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Abstract

Agricultural storage carries commodities across time, yet its system-wide implications for agrifood-system futures and production shocks remain poorly understood. Here we use traceable global stock-flow data to incorporate agricultural storage into a global multisector dynamic model and quantify its structural and shock-buffering roles. Global stocks of storable crops and products are projected to rise from about 6,000 petacalories (Pcal) in 2021 to 9,900 Pcal by 2100, while net stock accumulation slows and storage-associated losses become increasingly important. Making these flows explicit reveals that historically high stockbuilding can otherwise persist as hidden future demand, overstating long-run agricultural production and its land, water, and emissions implications. Under biophysical yield shocks, storage reshapes how disruptions propagate through agricultural markets, mediating responses across production, harvested area, and trade, while consumption remains comparatively buffered. Storage reveals a critical temporal dimension of agrifood-system sustainability and resilience that global assessments have largely overlooked.

Introduction

Agricultural output is often concentrated in seasonal harvests, whereas consumption and trade continue throughout the year. Storage bridges this temporal mismatch by shifting commodities across time¹. Recent supply shocks and market disruptions have further underscored its role in buffering production variability, stabilizing consumption, and moderating price volatility in global food systems^{2–4}. Between 2010 and 2022, global stocks of cereal grains and products increased by more than 90%, rising by 650 million tonnes (Mt) to 1350 Mt—about 45% of global consumption in 2022 (**Fig. 1A**). China accounted for more than half of this increase (**Fig. 1B**), amid rising domestic demand and policy support for stockholding⁵. Annual stock changes varied markedly across regions and years, e.g., from a 20 Mt per year (Mt yr⁻¹) drawdown in North America in 2020 to a 78 Mt yr⁻¹ accumulation in China in 2015, against a global average net accumulation of 54 Mt yr⁻¹ over the period (**Fig. 1C**). Heterogeneity is also evident on a per capita basis and across supply-chain stages (**Fig. 1D**). About 70% of global grain stocks in 2022 were held as primary commodities and 30% as processed products (e.g., wheat flour and milled rice). Despite its central role in agricultural markets, storage remains poorly resolved in global economic multisector dynamic models used to assess agrifood systems^{6–8} and multisectoral futures^{9–11} (**Supplementary Section 1**).

One barrier to explicit representation is the difficulty of comprehensively measuring stocks consistently across regions, commodities, and supply-chain stages. Storage is embedded in the balance structure of supply utilization accounts (SUA), in which opening stocks, production, and imports balance domestic utilization, exports, and closing stocks¹². Recent harmonization of food balance sheets (FBS) using a primary commodity equivalent (PCe) approach enables stocks and flows at different processing stages to be expressed consistently across commodities and regions¹³ (**Methods**). These data reveal pronounced regional and commodity heterogeneity in stock variation, stock-to-gross-use ratios, and storage-loss rates (**Fig. 2**). When expressed in dietary-energy terms, global crop stocks in 2022 were equivalent to 2115 kilocalories per capita per day (kcal/ca/d), about 71% of global food availability that year (2975 kcal/ca/d). Cereal grains and products accounted for roughly two-thirds of this stored energy, with regionally uneven contributions from other sectors. This empirical advance provides a basis for reassessing storage in global multisector dynamic projections.

A second barrier is that stockholding is an intertemporal economic decision that is neither passive nor costless. Competitive storage models describe rational agents as weighing current use against expected future values, with the consideration of financial costs, physical losses, and price risk^{14–16}. Embedding this behavior within large-scale multisector equilibrium frameworks, however, remains challenging^{17,18}. In many applications, inventories are omitted or prescribed exogenously, while unrepresented stock changes and losses are absorbed into residual accounting categories or calibration procedures^{19–21}. Consequently, omitting endogenous inventory adjustment may distort the transmission of supply shocks, a central focus of impact evaluation^{21–25}, by amplifying short-run price and quantity adjustments that would otherwise be partially absorbed through stock accumulation or drawdown.

Beyond this temporal buffering role, net stock accumulation and storage losses also create distinct sources of commodity demand, i.e., accumulation raises demand during stock-building periods, whereas losses generate recurring replacement demand. Failing to represent these flows separately and endogenously may therefore alter long-run production trajectories and associated resource use. The implied scale is nontrivial: the 650 Mt increase in global cereal stocks between 2010 and 2022, together with an estimated 590 Mt of storage-associated losses, would have required 310 million hectares (Mha) of cumulative harvested area at an average yield of 4 tonnes per hectare. The effects would be more pronounced when broader agricultural commodities and products are considered. Yet when storage is overlooked, these demands remain “hidden” within

aggregate accounting categories, obscuring their contribution to both near-term and long-term agroeconomic and environmental projections. Their system-wide implications remain largely unquantified.

Here we develop and evaluate an explicit representation of agricultural storage in the Global Change Analysis Model (GCAM), an open-source global multisector dynamic model (**Methods** and **Supplementary Section 2**). Building on the recompiled traceable FBS data, the representation separately tracks opening stocks, closing stocks, and storage-associated losses for storable crop commodities across regions, and allows agents to allocate commodities between current utilization and future availability (stockholding) in response to intertemporal economic incentives (**Fig. 3**). We design six scenarios spanning three storage representations—Dynamic, Hidden, and Fixed-Ratio Storage—and smooth versus spatially and temporally varying biophysical yield trajectories (**Fig. 3C**) to distinguish the effects of explicit stock accounting from those of endogenous stockholding behavior. We find that explicit treatment of stock-related flows primarily reshapes long-run agricultural demand and associated resource trajectories, whereas endogenous stockholding is particularly consequential for how biophysical yield shocks are redistributed across inventories and other market responses. These results reveal agricultural storage as both a structural demand margin and a temporal buffer in global agrifood-system futures.

Results

Global agricultural storage in agrifood system futures

Reconstructed and harmonized food and commodity balances enable consistent measurement of stocks and storage-associated losses, extending beyond the traditional focus on primary cereal grains (**Figs. 2 and Supplementary Section 2.1**). The resulting accounts reveal pronounced regional and sectoral heterogeneity and provide the empirical basis for explicitly representing storage in GCAM. Expressed in dietary-energy terms for a consistent aggregation, stocks of storable crops and their products totaled approximately 6,000 petacalories (Pcal) in the 2021 base year.

Under the Dynamic Storage scenario, global stocks of storable crops and products are projected to reach 9,900 Pcal by 2100, 65% above 2021 levels (**Fig. 4A**). As stocks grow faster than global population (+26%), the per capita dietary-energy equivalent rises by 31%, to 2,721 kcal/ca/d. Cereal grains and products remain the largest component, but their share declines from 69% to 54% globally as stocks of oil crops and other non-staple food commodities expand more rapidly, consistent with the diversification of agrifood demand as incomes rise. Stock growth is regionally uneven (**Fig. 4B**). Africa accounts for a substantial share of the increase across commodity groups, whereas China's grain stocks decline over the long term. Nevertheless, total per-capita stocks increase in all regions by 2100, ranging from 16% in Europe to 84% in Africa (**Supplementary Fig. 7**).

Global net stock variation varies markedly across model periods, ranging from a 30 Pcal yr⁻¹ drawdown to a 290 Pcal yr⁻¹ accumulation (**Fig. 4C**). By contrast, storage-associated losses rise steadily as inventories expand, reaching 440 Pcal yr⁻¹ in 2100. The global weighted-average loss rate increases from 3.9% in 2021 to 4.5% in 2100, largely reflecting a growing share of inventories in regions with relatively higher loss rates. The static benchmarks illustrate why mechanically extrapolating recent historical flows can be misleading. Holding positive stock additions fixed implies continued accumulation, while fixing losses understates replacement demand as inventories expand.

For grains, stocks reach 1,720 Mt by 2100, but annual accumulation slows substantially, averaging 8.4 Mt yr⁻¹ over 2021–2050 and 5 Mt yr⁻¹ over 2021–2100 (**Fig. 4D**), compared with over 50 Mt yr⁻¹ during 2010–2022. Notably, grain storage losses average 67 Mt yr⁻¹ during 2021–2100, more than an order of magnitude greater

than net stock accumulation. These storage trajectories are part of internally consistent projections of agricultural production, trade, land use, water use, and emissions, which form the baseline for scenario comparisons (**Supplementary Fig. 8**).

Storage dynamics alter long-term agroeconomic and environmental pathways

When stock-related flows remain “hidden” (Hidden Storage), the stock-related component of projected commodity demand is considerably higher than under Dynamic Storage. Averaged over 2021–2100, grain stock-related demand under Dynamic Storage is 72 Mt yr⁻¹ (5 Mt yr⁻¹ of net accumulation and 67 Mt yr⁻¹ losses), whereas the corresponding implied component under Hidden Storage averages 166 Mt yr⁻¹, +94 Mt yr⁻¹ or 130% higher (**Supplementary Figs. 9–10**). Higher implied stock-related demand is also observed for oil crops (+50%; +15 Mt yr⁻¹), sugar crops (+37%; +23 Mt yr⁻¹), and other storable crops (+97%; +37 Mt yr⁻¹). This divergence arises because historical calibration periods were characterized by positive stock accumulation, and stock-related flows under Hidden Storage subsequently inherit the generic demand responses of “other uses”. In contrast, when represented explicitly, net accumulation slows markedly over the long term, while storage-associated losses grow only moderately as they evolve with changing stock levels and regional composition.

This difference in stock-related demand propagates through agricultural markets to production and broader multisectoral outcomes. After a small transitional increase in 2025, global crop production is generally lower under Dynamic Storage than under Hidden Storage in the long run, with the gap reaching about 150 Mt for grains by 2100 (**Fig. 4E**). Lower production reduces associated resource requirements, including annual irrigation withdrawals by about 95 bcm by 2100 and cumulative total irrigation withdrawals by 2,800 bcm over 2021–2100 (**Fig. 4F, I**). Cropland for storable crops is about 38 Mha lower by 2100, allowing greater pasture, forest, and other natural land relative to Hidden Storage (**Fig. 4G**). Agricultural CH₄ and N₂O emissions and losses in terrestrial carbon also decline, with cumulative net land use change CO₂ emissions lower by 3.3 GtCO₂ over 2021–2100 (**Fig. 4H, J**).

Although modest relative to the global reference trajectory, these effects are directionally consistent across production, resource requirements (including land, irrigation water, fertilizer, labor, and capital inputs), and agricultural emissions (**Supplementary Fig. 10**). Moreover, regional and sector effects are more heterogeneous and can be more pronounced as production and trade are reallocated across markets (**Fig. 4I, J**), e.g., sugar crop production increases in Latin America as exports expand, increasing associated land and water use.

These long-term effects are robust to alternative yield and storage assumptions. The same directional responses persist when the Dynamic–Hidden comparison is repeated under biophysical yield shocks (S3 vs. S4), when Fixed-Ratio Storage is compared with Hidden Storage (S5 vs. S2), and when the cross-period carryover adjustment is disabled in Dynamic Storage (**Supplementary Figs. 11–13**). Across these comparisons, explicit storage leads to lower long-run crop production, irrigation-water withdrawals, and agricultural emissions than Hidden Storage. The similarity between the Dynamic and Fixed-Ratio comparisons suggests that long-run effects are driven mainly by explicitly representing stock accumulation and storage-associated losses, whereas price-responsive stockholding is more consequential for the transmission of biophysical yield shocks.

Storage dynamics alter the transmission of biophysical yield shocks

Agroeconomic responses to the cumulative biophysical yield shocks are heterogeneous across regions and commodities but exhibit a systematic pattern of market adjustment over time (**Supplementary Fig. 14**). By 2050, under Dynamic Storage, realized yield shows near-proportional transmission of the biophysical

perturbation, while harvested area responds in the opposite direction ($\beta = -0.50$), reducing the production response to about half the magnitude of the initial shock ($\beta = +0.50$; **Fig. 5A**, **Supplementary Fig. 15** and **Supplementary Table 7**). Trade provides an additional mediating margin. Exports are highly responsive, whereas imports respond more moderately in the opposite direction ($\beta = -0.21$); producer prices also move inversely ($\beta = -0.26$), while domestic consumption is inelastic ($\beta = 0.04$). This propagation from biophysical productivity through production and trade, with progressively weaker transmission to consumption, is broadly consistent with previous global assessments^{21,23}. Notably, cumulative transmission to stocks under Dynamic Storage is statistically insignificant in 2050 but positive and significant by 2100 ($\beta = 0.075$, $P = 0.004$; **Supplementary Fig. 16**). Storage buffering can therefore remain evident in cumulative assessments, but its apparent strength is path- and horizon-dependent, as preceding stockbuilding and drawdown can offset one another.

Resolving transmission between successive model periods provides a more temporally informative view of market adjustment (**Fig. 5B**; **Supplementary Figs. 17–19**). The temporal role of storage becomes particularly evident in these period-to-period responses. Under Dynamic Storage, closing stocks respond positively to yield perturbations ($\beta = 0.18$, $P < 0.001$), implying stockbuilding following higher yields and drawdown following lower yields. Compared with the cumulative 2050 relationships, adjustment through harvested area is weaker ($\beta = -0.36$ versus -0.50), as are trade responses, particularly imports ($\beta = -0.10$ versus -0.21), while a larger share of the yield perturbation is transmitted to production.

Comparing storage representations confirms that this temporal adjustment depends strongly on how inventories are represented (**Fig. 5C**). The pooled closing-stock transmission elasticity under Dynamic Storage ($\beta = 0.18$) is nearly five times that under Fixed-Ratio Storage ($\beta = 0.04$), with the pairwise Wald test confirming that the two coefficients differ significantly (**Supplementary Tables 7–8**). Hidden Storage does not represent inventories as a distinct adjustment margin and therefore provides no separately identifiable stock-transmission response. Considerable heterogeneity also occurs across region–crop markets, with the interquartile range of market-specific stock transmission elasticities spanning 0.11–0.39 under Dynamic Storage, compared with 0.01–0.10 under Fixed-Ratio Storage (**Fig. 5C**).

These storage adjustments are accompanied by systematic changes in transmission through other market margins. Relative to Hidden Storage, Dynamic Storage weakens the compensating harvested-area response ($\beta = -0.36$ versus -0.47) and allows greater transmission to production ($\beta = 0.63$ versus 0.54), while reducing adjustment through exports ($\beta = 0.89$ versus 1.06) and producer prices ($\beta = -0.21$ versus -0.27). For harvested area, production, exports, and prices, Fixed-Ratio Storage generally yields transmission elasticities between those under Dynamic and Hidden Storage, whereas differences in realized yield and consumption are comparatively small. These patterns are robust to alternative fixed-effect specifications (**Supplementary Table 9**). Overall, endogenous storage does not uniformly dampen yield-shock transmission; rather, it redistributes adjustment across time and among production, land, trade, and prices, while consumption remains comparatively buffered.

Discussion

Agricultural storage links present production to future availability, yet this temporal dimension remains largely absent from global agrifood and multisector assessments. By making stocks and associated losses explicit in traceable global food balance sheets and integrating them into a global multisector dynamic model, we show that storage shapes long-term agricultural demand and resource use and alters how supply shocks propagate through global agrifood markets.

Our projections suggest that global stocks of crops and products continue to rise, but net stockbuilding slows sharply as population and agricultural demand growth moderate. For cereal grains, which account for the largest share of agrifood inventories, average accumulation falls from more than 50 Mt yr⁻¹ in 2010–2022 to about 5 Mt yr⁻¹ over 2021–2100. This distinction between rising stock levels and slowing stockbuilding is critical for food-system and multisector assessments. Omitting explicit storage does not necessarily imply an absence of future stockbuilding or associated losses. Instead, positive stock accumulation embedded in the calibration-period commodity balance can inherit the generic growth of aggregate demand categories, effectively turning a transitory stockbuilding flow into persistent future demand. Such treatment can therefore overstate long-run agricultural demand, as demonstrated in our analysis.

As net stockbuilding slows, storage-associated losses become increasingly important in future supply–utilization balances. For grains, those losses average 67 Mt yr⁻¹ over 2021–2100 and dominate long-term stock-related demand. This finding complements recent food-system transformation studies that identify reducing food loss and waste as an important lever for lowering agricultural production and environmental pressures^{8,27}, while extending this literature by treating storage-associated loss as a distinct component of post-harvest loss that evolves with inventory levels and their regional distribution. In our projections, we hold region–commodity loss rates at their calibrated values. Future work is needed to improve the granularity of storage data and model representation by distinguishing technologies and management practices, together with their capacities, costs, and loss rates, across commodities, regions, and supply-chain stages. This would allow future loss scenarios to reflect evolving infrastructure, local operating and ambient conditions, and the adoption of improved storage systems^{28–31}.

The implications of explicitly accounting for storage and related losses extend beyond agricultural demand to the environmental footprints and multisectoral outcomes. Although annual effects are modest, representing storage explicitly rather than leaving stock-related flows hidden reduces cumulative net terrestrial carbon emissions by 3.3 GtCO₂ over 2021–2100, alongside lower irrigation water demand, cropland use, and agricultural emissions. These results reveal a temporal counterpart to production- and consumption-based environmental accounting, which has largely focused on embodied impacts transferred across regions through international trade^{32,33}. Just as trade reallocates embodied impacts across space, storage reallocates them across time. Stockbuilding carries the land, water, and emissions embodied in current production into future availability, whereas drawdown supports current use with resources committed earlier. Analogous work on capital accumulation has shown that stock formation can shift the attribution of embodied emissions across periods³⁴. Our framework provides a basis for attributing future agricultural footprints more consistently across both space and time.

Global economic analyses of agrifood system shock transmission have largely overlooked storage as a distinct buffering margin^{21,23,24}. By tracing exogenous yield perturbations through responses in area harvested, production, trade, and consumption, these studies showed how shocks distribute across markets but generally focused on cumulative or mean impacts over a period. Introducing stock-flow-consistent competitive storage adds this missing temporal margin and extends analysis to period-to-period transmission. Our analysis of biophysical yield shocks in GCAM revealed a global short-term (5-year) inventory-transmission elasticity of 0.18. That is, a 1% yield perturbation is associated with, on average, a 0.18% inventory response in the same direction. When endogenous storage is represented, price, area harvested, and trade responses are also less pronounced than when storage remains hidden. Adding a temporal storage margin therefore redistributes adjustment across the other market responses and provides a more complete account of shock transmission.

International trade remains a major market-mediated response to supply shocks even after introducing the temporal buffering channel, although the transmission elasticity for exports decreased from 1.06 to 0.89. This

interaction is important because international trade has been widely recognized as a mechanism for redistributing agricultural shocks across regions³⁵. Our results suggest that omitted inventory responses may have contributed to the discrepancy between time-series and cross-sectional trade-elasticity estimates identified in previous studies³⁶, which warrants future empirical testing. While our analysis focuses on biophysical yield shocks, the same framework can be extended to broader socioeconomic and policy shocks for which inventories may provide a critical temporal adjustment margin. Future work should also move toward annual or sub-annual resolution and represent greater temporal granularity in production decisions^{21,24}.

Our study shows that crop inventories have two system-wide roles: they are a structural source of long-term demand and associated resource use, and a temporal margin that buffers and redistributes shocks. The same stock-flow logic may also apply to broader agrifood products and other stored resources, including energy carriers, materials, and water, although their technologies, costs, losses, and constraints require sector-specific treatment. Our findings also have implications for global economic and multisector dynamic modeling. While increasingly spatially explicit data and higher geographic resolution have substantially advanced assessments of agriculture, water and land systems¹⁰, future model development should complement spatial refinement with greater sectoral, supply-chain and temporal detail. Our study lays the groundwork for integrating storage more consistently into global agrifood and multisector assessments. Further interdisciplinary research is needed to improve inventory data and behavioral representation and to evaluate how storage shapes sustainable and resilient pathways under broader environmental and socioeconomic shocks.

Methods

Structural role of storage in food and commodity balances

Stocks and stock variation are core elements of the Food and Agriculture Organization of the United Nations (FAO)'s Supply Utilization Accounts (SUA), which cover nearly 500 agrifood commodities across regions from 2010 onward³⁷. These accounts record production, trade, utilization, losses, and stocks in a balanced framework in which regional supply—opening stocks, production, and imports—equals regional demand—current utilization, exports, and closing stocks—within each region and year. Closing stocks in one year become opening stocks in the next, linking commodity balances across time¹².

We use the traceable Food Balance Sheets (T-FBS), recompiled from the detailed SUA using a primary commodity equivalent (PCe) approach¹³. The PCe framework expresses processed products in terms of their underlying primary commodities while preserving regional supply-demand balances, global trade balances and stock carryover across years. It therefore enables inventories held at different processing stages to be combined consistently. For example, sugarcane and sugar beet are not generally stored interannually, whereas refined sugar and related products can be stored and are represented in sugar-crop equivalents.

The reconstructed balances are harmonized to 15 crop and 6 livestock commodities for integration into GCAM (**Supplementary Fig. 2** and **Supplementary Table 3**). This study explicitly represents storage for 13 storable crop commodities. Vegetables and fruits are excluded because of their limited potential for large-scale interannual storage, while livestock requires future developments to reflect the biological capital dynamics of live animals alongside inventories of processed products.

Closing stocks in the SUA and T-FBS are reported net of loss, whereas storage-specific losses are not identified separately. The reported post-harvest loss account encompasses losses during handling, transport, processing, and storage. We infer a region- (r) and commodity-specific (c) storage loss rate, $\lambda_{r,c}$, as the lower of reported post-harvest losses relative to production and relative to current domestic utilization, $\lambda_{r,c} =$

$\min\left(\frac{L'_{r,c}}{P_{r,c}}, \frac{L'_{r,c}}{U_{r,c}}\right)$, where L' , P and U denote reported post-harvest loss, production, and current utilization, respectively. This generally corresponds to using the loss-to-production ratio for net exporters and the loss-to-utilization ratio for net importers, limiting the double attribution of losses associated with traded commodities. The resulting global-average inferred storage loss rates are approximately 5% (grains) to 8% (other storable crops) in 2022 (**Fig. 2C**), with larger regional and commodity differences (**Supplementary Fig. 5**).

Throughout this study, “closing stocks” refers to inventories remaining after storage-associated loss and carried over to the next period. In the annual historical accounts, closing stocks in year t become opening stocks in the next year ($t + 1$). The inferred storage-associated loss is reclassified from, rather than added to, the reported post-harvest loss account. The remaining portion continues to represent other post-harvest and supply-chain losses, preserving the original commodity balance.

In addition, we define the stock-to-gross-use (StGU) ratio as net closing stocks (S) divided by gross domestic use, comprising current domestic utilization U , net closing stocks, and storage-associated losses (L), $\text{StGU} = \frac{S}{U+S+L}$. StGU is bounded between zero and one and is used for cross-region and cross-commodity comparisons. **Supplementary Section 2.1** further discusses storage measurement.

For analysis and reporting, the 13 storable commodities are further aggregated into four groups: grains, oil crops, sugar crops, and other (storable) crops (**Supplementary Table 3**), and results are reported using IPCC R10 regions (**Supplementary Table 4**). Aggregate stocks are also expressed in dietary-energy units using

base-year region-commodity conversion coefficients, facilitating comparisons across commodities with different physical characteristics.

Integrated modeling of agricultural stockholding in GCAM

The Global Change Analysis Model (GCAM) is an open-source, multisector dynamic, global economic equilibrium model that links the economy, energy, agriculture, land, water, and emissions systems^{38,39}. GCAM has been widely used to explore long-term agroeconomic futures^{19,40} and has contributed to the development of the Shared Socioeconomic Pathways (SSPs)⁴¹ and recent food-system transformation assessments^{6,8}. Additional model information is available in **Supplementary Section 2.2**, the online documentation (<http://jgcri.github.io/gcam-doc/>), and recent applications^{11,42–44}.

We use GCAM v9.1, configured for 32 global regions (**Supplementary Table 4**), with a final base calibration year of 2021 (2020-2022 average for the agrifood system). Projections begin in 2025 and proceed at five-year intervals through 2100 within a recursive-dynamic framework. The agricultural system maps FAO commodities to GCAM sectors, including 17 crop commodities (including 13 storable crops, vegetables, fruits, and two fodder crops) and six livestock sectors (**Supplementary Table 3**). Dedicated energy crops are introduced from 2030 onward. Crop production technologies are represented at the water-basin level, allowing irrigation and nitrogen fertilizer use to vary by production technology. Regional agricultural markets are linked through a logit-based Armington structure⁴⁵, and agricultural commodities are allocated among food, feed, bioenergy, and other uses. Future projections are driven by SSP2 socioeconomic assumptions and exogenous productivity improvements.

When explicit storage is disabled, base-year stock-related flows remain embedded within “other uses”, an aggregate demand category comprising industrial and miscellaneous uses together with residual balancing terms. In GCAM v9.1, other uses respond, on a per-capita basis, to commodity prices and income, such that the embedded stock component inherits these generic demand responses. However, opening and closing stocks are not tracked separately, no explicit inventory carryover links successive periods, and storage-associated losses do not evolve with the quantity held in storage. This configuration (**Fig. 3A**) defines the Hidden Storage scenarios.

Here, we extend the framework to an explicit storage representation. Regional agents make intertemporal decisions to allocate available commodities between current utilization and storage for future use, following the economic intuition of competitive storage theory^{14,15,17} (**Fig. 3B**). We use a logit-sharing formulation^{46,47} in which the ratio of the quantity allocated to storage before loss (gross closing stocks), $S_{r,c,t}^g$, to current utilization, $U_{r,c,t}$, for region r , commodity c , in period t , responds to the relative value of storage:

$$\frac{S_{r,c,t}^g}{U_{r,c,t}} = \frac{\alpha_{r,c}^S}{\alpha_{r,c}^U} \left(\frac{p_{r,c,t}^{storage}}{p_{r,c,t}^{market}} \right)^\gamma \quad (1)$$

where α^S and α^U are calibrated share weights, p^{market} is the contemporaneous regional commodity price and γ governs the responsiveness of stockholding to relative economic incentives. The value of allocating one unit of a commodity to storage, $p_t^{storage}$, is defined as the expected value of carrying that unit into the subsequent period, net of storage costs and losses:

$$p_{r,c,t}^{storage} = (E_t[p_{r,c,t+1}^{market}] - c_{r,c,t}^{storage})(1 - \lambda_{r,c,t})(1 + \tau)^{-1} \quad (2)$$

where $E_t[p_{r,c,t+1}^{market}]$ is the expected next-period market price, $c^{storage}$ is the interannual storage cost per unit output, λ is the storage loss rate, and τ is the discount rate. For tractability, we adopt a lagged-price

expectation in which $E_t[p_{t+1}^{market}] = p_{t-1}^{market}$, formed sequentially rather than under perfect foresight, consistent with the recursive-dynamic framework. The loss rate λ is also applied to gross closing stocks S^g , yielding net closing stocks, $S = (1 - \lambda)S^g$. Net closing stocks are then adjusted by a cross-period stock factor (δ), to determine opening stocks in period $t + 1$, thereby maintaining temporal consistency of inventories ($\delta = 1$ in annual modeling). Because GCAM v9.1 operates in five-year time steps, the default specification allows δ to scale with regional population growth while imposing a lower bound of $\delta = 1$, providing flexibility to represent stock changes over intervals longer than one year. As a sensitivity test, we remove this cross-period stock carryover adjustment by setting $\delta = 1$, so that opening stocks equal the preceding period's net closing stocks without additional population-linked scaling, while endogenous stockholding remains active.

This structure introduces an intertemporal dimension analogous to spatial allocation in the Armington trade structure, where demand is differentiated by region of origin. Here, supply is differentiated across time between present use and carryover stocks. Intertemporal adjustment is typically less elastic than spatial substitution, as storage entails costs, loss rates, and time discounting. We set $\gamma = 1$, implying unity substitution elasticity, across regions and storable crop sectors in the Dynamic Storage scenarios. This permits moderate intertemporal adjustment while remaining less responsive than GCAM's spatial Armington substitution, for which crop elasticities range from 1.3 to 4.5^{45,48}. We also test sensitivity scenarios of $\gamma = 0$ in Fixed-Ratio Storage scenarios, whereas price-responsive stock reallocation is disabled.

Storage is represented on the regional demand side because inventories are more closely associated with regional use than with regional production. International trade separates the location of production from the location of utilization, producing substantially greater regional variation in stock-to-gross-production ratios than in stock-to-gross-use ratios (**Supplementary Fig. 4**). The demand-side representation also aligns with the PCe framework, which traces inventories across primary and processed commodity uses.

Empirical estimates of storage costs are limited and concentrated primarily on selected grain markets. We include only costs associated with carryover across periods; intraannual handling and pipeline costs are assumed to be embedded in contemporaneous commodity prices. Based on the available estimates, the baseline interannual storage cost is set to 3% of base-year producer prices across regions and sectors and held constant over time (**Supplementary Table 6**). Region-commodity storage loss rates are also held constant, although the global weighted-average loss rate can change as the regional and commodity composition of inventories evolves.

By introducing storage as a price-responsive intertemporal allocation mechanism, inventories become an endogenous component of market adjustment. Storage decisions interact with production, trade, and land-use responses through price signals, providing a structural channel through which stockholding influences long-term agri-food system dynamics.

Scenario design

To evaluate how storage dynamics affect long-term structural outcomes and responses to biophysical yield shocks, we construct six scenarios combining three storage representations with two crop-yield trajectories (**Fig. 3C**). The **Dynamic Storage** reference scenario (S1) follows SSP2 socioeconomic assumptions^{49,50} and smooth long-term agricultural productivity growth based on FAO projections^{51,52}. The **Hidden Storage** scenario (S2) uses the same assumptions, but stock-related flows remain embedded within “other uses” and inherit its generic price and income responses; opening and closing stocks, carryover, and storage-associated losses are not tracked separately. Hidden Storage represents the legacy GCAM configuration in which explicit storage is disabled and is consistent with the implicit treatment commonly used in global economic models. The **Fixed-Ratio Storage** scenario (S5) explicitly tracks stocks, carryover, and losses, but holds the stock-to-gross-use

ratio at its calibrated initial value by setting the logit exponent to zero ($\gamma = 0$) for all storable crops and regions. This scenario effectively disables price-responsive stock reallocation while preserving accounting consistency.

The corresponding shock scenarios apply identical spatially and temporally varying biophysical yield shocks under Dynamic Storage (S3), Hidden Storage (S4), and Fixed-Ratio Storage (S6). The shocks are derived from Inter-Sectoral Impact Model Intercomparison Project 2b (ISIMIP2b)²⁶ simulations generated by the global gridded crop model GEPIC, with carbon fertilization enabled, and driven by the HadGEM2-ES Earth system model under Representative Concentration Pathway (RCP) 6.0. We process the gridded yield outputs using *osiris*⁵³ and aggregate them to GCAM crop-production technologies, regions, and model periods. The resulting biophysical yield shocks are presented in **Supplementary Fig. 6**. This Earth system–crop–economic modeling chain follows established practice in global agricultural impact assessments^{23,25,54}, although the magnitude and timing of the shocks remain conditional on the selected models, forcing pathways, and processing assumptions^{55,56}.

The primary long-term structural comparison is S1 versus S2. Biophysical yield shock transmission is evaluated from shock-induced deviations within each storage representation: S3 relative to S1, S4 relative to S2, and S6 relative to S5. Long-term sensitivity analyses additionally compare S3 with S4, S5 with S2, and a Dynamic Storage sensitivity without the cross-period stock carryover adjustment ($\delta = 1$) with S2. Within each paired comparison, socioeconomic assumptions and all other model parameters are held constant; yield inputs differ only where specified by the smooth and shock trajectories.

Long-term agroeconomic and environmental analysis

Explicit stockholding influences long-term structural trajectories, as it functions as working capital within the agri-food system, trade patterns, and resource allocation even in the absence of acute shocks. We evaluate long-term structural effects primarily as differences between Dynamic and Hidden Storage under smooth yields, reported as S1 vs. S2. We report production, irrigation-water withdrawals, prices, factor inputs, and land use as absolute or relative differences in individual GCAM model years.

Annual stock variation is defined as the difference between closing and opening stocks in a given year, while the average annual stock change over a period (e.g., 2021–2100) is calculated as the difference between closing stocks at the end of the period and opening stocks at the beginning, divided by the number of years. We calculate cumulative irrigation water and emissions impacts by linearly interpolating GCAM outputs to annual resolution and summing from 2021 to each reporting horizon. Agricultural methane (CH₄) and nitrous oxide (N₂O) emissions are converted to CO₂-equivalent using IPCC AR6 100-year global warming potentials of 27 and 273, respectively, while land use, land-use change and forestry (LULUCF) CO₂ emissions are reported directly.

Robustness of the long-term results is evaluated using three additional comparisons: Dynamic vs. Hidden Storage under biophysical yield shocks (S3 vs. S4), Fixed-Ratio vs. Hidden Storage under smooth yields (S5 vs. S2), and Dynamic Storage without the cross-period stock carryover adjustment vs. Hidden Storage. These comparisons test sensitivity to the yield pathway, price-responsive stockholding, and the treatment of carryover between five-year model periods, respectively.

Biophysical yield shock transmission

To evaluate how storage alters the market-mediated response to biophysical yield shocks, we build on established approaches that relate exogenous yield perturbations to endogenous agricultural responses^{21–24}. Global assessments have characterized this propagation through realized yields, harvested area, production, consumption, international trade, and prices, with fitted slopes against the imposed yield shock interpreted as

transmission elasticities. We extend this framework by adding storage as an additional market-mediating margin and use transmission elasticities to summarize how biophysical shocks are transmitted across agricultural responses. Whereas previous applications have primarily evaluated cumulative responses at selected long-term horizons, such as mid-century, we further generalize the formulation to period-to-period transmission, where intertemporal storage adjustment can be resolved more directly.

For an agroeconomic outcome X , we first quantify the cumulative shock-induced response (R) from the base year (t_0) to a future horizon (T) as the difference in logarithmic changes between the biophysical-shock and smooth-yield scenarios:

$$R_{X,r,c,T,t_0} = \log\left(\frac{X_{r,c,T}^{shock}}{X_{r,c,t_0}^{shock}}\right) - \log\left(\frac{X_{r,c,T}^{smooth}}{X_{r,c,t_0}^{smooth}}\right) \quad (3)$$

where r and c denote region and crop group, respectively. The corresponding biophysical yield perturbation, Z_{r,c,T,t_0} , is calculated using the same formulation for imposed biophysical yield. Because the shock and smooth-yield scenarios share the same base-year conditions, Eq. (3) simplifies to $\log(X_{r,c,T}^{shock}/X_{r,c,T}^{smooth})$.

Following previous global assessments²³, we relate responses across region–crop markets to the corresponding yield perturbations using ordinary least-squares regression with an intercept:

$$R_{X,r,c,T,t_0} = \alpha_{X,T,t_0} + \beta_{X,T,t_0} Z_{r,c,T,t_0} + \varepsilon_{X,r,c,T,t_0} \quad (4)$$

where ε is the regression residual and the fitted slope β is interpreted as the cumulative yield-shock transmission elasticity.

To resolve intertemporal adjustment, we generalize the same log-difference formulation to successive model periods. For each transition from $t - 1$ to t , the shock-induced response is defined as

$$R_{X,r,c,t,t-1} = \log\left(\frac{X_{r,c,t}^{shock}}{X_{r,c,t-1}^{shock}}\right) - \log\left(\frac{X_{r,c,t}^{smooth}}{X_{r,c,t-1}^{smooth}}\right) \quad (5)$$

with the corresponding period-to-period biophysical yield perturbation, $Z_{r,c,t,t-1}$, calculated analogously. The cumulative response in Eq. (3) is recovered by summing these successive period-to-period responses over the corresponding interval. This finer temporal representation is particularly relevant for storage because stock accumulation following one perturbation can be followed by drawdown after another, such that intertemporal adjustments may partly offset in cumulative endpoint responses.

For each storage representation, we relate the period-to-period responses in Eq. (5) to the corresponding biophysical yield perturbations using the same regression framework:

$$R_{X,r,c,t,t-1} = \alpha_X + \beta_X Z_{r,c,t,t-1} + \varepsilon_{X,r,c,t,t-1} \quad (6)$$

where the regression is pooled across region–crop markets and model-period transitions, and the fitted slope β is interpreted as the period-to-period yield-shock transmission elasticity. For both cumulative and period-to-period analyses, a coefficient of one indicates proportional positive transmission of the biophysical perturbation to the outcome, coefficients closer to zero indicate weaker transmission, and negative coefficients indicate an offsetting response. Eq. (6) is estimated separately for Dynamic, Hidden, and Fixed-Ratio Storage, allowing the magnitude and direction of market adjustment to be compared across storage representations.

The biophysical yield shocks from ISIMIP2b are applied in GCAM at the model region-basin and crop-sector resolution. For transmission analysis and reporting, the resulting shocks and model responses are subsequently aggregated to IPCC R10 regions and four crop groups (grains, oil crops, sugar crops and other storable crops). The cumulative analysis therefore includes 40 region–crop observations at each horizon, with 2050 used as a primary benchmark and 2100 as a horizon-sensitivity comparison. The 17 model years from 2021 to 2100 define 16 successive transitions, yielding up to 640 region–crop–transition observations for each storage representation in the period-to-period analysis.

The aggregated yield shocks retain considerable spatial, sectoral and temporal heterogeneity (**Supplementary Fig. 6**). Cumulative deviations from the smooth-yield trajectory reach approximately –5% for grains, –9% for sugar crops and –1% for oil crops and other storable crops globally by 2100 (**Supplementary Fig. 6A**), whereas period-to-period deviations generally range within approximately –10% to +10%, with larger perturbations in some region–crop periods (**Supplementary Fig. 6B**). Because the magnitude and timing of biophysical impacts are sensitive to the Earth system model, crop model, forcing and related assumptions, this single internally consistent realization is used as a common perturbation for comparing market responses across storage representations rather than to characterize the full uncertainty in future crop yields.

We report transmission-elasticity estimates with standard errors and 95% confidence intervals (**Fig. 5** and **Supplementary Table 7**). We additionally estimate period-to-period slopes for individual region–crop markets and summarize their distribution using the median and interquartile range. Differences between storage representations are evaluated using Wald F tests of equality of scenario-specific yield-shock coefficients in interacted regressions (**Supplementary Table 8**). To assess specification sensitivity, we repeat the period-to-period analysis with region fixed effects and with region–crop fixed effects (**Supplementary Table 9**). Reported uncertainty describes the fitted regression relationships conditional on the simulated outcomes and imposed yield trajectory.

Data availability

We will make the GCAM simulation results and processed data used for analysis in this study available upon acceptance or upon request by editors and reviewers.

Code availability

GCAM is an open-source model available at github.com/JGCRI/gcam-core. The specific model version used in this study, along with the code for generating the main figures, is also available in a public repository (citation and link will be added upon acceptance or upon request by editors and reviewers).

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Contributions

X.Z. conceptualized the study. X.Z., P.P., and E.L. contributed to model development and improvement. X.Z. conducted the simulations, performed the formal analysis, and wrote the initial draft. All authors (X.Z., P.P., S.M., E.L., M.B., K.C., T.W., J.E., and M.W.) contributed to result interpretation, manuscript review, and editing.

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Competing interests

The authors declare no competing interests.

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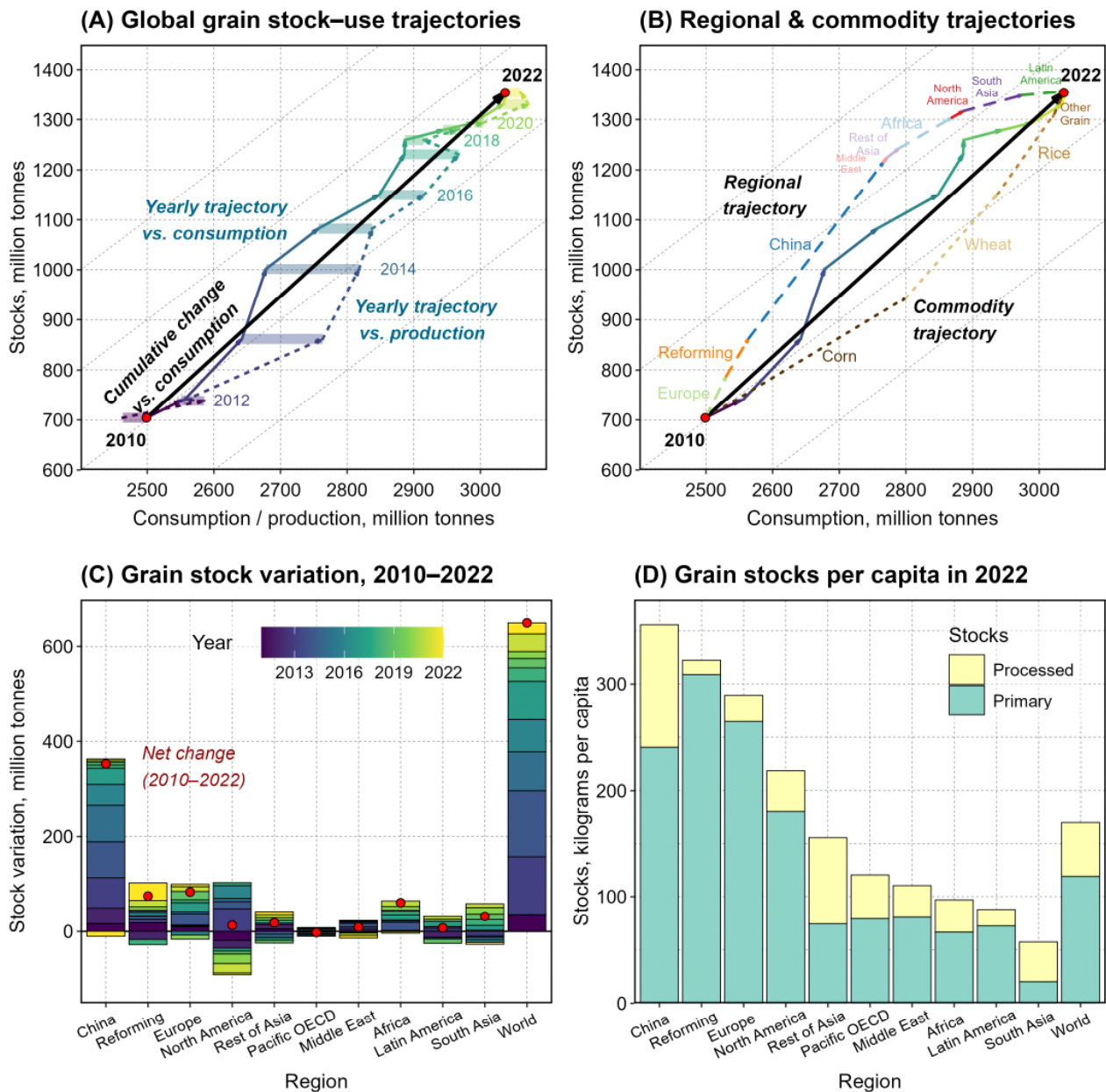


Fig. 1 | Global and regional patterns of cereal grain stocks and stock variation. **Panel A**, Global grain stock–use trajectories. The black arrow shows the cumulative shift from 2010 to 2022. The solid trajectory plots annual global grain stocks against consumption, whereas the dotted trajectory plots stocks against production; colors indicate year. At the global level, net trade sums to zero, so the horizontal separation between the production and consumption trajectories represents annual stock variation. Grey diagonal lines are slope-one guides. **Panel B**, Regional and commodity decomposition of the global grain trajectory. Dashed paths decompose the cumulative 2010–2022 shift by IPCC R10 regions, whereas dotted paths decompose it by GCAM cereal grain commodities (Corn, Wheat, Rice, and OtherGrain). Each path begins at the 2010 global point and sequentially adds regional or commodity contributions to reach the common 2022 endpoint. **Panel C**, Annual grain stock variation by region. Colored bar segments show annual net changes in grain stocks from 2010 to 2022; positive values indicate stock accumulation and negative values indicate stock drawdown. Red points show the cumulative net stock change over 2010–2022. **Panel D**, Grain stocks per capita in 2022 by region. Stacked bars partition closing stocks between primary grain commodities and processed grain products. Stock variation denotes the net change between opening and closing stocks in annual food balance sheets; stock levels are based on closing stocks. All mass quantities are expressed in primary-equivalent units. Commodity and region mappings are provided in **Supplementary Tables 3 & 4**. Data sources: FAOSTAT and gcamfaostat.

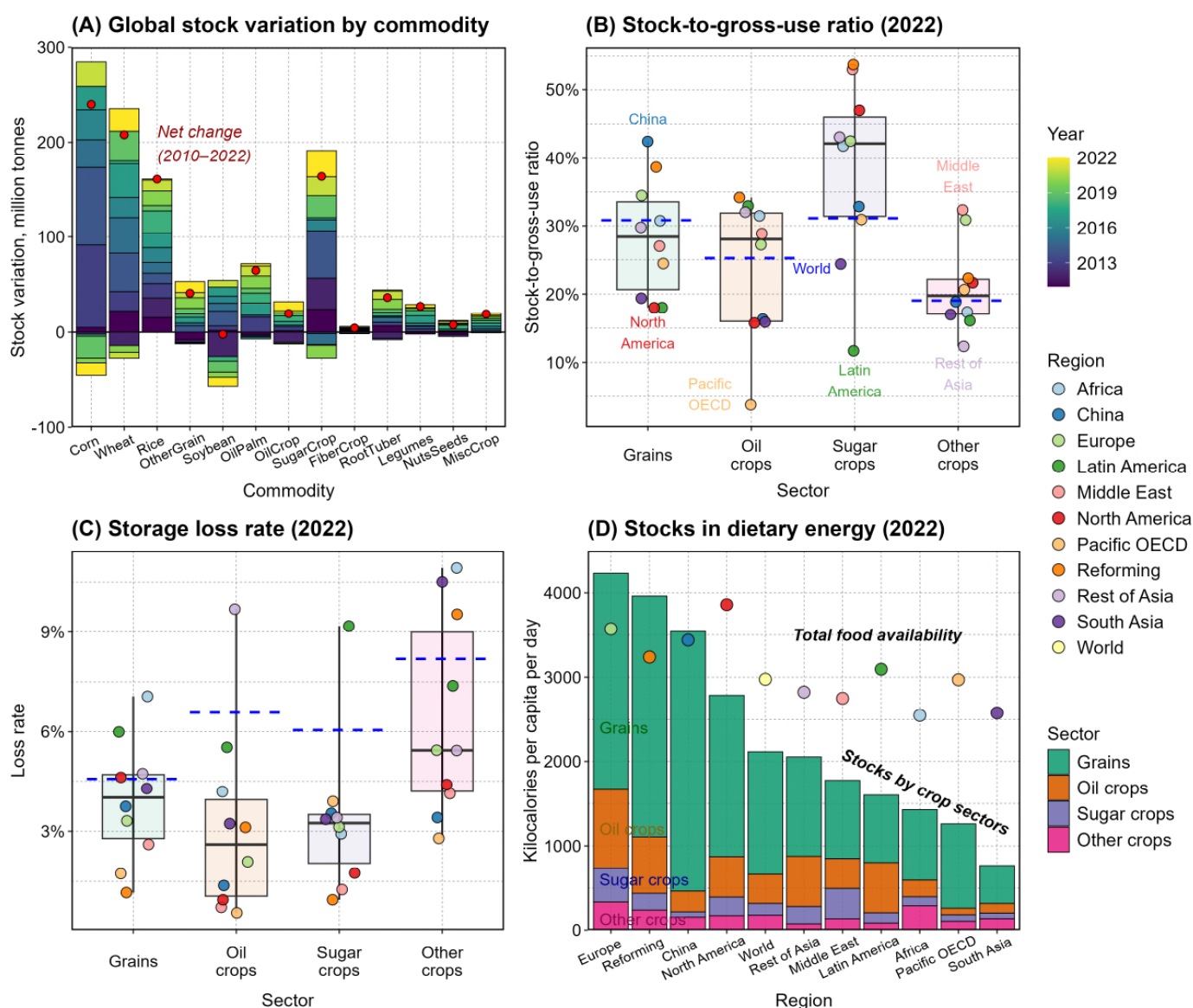


Fig. 2 | Agricultural stock variation and stock-related metrics. **Panel A**, Global stock variation by GCAM storable crop commodity, excluding vegetables and fruits, over 2010–2022. Colored bar segments show annual net stock changes, and red points show the net cumulative stock change over 2010–2022. **Panels B & C**, Stock-to-gross-use ratios (**B**) and Storage loss rates (**C**) in 2022 by crop sector. In both panels, boxplots show the median, interquartile range (25th–75th percentiles; boxes), and full IPCC R10 regional range (whiskers); colored points show regional values; and blue dashed lines indicate world averages by sector. Stock-to-gross-use ratio is defined as net closing stocks divided by gross domestic use, comprising current domestic utilization, net closing stocks, and storage-associated losses. Storage loss rates are derived based on food-balance-sheet post-harvest loss-related estimates. **Panel D**, Regional crop stocks in dietary-energy terms in 2022. Stacked bars show closing stock levels by crop sector, converted to kilocalories per capita per day. Points show total food availability (utilization), including all food commodities, for comparison. Mass-based quantities and ratios are derived from food balance sheets expressed in primary-equivalent units. The Supplementary Information provides region, sector, and commodity mappings, along with additional details. Data sources: FAOSTAT and *gcamfaostat*.

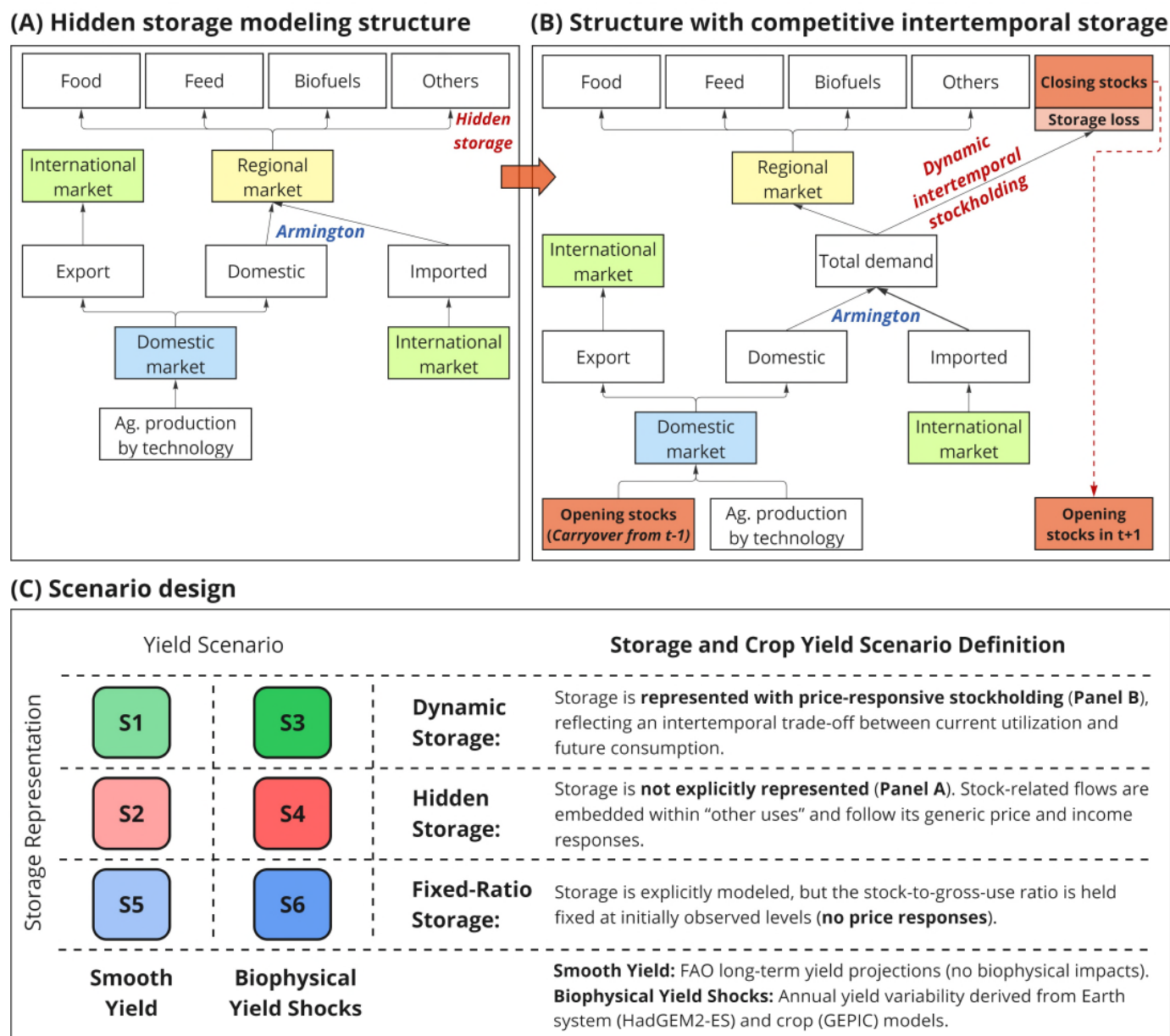


Fig. 3 | Modeling structure and scenario design. Panel A shows the regional agricultural market structure under Hidden Storage, in which stock-related flows remain embedded within “other uses” and stocks are not separately tracked across model periods. Panel B shows Dynamic Storage, which explicitly links opening stocks, closing stocks, and storage-associated losses across periods. Panel C summarizes the six scenarios combining Dynamic, Hidden, and Fixed-Ratio Storage with smooth and biophysically shocked yield trajectories. S1 and S2 are the smooth-yield Dynamic and Hidden scenarios; S3 and S4 apply common biophysical yield shocks under Dynamic and Hidden Storage; and S5 and S6 are the corresponding Fixed-Ratio scenarios. See **Methods** for details on scenario description.

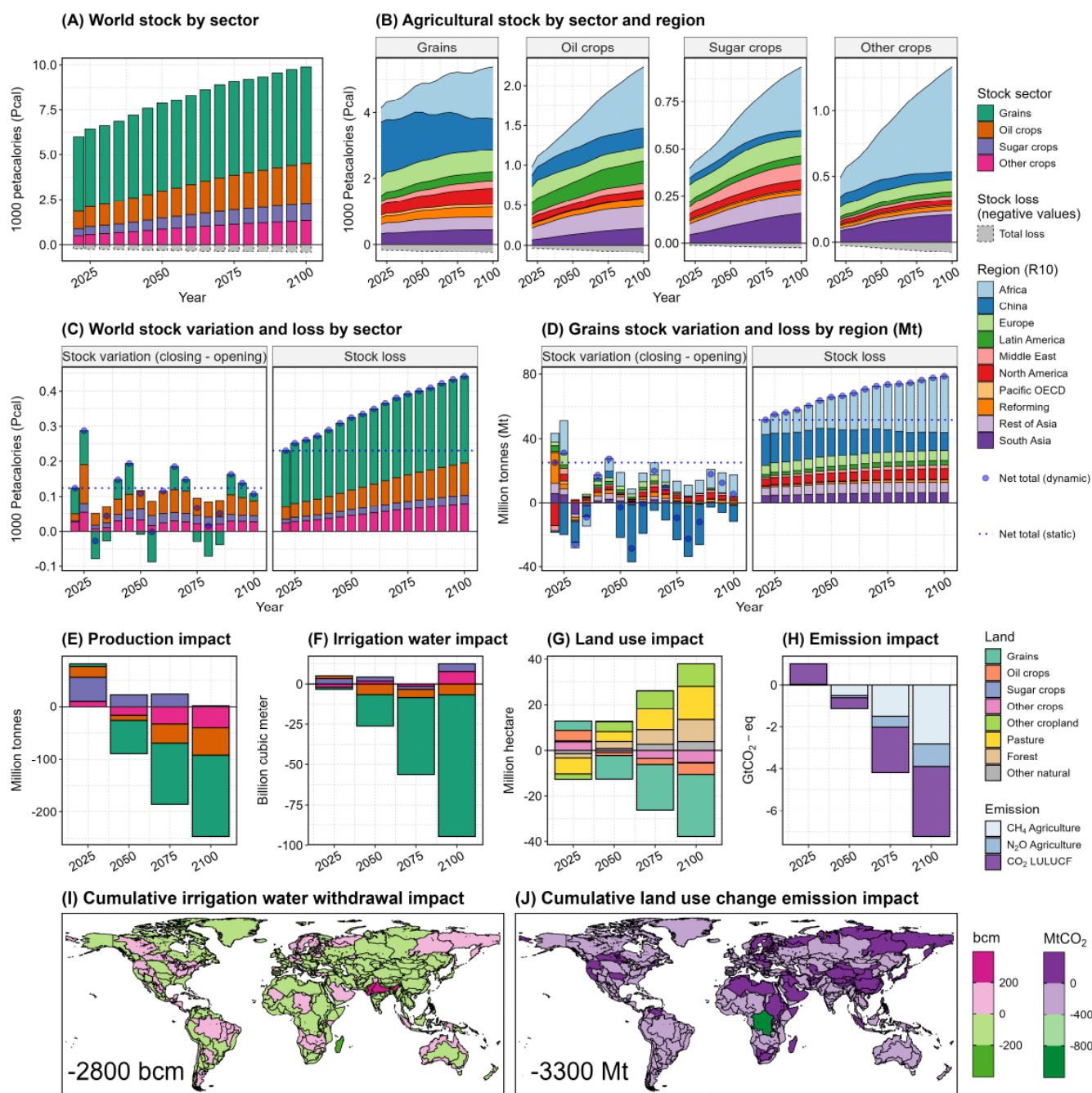


Fig. 4 | Global agricultural storage dynamics and multisectoral impacts. Panels A–B show projected agricultural closing stocks toward the end of the century for crop sectors with explicit storage representation in GCAM, by sector and by sector–region combination, based on GCAM projections from the reference scenario **S1**, with total storage-associated losses shown as negative values (grey). Panels C–D decompose storage dynamics into net stock variation (closing minus opening stocks) and storage losses, shown globally by sector in dietary energy units (Panel C) and for grains by region in million tonnes (Panel D), respectively. Points denote totals under dynamic competitive storage modeling, while dotted lines show constant-initial-value benchmarks. Panels E–H show global multisectoral impacts of explicit storage representation, quantified as differences between the competitive storage scenario (**S1**) and the hidden storage scenario (**S2**), including effects on agricultural production, irrigation water withdrawals, land use change, and cumulative emissions (from 2021 to the displayed horizons) from agricultural CH₄ and N₂O, and land use change CO₂ (LULUCF). Panels I–J show the spatial distribution of cumulative irrigation water withdrawal impacts (aggregated across all crops) and cumulative LULUCF emissions, respectively, at the river-basin scale. Data source: GCAM simulation results.

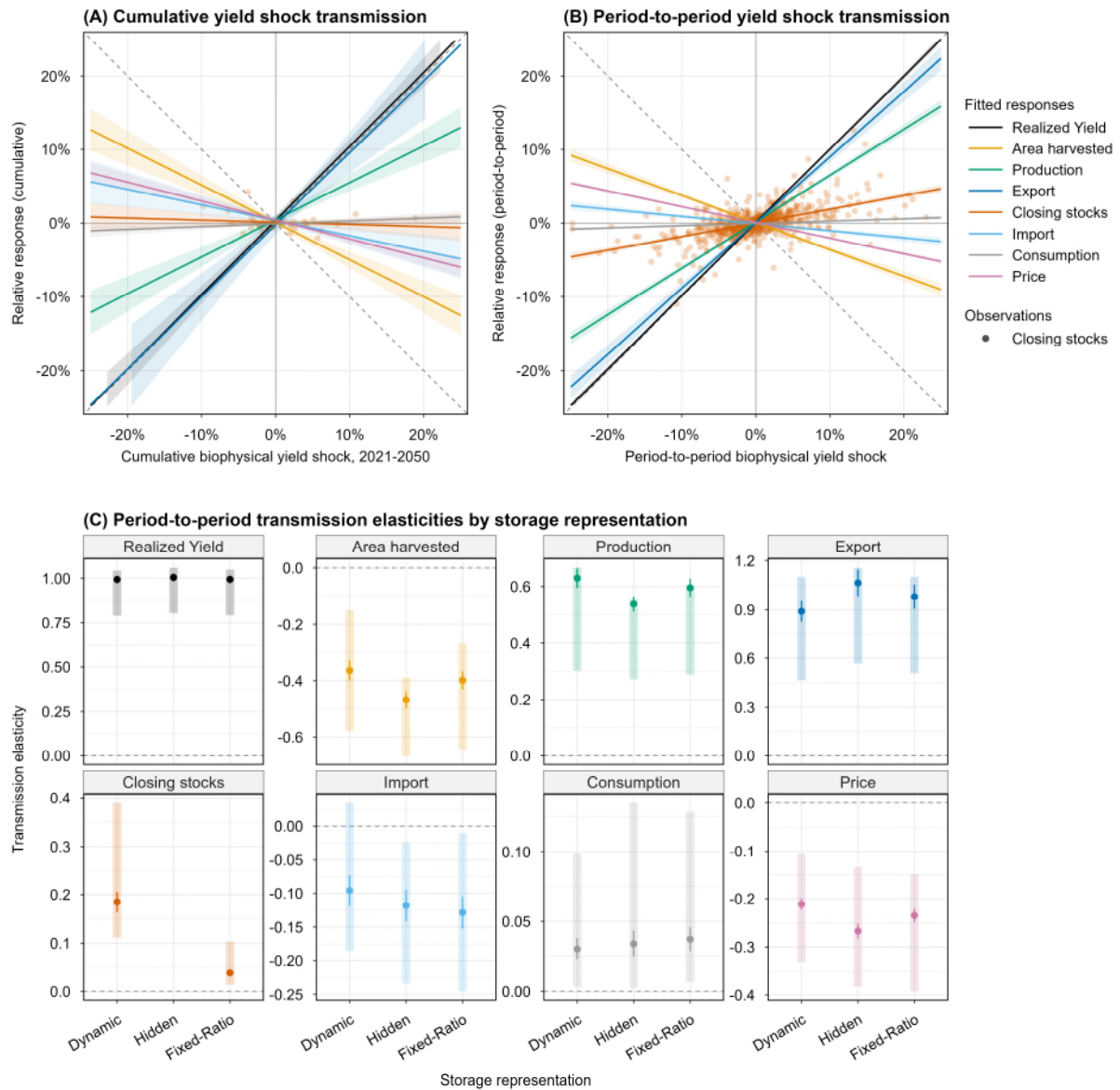


Fig. 5 | Storage dynamics alter the transmission of biophysical yield shocks. **Panel A**, Cumulative transmission from 2021 to 2050 under Dynamic Storage. Lines show ordinary least-squares fits with an intercept between cumulative biophysical yield shocks and responses in realized yield, harvested area, production, export, closing stocks, import, total consumption, and price; shaded bands indicate 95% confidence intervals for the fitted mean relationships. For visual comparability, both axes are restricted to -25% to $+25\%$; confidence bands extending beyond these limits are clipped. **Panel B**, Period-to-period transmission under Dynamic Storage, pooled across successive GCAM model-period transitions from 2021 to 2100. Lines and 95% confidence bands show the corresponding fitted relationships. In **Panels A** and **B**, individual observations are shown only for closing stocks to highlight the intertemporal storage response; grey dashed diagonals indicate unit-elastic positive and negative transmission. **Panel C**, Period-to-period transmission elasticities under Dynamic, Hidden, and Fixed-Ratio Storage. Points and narrow bars show pooled OLS estimates and 95% confidence intervals, consistent with the fitted relationships in Panel B; wide translucent bars show the interquartile range of slopes estimated for individual region-crop markets, indicating cross-market heterogeneity. Closing stocks denote net inventories remaining after storage-associated loss. Consumption denotes aggregate current domestic consumption and excludes closing stocks and storage-associated losses. Hidden Storage does not report explicit closing stocks. Complete cumulative and period-to-period results are provided in **Supplementary Figs. 14–19**. **Supplementary Table 7** reports coefficient estimates and cross-market heterogeneity summaries; **Supplementary Table 8** reports pairwise tests of transmission coefficients across storage representations; and **Supplementary Table 9** reports fixed-effect robustness results.

Supplementary Files

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