

Resilience Thresholds and the Adaptive Cycle: Spatiotemporal Evolution and Driving Mechanisms of Grain Production Resilience in Arid Regions

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Abstract

Arid grain systems must stay productive under a resource ceiling that does not move. Whether they do so by accumulating resilience or by accumulating rigidity is an open question. We build a grain production resilience index for 13 prefecture-level divisions of Xinjiang, China, over 2014–2024, organised around the adaptive cycle's three capacities: absorptive, restorative and adaptive. Entropy weighting, kernel density estimation, spatial statistics and a Dagum decomposition describe the pattern; fixed-effects and threshold models identify the drivers. Resilience rose from 0.294 to 0.358 and its dispersion fell by 21 per cent, so the distribution converged upward. The northern grain belt remained a high-high cluster and the southern oases low-low; quartile membership was strongly persistent. A robust threshold appears in grain specialisation at a sown-area share of about two-thirds: below it, a ten-percentage-point increase in the grain share raises resilience by 0.012 index points, and above it the association disappears. Fertiliser intensity shows no comparable threshold: the reversal a two-regime search produces is a specification artefact. Within units, resilience rises with income, mechanisation and specialisation, while the association with fertiliser intensity is negative but imprecise. The binding constraint is not the level of inputs but the point at which specialisation stops paying.

1. Introduction

Grain production in arid regions is a bet against a fixed resource ceiling. The water available to agriculture is bounded, the land that can be irrigated is bounded, and the population that must be fed is not. How a regional grain system behaves as it approaches those bounds — whether it absorbs the pressure, adapts around it, or accumulates the kind of rigidity that turns a shock into a collapse — is the question this paper addresses.

That question has become urgent for a practical reason. Global grain demand is projected to keep rising while the water and land available to meet it are being reallocated to cities, industry and ecological restoration ^[1]. Extreme climate events now impose measurable losses on the crops that supply most of that demand ^[2]. Those losses propagate across borders through trade ^[3]. In China, the tension is sharpest in the northwest, where grain output has expanded rapidly into an environment that can support it only through irrigation ^[4]. Studies of Chinese grain production resilience have begun to map this expansion. Ding and Tang ^[5] measured county-level grain production resilience across China from 2001 to 2023 and found a fluctuating upward trend with a north-eastern high-value core. Liu et al. ^[6] used provincial panel data for 2004–2022 to show that grain production resilience is positively spatially correlated and exhibits spillovers. Both studies establish that resilience can be measured and that it varies systematically in space. Neither asks what happens when the system that has been accumulating resilience reaches the limits of the resource base that made the accumulation possible.

Resilience theory supplies the missing frame. Holling ^[7] defined resilience as the magnitude of disturbance a system can absorb before its controlling variables reorganise — a property distinct from productivity. Folke et al. ^[8] distinguish resilience, adaptability and transformability as three distinct

properties of a coupled social–ecological system. Walker et al. ^[9] made the crucial observation that a system can move from a highly productive state to a much less productive one without any change in the pressures acting on it, because the slow accumulation of internal connectedness erodes the capacity to respond. Such transitions can be abrupt and difficult to reverse ^[10]. In food systems the concept is newer and the measurement frameworks remain unsettled ^[11]. Recent work on Chinese food security argues that the policy objective should shift from a self-sufficiency ratio towards the resilience of the food system as a whole ^[12]. The implication for an arid grain region is direct: a system that raises output by increasing its dependence on a single scarce input may be reducing its resilience in the very act of appearing to build it.

The empirical literature on Chinese grain production resilience has not yet tested this implication. The dominant approach measures a composite index, decomposes its spatial pattern and regresses it on covariates ^[13]. That approach answers where resilience is high and what correlates with it. It does not answer whether the relationship between a driver and resilience changes at a critical level of that driver, which is the question resilience theory poses. Nor does it distinguish the phases of the adaptive cycle, which is what determines whether a high-resilience unit is on its way up or on the verge of release ^[14]. It also does not ask whether the mechanisms differ across the region's two halves.

This paper addresses all three gaps in a setting where the resource constraint is binding rather than hypothetical. Xinjiang is China's largest arid region and one of its principal grain backstops; its southern prefectures depend on irrigation water drawn from rivers fed by the Karakoram and Tien Shan glaciers ^[15]. We construct a grain production resilience index for 13 prefecture-level divisions over 2014–2024 from annual output series, following recent measurement practice ^[16], organised explicitly around the three capacities that correspond to the adaptive cycle, and ask three questions. First, how has grain production resilience evolved in space and time, and has the distribution converged or polarised? Second, is there a level of agricultural specialisation or input intensity beyond which the marginal resilience return disappears? Third, which mechanisms drive resilience once unit and year effects are removed, and do they operate differently in the north and the south?

The contribution is threefold. Methodologically, we show that the two-regime threshold model routinely used to identify resilience thresholds can produce a spurious sign reversal when the two regimes are estimated together, and we propose a simple specification test that detects it. Substantively, we identify a saturation threshold in grain specialisation rather than in input intensity, which redirects attention from how much farmers apply to how concentrated the cropping system has become ^[17]. Empirically, we provide, to our knowledge, the first adaptive-cycle reading of grain production resilience in an arid Chinese region, showing that the northern grain belt and the southern oases occupy different phases of the cycle and face different transition risks.

The remainder of the paper is organised as follows. Section 2 reviews the literature. Section 3 develops the theoretical framework and states the hypotheses. Section 4 describes the data, variables and

methods. Section 5 reports the results. Section 6 reports further robustness checks. Section 7 discusses the findings against the literature. Section 8 concludes.

2. Literature Review

2.1 International research on resilience and food systems

The concept of resilience entered ecology as the persistence of relationships within a system and the ability of that system to absorb change without crossing a threshold into a different set of controlling variables. The analytical content of the idea lies in two separate properties: the time a system takes to return to its former state, and the size of the basin from which it can return. A system may be quick to recover while remaining vulnerable to perturbations arriving from a different direction. These two properties remain central to the field.

The extension to coupled social–ecological systems followed from the recognition that social institutions mediate ecological resilience. The separation of resilience, adaptability and transformability matters because a system may absorb shocks while being unable to transform, and may transform while losing the functions that made it valuable. The resulting dynamic is the adaptive cycle, in which a system moves through exploitation, conservation, release and reorganisation. The conservation phase is the most dangerous because it looks the most successful: the accumulation of connectedness that raises productivity also narrows the repertoire of responses available when the environment changes ^[18].

In food systems, resilience has been defined as the capacity over time to ensure food security in the face of disruptions and stresses. The measurement of that capacity remains contested, and the available frameworks disagree about whether resilience should be inferred from outcomes or from the capacities that are supposed to produce them ^[19]. A recurring concern is that resilience language can obscure the question of who bears the cost of adaptation. The same concern has been raised for China: the redundancy that makes a food system resilient is being traded away in the pursuit of self-sufficiency.

2.2 Chinese research on grain production resilience

Chinese scholarship on grain production resilience has grown quickly and has converged on a common template: construct an index from indicators spanning production capacity, resource base and economic conditions; weight it by entropy; describe its spatial and temporal pattern; and identify drivers by regression or with a geographical detector ^[20]. The two studies reviewed above apply that template at different scales: at county scale for 2001–2023, yield per unit area, the multiple cropping index, mechanisation, informatisation and agricultural investment all had positive effects, while the provincial panel for 2004–2022 found positive spatial correlation and spillovers, with heterogeneous regional effects. A parallel strand measures production efficiency rather than resilience and finds a similar spatial concentration ^[21]. Work on the agricultural economy proper finds that agglomeration and technological innovation both propagate across space ^[22]. Technology affects resilience through measurable channels

^[23]. A further strand evaluates drought resilience as a system property in its own right ^[24]. Another models the nonlinear response of crop production to risk ^[25].

Two features of this literature are relevant here. First, the geographical focus is overwhelmingly on the major grain-producing plains of the northeast, the North China Plain and the middle and lower Yangtze, where water is not the binding constraint ^[26]. Arid and semi-arid regions appear mainly as comparison cases, and where they are studied it is usually vegetation condition that is measured rather than grain production ^[27]. Second, driver analysis is almost always conducted in a linear framework. Where nonlinearity is allowed, it is handled by adding a squared term or by machine learning, and neither identifies a threshold at which the sign or the magnitude of a relationship changes ^[28].

2.3 Gaps this paper addresses

Three gaps follow. There is no adaptive-cycle reading of grain production resilience in China: existing work measures a level but does not locate units within the cycle, so it cannot say whether a high score reflects a system that is still building capacity or one that has accumulated the rigidity that precedes release. There is no credible estimate of a resilience threshold in an arid grain system: the threshold methodology exists but its standard implementation is fragile in the short panels typical of prefecture-level data in China. And there is no evidence on how the mechanisms differ between the northern and southern halves of Xinjiang, which differ in water endowment, income and cropping pattern ^[29]. This paper addresses all three.

3. Theoretical Analysis and Research Hypotheses

3.1 The grain production system as a coupled social–ecological system

A grain production system has three properties that make the adaptive-cycle framework applicable. It accumulates a slowly growing stock — irrigation infrastructure, machinery, soil quality, farmer skill — that is not easily reversed ^[30]. It develops connectedness as that stock grows, because the most efficient way to use a given infrastructure is to specialise around it. It is also subject to recurrent fast disturbances in the form of drought, frost, pests and price shocks ^[31]. The first property makes the system's trajectory path-dependent; the second makes it progressively less able to absorb the disturbances described in the third.

We represent resilience as three capacities that correspond to the recovery mechanisms the system has available at each point in the cycle. Absorptive capacity is the ability to sustain output when a disturbance hits, which depends on the biophysical headroom of the production system: how much output each hectare yields, how much machinery power is available per person, and how much grain is available per person. Restorative capacity is the ability to rebuild function afterwards, which depends on the resource base that can be replanted: the grain area available per person and the efficiency with which

purchased inputs are converted into output. Adaptive capacity is the room to reorganise, which depends on the economic resources the farm population commands: rural income and agricultural value added per person. The three capacities are not substitutes. A system may be strong in absorptive capacity because it is intensively irrigated and weak in adaptive capacity because the farms that operate it have no alternative income.

3.2 The rigidity trap in an irrigated grain system

The adaptive cycle predicts a specific failure mode for this system. In the exploitation phase, output grows rapidly as irrigation is extended and machinery is adopted, and resilience rises with it ^[32]. In the conservation phase the system becomes efficient. The cropping pattern narrows around the crops the infrastructure suits best, and inputs are applied at rates calibrated to maximum yield ^[33]. The institutions that allocate water and land harden around that pattern ^[34]. Measured resilience, if it is measured as capacity or output, continues to look strong. What declines is the capacity to respond to something the system has not seen, because the options that would have allowed a response have been traded away.

Two observable implications follow. First, the marginal resilience return to further specialisation should fall to zero once the cropping pattern is sufficiently concentrated, because additional concentration adds connectedness without adding capacity. Second, the marginal resilience return to intensification should be non-positive throughout, because in a system that is already at the input frontier, more purchased input buys yield at the cost of the economic buffer that would fund a change of course. The first of these implies a saturation threshold rather than a cliff-edge threshold: the relationship flattens rather than reverses. Figure S1 sets out the resulting cycle.

3.3 Hypotheses

H1. Grain production resilience in Xinjiang rises over 2014–2024 and its cross-sectional dispersion narrows, so the distribution converges upward rather than polarising.

H2. The spatial pattern is organised around a north–south divide: the northern grain belt forms a persistent high-high cluster and the southern oases a persistent low-low cluster, and the strength of that clustering increases over the period.

H3. The association between grain specialisation and resilience is regime-dependent, with a threshold below which specialisation raises resilience and above which the marginal effect is not distinguishable from zero.

H4. Once unit and year effects are removed, resilience rises with income per capita, mechanisation and grain specialisation, and falls with fertiliser intensity.

H5. The mechanisms differ between the north and the south, with specialisation mattering more in the north, where the resource base supports it, than in the south.

4. Data, Variables and Methodology

4.1 Study area

The study covers 13 prefecture-level divisions of the Xinjiang Uygur Autonomous Region: five in the south (Bayingolin, Aksu, Kizilsu, Kashgar, Hotan) and eight in the north and east (Urumqi, Turpan, Hami, Changji, Bortala, Ili, Tacheng, Altay). Together they produced 18.8 million tonnes of grain in 2024; the remainder of the regional total comes from divisions administered by the Xinjiang Production and Construction Corps, which report separately from the prefecture statistics used here. Karamay is excluded because its statistical bulletins do not publish a grain output series; it is an oil-extraction city in which grain occupies between about 3,000 and 7,000 hectares, roughly 0.2 per cent of the region's grain land, and its contribution to the regional total is correspondingly negligible.

The two halves differ in ways that matter for the analysis. The south has a drier climate, far less water available for irrigation, a much larger share of the population in agriculture and much lower rural incomes. Its cultivated land is also more fragmented, which raises the cost of irrigation and of moving machinery between plots. The north contains the Ili and Tacheng grain belts, which are the region's most productive and most mechanised ^[35]. The north also holds the piedmont oases that receive the larger share of the glacier-fed runoff ^[36]. Land degradation is an active constraint across the region: salinisation affects the irrigated districts and desertification has advanced along the margins ^[37]. This contrast is the source of the heterogeneity we test in H5. Figure 1 maps the study area.

4.2 Data

The panel was compiled manually from primary sources because no open database publishes a consistent prefecture-level series for these variables. The sources are the annual statistical communiqués of each prefecture for 2014–2024, the published tables of the Xinjiang Statistical Yearbook, and the regional water resources bulletins. The communiqués are the authoritative annual statement of a prefecture's agriculture and are published by the prefecture statistical bureau jointly with the local office of the National Bureau of Statistics.

For 2025 we extended the core agricultural series where the bulletins had been released by the time of writing. The region comprises 14 prefecture-level divisions, of which 13 form the analysis sample; grain output for 2025 is available for 12 of the 14 and grain sown area for 13, sourced from each prefecture's own 2025 communiqué, except for Aksu, whose communiqué had not been released when the data were compiled and for which the regional statistical office's bulletin was used instead. The remaining variables needed for the index were not reported consistently in the 2025 releases, so the resilience index is estimated on 2014–2024 and the 2025 values are used only to establish the most recent level of grain output.

Coverage and treatment of missing values are disclosed because they condition the interpretation. The seven indicators entering the index are complete for all 143 unit-years, but completeness is not the same as direct observation. Of the 1,001 indicator cells, 628 are directly sourced from a cited document: grain output in 106 unit-years, grain sown area in 107, primary value added in 114, rural income in 94, machinery power in 89, fertiliser use in 67 and population in 51. The remaining cells were filled by linear interpolation within prefecture or carried forward from the nearest reported year. Grain output and grain sown area, the two series on which the yield indicator depends, are therefore directly reported in about three quarters of the sample, while population – the denominator of five indicators – is directly reported in about a third. For the driver variables, complete cases number 110 of the 143 unit-years, the shortfall coming from per-capita GDP (132 observed) and the grain area share (121 observed). All monetary values are in current prices; the year fixed effects absorb the common price trend.

4.3 Dependent variable: the grain production resilience index

The index is built from seven indicators grouped into three capacities. Absorptive capacity comprises grain yield (tonnes per hectare), mechanisation per thousand persons (kilowatts) and grain availability per thousand persons (tonnes). Restorative capacity comprises grain area per thousand persons (hectares) and fertiliser efficiency (tonnes of grain per tonne of fertiliser applied). Adaptive capacity comprises rural income per person (yuan) and agricultural value added per person (yuan). Each capacity is a sub-index: the weighted sum of its own standardised indicators, with the entropy weights renormalised within the group, so that the three capacities and the overall index lie on a common scale.

Two design choices require explanation. First, mechanisation is expressed per person rather than per hectare of grain sown area, and fertiliser enters as an output-to-input ratio rather than as an application rate. Both series are prefecture totals that serve all crops, so dividing them by grain area alone would assign a spurious intensity to urbanised units with small grain areas. Expressing them per person, or as tonnes of grain per tonne of fertiliser, measures the load the system carries relative to the population it feeds, which is the relevant quantity for a resilience argument. Second, fertiliser enters as output per unit of input rather than as tonnes applied per hectare, because the application rate has a heavy right tail that distorts min–max scaling.

All seven indicators are oriented so that a higher value raises resilience. Raw values are winsorised at the 1st and 99th percentiles, scaled to the unit interval, and combined with entropy weights computed on the pooled 143 unit-years. The entropy method assigns larger weights to indicators with greater dispersion, which is appropriate here because the index is a ranking instrument rather than a welfare measure. The resulting weights are 0.071 for yield, 0.101 for mechanisation, 0.194 for grain availability, 0.206 for grain area per thousand persons, 0.174 for fertiliser efficiency, 0.111 for rural income and 0.143 for agricultural value added. No single indicator dominates, which was not true of an earlier specification in which both technology measures were divided by grain area. Table 1 lists the indicators, their definitions and the resulting weights.

Table 1
Indicator system for the grain production resilience index, with entropy weights.

Capacity	Indicator	Definition	Unit	Direction	Weight
Absorptive	Grain yield	Grain output / grain sown area	t per ha	+	0.071
Absorptive	Mechanisation	Machinery power / population	kW per 1000 persons	+	0.101
Absorptive	Grain availability	Grain output / population	t per 1000 persons	+	0.194
Restorative	Grain land	Grain sown area / population	ha per 1000 persons	+	0.206
Restorative	Fertiliser efficiency	Grain output / fertiliser applied	t per t	+	0.174
Adaptive	Rural income	Rural disposable income per capita	yuan	+	0.111
Adaptive	Agricultural value added	Primary value added / population	yuan	+	0.143

4.4 Explanatory and mechanism variables

Six drivers enter the baseline specification: log GDP per capita, the agricultural share of GDP, fiscal expenditure as a ratio of GDP, mechanisation intensity, fertiliser intensity and the grain share of sown area, referred to below as grain specialisation. The first three capture the level of development, the structure of the local economy and the intensity of public support ^[38]. The last three capture the technology and structure of the grain system itself ^[39]. Mechanisation intensity and fertiliser intensity are measured per hectare of grain land in the driver regressions, where the purpose is to characterise the production technology; specifications using the per-capita versions are reported as a robustness check in Section 6 ^[40].

4.5 Methods

The analysis proceeds in seven steps, each with its own notation. Equations are numbered in order of first appearance, and every symbol is defined in the sentence immediately following the equation in which it is introduced. All computations were carried out in Python 3.12.7, using NumPy 2.5.3, pandas 3.0.6, SciPy 1.18.1 and statsmodels 0.15.0; spatial boundaries were handled with GeoPandas 1.1.4 and every figure was produced with Matplotlib 3.11.2.

4.5.1 Entropy-weighted index of grain production resilience

The index combines seven indicators that carry different units but the same direction of effect: for each of them a higher value raises resilience, so Eq. (1) is applied to all seven. Eq. (2) is the reverse orientation, which this set of indicators does not require and which is given for completeness.

$$x'_{ij} = (x_{ij} - \min(x_j)) / (\max(x_j) - \min(x_j)) \quad (1)$$

$$x'_{ij} = (\max(x_j) - x_{ij}) / (\max(x_j) - \min(x_j)) \quad (2)$$

where x_{ij} is the observed value of indicator j for unit-year i , x'_{ij} is its standardised value, and $\max(x_j)$ and $\min(x_j)$ are the maximum and the minimum of indicator j across all unit-years.

The weight of an indicator is determined by the information it carries rather than by judgement. The proportion of unit-year i in indicator j is given by Eq. (3), the entropy of indicator j by Eq. (4), and the weight of indicator j by Eq. (5).

$$p_{ij} = x'_{ij} / \sum_{i=1}^n x'_{ij} \quad (3)$$

$$e_j = -k \sum_{i=1}^n p_{ij} \ln p_{ij}, k = 1 / \ln(n) \quad (4)$$

$$w_j = (1 - e_j) / \sum_{j=1}^m (1 - e_j) \quad (5)$$

where p_{ij} is the proportion, e_j the entropy and w_j the weight of indicator j ; n is the number of unit-years, m is the number of indicators, and k is a normalising constant that keeps e_j within the unit interval. The procedure is standard in composite resilience assessment ^[41].

The grain production resilience index of unit-year i is the weighted sum of its standardised indicators,

$$GPRI_i = \sum_{j=1}^m w_j x'_{ij} \quad (6)$$

where $GPRI_i$ is the index value of unit-year i , which lies in the unit interval. The index is a relative ranking computed on this sample: its level is not comparable across studies, and its weights would change with a different set of units.

4.5.2 Kernel density estimation

The evolution of the distribution is described by its kernel density, estimated with a Gaussian kernel and a Silverman bandwidth,

$$f(x) = [1 / (nh)] \sum_{i=1}^n K[(x - x_i) / h] \quad (7)$$

where $f(x)$ is the estimated density of the resilience index at value x , x_i is the value observed in unit-year i , h is the bandwidth, and $K(\cdot) = (1/\sqrt{2\pi})\exp(-u^2/2)$ is the Gaussian kernel. The dispersion of the same distribution is tracked by its coefficient of variation and Gini coefficient ^[42].

4.5.3 Spatial correlation

Two statistics are used. Global Moran's I measures whether units with similar resilience tend to lie near one another,

$$I = [n / \sum_i \sum_j w_{ij}] \times [\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})] / [\sum_i (x_i - \bar{x})^2] \quad (8)$$

and the local indicator of spatial association identifies, for each unit separately, the type of association that unit forms with its neighbours,

$$I_i = [(x_i - \bar{x}) / S^2] \sum_j w_{ij} (x_j - \bar{x}) \quad (9)$$

where n is the number of units, x_i and x_j are the resilience indices of units i and j , $\bar{x}$ is the sample mean, S^2 is the sample variance, and w_{ij} is the element of the row-standardised spatial weight matrix linking i and j . Because the analytic randomisation variance is unreliable with 13 units, inference uses a permutation test with 9,999 replications for the main series and 4,999 for the weight-matrix sensitivity, which is reported for $K = 2, 3$ and 4 nearest neighbours and for inverse-distance weights raised to the first and second powers, five specifications in all ^[43].

4.5.4 Decomposition of regional inequality

The Gini coefficient of the resilience index is

$$G = \sum_j \sum_h \sum_i \sum_r |y_{ji} - y_{hr}| / (2 n^2 \mu) \quad (10)$$

and is decomposed into three components,

$$G = G_w + G_{nb} + G_t \quad (11)$$

where y_{ji} is the resilience index of unit i in group j and the four sums run over the groups j and h and over the units i and r within them; n is the total number of units and n_j the number in group j , μ is the overall mean, G_w is the within-group component, G_{nb} is the between-group component, and G_t is the transvariation component, which measures the overlap of the two regional distributions ^[44].

4.5.5 Adaptive-cycle phases

Each unit-year is assigned to one of four phases using the level and the direction of potential. Potential is the resilience index standardised within year, so its zero point is the annual mean of the cross-section; direction is the within-unit change from the previous year. A unit above the annual mean whose potential is still rising is in conservation (K); one above the annual mean whose potential is falling is in release (Q); one below the annual mean whose potential is rising is in exploitation (r); and one below the annual

mean whose potential is not rising is in reorganisation (α). The classification is available for 130 of the 143 unit-years, the first year of each series having no predecessor. Connectedness, measured as the negative of fertiliser efficiency standardised within year, enters as a determinant of transitions rather than as part of the classification.

4.5.6 Drivers of resilience

The baseline specification is a two-way fixed-effects model,

$$\text{GPRI}_{it} = \alpha + \beta' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

where GPRI_{it} is the resilience index of unit i in year t , X_{it} is the vector of six drivers, α is a constant, β is the vector of coefficients to be estimated, μ_i is a unit fixed effect, λ_t a year fixed effect, and ε_{it} the idiosyncratic error. The model is estimated by the within transformation, with standard errors clustered by prefecture. The number of clusters ranges from 10 to 12 across specifications, because unit-years with a missing driver drop out and three units lose all of their observations; with so few clusters the asymptotic justification for clustering is weak, so we report cluster-robust p-values at full precision and treat conventional significance levels as indicative, and we check the main results against a first-difference specification in Section 6.

4.5.7 Threshold in grain specialisation

The threshold model allows the slope of the relationship to differ on either side of an unknown cut,

$$\text{GPRI}_{it} = \alpha + \beta_1 q_{it} \times 1(q_{it} \leq \gamma) + \beta_2 q_{it} \times 1(q_{it} > \gamma) + \mu_i + \lambda_t + \varepsilon_{it} \quad (13)$$

where q_{it} is the threshold variable, γ is the threshold value to be estimated, $1(\cdot)$ is the indicator function, and β_1 and β_2 are the slopes below and above the threshold. The threshold is estimated by least squares over a grid of candidate values,

$$\gamma = \text{argmin}_{\gamma} \text{SSR}(\gamma) \quad (14)$$

where $\text{SSR}(\gamma)$ is the residual sum of squares of Eq. (13) evaluated at the candidate threshold γ . The existence of a threshold, against the null of a single linear regime, is tested by a bootstrap of the likelihood-ratio statistic following Hansen ^[45].

Because the two regime regressors are constructed from the same variable, each candidate threshold is also evaluated with a specification test. The below-regime slope is re-estimated from a model that contains a level shift in place of the second slope,

$$\text{GPRI}_{it} = \alpha + \beta_1 q_{it} \times 1(q_{it} \leq \gamma) + \delta \times 1(q_{it} \leq \gamma) + \mu_i + \lambda_t + \varepsilon_{it} \quad (15)$$

where δ is the level shift between the two regimes. The below-regime slope is then estimated a third time, on the subsample of observations lying below the threshold, and a threshold is reported only when Eq. (13), Eq. (15) and that subsample estimate agree in sign and the two non-fragile estimates are significant at conventional levels.

5. Empirical Results

5.1 Descriptive statistics and the evolution of resilience

Grain production resilience averaged 0.304 across the sample with a standard deviation of 0.156, ranging from 0.083 to 0.716. The annual mean was flat between 2014 and 2020, moving within a band of 0.282 to 0.301, and then rose steadily from 0.306 in 2021 to 0.358 in 2024. The pattern is not one of continuous improvement but of a plateau followed by an acceleration, which means that the drivers present throughout the period cannot explain the change.

The distributional evidence sharpens this. The coefficient of variation fell from 0.599 in 2014 to 0.473 in 2024, and the Gini coefficient from 0.315 to 0.255. Skewness fell from 0.860 to 0.565, so the right tail compressed. Kernel density estimates show the mode shifting right while the left tail thins (Figure S2). Table 2 reports the descriptive statistics. Taken together, these statistics describe upward convergence: the low-resilience units gained faster than the high-resilience units, narrowing the gap without any unit falling behind in absolute terms. H1 is supported.

Table 2
Descriptive statistics, 143 unit-years (13 prefectures, 2014–2024).

Variable	N	Mean	SD	Min	Median	Max
Grain production resilience index	143	0.304	0.156	0.083	0.264	0.716
Absorptive capacity	143	0.353	0.212	0.000	0.350	0.939
Restorative capacity	143	0.231	0.169	0.000	0.176	0.750
Adaptive capacity	143	0.344	0.195	0.022	0.325	0.936
Grain yield (t per ha)	143	7.335	2.430	2.320	6.598	15.788
Mechanisation (kW per 1000 persons)	143	1177.229	615.148	80.737	1087.769	2415.270
Grain availability (t per 1000 persons)	143	819.870	692.848	11.420	668.428	3005.421
Grain land (ha per 1000 persons)	143	107.330	100.161	4.747	93.070	595.678
Fertiliser efficiency (t per t)	143	8.173	6.210	0.519	5.894	29.627
Rural income (yuan per person)	143	15720.678	5625.110	1252.000	16024.000	30836.000
Agricultural value added (yuan per person)	143	9781.605	6541.956	667.182	8652.212	32266.693
Log GDP per capita	132	10.816	0.666	9.104	11.030	11.996
Fiscal expenditure / GDP	143	0.528	0.523	0.103	0.315	2.737
Agricultural share of GDP	143	0.183	0.089	0.007	0.187	0.411
Mechanisation intensity (kW per ha)	143	22.522	34.350	4.044	12.573	199.808
Fertiliser intensity (t per ha)	143	1.827	2.067	0.308	0.989	9.633
Grain area share of sown land	121	0.576	0.243	0.114	0.534	0.984

5.2 The spatial pattern

The mean resilience of the northern units was 0.336 against 0.255 in the south, and the ranking was stable throughout the period. Tacheng (period-mean index 0.665), Bortala (0.449), Changji (0.432) and Ili (0.427) occupied the top four positions, all of them northern grain producers. Urumqi (0.109), Turpan (0.138), Hotan (0.143) and Hami (0.188) occupied the bottom four positions. The ordering is consistent

with the agronomic geography of the region: the northern belt has the better access to irrigation water and its cropland is less pressed by population (Fig. 2) ^[46].

Under the three-nearest-neighbour weights used as the default, global Moran's I moved from approximately zero in 2014 (0.022) to 0.236 in 2024, indicating increasing spatial clustering. The increase was not monotone: the statistic hovered around zero until 2018, rose sharply between 2019 and 2021 and then held that level, so what the series records is the emergence of clustering rather than its steady intensification. The result is sensitive to the weight matrix, however: with $K = 2$ the 2024 statistic is 0.449 ($p = 0.041$), while with $K = 4$ it is 0.105 ($p = 0.606$) and not significant. With 13 units and a sparse graph the global statistic has limited power, and we therefore treat the local pattern as the more informative evidence.

The local indicators are stable and interpretable. Ili, Bortala and Tacheng formed a high-high cluster in the north-west throughout the period, joined by Altay and, by 2024, by Aksu, whose irrigated districts lie on the same Tien Shan piedmont; the spatial cluster is therefore not identical to the administrative north-south division used in Sections 5.3, 5.4 and 5.8. Kizilsu, Hotan, Kashgar, Turpan and Hami form a low-low cluster in the south and east throughout (Fig. 3). The high-low outliers are Bayingolin and Changji, both large and productive units surrounded by lower-scoring neighbours. This is a core-periphery structure with a gap between the two clusters rather than a smooth gradient, and it did not close over the period. H2 is supported, with the caveat that the global statistic is not robust to the weight specification.

5.3 State persistence and regional inequality

The quartile transition matrix shows strong persistence and no leapfrogging. Diagonal probabilities are 0.912, 0.818, 0.774 and 0.875 for the first to fourth quartiles, respectively. No unit ever moved from the lowest to the third quartile, or from the highest to the second, in a single year. The ergodic distribution concentrates 70 per cent of the mass in the top two quartiles, implying that the long-run tendency of the system as currently parameterised is toward the upper half of the distribution, but the transition probabilities imply that this will take a long time.

The Dagum decomposition of the Gini coefficient, pooling the eleven years, attributes 52.6 per cent of overall inequality to differences within the northern and southern groups, 22.3 per cent to the difference between them, and 25.2 per cent to transvariation, that is, to overlap between the two regional distributions. The within-group share is the largest, and it is the north that drives it: the northern Gini is 0.309 against 0.164 in the south, and the gap between Tacheng and Hami is larger than the average gap between the two regional means. The north's own Gini coefficient, 0.309, is nearly twice the south's, 0.164. Over time the within-group component fell from 0.164 to 0.128 while the between-group component rose from 0.069 to 0.074 and transvariation fell from 0.083 to 0.053. The two regional distributions are therefore pulling apart even as each becomes internally more alike, which is a more precise statement of the convergence result than the aggregate Gini alone suggests ^[47].

5.4 Adaptive-cycle phases

Assigning unit-years to phases produces a clear regional contrast. In the north, 28 of the 80 classified unit-years are in conservation and 28 in exploitation, with 14 in release and 10 in reorganisation. In the south, 21 of the 50 classified unit-years are in exploitation and 15 in reorganisation, with 11 in conservation and only 3 in release. The northern grain belt spends most of its time in the upper half of the cycle, either accumulating capacity or holding it (Figure S3). The southern oases spend most of their time in the lower half, and a substantial share of that time in reorganisation, which is the phase that follows a release that has already happened.

Phase transitions are highly structured, and the diagonal dominates every row. Conservation is the most persistent state: 0.750 of transitions remain in it, 0.219 go to release and 0.031 to exploitation. Exploitation persists with probability 0.667, and its remaining transitions go almost entirely to reorganisation (0.289), with 0.022 to each of conservation and release. Release and reorganisation are the least persistent. From release, 0.529 of transitions go to conservation, 0.412 remain in release and 0.059 move to reorganisation, so a unit in release typically recovers to a high-potential state rather than continuing downward. From reorganisation, 0.565 return to exploitation, 0.348 remain and 0.087 go to conservation. Figure S4 shows the transition probabilities and the regional phase composition.

The most informative result concerns what precedes release. Units that enter release sit 1.13 standard deviations above the annual mean, against -0.17 for units that do not, a gap of 1.29 standard deviations ($t = 5.40$, $p < 0.001$). Part of that gap follows from the classification rule, since release is defined as being above the annual mean with falling potential; what is not mechanical is the magnitude, which is above one standard deviation rather than marginal. Connectedness, measured as input lock-in, does not predict release entry ($t = -1.45$, $p = 0.149$). The transition into release is therefore preceded by high accumulated potential rather than by high rigidity. This is consistent with the adaptive-cycle reading in which a system at the top of the conservation phase has the furthest to fall, and it cautions against interpreting a high resilience score as safety. Table S1 gives the full transition matrix.

5.5 A threshold in grain specialisation

The threshold search over the grain share of sown area, estimated on the 121 unit-years for which the share is directly observed, identifies a break at 0.660, with a 95 per cent confidence set of 0.599 to 0.686 and a bootstrap p-value for the existence of a threshold of 0.005. The break is a plateau rather than a unique point: the sum of squared residuals is identical for every candidate between 0.615 and 0.675, so the regime slopes and the subsample statistics below are invariant across that range (80 unit-years below the plateau and 41 above it), and we report 0.660 as a representative value inside it. What the data identify is therefore a plateau rather than a single cutoff: the relationship changes at some point between a grain share of 0.615 and one of 0.675, that is, at about two-thirds of sown land. Below the threshold the within-unit association between specialisation and resilience is positive and significant: $+0.115$ index points per unit (0–1) increase in the grain share, that is, about 0.012 points, or 7 per cent of a standard deviation of the index, for a ten-percentage-point increase, from the subsample estimate ($p = 0.003$),

against + 0.105 from the two-regime model and + 0.108 ($p = 0.013$) from the level-shift specification. Above the threshold the association is indistinguishable from zero: +0.007 in the subsample ($p = 0.941$) and + 0.177 in the two-regime model, which is not significant. The three specifications agree on the regime in which the effect exists, and that effect is the one the theory predicts.

The interpretation is a saturation threshold rather than a reversal. Below a grain share of about two-thirds of sown land, moving further toward grain raises resilience, because the production system is still building the capacity that grain specialisation supports: irrigation is used more efficiently, machinery is better matched to the crop, and the local institutions that handle grain – procurement, storage, extension – deepen. Above that level the marginal return disappears. Additional concentration adds connectedness, in the adaptive-cycle sense, without adding capacity. This is the plateau that precedes the conservation phase; it occurs at a specific, estimable level of specialisation (Fig. 4). H3 is supported.

5.6 Fertiliser intensity: a non-threshold

The same search applied to fertiliser intensity appears to identify a threshold at 0.597 tonnes per hectare with a bootstrap p -value of 0.003, and the two-regime model reports a positive slope of + 0.078 below the threshold and – 0.013 above it, which would be a textbook case of diminishing returns becoming negative. The result does not survive the specification test. When the below-regime slope is estimated with only a level shift and no second slope, it becomes – 0.020 with a p -value of 0.901. When it is estimated on the below-threshold subsample it becomes – 0.300 with a p -value of 0.029. The sign flips from positive to negative once the above-regime observations are prevented from contributing to the below-regime slope, and the two non-fragile estimates therefore disagree with the two-regime estimate. The apparent reversal is an artefact of the specification, not a property of the data.

The mechanism is a combination of two features of the design. First, the two regime regressors are two disjoint pieces of the same variable, and after the within transformation they are negatively correlated ($\rho = -0.301$), so each slope is identified partly off the other's variation. Second, the two-regime specification contains no separate level shift, so its below-regime slope also absorbs the level difference between the two regimes; once that difference is estimated separately, the slope is left to capture only the gradient within the below-regime observations and it turns negative. With 30 observations below the cut and 113 above, neither specification has much information with which to separate the two pieces, and the likelihood-ratio statistic cannot tell them apart. We report this because the two-regime threshold model is the standard tool in the grain-resilience literature and the failure mode is not obvious from the output: the model returns a significant likelihood-ratio statistic, a plausible threshold and coefficients of the expected signs, and the reported reversal is spurious.

What the data do support is a negative within-unit association between fertiliser intensity and resilience. In a single-slope specification on the 143 unit-years it is estimated at – 0.0154 ($p = 0.011$)^[48], and the above-threshold subsample gives a similar – 0.0141 ($p = 0.021$); the preferred specification of Section 5.7 puts it at – 0.0147 ($p = 0.138$). Units that raise fertiliser application relative to their grain area do not

gain resilience, and the point estimate suggests they lose it. This is consistent with the reasoning in Section 3.2: in a system already near the input frontier, additional purchased input buys yield at the cost of the economic buffer that would fund a change of course.

5.7 Driving mechanisms

The baseline two-way fixed-effects results are reported in Table 3. In the core specification with development and structure variables, log GDP per capita enters at + 0.087 ($p < 0.001$). Adding mechanisation leaves it essentially unchanged. Adding fertiliser intensity raises the within- R^2 from 0.161 to 0.450, and both technology variables become highly significant: mechanisation intensity enters at + 0.00105 ($p < 0.001$) and fertiliser intensity at - 0.0230 ($p < 0.001$). Adding the grain area share, which reduces the sample to 110 complete cases, gives the preferred specification with a within- R^2 of 0.540, in which log GDP per capita (+ 0.068, $p = 0.036$), mechanisation intensity (+ 0.00106, $p = 0.065$) and grain area share (+ 0.173, $p = 0.020$) are positive and fertiliser intensity is negative (- 0.0147, $p = 0.138$).

The economic reading of these coefficients is as follows. The coefficient on log GDP per capita is the largest in standardised terms: a one-standard-deviation increase in log GDP per capita is associated with a rise of about 0.045 index points, or 29 per cent of a standard deviation of resilience. The mechanism is straightforward. Higher income supports off-farm employment, which supplies the household-level buffer that allows a farm to absorb a bad year, and it supports the local fiscal base that funds irrigation maintenance. Mechanisation operates through a different channel: it substitutes capital for labour at the peak of the season, which is precisely when an arid grain system is most vulnerable to a shortage of hands ^[49]. The grain share operates through the deepening of the local grain economy described in Section 5.5. The negative fertiliser coefficient is the mirror image of the efficiency result: high application rates relative to the grain area are a marker of a system that has exhausted the yield response and is substituting purchased input for management.

Estimating the same specification separately for the three capacities clarifies where these effects act. Adaptive capacity is dominated by structure rather than technology: the agricultural share of GDP enters at + 1.159 ($p < 0.001$), fiscal expenditure at + 0.064 ($p < 0.001$) and log GDP per capita at + 0.087 ($p = 0.015$). For restorative capacity the largest coefficient is grain specialisation (+ 0.377, $p = 0.080$), which falls short of significance at the 5 per cent level. Absorptive capacity is associated weakly with log GDP per capita (+ 0.072, $p = 0.077$) and negatively with fiscal expenditure (- 0.024, $p = 0.095$). The pattern is coherent: the economic capacities respond to economic variables, and the resource capacity responds to land allocation. H4 is supported for log GDP per capita and grain specialisation; the mechanisation and fertiliser coefficients carry the predicted signs but are individually insignificant in the preferred specification ($p = 0.065$ and $p = 0.138$), and both are significant in the larger sample of 132 unit-years reported in the first three columns of Table 3.

Table 3

Two-way fixed-effects estimates of the drivers of grain production resilience. Standard errors clustered by prefecture in parentheses; significance is marked at the 1, 5 and 10 per cent levels with three, two and one asterisk respectively.

Variable	M1 core	M2 + technology	M3 + input intensity	M4 + structure
Log GDP per capita	0.08733*** (0.01676)	0.08663*** (0.01704)	0.07407** (0.02759)	0.06764** (0.02741)
Agricultural share of GDP	0.10546 (0.18563)	0.10709 (0.18793)	0.10969 (0.14151)	0.18450 (0.10981)
Fiscal expenditure / GDP	0.01917 (0.01338)	0.01901 (0.01353)	0.01007 (0.01367)	0.00517 (0.00817)
Mechanisation intensity		-0.00006 (0.00018)	0.00105*** (0.00020)	0.00106* (0.00051)
Fertiliser intensity			-0.02302*** (0.00446)	-0.01474 (0.00907)
Grain area share				0.17310** (0.06154)
N	132	132	132	110
Within R2	0.161	0.161	0.450	0.540
Prefectures (clusters)	12	12	12	10

5.8 Heterogeneity between north and south

When the drivers are interacted with a southern dummy, the only coefficient that differs significantly between the two halves is that of the grain share (-0.288 , $p = 0.031$). The interaction model therefore implies a southern grain-share slope of -0.112 , the sum of its main effect ($+0.176$, $p = 0.024$) and the interaction, which would make the positive association a northern phenomenon and leave it absent in the south. Estimating the two halves separately gives $+0.172$ ($p = 0.026$) in the north, where mechanisation also enters at $+0.0011$ ($p = 0.032$) and fertiliser at -0.017 ($p = 0.062$), but $+0.221$ ($SE = 0.249$) in the south, which is indistinguishable from both zero and the implied southern slope. The fiscal term in the south is indistinguishable from zero as well ($+0.0003$, $p = 0.979$). The southern split rests on three clusters, so we read the pooled interaction rather than the split sample. What the southern data do show is that the agricultural share of GDP dominates there, at $+0.299$ ($p = 0.009$), which is the same economic-capacity channel identified in Section 5.7 ^[50].

The asymmetry has a resource interpretation. In the north, the soils, the water and the institutional infrastructure support a grain-centred system, so concentrating land in grain converts into resilience. In the south, the same allocation does not, because the binding constraint is not the cropping pattern but the availability of water and the weakness of the local economy. Policies that treat specialisation as

universally resilience-enhancing would therefore misallocate effort in the south (Figure S5) ^[51]. H5 is supported.

5.9 The 2025 update

Grain output in 2025 was reported for 12 of the region's 14 divisions, Karamay and Hotan being the two without a figure. The twelve divisions with a published figure produced 18.6 million tonnes between them. The southern prefectures continued to expand: Kashgar produced 3.45 million tonnes, up 2.4 per cent on 2024, and Aksu 2.79 million tonnes. In the north, Ili's prefecture-direct area produced 4.13 million tonnes, Tacheng 2.98 million tonnes and Changji 1.55 million tonnes. The pattern of 2014–2024 is unchanged in the most recent year: the northern belt remains the region's grain base and the southern oases continue to expand grain area without closing the resilience gap, since the drivers that separate them — income, mechanisation and the economic buffer — move slowly.

6. Robustness Checks

6.1 Alternative index constructions

The baseline conclusions do not depend on the entropy weighting. Replacing the entropy weights with equal weights leaves the driver coefficients similar and, if anything, larger: log GDP per capita + 0.078 ($p = 0.004$), the agricultural share + 0.312 ($p = 0.001$) and the grain share + 0.101 ($p = 0.042$). Replacing the composite index with the first principal component of the seven standardised indicators, which explains 52.2 per cent of their variance, gives log GDP per capita + 0.127 ($p = 0.002$), the agricultural share + 0.444 ($p = 0.001$) and the grain share + 0.199 ($p = 0.017$). Mechanisation remains positive in both, at the 10 per cent level ($p = 0.057$ and $p = 0.094$). Table S2 collects the estimates and Figure S6 shows the full set of coefficients across specifications. Using the per-capita technology measures in place of the per-hectare intensities, the alternative described in Section 4.4, leaves the grain-share coefficient positive and significant (+ 0.125, $p = 0.004$); those two measures are themselves components of the index, however, so the exercise is partly mechanical and we do not rely on it. The negative fertiliser coefficient is smaller in magnitude and no longer significant in the equal-weight and principal-component specifications (-0.007 , $p = 0.271$ and -0.004 , $p = 0.691$), which is expected since both alter the relative weight of fertiliser efficiency within the index.

6.2 Sample and specification variation

Excluding Urumqi, which is an urban unit with a residual agricultural sector and the highest leverage in the sample, leaves the coefficients essentially unchanged (log GDP per capita + 0.070, $p = 0.046$; grain share + 0.183, $p = 0.016$). Excluding the pandemic years 2020–2022 raises the within- R^2 to 0.646 and increases the magnitudes of the technology coefficients: mechanisation + 0.0020 ($p = 0.014$) and fertiliser -0.0253 ($p = 0.025$). Lagging all regressors by one year preserves the coefficient on log GDP per capita (+ 0.094, $p = 0.007$) and attenuates the others, which is what one would expect if the drivers move slowly relative to the annual variation in resilience.

The first-difference specification, also reported in Table S2, is the most informative of the robustness checks because it removes any unit-specific level effect. It yields the agricultural share at + 0.234 ($p < 0.001$), mechanisation at + 0.0009 ($p = 0.001$), fertiliser at - 0.0164 ($p = 0.001$) and the grain share at + 0.182 ($p = 0.006$). The coefficient on log GDP per capita, which was the strongest in levels, becomes small and insignificant (+ 0.008, $p = 0.750$), suggesting that the income effect operates across units over the long run rather than within units from year to year.

6.3 Spatial inference

The sensitivity of global Moran's I to the weight matrix, reported in Section 5.2, deserves restating as a limitation rather than a result. Across five weight specifications the 2024 statistic ranges from 0.065 to 0.449, significant at the 5 per cent level only for the two-nearest-neighbour graph. The local cluster assignments, by contrast, are stable across specifications and across years, and the north–south gap in mean resilience, 0.336 against 0.255, widens slightly over the period. We therefore treat the spatial structure as established at the local level and unresolved at the global level.

6.4 Threshold robustness

The grain specialisation threshold is recovered wherever the subsample is large enough to identify it. Excluding Urumqi it is 0.661, in the north alone 0.651 and over 2014–2019 0.602, in each case with a positive below-regime slope (+ 0.102, + 0.075 and + 0.113, against + 0.105 for the full sample; the north-only estimate is the lowest of the three). It is not recovered in the southern subsample alone, where the search returns a much lower break at 0.363 with two positive regime slopes, nor over 2020–2024, where the break falls to 0.372 and the below-regime slope turns negative. Neither pattern is the saturation relationship the theory describes, so we treat the threshold as unidentified in those two cases rather than as evidence against it. The instability after 2020 is consistent with Section 5.1, where resilience began rising only from 2021: a threshold estimated on a period in which the dependent variable is trending will be poorly identified. Table 4 reports the estimates and the specification test for both variables. We report the threshold as a feature of the northern grain system over the full period, not as a universal constant.

Table 4

Threshold estimates and the specification-fragility test. A threshold is reported only where the two-regime, level-shift and subsample estimates agree. For the grain share the break is identified over a plateau rather than at a unique point, so the representative estimate is given with the plateau in parentheses and the confidence set is the union over search grids.

Threshold estimate	Grain area share	Fertiliser intensity
	0.660 (0.615–0.675)	0.597
95% confidence set	0.599–0.686	0.597–0.649
Observations below / above	80 / 41	30 / 113
Two-regime slope, below	+ 0.1054	+ 0.0784
Two-regime slope, above	+ 0.1765	-0.0132
Level-shift slope, below	+ 0.1080 (p = 0.013)	-0.0204 (p = 0.901)
Subsample slope, below	+ 0.1145 (p = 0.003)	-0.3002 (p = 0.029)
Subsample slope, above	+ 0.0073 (p = 0.941)	-0.0141 (p = 0.021)
Bootstrap p (no threshold)	0.0050	0.0025
Verdict	credible	artefact of collinearity

7. Discussion

7.1 Comparison with the literature

The upward convergence we document is not what the persistent spatial clustering reported for Chinese grain production would predict, and it rests on the thinning of the low tail rather than on any change in the cluster structure. The provincial-scale evidence found positive spatial correlation and spillovers; we find the same direction of spatial association but much weaker global significance, which is expected given that our panel contains 13 units rather than 31 and that we are estimating within a single region where the between-unit heterogeneity in climate and institutions is smaller. The substantive difference is that their provincial sample mixes regions with and without binding water constraints, so the spatial correlation they detect partly reflects the spatial clustering of the water constraint itself. Within Xinjiang the constraint is common to all units, and what remains is the finer gradient we describe.

The principal contrast is with the county-level evidence, which found positive effects of yield per unit area, the multiple cropping index, mechanisation, informatisation and agricultural investment. Our mechanisation result agrees. Our income result agrees with the development channel that this literature emphasises. Where we depart is on input intensity: their specification does not separate the yield effect of inputs from the resilience effect, and our within-unit estimates suggest these have opposite signs. A

county can raise output per hectare through fertiliser and lose resilience in the process, and an index that does not weight the economic buffer independently will not capture this.

The saturation threshold in specialisation speaks to the debate about efficiency and resilience in food systems. The argument in the food-systems literature is that the global food system has traded redundancy for efficiency. Our result locates the trade-off at a specific margin — land allocation between grain and other crops — and estimates the point at which it binds. Below a grain share of about two-thirds, specialisation and resilience are complements, because the system is still building the institutions and infrastructure that grain production requires. Above it they become unrelated. The finding that the relationship flattens rather than reverses is important for policy: it means that a system at the plateau is not in immediate danger, but that further specialisation should not be justified on resilience grounds.

The result that release is preceded by high accumulated potential rather than by high rigidity is a partial departure from the emphasis in the resilience literature on the conservation phase as the dangerous one. High potential does predict release, which is consistent with that reading. But our measure of connectedness — input lock-in measured by fertiliser efficiency — does not add explanatory power. Two interpretations are available. The first is that our connectedness proxy is too narrow: fertiliser dependence is one of several forms of lock-in, and a measure that included water-source dependence or crop-pattern concentration might perform better. The second is that in this system the connectedness that matters has already been absorbed into potential, so that the two are observationally hard to separate with 143 observations. Both point to the same conclusion: the distinction between potential and connectedness is theoretically important but empirically difficult to operationalise in short panels, and this is a limitation of the present study rather than a refutation of the theory.

7.2 Methodological implication

The failure of the two-regime threshold model on fertiliser intensity is worth generalising. The model is standard in the grain-resilience literature and produces plausible output when it fails. The failure is not detectable from the likelihood-ratio statistic, which was 26.7 with a bootstrap p-value of 0.003, nor from the sign pattern, which matched the prior. It is detectable only by re-estimating the regime slope in a specification that does not let the other regime's observations contribute to it. Our recommendation is that any threshold result from this class of model in a short panel be accompanied by that check, since the specification is otherwise easy to accept on the basis of plausible-looking output. The check is inexpensive to run and, in our case, it changed the conclusion.

A second methodological point concerns the spatial statistics. With 13 units, the global Moran's I has an effective sample size too small for the asymptotic variance to be meaningful, and the statistic varies by a factor of seven across the five weight matrices considered. Reporting a single value and a p-value would have been misleading. Reporting the range, as we do, is more informative and would strengthen the reporting of studies that apply this tool to small panels.

7.3 Policy implications

Three implications follow for the region studied, and they generalise with care to other arid grain systems.

First, the binding constraint is not the level of inputs. Fertiliser is being applied at rates that no longer raise resilience: the within-unit association is negative, though imprecisely estimated in the preferred specification. The policy lever is therefore not additional input subsidy but the efficiency with which existing inputs are converted into output, which argues for extension on timing and placement rather than on quantity ^[52].

Second, specialisation policy should be regime-aware. In the northern grain belt, where the resource base supports grain, concentrating land in grain still pays in resilience terms. In the southern oases the pooled interaction suggests that it does not, and the same policy applied there would add rigidity without adding capacity. The southern priority is the economic buffer – income diversification, off-farm employment and fiscal expenditure relative to GDP – which is what the adaptive capacity dimension responds to in the pooled sample ^[53].

Third, the southern oases are already spending a substantial share of their time in the reorganisation phase. This is not a description of a system in decline; reorganisation is where novelty is generated. But it does mean that interventions designed for a mature grain system will be poorly matched to the southern reality, and that the southern question is not how to protect an existing production structure but how to build one that fits the water that will be available ^[54].

8. Conclusion and Policy Implications

8.1 Conclusions

This paper set out to determine whether grain production resilience in an arid region accumulates without limit or reaches a point at which additional effort stops building it. This paper uses a manually compiled panel of 13 prefecture-level divisions of Xinjiang over 2014–2024, organised around the three capacities of the adaptive cycle. Four findings emerge.

Resilience rose and the distribution converged upward. The annual mean index rose from 0.294 in 2014 to 0.358 in 2024, the coefficient of variation fell by 21 per cent and the Gini coefficient from 0.315 to 0.255. The northern grain belt remained a persistent high-high spatial cluster and the southern oases a persistent low-low cluster, with a gap that did not close; the Dagum decomposition shows the within-region component accounting for 52.6 per cent of inequality and the between-region component for 22.3 per cent, with the two regional distributions diverging even as each became internally more alike.

A robust saturation threshold exists in grain specialisation, at a grain share of about two-thirds of sown land. Below it, a ten-percentage-point increase in the grain share raises resilience by about 0.012 index points, or 7 per cent of a standard deviation; above it the association is indistinguishable from zero. No

comparable threshold exists in fertiliser intensity, and the sign reversal that the standard two-regime model reports is an artefact of the specification rather than a property of the data.

The two halves of the region differ in the mechanism that matters most. In the north, resilience responds to mechanisation and grain specialisation; in the south, where the estimates rest on few clusters and should be read as descriptive, it responds to the agricultural share of GDP, while the fiscal term there is indistinguishable from zero. The transition into the release phase is predicted by high accumulated potential rather than by input lock-in, which means that the highest-scoring units are the most exposed to release.

8.2 Policy implications

For regional policy, the results argue for replacing a uniform grain-expansion target with a differentiated one. The northern belt can continue to specialise; the southern oases should be supported to diversify income and to raise fiscal expenditure relative to GDP, because those are the variables to which adaptive capacity responds. Input subsidies should be evaluated on efficiency rather than on volume, since the within-unit evidence points to a negative association between application intensity and resilience, although the preferred estimate of it is imprecise.

For the national grain-security framework, the more general implication is that resilience and capacity are not the same objective and can diverge. A region can hit its output target while losing the buffer that protects the target. Monitoring that tracks output alone will not detect the divergence, which argues for including a resilience measure of the kind developed here in the regular statistical assessment of grain-producing regions.

8.3 Limitations and future research

Four limitations should be stated plainly. The sample is 13 units, which limits the power of the clustered inference and the reliability of the global spatial statistics; the local results are the more reliable. The resilience index is a relative ranking instrument computed on this sample, so its level is not comparable across studies and its weights would change with a different unit set. The connectedness measure is a single proxy for input lock-in and does not capture water-source dependence or institutional rigidity, which are likely to matter in this setting. Finally, the 2025 data are available only for grain output and area, so the most recent year could not be incorporated into the index.

Three extensions follow. The index could be extended to county level, which would raise the number of units by an order of magnitude and would permit both credible spatial inference and a properly powered threshold analysis. Water-source dependence could be incorporated as a second measure of connectedness using the allocation records of the irrigation districts, which would allow the rigidity-trap hypothesis to be tested with the variable the theory specifies. And the reorganisation phase in the southern oases could be studied directly, since the question of what a viable grain system looks like under a reduced water allocation is one the region will have to answer within the next decade.

Declarations

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Author Contribution

B.T. designed the study, compiled the panel from the primary statistical sources, carried out the statistical analysis and drafted the manuscript. X.L. supervised the study, contributed to the analytical design and the interpretation of the results, and revised the manuscript. Both authors read and approved the final manuscript.

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The authors thank the statistical bureaux of the prefectures of Xinjiang for publishing the annual communiqués on which the panel is built.

Data Availability

The dataset analysed here was compiled by the authors, because no open database publishes a consistent prefecture-level series for these variables in Xinjiang. It covers 14 prefecture-level divisions over 2014–2025 and was assembled from the annual statistical communiqués of each division, the published tables of the Xinjiang Statistical Yearbook and the regional water resources bulletins. Every accepted observation is recorded together with the document it came from and the verbatim sentence it was taken from, so the compilation can be audited cell by cell. The compiled panel, the resilience index and its three capacities, the analysis dataset joining the index to the drivers, the entropy weights, the spatial weight specifications, the phase classification and the threshold estimates are provided as Supplementary Data. The cell-level provenance record is included in the same deposit. The primary sources are public documents: the annual statistical communiqués of the 14 divisions for 2014–2025, the published tables of the Xinjiang Statistical Yearbook, and the regional water resources bulletins; the 2025 bulletins were obtained from each division's statistical bureau, from the official Aksu bulletin and from the regional statistical office. Karamay is excluded from the analysis because its bulletins do not publish a grain output series. The data that support the findings of this study are available from the corresponding author on reasonable request.

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Figures

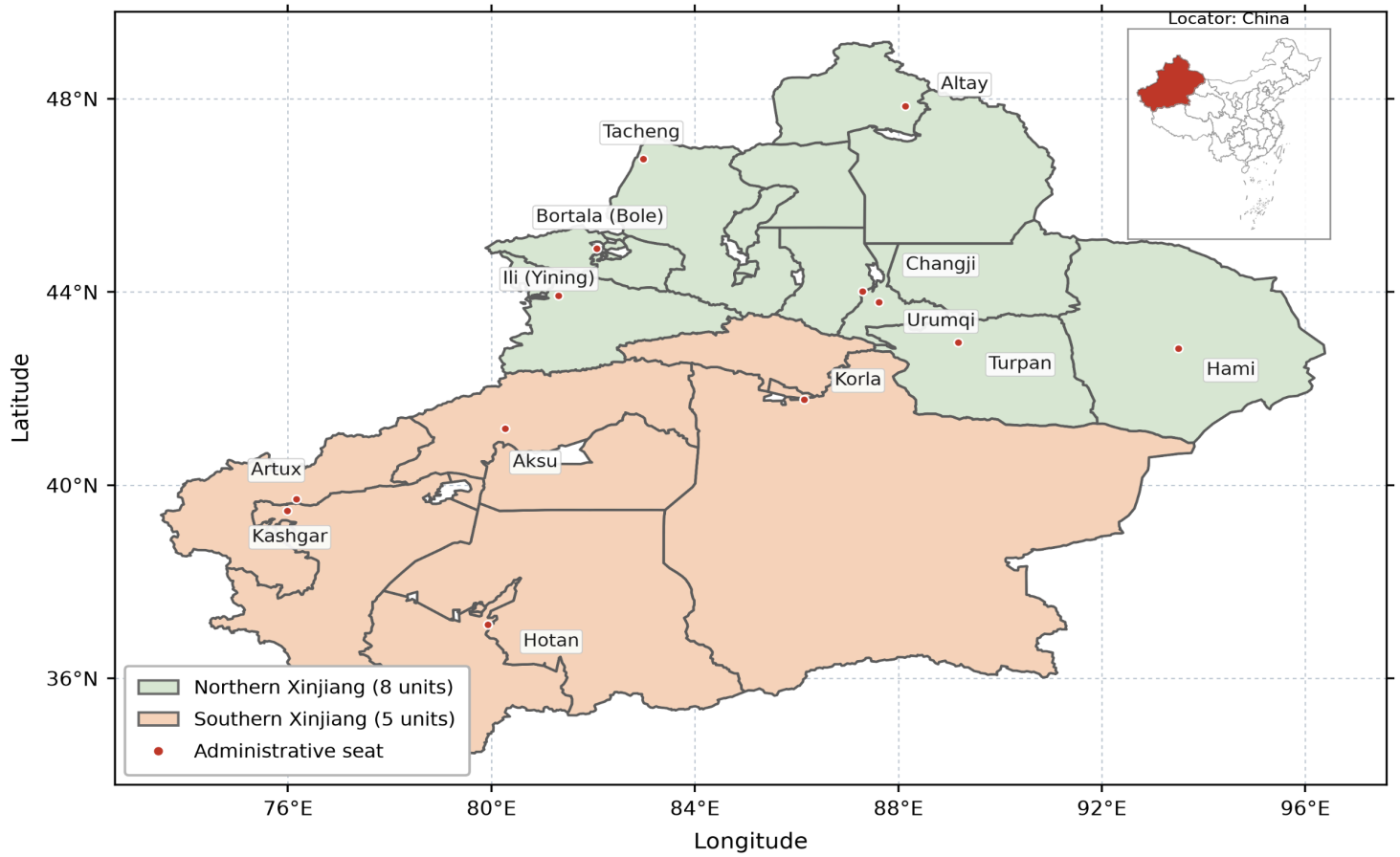


Figure 1

The study area. Green: northern and eastern divisions. Orange: southern divisions. Boundaries from the DataV administrative boundary service.

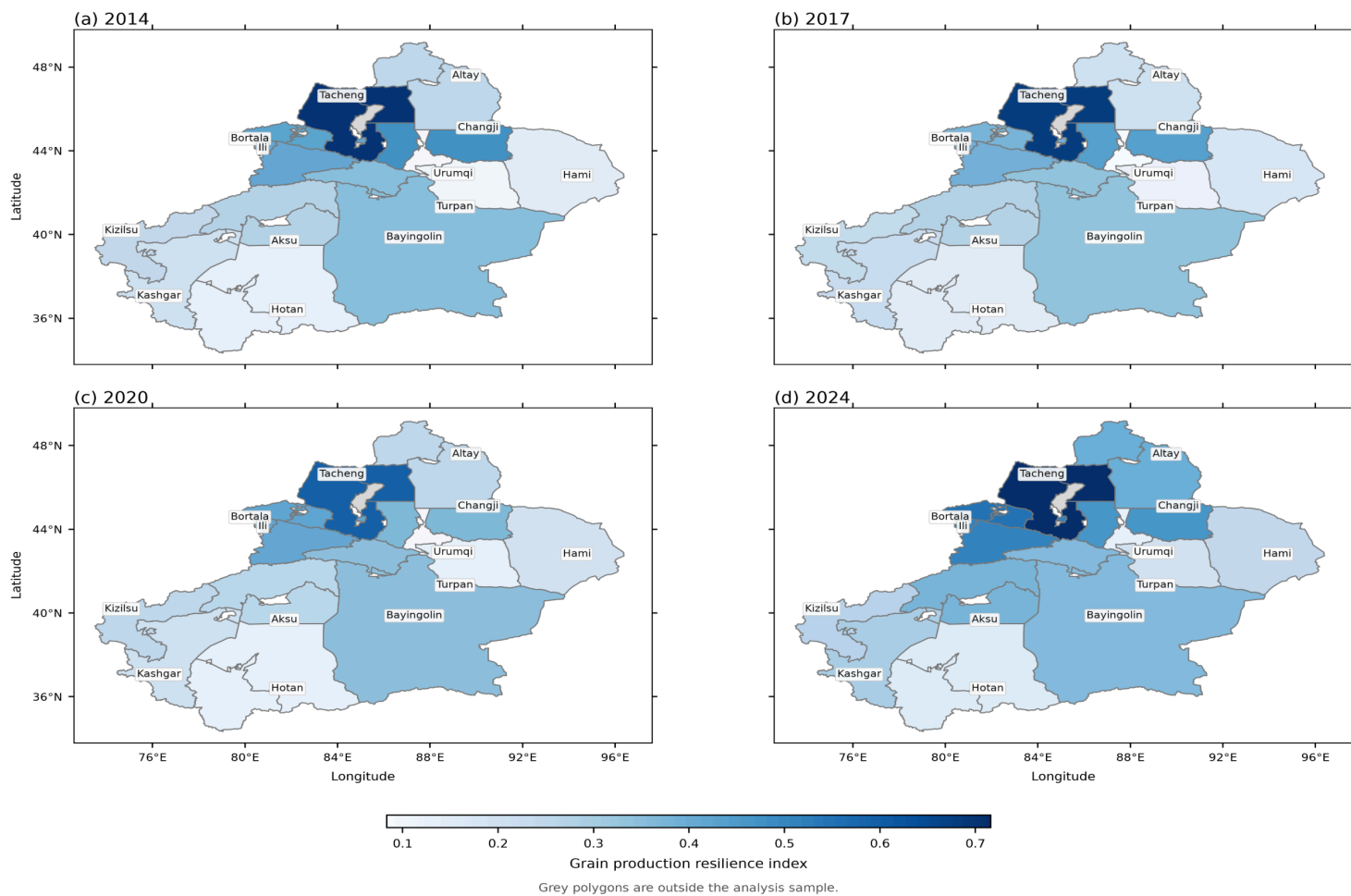


Figure 2

Spatiotemporal evolution of the grain production resilience index, 2014–2024.

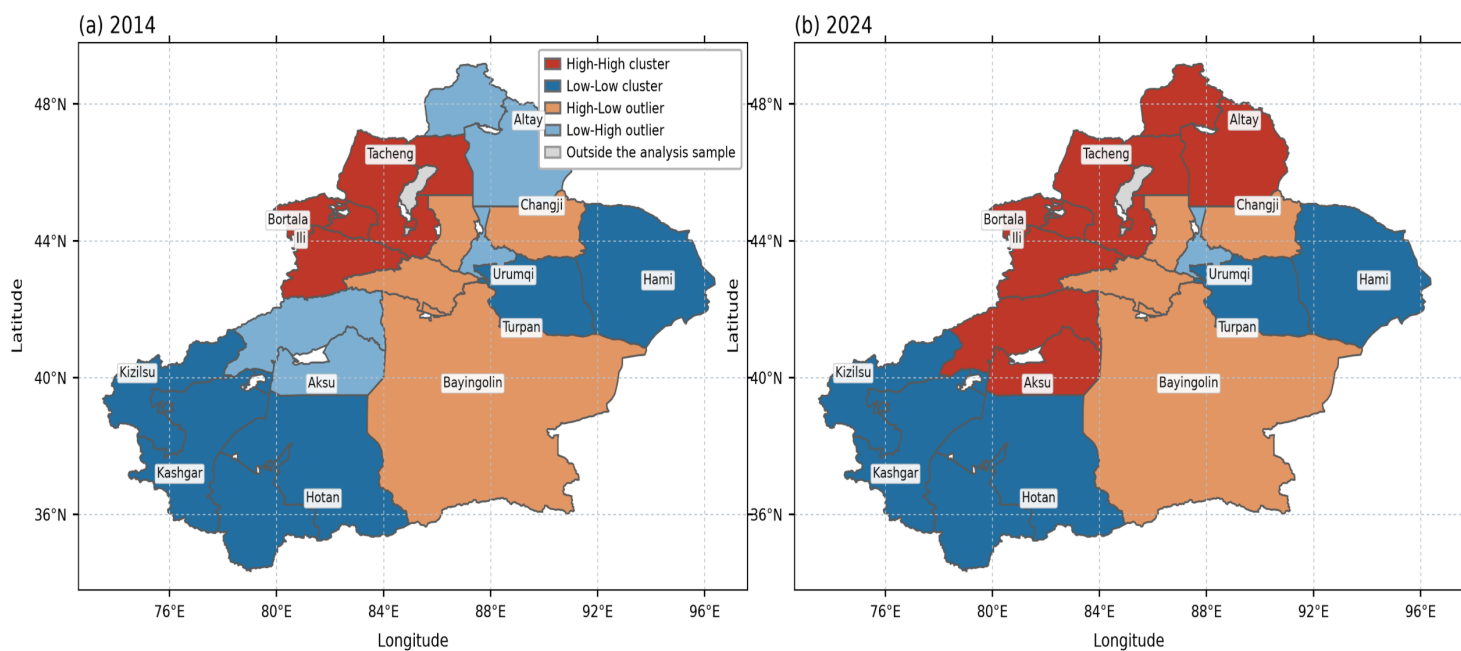


Figure 3

Local indicators of spatial association, 2014 and 2024.

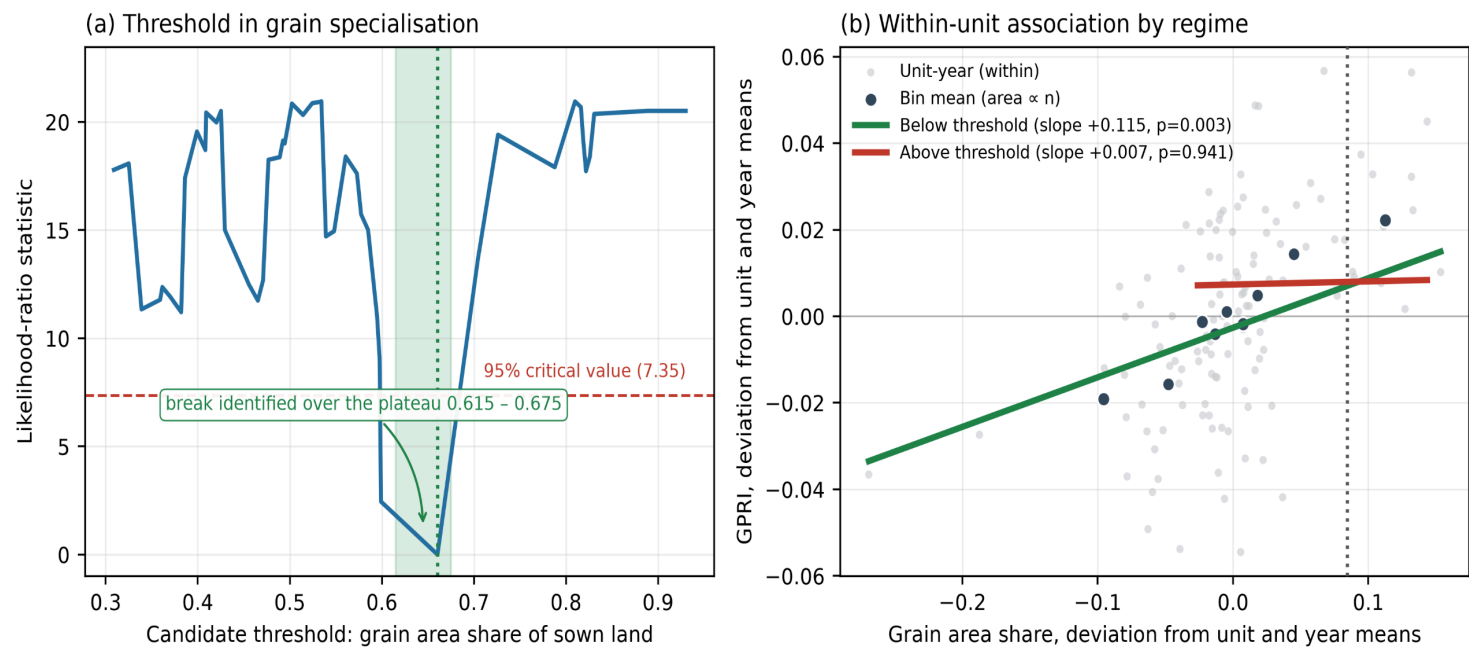


Figure 4

Threshold in grain specialisation. Panel (a) is the likelihood-ratio profile, with the plateau over which the break is identified shaded; panel (b) is a binned within-unit scatter, with the lines drawn at the estimated subsample slopes.