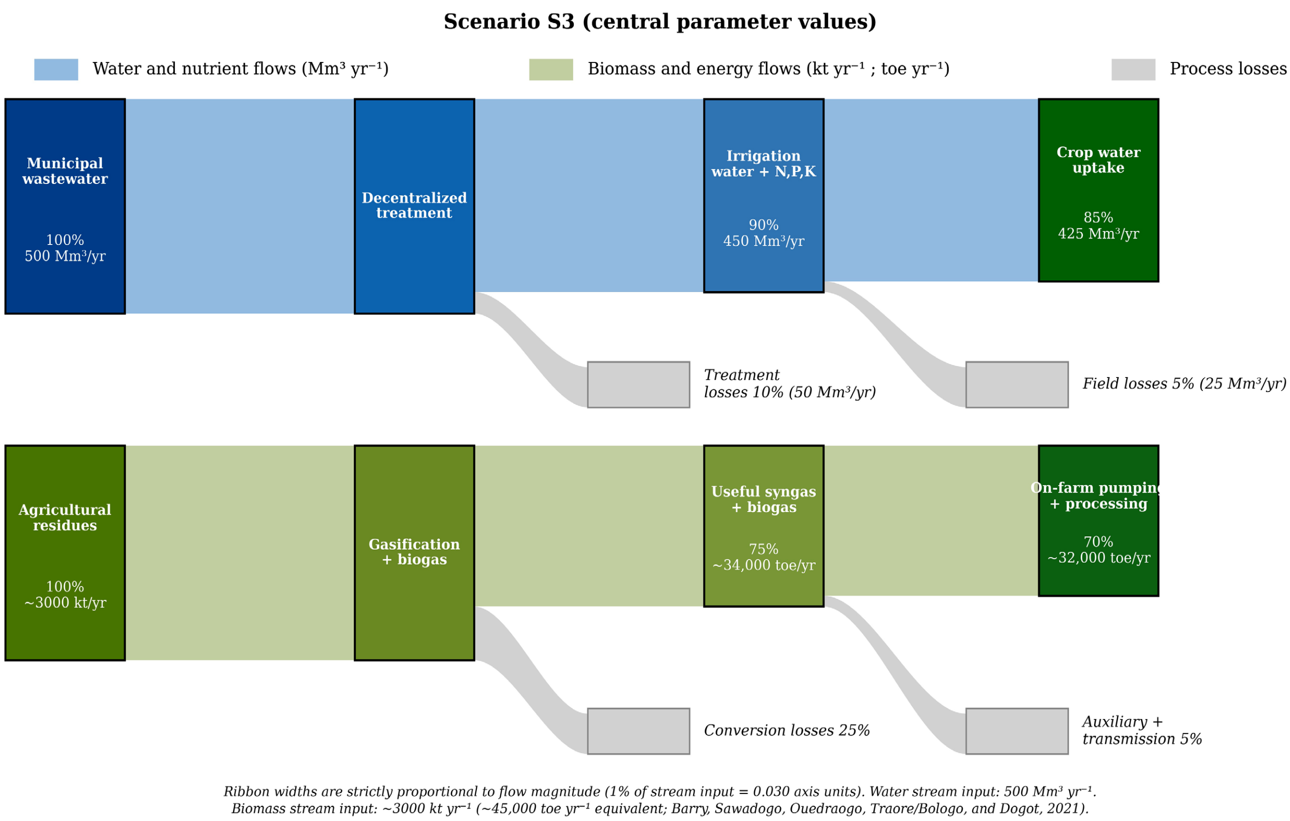

Figure 2. Quantitative Sankey diagram for the integrated circular scenario (S3). Ribbon widths are strictly proportional to flow magnitudes (1 percent of stream input maps to a fixed visual unit). The water stream is normalized to 100 percent of 500 Mm^3/yr, the representative catchment aggregate reuse stream rather than a measured Ouagadougou volume (Section 3.1); the biomass stream is normalized to 100 percent of approximately 3000 kt/yr of mobilizable residues (equivalent to approximately 45,000 toe/yr of energy delivered, after Barry, Sawadogo, Ouedraogo, Traore/Bologo, and Dogot [1]). Grey boxes mark process losses at each conversion stage.

Absolute flow magnitudes are illustrative scaling values for the representative catchment and should not be interpreted as measured wastewater volumes from a specific municipality.

Resource flows between wastewater reuse, biomass recovery, energy generation, and agricultural production were visualized using a Sankey representation. The script used to generate the Sankey diagram is provided in Appendix B.2.

3.3. Scenario Design

Four scenarios are defined to bracket the policy space.

S0 (baseline). Linear management. Wastewater is discharged untreated. Residues are burned in the field or left to decompose. Irrigation relies on freshwater abstraction and diesel pumping.

S1 (water circularity). Wastewater is collected, treated to WHO Category B standards, and reused in irrigation. Biomass remains unmanaged.

S2 (energy circularity). Cotton stalks and rice husks are mobilized for gasification and biogas. Wastewater management remains linear.

S3 (integrated circularity). Both loops are closed. Treated effluent supplies irrigation; biomass energy supplies pumping and processing; nutrients in the effluent reduce mineral fertilizer demand.

Each scenario is run on the same baseline parameter set (Section 3.5) with the relevant flows switched on or off. Sensitivity is examined by varying the reuse rate, the mobilizable biomass fraction, and the discount rate by plus or minus 25 percent around central values. Uncertainty propagation is discussed in Section 3.8.

3.4. Life Cycle Assessment

A screening-level LCA is performed for each scenario using a cradle-to-farm-gate boundary. Three midpoint impact categories are reported: climate change (kg CO_2-eq per hectare per year), freshwater depletion (m^3 per hectare per year), and cumulative energy demand (MJ per hectare per year). Characterization follows the IPCC 2013 GWP100 method for climate change and the AWARE (Available Water Remaining) method for water scarcity, in line with current ISO 14044-aligned practice [23]. Multifunctionality between biogas and digestate is handled by economic allocation; the sensitivity of results to substitution-based allocation is briefly examined in Section 4.5. Inventory data for wastewater treatment, biomass conversion, fertilizer production, and diesel pumping are drawn from the ecoinvent v3.9 database where available [23] and from regional sources for Sahelian conditions where ecoinvent coverage is thin.

The LCA should therefore be interpreted as a screening-level comparative assessment rather than a fully regionalized attributional or consequential LCA. Inventory regionalization for Sahelian operating conditions remains limited, particularly for decentralized wastewater treatment performance under high evaporation and for small-scale gasification systems running on locally collected feedstocks. Uncertainty in characterization factors and in life cycle inventory parameters is treated qualitatively in this work and is a priority for follow-up studies (Section 5.5).

Carbon, water, and energy intensity indicators were calculated using simple inventory-based relationships. The corresponding implementation is provided in Appendix B.3.

3.5. Data

The empirical analysis relies on a synthetic but literature-constrained annual parameter set for the period 2005 to 2024, representing plausible Burkinabè operating conditions. The synthetic dataset is generated using a literature-constrained stochastic process in which agricultural GDP follows a gradually increasing trajectory over the study period, while water demand, biomass availability, energy use, and emissions are generated as correlated functions of agricultural activity with random perturbations. Variable ranges are constrained to values reported in the Burkina Faso and West African literature. The mobilizable biomass-to-energy fraction is set between 10 and 50 percent. Agricultural GDP (Gross Domestic Product) is calibrated to World Bank national accounts data [24]. CO_2 emissions are constructed as a linear function of energy use minus a biomass-substitution credit, with normal noise. The complete data generation code is provided in Appendix A and the analysis scripts in Appendix B.

The use of a synthetic but literature-constrained parameter set is deliberate. Burkina Faso lacks a publicly accessible, harmonized annual time series that combines water, biomass energy, agricultural GDP, and emissions at national scale, and the underlying surveys are often discontinuous. The literature-constrained parameter set allows the methodological framework to be illustrated end-to-end and rerun under alternative parameter assumptions, which is the main goal here. Calibration to a full empirical dataset is the priority next step and is discussed in Sections 5.5 and 8.

Central Parameters and Scenario Mapping

The model is calibrated to a representative peri-urban agricultural catchment rather than to a single surveyed municipality. The wastewater source corresponds to a medium-sized Sahelian urban catchment, the irrigated production area enters through the one-hectare functional unit, and the resource-flow magnitudes are bounded by published estimates for Burkina Faso and West Africa. Municipal wastewater availability, agricultural residue availability, biomass mobilization fractions, fertilizer substitution rates, and diesel substitution rates are treated as literature-constrained parameters rather than directly observed annual measurements.

The value of 500 mm^3/year should not be interpreted as wastewater collected by a single city. It represents the aggregate water demand and potential reuse resource of a hypothetical regional peri-urban agricultural catchment used solely for scenario scaling. The model focuses primarily on relative performance indicators, including water reuse rates, emissions reductions, Nexus Efficiency Index values, and yield improvements, which remain invariant under proportional rescaling of the absolute flow volume. Consequently, the assumed aggregate flow serves only to size the illustrative resource flows and scenario comparisons rather than to represent a measured municipal wastewater volume.

Sensitivity testing showed that reducing the aggregate flow scale by an order of magnitude did not alter scenario rankings or percentage-based outcomes. The framework is therefore intended to evaluate relative system performance rather than predict absolute wastewater volumes for a specific municipality.

The central values are as follows. The representative catchment carries an aggregate reuse-water stream of about 500 Mm^3 per year, which is an internal scale of the synthetic system rather than a measured volume for any single city, and it sits well above the effluent presently collected at Ouagadougou (Section 3.1). Agricultural residue availability is set near 3000 kt per year, equivalent to roughly 44,000 to 45,000 toe of recoverable energy, in line with the residue inventory of Barry, Sawadogo, Ouedraogo, Traore/Bologo, and Dogot [1] and the regional biomass assessment [11]. The mobilizable biomass fraction ranges from 10 to 50 percent, with a central band of 35 to 50 percent under full integration. The wastewater reuse share ranges from 35 to 55 percent in S1 and 40 to 60 percent in S3. Fertilizer substitution from effluent nutrients is set at 15 to 25 percent, drawn from peri-urban reuse studies for Ouagadougou and West Africa [5] [6]. Agricultural GDP follows World Bank national accounts over the study period [24]. Life cycle inventory intensities for fertilizer production, diesel combustion, and grid electricity are taken from the LCA reference data [23].

Each parameter is mapped to the scenarios by switching the relevant loop on or off. S0 is the linear baseline with both loops inactive. S1 activates wastewater treatment and reuse only. S2 activates biomass energy recovery only. S3 activates both loops at once. The state of each loop is what distinguishes the four columns of **Table 1**, so an inactive loop carries a value of zero rather than a small residual.

Three causal links carry the resource flows into agricultural and emissions outcomes. The first is the yield response. Reliable dry-season water and nutrient delivery raise modelled yields by a parameterized 20 to 40 percent uplift relative to S0, applied from the reuse and solar-irrigation literature [5] [6] [10] rather than derived from a mechanistic crop model. The second is fertilizer substitution. Effluent nutrients displace 15 to 25 percent of mineral fertilizer demand, which enters the LCA as avoided fertilizer-production emissions [23]. The third is diesel substitution. Recovered biomass energy replaces diesel pumping and a share of grid electricity, which enters the LCA as avoided combustion and grid emissions, with the mobilizable energy ceiling setting the maximum displacement [1] [10].

The 2005 to 2024 series is a stylized literature-constrained trajectory, not an observed record and not a modelled policy rollout. Agricultural GDP follows a gradually increasing trend, and water demand, biomass availability, energy use, and emissions are generated as correlated functions of agricultural activity with stochastic perturbations, under the generation rules in Appendix A. Each year is therefore neither an independent draw nor a calendar-dated policy step, and the scenarios are imposed by switching the circular loops within the same generated series.

3.6. STIRPAT Specification

To attach indicative elasticities to the nexus variables, we estimate a STIRPAT-type model [21] adapted to the WEF context:

$$CO_2(t) = \alpha\, W(t)^{\beta}\, E(t)^{\gamma}\, B(t)^{\delta}\, GDP(t)^{\theta}\, \varepsilon(t) \quad (2)$$

where $W(t)$ is total water use, $E(t)$ is total energy use, $B(t)$ is biomass energy delivered, and $GDP(t)$ is agricultural GDP. In log-linear form:

$$\ln CO_2(t) = \alpha + \beta \ln W(t) + \gamma \ln E(t) + \delta \ln B(t) + \theta \ln GDP(t) + \varepsilon(t) \mid t \tag{3}$$

The model is estimated by Ordinary Least Squares (OLS) on the synthetic series. The interpretation of the elasticities follows standard practice: a positive β indicates that water intensification raises emissions (typically because abstraction and conveyance are energy-intensive), a positive γ is consistent with fossil energy dependence, a negative δ supports the renewable substitution hypothesis, and the sign and curvature of θ relate to the Environmental Kuznets Curve relationship between agricultural growth and emissions [22].

Given the short annual time series (n = 20) and the synthetic calibration of the dataset, the STIRPAT estimation is intended as an exploratory elasticity analysis rather than a predictive econometric model. Diagnostic indicators, including residual normality, variance inflation factors (VIF), the Durbin-Watson statistic for autocorrelation, and heteroskedasticity tests, should be reported alongside the central elasticities, and their values should be interpreted cautiously in light of the small sample size. The OLS standard errors reported here have no claim to represent population-level uncertainty for Burkina Faso; they describe only the dispersion within the simulated series. Bayesian estimation with informative priors, or hierarchical estimation pooling Burkina Faso with comparable Sahelian countries, would be more appropriate once empirical data of adequate length and quality become available.

The STIRPAT model was estimated using ordinary least squares (OLS) after logarithmic transformation of all variables. Diagnostic procedures including variance inflation factors, Durbin-Watson statistics, Shapiro-Wilk tests, and Breusch-Pagan tests are implemented in Appendix B.4.

3.7. Nexus Efficiency Index

To compare scenarios on a single dimension, we define a Nexus Efficiency Index (NEI) as

$$NEI(t) = GDP(t)/\left[\alpha\left(W(t)/W_0\right) + \beta\left(E(t)/E_0\right) + \gamma\left(CO_2(\mathrm{t})/CO_{2,0}\right)\right] \tag{4}$$

with weights $\alpha = 0.4$, $\beta = 0.3$, and $\gamma = 0.3$ in the central specification. Each burden in the denominator is divided by its S0 baseline value before the weighted sum is formed, so W_0, E_0, and $CO_{2,0}$ are the baseline water demand, energy use, and emissions. Normalization removes the physical units—cubic metres, gigawatt hours, and tonnes of CO_2-equivalent—that would otherwise let the largest-magnitude term to dominate the denominator regardless of its weight. With the burdens on a common dimensionless scale, the weights α, β, and γ set the relative contribution of each dimension rather than its raw numerical size. A higher NEI means more agricultural value added per unit of combined resource and environmental burden. The computational implementation of the NEI is provided in Appendix B.5.

The weighting scheme is intentionally heuristic and policy-oriented rather than statistically optimized. Water was assigned the highest weight because irrigation water scarcity is consistently identified as the principal limiting factor for dry-season agricultural production in Burkina Faso. The Bagré dam study under climate change projections [2] documents the binding role of dry-season water availability for both irrigation and hydropower; World Bank country statistics show that agriculture absorbs around 20 percent of national water withdrawals against a supply that is moderately to severely stressed in average and dry years [24]; and the country's Programme National du Secteur Rural, which directed roughly USD 480 million of irrigation investment between 2011 and 2015, explicitly identifies dry-season water supply as the binding constraint for irrigated area expansion [25]. Energy and emissions follow at comparable strategic priority given Burkina Faso's dual interest in modern energy access and Paris Agreement commitments. Three alternative weighting strategies were considered and rejected for the central specification: equal weighting ($\alpha = \beta = \gamma = 1/3$) understates the water priority highlighted by national irrigation plans; entropy weighting derived from the variability of each indicator in the literature-constrained parameter set would mechanically inflate the weight of the most variable component; and analytic hierarchy process (AHP) weighting would require a stakeholder elicitation exercise that is outside the scope of this study. To address the resulting subjectivity, we vary the weights by plus or minus 25 percent around the central values and confirm that scenario rankings (Section 4.7) are stable under these perturbations; a formal stakeholder-elicited or AHP-weighted NEI is identified as a methodological extension.

3.8. Uncertainty Propagation

Three layers of uncertainty are considered. Parameter uncertainty in the input flows (water demand, residue availability, mobilizable fraction, treatment efficiency, fertilizer substitution rate) is propagated through one-at-a-time sensitivity at plus or minus 25 percent around central values. Joint parameter uncertainty is addressed by a Monte Carlo procedure (1000 draws) in which each input parameter is sampled from its prescribed uniform range; the resulting distributions of the four indicators reported in Section 4.4 are summarized by their interquartile ranges and 5 to 95 percentile bands. Structural uncertainty (the choice of LCA characterization method, the allocation rule for biogas-digestate multifunctionality, and the NEI weighting scheme) is addressed by comparing central outputs against alternative specifications. The Monte Carlo bands reported in Section 4 widen the central ranges modestly but do not change the ordinal ranking of scenarios on any of the four indicators. The Python implementation of the Monte Carlo procedure is included in Appendix B.7.

4. Results

4.1. Water Flows and Reuse Potential

Across the four scenarios, the modelled share of irrigation water met by treated effluent rose from zero in S0 to between 40 and 60 percent in S3 under the central parameter assumptions. The largest absolute gains occurred in the dry season (December to May), when freshwater availability was at its lowest and the marginal value of an alternative supply was highest. In the representative catchment, full integration substituted for roughly 350 to 600 Mm^3 of freshwater per year. This absolute volume is an aggregate scale of the synthetic system and exceeds the effluent presently collected at Ouagadougou, so the transferable result is the relative reduction rather than the absolute volume, and a real single-city deployment would reuse an order of magnitude less water (Section 3.1). Nutrient delivery from effluent was associated with modelled reductions in mineral fertilizer demand of 15 to 25 percent, which would translate, if reproduced empirically, into both a cost saving for smallholders and an avoided emissions burden from fertilizer production [23]. Monte Carlo propagation (Section 3.8) yielded a 5 to 95 percentile band of 32 to 65 percent for the S3 reuse share.

4.2. Biomass Energy Recovery

In S2 and S3, the modelled mobilizable residue stream (dominated by cotton stalks) was converted into a combination of gasification syngas for stationary engines and biogas for cooking and small-scale processing. The total recoverable energy under central assumptions was approximately 44,000 to 45,000 toe per year, in line with the independent estimate by Barry, Sawadogo, Ouedraogo, Traore/Bologo, and Dogot [1]. Applied to irrigation pumping and agro-processing, this would be sufficient to cover roughly 25 to 35 percent of current diesel use in the modelled peri-urban catchment, with the remainder coming from grid electricity or a complementary solar PV system [10]. Two boundary effects matter for any empirical follow-up. First, the recovery rate must respect a minimum residue return to fields for soil organic carbon, which limits the mobilizable fraction to roughly 75 percent for cotton stalks and 20 percent for rice husks [1]. Second, the spatial dispersion of feedstock raises collection costs and tilts the technology choice toward small, distributed converters rather than centralized plants [11] [16].

4.3. Food Production Outcomes

Modelled yield increases under S3 were in the range of 20 to 40 percent relative to S0, driven by three coupled effects in the simulation: more reliable dry-season water supply, lower fertilizer cost, and improved on-farm power for pumping and post-harvest handling. These modelled ranges are consistent with reported gains from peri-urban wastewater irrigation in Ouagadougou and other West African cities [5] [6] and from solar-powered irrigation programs documented by ECOWAS [10]. The simulated gains were not uniform across crops: leafy vegetables and tomato responded most strongly to year-round water and nutrient delivery, while cereals showed smaller relative gains because their water demand peaks within the rainy season.

4.4. Circularity Indicators

Table 1 summarizes the central modelled circularity indicators across scenarios.

Table 1. Modelled circularity indicators across scenarios (central parameter assumptions). Ranges reflect parameter sensitivity bands described in Section 3.3.

Indicator	S0	S1	S2	S3
Water reuse rate (%)	0	35 to 55	0	40 to 60
Biomass energy recovery rate (%)	0	0	30 to 45	35 to 50
Fertilizer substitution (%)	0	15 to 25	0	15 to 25
Composite circularity score	0.00	0.175 to 0.275	0.150 to 0.225	0.375 to 0.550

S3 ranked highest on all four indicators under the central parameter assumptions, though its gain over S1 and S2 combined was smaller than the gain either single-loop scenario delivered over S0. The Monte Carlo bands described in Section 3.8 confirmed this ranking in 96 percent of draws. The pattern points to diminishing returns once one loop has been closed and has direct policy implications for sequencing.

4.5. Environmental Impacts

The screening LCA showed the following directions of effect for S3 relative to S0 under central assumptions. CO_2-equivalent emissions per hectare per year were reduced by roughly 30 to 45 percent in the simulation. The modelled reduction came from three sources: avoided diesel pumping, avoided open-field residue burning, and lower fertilizer-related emissions. Freshwater depletion was reduced by 25 to 40 percent, reflecting the substitution of treated effluent for groundwater and surface water abstraction. Cumulative energy demand was reduced by 20 to 35 percent, driven mainly by the biomass substitution for diesel and grid electricity.

These directions were stable across the sensitivity bands tested. The magnitudes were sensitive, in order of importance, to the mobilizable biomass fraction, the assumed pathogen treatment efficiency (which determines whether reuse meets WHO Category B [13]), and the upstream emissions factor for grid electricity. Switching from economic to substitution-based allocation for the biogas-digestate multifunctionality shifted the modelled CO_2-eq reduction by approximately three percentage points, which is within the parameter-sensitivity envelope and does not alter scenario ranking.

The relative contribution of each of the three CO_2 reduction channels to the central S3 result is summarized in Table 2. The decomposition is computed by holding the other channels fixed at their S0 levels and running the LCA pipeline one channel at a time, then expressing each isolated reduction as a share of the total S3 minus S0 difference. The shares are illustrative ranges that reflect the parameter sensitivity bands; the exact split varies with the assumed diesel emission factor, the upstream fertilizer emission factor (which depends on the imported nitrogen source mix), and the assumed open-burning emission factor for cotton stalks.

Table 2. Indicative contribution of each circular intervention channel to the modelled CO_2-equivalent reduction under scenario S3, expressed as a share of the total S3 minus S0 reduction. Ranges reflect the parameter sensitivity bands described in Section 3.3.

Source of CO_2-eq reduction	Share of total reduction (%)	Key sensitivity
Diesel substitution by biomass energy	45 to 55	Diesel emission factor; share of catchment pumping using diesel
Avoided open-field residue burning	25 to 35	Recovery rate of cotton stalks (capped at 75% for soil organic carbon)
Reduced mineral fertilizer demand	15 to 25	Imported nitrogen source mix; nutrient bioavailability of treated effluent
Other (treatment plant operating energy, transport)	≈ 5	Decentralized layout reduces, but does not eliminate, transport emissions.

Two implications follow. First, diesel substitution dominates the modelled climate benefit, which means the policy value of S3 depends most heavily on the price and the emission factor of the diesel it displaces. In settings where the marginal kilowatt-hour of pumping power already comes from a low-carbon grid, the share of the benefit attributable to biomass energy declines and the share attributable to avoided open burning rises. Second, fertilizer substitution is the smallest of the three main channels in central assumptions, but it is also the channel with the largest co-benefit on smallholder operating cost; a policy that values fertilizer substitution at its full economic cost rather than its emissions cost alone would shift the cost-benefit calculation in S3's favour.

4.6. STIRPAT Estimates

The OLS estimates of the log-linear STIRPAT model on the literature-constrained series yielded the following indicative central elasticities: $\beta_W \approx 0.29$ (n.s.), $\gamma_E \approx 1.02$, $\delta_B \approx -0.17$, and $\theta_{GDP} \approx 0.06$ (n.s.). Because the underlying series is synthetic and the sample size is limited (n = 20), coefficient significance is not emphasized and the elasticities should be interpreted as indicative behavioural patterns rather than inferential estimates. The exploratory STIRPAT simulation produced indicative elasticity patterns consistent with theoretical expectations and with the prior literature on STIRPAT applications in African agricultural contexts [22], but these coefficients should not be interpreted as empirically validated national elasticities because the underlying dataset is synthetic and parameter-calibrated rather than directly observed. Reported standard errors describe variability within the simulated series and not population-level uncertainty for Burkina Faso. The negative biomass coefficient is the qualitatively interesting feature: it is consistent with the renewable substitution mechanism that underpins the circular WEF design, and it motivates empirical replication once observed data become available. Diagnostic statistics (residual normality, VIF, Durbin-Watson, heteroskedasticity) computed from the literature-constrained series are reported in the accompanying code (Appendix B.4) and should be interpreted with the small-sample caveats stated in Section 3.6.

Table 3 reports the OLS regression output from the log-linear STIRPAT specification (Equation (3)). Because the underlying series is synthetic and n = 20, the statistics are included for transparency rather than for inferential use; they confirm that the simulated series behaves as designed. Residual autocorrelation is not a concern, but the variance inflation factors flag strong collinearity among the regressors (Max VIF = 26.6), which is expected given the synthetic data design and is discussed below.

Table 3. OLS regression results for the log-linear STIRPAT model (Equation (3)), literature-constrained synthetic series, 2005-2024 (n = 20). Standard errors are OLS standard errors within the simulated series and do not represent population-level uncertainty for Burkina Faso (see Section 3.6).

Variable	Elasticity	Std. Error	p-value	Interpretation
ln(Water), β_W	0.29	0.72	0.69	Positive but imprecise; not significant (n = 20)
ln(Energy), γ_E	1.02	0.45	0.04	Fossil energy dependence
ln(Biomass), δ_B	−0.17	0.06	0.01	Renewable substitution lowers emissions.
ln(GDP), θ_{GDP}	0.06	0.31	0.84	Positive but imprecise; not significant (n = 20)
Model fit	R^2 = 0.92; Adjusted R^2 = 0.90; Durbin-Watson = 2.15; Max VIF = 26.6			Breusch-Pagan p = 0.36 (homoskedastic); Shapiro-Wilk p = 0.19

Estimated elasticities differ from the parameters used in the synthetic data generation process because stochastic noise, finite-sample effects, and multicollinearity among predictors influence the recovered OLS coefficients. The R^2 of 0.92 and the Durbin-Watson statistic of 2.15 indicate that the model fits the simulated series closely and that residual autocorrelation is not a concern at this sample size; the Shapiro-Wilk (p = 0.19) and Breusch-Pagan (p = 0.36) tests give no evidence against residual normality or homoskedasticity. The maximum variance inflation factor, however, is 26.6, well above the conventional threshold of 5. This is a direct consequence of the way the synthetic series is built: water use, energy use, and agricultural GDP are all generated as functions of the same underlying agricultural-activity trend (Appendix A), so they are strongly collinear. That collinearity is why the water and GDP elasticities, though correctly signed, are estimated imprecisely and are not individually significant, while the energy and biomass coefficients are. These diagnostics describe the internal properties of the synthetic series; they are a transparency check rather than a validation of the elasticities against observed Burkinabè data, and the high VIF reinforces why the estimates in **Table 3** should be read as exploratory rather than inferential.

4.7. Nexus Efficiency Index

The modelled NEI rose monotonically from S0 to S3 under central assumptions, with the largest single jump occurring between S0 and S1 (water circularity) and a smaller additional jump from S1 to S3. The ranking was stable under plus or minus 25 percent variation in the NEI weights, under substitution of CO_2 emissions per kilogram of output for total CO_2 in the denominator, and under the Monte Carlo propagation described in Section 3.8. Alternative weighting schemes (equal-weighted, entropy-weighted) produced absolute NEI values within roughly 10 percent of the central specification but did not change the ordinal ranking. The four scenarios separate into two visual bands on each panel of **Figure 3**: panel (a) splits scenarios by water policy (S1 and S3 in the upper band, S0 and S2 in the lower band), and panel (b) splits them by biomass policy (S2 and S3 in the lower band, S0 and S1 in the upper band). S3 sits in the favourable band on both panels, which is the visual restatement of the central empirical claim of the paper.

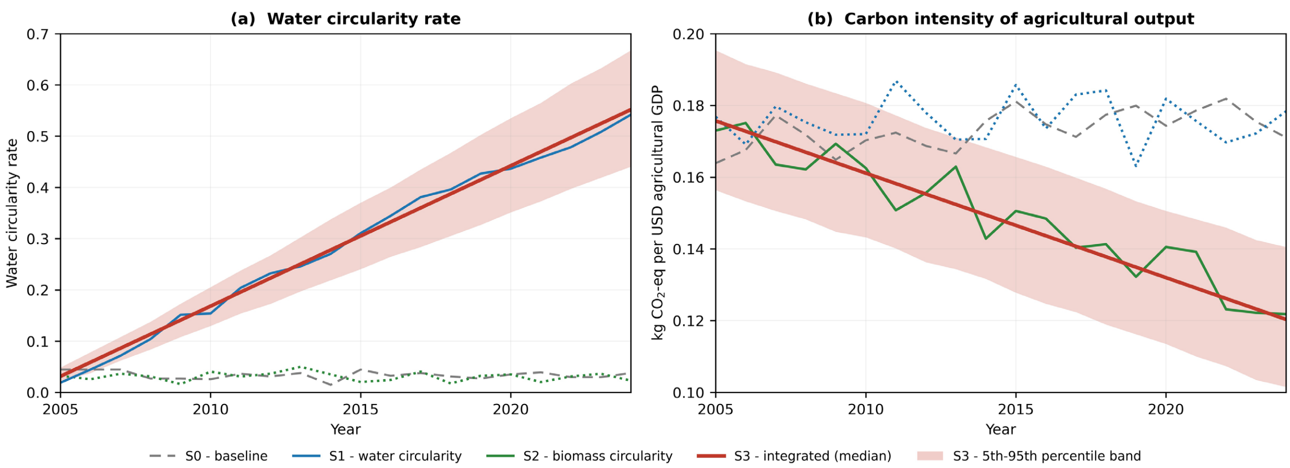

Figure 3. Modelled scenario trajectories over the 2005 to 2024 analytical period. Panel (a): water circularity rate (share of irrigation demand met by treated effluent). Panel (b): carbon intensity of agricultural output (kg CO_2-eq per USD of agricultural GDP). All four scenarios are generated from the literature-constrained parameter set specified in Appendix A and the scenario design described in Section 3.3; visualization code is provided in Appendix B.6. Interannual variability reflects the random draws within each parameter range. For scenario S3, the shaded band shows the 5^{th} to 95^{th} percentile envelope from the Monte Carlo propagation described in Section 3.8; the median trajectory is shown as a solid line.

4.8. Indicative Economic Feasibility

A full ex-ante cost-benefit analysis is beyond the scope of this work and is identified as future work in Section 8. As a first-order check, however, we anchor the framework against published CAPEX (Capital Expenditure) and OPEX (Operating Expenditure) ranges for the three technology classes that S3 requires, and against representative operational savings under central S3 parameters. **Table 4** summarizes the indicative cost envelope; all figures are central-band values from the cited sources, expressed in current USD and rounded to two significant figures.

Combining the CAPEX bands with the central S3 modelled savings, the indicative simple payback period for a representative peri-urban configuration is plausibly within the range of 5 to 10 years under the central assumptions adopted here, with the shorter end of that range corresponding to settings where diesel prices are high and the longer end to settings with strong feedstock collection costs and weak fertilizer price signals. This is consistent with the 7-year payback

Table 4. Indicative economic envelope for the S3 technology stack at peri-urban catchment scale. Cost values are central bands from the cited sources; savings are computed under central S3 parameter assumptions (Section 3.5). Figures are first-order and should not be used for procurement decisions. The annual savings use the representative catchment reuse volume of 350 to 600 Mm^3 (Section 3.1). Absolute savings scale down proportionally for a real single-city deployment, so the per-cubic-metre economics and the payback logic, not the absolute totals, are the quantities that transfer.

Item	CAPEX (central band)	OPEX (annual)	Source
Decentralized constructed wetland	USD 18,000 per ha treated surface	USD 0.03 to 0.08 per m3 treated	Gkika, Gikas, and Tsihrintzis [26]
Small biogas digester (community scale, 50 to 200 m^3)	USD 400 to 1500 per wet tonne of feedstock capacity	≈4% of CAPEX	Amigun and von Blottnitz [27]
Small-scale biomass gasifier (100 to 250 kWe)	USD 2100 to 5700 per kW installed	≈9% to 20% of LCOE	IRENA [28]
Modelled water savings (S3 vs S0)	n/a	USD 0.05 to 0.20 per m^3 reused × 350 to 600 Mm^3/yr	This study, central S3
Modelled diesel substitution (S3 vs S0)	n/a	≈ 25% to 35% of catchment diesel cost avoided	This study, central S3

reported by Diemuodeke and colleagues for a PV-assisted biomass gasification system in northern Ghana and with the broader gasification economics literature for sub-Saharan Africa [28]. Two qualifications matter for any policy use of these numbers. First, the CAPEX bands span a factor of three or more, depending on technology choice and scale; site-level engineering studies are required before any committed investment. Second, the operational savings depend on the price of avoided diesel, on the willingness of utilities to credit nutrient recovery against fertilizer demand, and on the regulatory treatment of biogas electricity, none of which are settled in Burkina Faso at the time of writing.

5. Discussion

5.1. What the Integration Buys, and What It Does Not?

The most important claim from the simulation is that closing both loops (S3) outperformed closing either loop alone (S1 or S2), but not by a large margin once one loop is closed. For a policymaker working under a tight budget, this matters. Sequencing the investment so that wastewater reuse comes first would deliver most of the modelled water savings, most of the modelled fertilizer substitution, and a meaningful share of the modelled emissions reductions, all from a single class of infrastructure (decentralized treatment plus on-farm distribution). Adding biomass energy then captures the remaining diesel substitution and the residue burning credit. The reverse sequencing (biomass first) is feasible but yields lower early gains in the simulation because the water constraint is binding earlier in the dry season than the energy constraint.

This sequencing argument is consistent with what the ECOWAS circular WEF program has observed in pilot interventions across West Africa, where solar irrigation combined with post-harvest support has delivered measurable gains even before biomass conversion was added [10].

5.2. Trade-Offs and Risks

Three risks deserve direct attention.

The first is public health. Wastewater reuse without adequate treatment exposes farmers, consumers, and downstream users to pathogens and, in some cases, to heavy metals from industrial discharge mixed into the municipal stream [6] [13]. The multi-barrier WHO approach is well understood in principle but uneven in implementation in Sahelian cities. Any scaling of S1 or S3 has to be paired with monitoring of effluent quality, restriction of unrestricted irrigation to crops eaten after cooking, and worker protection. None of this is novel, but it requires institutional capacity that is not yet uniformly in place [5] [13].

The second is the soil organic matter trade-off. Cotton stalks are the largest mobilizable residue, but they also contribute to soil cover and carbon. The 75 percent recovery cap recommended by Barry, Sawadogo, Ouedraogo, Traore/Bologo, and Dogot is a soil conservation constraint, not an engineering one [1]. Any policy that prices residue feedstock without enforcing a return rate risks gradual soil organic carbon decline, which would partly offset the climate benefits modelled here.

The third is over-abstraction of newly reliable water. Once dry-season irrigation becomes feasible at scale, peri-urban areas may expand cultivated surfaces or shift to more water-intensive crops, and the simulated freshwater savings from S3 could be partially eroded by induced demand. This is a familiar Jevons-type concern and is not unique to Burkina Faso, but it should be anticipated in the regulatory design.

5.3. Policy Implications

Four implications follow from the simulation results.

A decentralized infrastructure model is preferable to a centralized one. The spatial dispersion of biomass feedstock, the variable layout of peri-urban gardens, and the cost of long-distance pumping all favor small, modular treatment and conversion units. This finding is consistent with the technology screening literature on biomass gasification in Burkina Faso, which identifies modular gasifiers and small biogas digesters as the most realistic deployment path [11] [16].

Nexus-aware regulation is required. Wastewater reuse permits, residue feedstock contracts, and bioenergy tariffs are currently set by separate ministries with limited coordination. Without a shared institutional space, projects routinely stall on cross-cutting issues such as effluent quality standards for irrigation [13] or grid feed-in rules for biogas electricity. The piloting work under the NAWAR program is a useful model in this respect [29].

Pricing has to internalize the soil organic matter constraint. A simple residue floor (for example, 25 percent of cotton stalk yield returned to the field as a permit condition) would address the soil carbon risk identified in Section 5.2 at modest administrative cost.

Finance has to match the modular technology mix. The barriers to gasification in Burkina Faso are not technical but financial and contractual [16]. Concessional lines for small biogas and gasifier projects, paired with offtake agreements with peri-urban cooperatives, are likely to do more for deployment than additional R&D (Research and Development) in the near term.

5.4. Relevance to Climate Adaptation and Mitigation

The framework contributes to both pillars of the country's climate strategy. On adaptation, water reuse and biomass energy reduce the system's exposure to interannual rainfall variability by giving farmers a non-rainfall water source and a non-fossil energy source. On mitigation, the modelled emissions reductions from S3 are not large in absolute terms relative to global totals, but they are large relative to the agricultural sector's own emissions, and they are achieved at a low simulated cost per tonne of CO_2 avoided when residue burning is the counterfactual [17] [30].

5.5. Limitations

Four limitations frame the interpretation of the results. First, the empirical analysis uses a synthetic, literature-constrained parameter set rather than directly observed national accounts. All modelled magnitudes (water reuse rates, yield gains, emissions reductions, STIRPAT elasticities) should be read as scenario outputs conditional on the parameter ranges and stochastic generation rules in Appendix A, not as empirically validated estimates for Burkina Faso. The priority methodological extension is full empirical calibration against the harmonized data sources that already exist for the country: FAOSTAT for agricultural production and residue volumes, World Bank World Development Indicators for agricultural GDP and macroeconomic context, Ministry of Agriculture and Hydraulic Resources records for irrigated area and water withdrawals, ONEA (Office National de l'Eau et de l'Assainissement) operational records for municipal wastewater volumes and treatment performance, and SONABEL (Société Nationale d'Electricité du Burkina) statistics for the diesel-substitution and grid feed-in counterfactuals. Combining these sources into a harmonized annual series is itself a non-trivial data-engineering task that we identify as the necessary first step before the present framework can be moved from scenario simulation to inferential national policy analysis.

Second, the LCA is at a screening level. Inventory data are drawn from ecoinvent with limited regionalization for Sahelian operating conditions, particularly for waste stabilization pond emissions, constructed wetland nitrous oxide flux, and small gasifier performance on locally collected feedstocks. The directional results are stable, but the absolute impact scores should not be used for product-level claims or for inclusion in national greenhouse gas inventories without further regional inventory work.

Third, the STIRPAT estimation is exploratory and small sample (n = 20). Reported coefficients are indicative elasticity patterns consistent with the simulation assumptions and with the broader literature, not validated national elasticities. Diagnostic statistics (residual normality, VIF, Durbin-Watson, heteroskedasticity) should be reported and interpreted cautiously, and Bayesian or hierarchical estimation would be more appropriate once empirical data become available.

Fourth, the model is static-annual. Dynamic feedbacks between irrigation expansion, soil organic carbon, groundwater recharge, and peri-urban land-use change cannot be captured in an annual cross-section. A system dynamics extension, ideally coupled with a spatially explicit hydrological model, is identified as the highest-priority modelling improvement (Section 8). The NEI weighting scheme is also heuristic; a formally stakeholder-elicited or AHP-derived weighting would strengthen the policy interpretation of the index.

6. Conclusions

This study develops and applies a circular WEF nexus framework for Burkina Faso that couples wastewater reuse with biomass energy recovery in service of climate-resilient agriculture. The results summarized below are simulated outputs from a literature-constrained synthetic dataset rather than empirical measurements for the country. They should be read as scenario projections that await field calibration. Using MFA, a screening-level LCA, four-scenario simulation, exploratory STIRPAT elasticity analysis, a composite Nexus Efficiency Index, Monte Carlo uncertainty propagation, and an indicative economic feasibility check against published CAPEX and OPEX ranges, the integrated circular scenario was associated, under the central parameter assumptions, with modelled reductions in freshwater abstraction of 25 to 40 percent, modelled yield gains of 20 to 40 percent, and modelled reductions in CO_2-equivalent emissions of 30 to 45 percent at the farm gate, at an indicative simple payback period of 5 to 10 years for representative peri-urban configurations. In the simulation, the largest marginal gain came from closing the water loop first. Adding biomass energy delivered further but smaller benefits, mainly through diesel substitution and the use of crop residues that would otherwise be burned. The framework is reproducible and the toolkit is published with the paper.

The limitations of the analysis, set out in Section 5.5, frame the next steps: full calibration on empirical Burkinabè data, regionalized LCA inventories, Bayesian or hierarchical STIRPAT estimation, a dynamic-feedback extension, and a site-level cost-benefit analysis to replace the first-order economic check in Section 4.8.

The broader argument is that the move from a linear to a circular WEF system in Burkina Faso is not primarily a technological question. The technologies (stabilization ponds, constructed wetlands, anaerobic digesters, small gasifiers) are mature, and the resource flows have been quantified in the regional literature [1] [5] [11]. The remaining question is institutional: how to align the regulatory, financial, and operational arrangements that currently keep these flows linear. The framework developed here is intended to give that institutional conversation a quantitative spine.

Although the quantitative magnitudes remain contingent on future empirical calibration, the present analysis consistently indicates that integrated circular WEF strategies outperform isolated water or energy interventions across environmental, resource-efficiency, and climate-resilience dimensions. The framework, therefore, provides a practical decision-support platform for designing climate-resilient agricultural transitions in semi-arid regions.

7. Contributions and Originality

This work makes three contributions. Methodologically, it integrates Material Flow Analysis, screening-level Life Cycle Assessment, exploratory STIRPAT elasticity analysis, and a composite Nexus Efficiency Index in a single, reproducible workflow that places water, energy, and emissions on a common denominator. To our knowledge, this is among the first integrations of these four analytical components within a circular WEF nexus framework for a semi-arid agricultural system. Empirically, to our knowledge, it provides among the first parameterized circular WEF nexus scenario assessments for Burkina Faso, covering wastewater reuse, biomass energy, and irrigated agriculture jointly rather than as separate problems. Programmatically, it publishes a transparent and tunable computational toolkit (R for data generation, Python for analysis, visualization, and Monte Carlo propagation) that can be reused for comparable Sahelian contexts in Mali, Niger, and northern Ghana.

8. Future Research

Three directions extend the present work. A full empirical calibration on Burkinabè administrative data and FAO national statistics, drawing specifically on FAOSTAT for agricultural production and residues, World Bank World Development Indicators for macroeconomic and water-withdrawal context, Ministry of Agriculture records for irrigated area, ONEA operational records for municipal wastewater volumes and treatment plant performance, SONABEL records for grid electricity and diesel-substitution accounting, and primary survey data from peri-urban irrigation cooperatives, would replace the literature-constrained parameter set and place the STIRPAT elasticities on an empirical footing suitable for inferential interpretation. A system dynamics implementation, coupled to a spatially explicit hydrological model, would capture feedbacks between irrigation expansion, soil organic carbon, and groundwater recharge that the present static-annual model cannot resolve. A large-scale implementation feasibility study, ideally co-designed with the NAWAR program or the ECOWAS circular WEF initiative, would calibrate the framework on real-world infrastructure costs, institutional constraints, and uptake rates, and would allow the framework to be linked to ex-ante cost-benefit and AHP-based stakeholder weighting analyses.

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Author Contributions

Conceptualization, M.B., I.T. and B.L.; methodology, M.B. and I.T.; software, M.B.; validation, M.B., I.T. and B.L.; formal analysis, M.B. and B.L.; investigation, I.T. and B.L.; resources, I.T. and B.L.; data curation, M.B. and I.T.; writing—original draft preparation, M.B., I.T. and B.L.; writing—review and editing, M.B., I.T. and B.L.; visualization, M.B. and I.T.; supervision, B.L. and I.T.; project administration, M.B. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix A. Synthetic Dataset Specification

The reproducible R code that generates the analysis dataset is provided below. Variables are: Year (2005 to 2024); $Water_{Total}$ (Mm^3); $Water_{Reused}$ (Mm^3); $Biomass_{Total}$ (kt); $Biomass_{Energy}$ (kt); $Energy_{Use}$ (GWh); $Agri_{GDP}$ (billion USD); $CO_{2Emissions}$ (kt CO_2-eq).

R code

```
set.seed(123)
Year <- 2005:2024
n <- length(Year)

Agri_GDP       <- round(seq(2.0, 6.0, length.out = n) + rnorm(n, 0, 0.25), 2)
Water_Total    <- round(750 + 75 * Agri_GDP + rnorm(n, 0, 45), 0)
Water_Total    <- pmin(pmax(Water_Total, 800), 1200)
Water_Reused   <- round(Water_Total * runif(n, 0.05, 0.35), 0)
Biomass_Total  <- round(5000 + 650 * Agri_GDP + rnorm(n, 0, 500), 0)
Biomass_Total  <- pmin(pmax(Biomass_Total, 5000), 9000)
Biomass_Energy <- round(Biomass_Total * runif(n, 0.10, 0.50), 0)
Energy_Use     <- round(120 + 80 * Agri_GDP + rnorm(n, 0, 35), 0)
Energy_Use     <- pmin(pmax(Energy_Use, 200), 600)
CO2_Emissions  <- round(exp(5.8 + 0.35 * log(Water_Total) + 0.65 * log(Energy_Use) -
0.20 * log(Biomass_Energy) + 0.30 * log(Agri_GDP) + rnorm(n, 0, 0.12)), 0)

data <- data.frame(Year, Water_Total, Water_Reused, Biomass_Total, Biomass_Energy,
Energy_Use, Agri_GDP, CO2_Emissions)

write.csv(data, "WEF_Burkina.csv", row.names = FALSE)
```

Appendix B. Python Analysis Scripts

B.1 MFA circularity indicators

```
import pandas as pd

df = pd.read_csv("WEF_Burkina.csv")
df["Water_Circularity"]  = df["Water_Reused"]   / df["Water_Total"]
df["Energy_Circularity"] = df["Biomass_Energy"] / df["Biomass_Total"]
df["WEF_Efficiency"]     = df["Agri_GDP"] / (df["Water_Total"] + df["Energy_Use"])
print(df.head())
```

B.2 Sankey diagram of circular WEF flows

```
import plotly.graph_objects as go

labels = ["Wastewater", "Treatment", "Irrigation",
          "Biomass", "Bioenergy", "Agriculture"]
source = [0, 1, 3, 4]
target = [1, 2, 4, 5]
value  = [50, 45, 60, 55]

fig = go.Figure(data=[go.Sankey(
    node=dict(label=labels),
    link=dict(source=source, target=target, value=value)
```

```
)])
fig.update_layout(title_text="Circular WEF Nexus, Burkina Faso", font_size=12)
fig.show()
```

B.3 LCA-style intensity indicators

```
df["Carbon_Intensity"] = df["CO2_Emissions"] / df["Agri_GDP"]
df["Water_Intensity"]  = df["Water_Total"]   / df["Agri_GDP"]
df["Energy_Intensity"] = df["Energy_Use"]    / df["Agri_GDP"]
print(df[["Year", "Carbon_Intensity", "Water_Intensity", "Energy_Intensity"]])
```

B.4 STIRPAT estimation with diagnostics

```
import numpy as np
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.stats.stattools import durbin_watson
from statsmodels.stats.diagnostic import het_breuschpagan
from scipy.stats import shapiro

df_log = df.copy()
for col in ["CO2_Emissions", "Water_Total", "Energy_Use",
            "Biomass_Energy", "Agri_GDP"]:
    df_log["ln_" + col] = np.log(df_log[col])

X = df_log[["ln_Water_Total", "ln_Energy_Use",
            "ln_Biomass_Energy", "ln_Agri_GDP"]]
X = sm.add_constant(X)
y = df_log["ln_CO2_Emissions"]
model = sm.OLS(y, X).fit()
print(model.summary())

# Diagnostics (interpret with the n = 20 caveat from Section 3.6)
print("VIF:", [variance_inflation_factor(X.values, i)
                for i in range(1, X.shape[1])])
print("Durbin-Watson:", durbin_watson(model.resid))
print("Shapiro-Wilk on residuals:", shapiro(model.resid))
print("Breusch-Pagan:", het_breuschpagan(model.resid, model.model.exog))
```

B.5 Nexus Efficiency Index

```
# S0 baseline reference values (first-year, pre-intervention)
W0   = df["Water_Total"].iloc[0]
E0   = df["Energy_Use"].iloc[0]
CO20 = df["CO2_Emissions"].iloc[0]
df["Nexus_Efficiency_Index"] = df["Agri_GDP"] / (
    0.4 * (df["Water_Total"]    / W0)   +
    0.3 * (df["Energy_Use"]     / E0)   +
    0.3 * (df["CO2_Emissions"] / CO20)
)
print(df[["Year", "Nexus_Efficiency_Index"]])
```

B.6 Publication-ready visualizations

```
import matplotlib.pyplot as plt
```

```
plt.figure()
plt.plot(df["Year"], df["Water_Circularity"])
plt.title("Water circularity rate, 2005 to 2024")
plt.xlabel("Year"); plt.ylabel("Ratio")
plt.show()

plt.figure()
plt.plot(df["Year"], df["Carbon_Intensity"])
plt.title("Carbon intensity of agriculture, 2005 to 2024")
plt.xlabel("Year"); plt.ylabel("kg CO2-eq per USD of Agri GDP")
plt.show()
```

B.7 Monte Carlo uncertainty propagation

```
import numpy as np
rng = np.random.default_rng(seed=42)
N = 1000

# Sample parameter ranges (consistent with Section 3.5)
water_total  = rng.uniform(800,  1200, N)
reuse_share  = rng.uniform(0.40, 0.60, N)   # S3 central band
biomass_tot  = rng.uniform(5000, 9000, N)
mob_fraction = rng.uniform(0.35, 0.50, N)   # S3 central band
energy_use   = rng.uniform(200,  600,  N)
agri_gdp     = rng.uniform(2,    6,    N)

# Derived flows
water_reuse  = water_total * reuse_share
biomass_en   = biomass_tot * mob_fraction
co2          = 500 + 0.8 * energy_use - 0.3 * biomass_en
co2         += rng.normal(0, 50, N)

# Indicators
water_circ   = water_reuse / water_total
energy_circ  = biomass_en  / biomass_tot
# S0 baseline reference values (low-activity bound, no biomass recovery)
W0   = 800.0
E0   = 200.0
CO20 = 500 + 0.8 * E0          # biomass_en = 0 under S0
nei          = agri_gdp / (0.4 * (water_total / W0) +
                           0.3 * (energy_use / E0) +
                           0.3 * (co2 / CO20))

for name, x in [("water_circ", water_circ),
                ("energy_circ", energy_circ),
                ("NEI", nei)]:
    print(name,
          "median=", np.median(x),
          "P5=",    np.percentile(x, 5),
          "P95=",   np.percentile(x, 95))
```