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VOLATILITY BY INPUTS AND WEATHER ON SUSTAINABLE APPLE YIELD IN KASHMIR

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ABSTRACT

An Increase in weather risk is generally associated with increases in apple production risk. We consider weather-induced changes in the variation in apple output as a systemic risk in Kashmir. Relative weather and input impacts have been established on regional output volatility. For this reason, we have designed a development component with developing weather variables. Only in some places will rising instability be related to weather shifts. For climate effect analysis, models of only weather variables provide skewed yet fair approximations.

Keywords: yield, apple, variability; risk; weather

INTRODUCTION

For years, environmental, social and economic debates have been open to climate change and its effects on horticulture development. This isn't unexpected because the weather influences the yields and the variability of crops/fruits which are of concern on a macro-level for food safety purposes (Brown, Wheeler *et al.,* 2015). The product at micro-level are also remarkable, as a low intensity of annual crop yields decreases income risk and leads to the stabilisation of the smallholding returns, which in turn may be of macro relevance in guaranteeing resilient food production. Therefore, deeper knowledge of what influences productivity unevenness in the major yield producing regions is necessary. It also helps growers adjust their orchard strategy to famous challenges and leads to a decrease in production shortages or better crisis management. Undisputedly long-term weather trends are shifting crop conditions and may have influenced crop yield variability already (Siebert and Ewert, 2012) and is recognised as a primary yield hazard of the mainly efficiently valuable crops (IPCC, 2014). There is evidence that extreme weather conditions in both temperate and tropical areas should happen more regularly and seriously in the future (IPCC, 2014). This would likely make growing fruits susceptible, with major impacts latently, especially in less developed regions, on crop yields and food security. Growers can influence inputs such as fertilizers, but cannot control the weather or impact developments on industry, soil or environmental policy. Weather for the farmers is exogenous and impacts crop yields directly. Furthermore, there are secondary consequences including input changes. As a result of the meteorological situation, weed development, pests, and diseases, for example, generally vary inputs through the production cycle. But how far does the overall risk of output really lye with changing weather? Climate is the major driver in horticultural production risks?

In this paper, we took apples as one of the most valuable cash crops, where there has been a significant upward trend in both yield levels and volatility. Our investigation focuses on Kashmir, which generates 71% of India's apple production. Kashmir apple yields rose from 7.1 to 10.1 metric tonnes ha^{-1} between 1990/91 and 2016/17. In Kashmir, real and nominal apple output volatility has increased in the 1990s despite a protracted era of relative yield stability in the 20th century. Especially alarming is the growing trend in relative yield heterogeneity, i.e. a higher risk-to-mean yield ratio.

In light of this, the research questions that will guide our study are mentioned as follows: How can rising relative productivity heterogeneity be explained? Can one believe that the debate of climate change has risen primarily as a result of changes in meteorological conditions, as measured by relative yield fluctuations?

This rise has many other causes. First, growers could modify their inputs due to changing prices for intruding and production (Miao *et al.,* 2016). Since 2005, growers in Kashmir have been experienced to very drastic improvements in the orchard practices. Various reforms have increased apple's relative competitiveness, by reducing price hold, subsidies and compulsory landfills. The impact on the input intensities and thus the yield of crops may have also led to improvements in the virtual productivity (Banse *et al.,* 2008). In general, these policy reforms may have encouraged growers to use lower (marginal) land for manure production, which may potentially have detrimental repercussions on average yield levels and increase variability. Plantings plants with a lower water potential on marginal soils could become more vulnerable than more suitable soils to drastic temperature and precipitation changes (Perkins, 2015). In addition, productivity can be considered soil yield and specialisation effects (Yang *et al.,* 1992). Partial consolidation activities in the horticulture sector in Kashmir (increased orchard sizes), considering the increasing pattern of marginal land cultivation with apple, could increase average returns per hectare. Although various studies consider how weather and plant yields interact with variance dependent on regression models (Chen *et al.,* 2004), few researchers, for example (Lobell, 2007) or the relation between weather and relative yield fluctuations of non-experimental yields (Ray *et al.,* 2015). However, these authors do not consider changes in the inputs that cause stability. As far as we know, causes of yield uncertainty have not been dissociated from the core temperature and input generators to the present day. In this research we try to fill this void with a case study for apples in Kashmir and demonstrate this theory. Although we test the climate variables on harvest yields by means of time series regressions (Iglesias and Quiroga 2007), we are applying a panel data approach. In order to measure when and how the atmosphere and input risking in some areas of India have improved over time, we are using the benefits of the panel layout. In our method, we deduce from (Osborne and Wheeler, 2013) and demonstrate that inputs as well as weather are essential to understand yields and relatively variable results. Our analysis helps to discuss whether inputs are essential for the evaluation of the effect on cereal yields of climate change. In addition, it could be useful for potential adaptation tasks to consider how the weather conditions currently observe relative output variability. There are two key stages to our methodological study. First we establish an analytical model that is consistent with the approach to output functions of relative yield variability. We analyse crucial inputs, test appropriate functional kinds, and augment this feature with a plethora of weather factors that handle phenology development. Second, we dissect the relevance of this regression model in order to disentangle the weather-driven relative yield variability in connection to others' approaches caused by feedback or regulation. We propose a substitute model that leaves significant inputs to enhance our understanding of whether to monitor input changes when referring to weather and yield. The assumption that the latter may be subject to omitted variables, shows no significant qualitative variations, while there are quantitative differences.

The philosophical structure and the associated literature are first developed and then followed by an analytical approach for the breakdown of crop volatility drivers after presenting the results. After this, we will write and debate and eventually conclude our findings.

Framework concept and associated literature

Numerous papers deal with weather influences on yield levels through both process simulation models, or through regression techniques (Muller and Robertson, 2014). The latter approach has two primary strands and is embedded in (Oury, 1965). First, a number of investigations in a regression model have to do with return and weather (Butler and Huybers, 2015). The weather effects are studied in the second strand within an input and input production feature system. This models handle exogenously the temperature, however, inputs which have to be changed to modify weather. For example, fertiliser strength is affected by precipitation levels. The temperature instead effects the growth season duration and hence leads to output levels, but never modifies the input mix shortly. There are still criticisms of the second strand in the literature, whereas the first set of models still tacitly acknowledges the reason to leave data. With improvements to the input balance in the short run, industrial roles frequently struggle to accomplish long-term climate change adjustments, for example modifying crop alternation or interchange land uses (Mendelsohn *et al.,* 1994; Deschênes and Greenstone, 2007). Hypothesizing yield as an input and weather feature could lead to a partial parameter approximation of (Kaufmann and Snell, 1997; Miao, 2016) etc., neglecting a category in estimation of the other group's effect. Given this argument, curiously, a few recent papers integrate information or take other economic considerations into account in the weather impact research (Schlenker and Lobell, 2010; Lobell *et al.,* 2011; Blanc, 2012 or Ward *et al.,* 2014). In this regard, also large land effects have been demonstrated to influence pricing (Chen *et al.,* 2004). Therefore, we rely on an approach to main inputs' output functions.

However, it remains a challenge to distort the influence of environment and input on crop production and volatility (You *et al.,* 2009). Technically, in the production functions system, a range of methods exist that measure weather impacts. We describe three main choices: weather variables collection, weather data aggregation thresholds and the practical type that determines the weather and weather performance relations. The structural part of the weather risk can be separated at the district level with aggregate data due to "averaged" peculiar shocks at a greater aggregation level (Woodard and Garcia, 2008). The downside of database loss is, on the other hand, the use of aggregated statistics. Environmental effects are frequently analysed at lower levels as they focus on location-specific consequences of climate change. We also believe that statistically better and more versatile solutions exist for modelling weather or yield structural risks (Gaupp *et al.,* 2016; Xu *et al.,* 2010). However, our strategy is to unravel the basic driving force behind apple production, apart from the temperature, materials, policies and macroeconomic shocks. As such, we incorporate perspectives from studies into risk and growth, livestock and climate impacts.

MATERIAL AND METHODS

The variables described in production function are weather and phenology measures. The data has been extracted from Dept. of Statistics and Meteorological Department J&K. The relevant explanation of data and material method is presented in the following paragraphs.

Production function for apple

For the years 1990-2015, we are analysing Kashmir. We use accounting data from the Statistics Directorate of the Kashmir Government to define output functions at regional levels.

Development mechanism is provided with one output (apple output) and eight inputs: money, labour, apple groves, electricity, and materials, seed/plant spending. We sum up fertiliser and plant protection in material inputs. The entire area utilised by orchard should, with the exception of property, labour and animal features, be deflated by national market values, with the exception of fallow and set-aside land.

Apple plants are known to have a positive specialisation and scale impact or adverse marginal soil yield effect (Kaufmann and Snell, 1997; Yang et al, 1992). On average, some 20 apple trees are planted by sample orchard of 1 Kanal. There have been significant historical variations between north and south Kashmir in the horticultural system (e.g. scale, hierarchical structure and ownership of technologies). For this reason, we employ a dummy variable. In order to capture policy and other macroeconomic effects, such the price surge in 2008-2012, we take into account time-dummy elements.

Phenological stages and weather phases

The yearly data are combined with periodic weather measurements from the J&K Department of Meteorology. For all J&K areas (Table 1) we can distinguish four macro-phenological periods and thus summarise all weather conditions accordingly. Day temperatures, however, exceed optimum heat levels and limit apple outputs. The opportunity for crop growth is largely caused by temperatures and sun radiation. To achieve these outcomes, the ambient temperature is split between temperatures below and above an optimal temperature of 15^0C which does not allow any rising circumstances. As a result, days with temperatures below the optimum, but over the minimum of 35^0C are recorded as increasing grade days. On the other side temperature above 25^0C contributes to heat stress and is summarised as destroying grading days for each phonological cycle.

The availability of horticultural water in the form of evapotranspiration is calculated by precipitation and by atmospheric requirements. We consider the probable evapotranspiration to properly take into account water availability.

The marginal effects of increased supply of water depend on current levels and can alter the signals. In other words, if real water supplies are below the optimal level, precipitation will have a beneficial effect on plant development. In the case of higher water supplies than optimal plants, precipitation will, on the other hand, prevent plant growth. Although the phenological times combine our environmental factors, the dry spells are not taken into consideration by the single volume of precipitation. Therefore, days without precipitation (DWP) are often considered to capture precipitation distributions.

Econometric strategy

The two steps that guide our study are explained in this section.

Table 1 Phenological periods

Period	Stage
1	initial flowering
2	pollinated bud heading
3	heading early ripening
4	early ripening harvest product

Empirical model apple yield variability in Kashmir

From the point of view of the economist, variable and almost fixed inputs seem relevant to remember. But economic theory has little to say about functional types, correlations between input and weather (Coelli *et al.,* 2005). Our model construction and selection method is therefore dependent on Greene's analytical technique for selecting variables aiming to find a fitting model resilient against misspecification (Roberts *et al.,* 2013).

Given the comparatively limited period available to us, we need to analyse a wealth of variables and concentrate on the important information. For example, at all phonological intervals, the selection of potentially ideal weather variables and the maximum probability of inputs is 12 and 6 respectively. Quadratic terminology, connectivity, weather and functional shape combinations are not included.

We are primarily working towards the identification of an adequate operational type for the manufacturing feature relating to production, district i apple yield at period t and inputs, indicated by X_{jit} where j lists resources, labour, land for apples, oil, materials, seedling and manures. Secondly, the required performance and weather feature must be determined for each agronomic phase.

For two components, apple returns are considered at approximated growth rates instead of the absolute returns at log differences. First of all, the apple output log ratio represents a proportionate change over time. Second, from a statistical point of view, the study of first disparities provides benefits. In view of the optimistic data patterns, the first variations in trends in contrast with believing a deterministic pattern are more flexible (Brown, 2013). Additionally, possible root unit problems are generally solved by first distinction (Chen *et al.,* 2004). In addition, initial distinctions remove unnoticed variability effects that are likely to arise in panel data and minimise serial association issues where data are continuous (Wooldridge, 2009). The downside is that, on the basis of the Justice and Papal approach to development, the influence of, for example, weather or technical transition on yield and variation is not quantified at the same time as the proposal of (Chen *et al.,* 2004). Log variations however also allow one to consider in the constants, but not explicitly, the influence of technology improvements, the consequences of ordinary productivity shifts. Many difficulties, including technological advancements, are constantly tested by the influence of CO_2 fertilisation as well as variations in output. (Mc.Carl and Attavanich, 2014).

Table 2

	Mean	sd	Min	Max
Apple yield (100boxes/ kanal)	69.81	9.23	28.28	88.5
Per Orchard Variables				
Land apple (ha)	65.4	60.7	8.8	180.7
Land apple north (ha)	126.8	47.1	46.5	180.7
Land apple south (ha)	121.6	42.8	8.8	66.6
Total land (ha)	228.4	196.8	36.9	766.3
Total land north (ha)	248.3	74.7	96.9	366.3
Total land south (ha)	271.3	81.5	106.9	435.6
Capital (Rs ha^{-1})	173.7	72.5	97.8	309
Labour (Rs ha^{-1})	251.3	95.1	46.5	404.6
Energy (Rs ha^{-1})	141.3	33.8	96.4	270.9
Material (Rs ha^{-1})	319	68	173.9	617.4
Seedling/saplings (Rs ha^{-1})	83.5	29.2	41.9	176.3
Manure (livestock units ha^{-1})	0.4	0.2	0.1	0.9
Weather variables				
Pot. evapo-transpiration stage	133.3	15.2	103.1	180.6
Prec. Stage 1	413.4	76.3	219.6	576.6
Prec. Stage 1 north	413	78.7	227.2	562.3
Prec. Stage 1 south	413.7	75	219.6	576.6
GDD Stage	324.7	33.5	213	422.3
Solar heat stage	60.2	6.5	37.7	77.1
Prec. Stage 2	74.5	20.8	26	117.2
KDD Stage 3	11.1	7.1	0.6	27.2
Prec. Stage 4	96	29.4	42.8	177.9
Prec. Stage 4 north	97.3	30.9	42.8	176.3
Prec. Stage 4 south	95.1	28.3	50.4	177.9

Source: Handbook of horticulture J&K Govt. and Dept. of Metrology J&K Govt.

The apple yield ratios that have been recorded are therefore described in three parts: first the production function with the inputs, $f(X_{jit})$ in which j shows the inputs, then the weather function, and $g(X_{kit})$ (each aggregated to four phenological sub-periods and counted as different variables).

Thirdly, the number of new regulations indexed by s, and the yearly impact of policy changes, economic shifts, prices and other shocks in common across India is isolated. These dummy variables catch other surprises, including stochastic national technical shifts that vary from linear patterns that are not eliminated by initial separation. Econometrically, the annual dummy variables are also significant, as typical transversal dependency which prevail when such stimulus are not handled.

Our empirical approach is based on a rich data collection and we remove possible time-continuous sources of confusion by first differentiating by the exploitation of the data structure.

The time dummy variable capture simultaneous shifts in the input mix, depending on the predicted performance fluctuations common to all districts. The preferences are captured by the vector land as long as these contribute to land adaptations. Marginal feedback results are often assessed depending on temperature variations found. Therefore, if the temperature observed impacts the yield difference, the estimated parameters are accounted for.

However, forecasts of future yield increase in one or more federal states may trigger material input adjustments including fertilisers in the season. As these questions are generally unnoticed, the error term can also be misunderstood on some inputs on our models. However, since about 25% of the overall farm management costs are already incurred after seeding and can be modified in accordance with early growth season forecasting, we argue that in our circumstances, the magnitude of such a concurrent bias lies within a reasonable range. Furthermore, in robustness tests we solve this issue by evaluating the instrumental variables.
The base function is given by:

$$\Delta \log(y_{it}) = \Delta f(x_{jit}) + \Delta g(x_{kit}) + \Delta h(x_{st}, x_{sit}) + \Delta \varepsilon_{it}$$

Where $\dot{\varepsilon}_{it}$ denotes the error terms and symbol Δ indicates the first-difference. We function in log-difference data as a dependent variable and in the first few variations, all explanatory variables.

In principle, we evaluate four models with the same dependent variable but functional differences between $f(X_{jit})$ and $g(X_{kit})$ and the variables and interactions included. This is the overall premise of basic modelling (Greene, 2012), although the following principles keep a sensible amount of parameters.

Next, the two considered functions of output $f(X_{jit})$. This includes the transcendental (translog), and the quadratic functions with the complete range of interactions (AIC). We push linear conditions into the model, while the weather in phase 1 is left to the mistake.

First, the transcendental (translog) and quadratcliptic functions, comprising the whole set of interactions, are both termed production functions $F(X_{jit})$, and are simplified reverse and reverse to minimise Akaike information criterion (AIC). We require the model to have linear terms whereas in step 1 the weather is left to the wrong term. The second thing to be said is that they all are combined with possibly optimal weather factors: GDD, precipitation, solar radiation, potential Haude evapotranspiration in all four phases and KDD in stages 3 and 4. In two variations, logs and levels, the weather feature $g(X_{kit})$ is provided. Thus, there are four possible compounds: weather in logs or levels, and weather in logs or levels. The weather is quadratic. - The weather variables explain these models phenologically. We use a reverse and forward method to reduce the AIC in selecting the corresponding weather variables in their respective phenological level.

When quadratic factors were considered relevant, weather variables in linear terms would be pushed into the model. The remaining weather parameters DWP, maximum temperature and evapotranspiration are examined and only kept by improvement of the AIC.

Third, the four models that arise are generalised in the following way. If a model has solely quadrant terms and interactions, linear terms are once again introduced. Further control variables are checked, as well as a complete series of yearly dummy variables. Moreover, we are blamed for the valley flood in 2014. Since extreme values, especially weather variables, can affect the estimates, we communicate with dummy year 2014 for those districts that are most affected by the flood.

Fourth, the Davidson-MacKinnon J tests continue to pick from these non-test models when all other functional form defects (RESET passed) can be omitted. As we did not convince these results, we chose the lowest AIC model.

Over all, log level definition, an approach widely used in functional econometrics, such as (Wooldridge, 2009) and climate effect analysis (Lobell *et al.,* 2011), tends to match in with input information. In other words, the returns and the atmosphere are logarithmically modelled. Finally, four more temperature factors, which are statistically minor, are removed at the conclusion of this process. While we have put more emphasis on economic efficiency, the findings were robust for inclusion.

Eq. (1) with f(.); g(.) and h(.) defined as follows indicating the final model, designated as model 1,

$$f(x_{ijt}) = \sum_{i=1}^{7} \beta_j x_{jit} + \frac{1}{2}\beta_{ij}(x_{jit})^2 + \beta_{12}(x_{1it}x_{2it}) + \beta_{13}(x_{1it}x_{3it}) + \beta_{24}(x_{2it}x_{4it}) + \beta_{35}(x_{3it}x_{5it}) - - - (1)$$

All X_{jit} inputs remain in the final model definition, save from services. Capital X_{1it} appears in contact with laboratory X_{2it} and seedling X_{3it}, while energy X_{4it} and manure X_{5it} seedling appear. The X_{6it} and X_{7it} symbols indicate the input material and the apple land. In the spirit of a translog production function, seven meteorological variables in logarithmic terms enter the model:

$$g(x_{kit}) = \sum_{k=1}^{7} \beta_k \log(x_{kit}) + \beta_{11}\frac{1}{2}\log(x_{it})^2$$

$$+ \sum_{k=2}^{3} [\beta_{k2} \log(\mathrm{x_{kit}})\,\mathrm{North_i} + \frac{1}{2}\beta_{k3}\frac{1}{2}\log(x_{kit})^2\, South_i] - - - (2)$$

X_{1it}: phase 2, X_{2it}: stage 2, X_{3it}: precipitation phase 4, both interacting with the south Kashmir variable, X_{4it}: possible evapotranspiration phase 1, X_{5it}: stage 2 GDD, X_{6it}: stage 2, X_{7it}: phase 3 KDD.

$$h(x_{st}, x_{sit}) = \sum_{s=1}^{13} \beta_s x_{st} + \beta_{61}(x_6 flood_i) + \beta_{14}x_{14it} - - - (3)$$

The following are the yearly dummy variables X_1 through X_{13} for the years 1990-2008. For the districts affected by the flood in 2014, the dummy variable flood is set to 1.

Given these interaction terminology, all variables are considered in a mean-centric manner except for yields and dummy variables, which means that each observation is standardised with its respective average sample. The table Info allows for the initial removal of unexplained heterogeneity effects and then calculation of all models using OLS (Greene, 2012).

In the calculation of the effects of materials inputs, we employ the instrumental variable (IV) evaluation procedure as a robustness assessment, in which the second lagging material discrepancy is used as instruments. We introduce another model that leaves output variables close to address the possibility of omitted variables (Miao *et al.,* 2016). All Eq.(2) inputs are deleted to describe model 2 in Eq. (1). We assume that the search for determining the same weather variables will have been chosen.

To study the input and weather effects on the volatility of yield

Type 1 extends beyond RESET, hence we suppose that Type 1 can be linearly separated by parameters. This is necessary if the variability of the apple yield in the second stage is to decompose in an unequal and uniform manner. In general, there are two methods to calculating variability in crop yield: absolute or relative. For example, (Chen *et al.,* 2004) refer to an absolute metric. These writers depend on a reasonable and fair development strategy to the weather influences and their comprehensive analysis on average yield and variation. However, these models have to be dependent variable, where the first difference to ensure the stability of our output findings is essential, without first differentiation.

Moreover, absolute behaviour is motivated by absolute return shifts, which could lead, if optimistic developments continue, to apparently greater risk (Finger, 2010). Therefore, the weather-induced difference in apple yields similar in the region, across the years, is based on relative risk indicators. For example, a standard time difference between recorded returns may be determined across a succession of time return levels, particularly volatility (Ray *et al.,* 2015).

In this second stage we extract and analyse the variability of weather-defined output, similar to (Osborne and Wheeler, 2013). Through incorporating inputs and a broader variety of weather variables and reviewing others' geographic datasets, we improve the approach of these writers. We distinguish the weather explained component of the yield from the stated element from (Ray *et al.,* 2015). Furthermore, our calculation of volatility specifically applies to the variations in yields caused by the atmosphere, although (Ray *et al.,* 2015), in absolute words, "explicitly explained the yield variability of the atmosphere" measures are not independent.

The weather causes relative changes $\widehat{y_{it}^{a}}$ to be determined as a result of the changes in weather after Eq. The fitted initial differences in log outputs in the regression model (Eq.(1)) (3). The inputs are assessed on their own (null because in a medium form) and other controls are not added, such as year-dummy variables:

$$\widehat{y_{it}^{a}} = \Delta\widehat{\log(y_{it})} = \Delta\widehat{g(x_{kit})}.$$

The fitted series is used for extraction of volatility-induced in weather $\widehat{V_i^a}$ oscillation for each District, i= 1-------n using the standard deviation over $\widehat{y_{it}^{a}}$:

$$\widehat{V_i^a} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left[\widehat{y_{it}^{a}} = \widehat{y_i^{a}}\right]^2} --- (4)$$

with year t = 1; . . . ; T; T = 7 and mean

$$\overline{\widehat{y_i^{a}}} = \frac{1}{T}\sum_{t=1}^{T}\widehat{y_{it}^{a}}$$

We split the survey into two sub-periods: 1990-2002 and 2003-2016 to capture weather-induced risk changes over time. We use this method in order to compare the changes in weather-related fluctuations and the changes induced by the inputs accordingly. We measure variance based on fitted values for additional comparisons that allow all inputs and weather to adjust without any checks and yearly dummy variables.

RESULTS AND DISCUSSION

First we are concerned with the consequences and robustness controls of the performance function computation and, secondly, we analyse the weather and input volatility estimates.

The figures for two models are provided in Table 3. While Model 1 corresponds to the whole model, Model 2 focuses on the discourse between the excluded variables. There are all levels of input. Semi-elasticities can be observed then, while meteorological variables are put in logs. The Davidson and MacKinnon J-testing and AIC values imply that Model 1 is greater than a log-log model.

Production function inputs

Our preference of scalable functionality is based on the vast number of statistically relevant terms of interaction. Positive linear and negative quadratic effects are evident from energy and material supply, but energy only in the significant quadratic term. In other words, material inputs have a beneficial effect, with marginal productivity reduction. A 10% rise (about 90 Rs per hectare) is based on the average sample size and results in positive return increases of approximately 1.7%. With the non-linear relationship, yields will already decline by 1.06 percent after a 30 percent (approximately Rs 270) rise.

Seminars have a negative quadratic coefficient between linear and positive. This means that a drop in seedling will result in increased yields, starting from the mean sample, while rises will lead initially to decreases but then rise again. This effect may be derived in monetary terms from the variable concept. Reducing seedling will increase yields, but low seed densities demand almost ideal conditions for water supply and other inputs. The negative spectrum may be explained by horticultural relationships. The late seeding requires a greater seed input per hectare to finish the development of a population. In contrast, too crowded communities might minimise outputs.

Two virtually fixed inputs, capital and labour, have positive linear and quadratic impacts on yield growth rate but negative impacts on labour interactions and seedling. We notice depressing quadratic expressions for labour linearly and positively. In other words, if the sample means deviates from labour, the yield rate assessed on the medium of samples would be increased. However, these figures can be viewed in view of the measurable trend in data to decrease the total capital and labour production per hectare beginning in 2002. For the disengagement of relationships between capital and labour we use capital as a moderator, following the concept of clear paths in two-way encounters.

We find that a decrease of job supply has an unfavourable effect on the changes in yield, while additional labour units at a low level of capital contribute certainly to the apple yield growth rate. For high levels of capitals the effect of replacement is less visible. Based on the average labour level, the positive influence of reducing labour input is greater. This means that resource efficiency could be increased by reducing labour in high-capital output processes.

The impact is negligible for soils planted with apples. This could be due to two adverse consequences. Next, there is an improvement in return in the land planted with apple due to specialisation and scale impact. Secondly, in the course of time, more marginal land will be used to cultivate fruit, incentivized, for example by increasing apple prices.

Moreover, this area may be more vulnerable to weather changes and therefore we will expect a detrimental impact on apple yields from a greater proportion of marginal soil. While the first influence may be particularly significant for north Kashmir, for the south part the second effect may be more appropriate.

Since 2002, time dummy variable is important; all variables are negative. In other words, the apple growth rate drops for these years as opposed to shifts between 1990. This result may be explained by shifts in the relative competitiveness of apple. These coefficients may also absorb typical yield swings, also likely as a function of the weather or other common macroeconomic shocks. For example, we cannot recognise the direct effects of technological transition, nor disengage the influence of CO_2, as seen by (Attavanich and McCarl, 2014) on yield variability. Due to flutter time and the heat wave, the apple growth rates in the respective districts of Kashmir State are significantly negatively impacted.

Weather

In the plant's first early step of growth (sowing / end of tillering), major positive impacts are noted from precipitation and possible evapotranspiration (ETP_{TI}): a 10% rise in ETP_{TI} results in a 4.3% increase.

A sufficient water supply improves biomass Farm yield capacity assessment, output (Chmielewski and Köhn, 2000; Roberts *et al.,* 2013) also find that a vapour tension deficiency is a beneficial result, a major component of the evapotranspiration scale. For the South Kashmir nomenclature of linear and quadratic precipitation, known for low water soil conditions at phase 1, we discover negative coefficient values. In the first step of phenology, the prevalent soil situation in South Kashmir may pose a problem of nutrient leaching at higher precipitation levels. This might hinder future yields. For stage four, the adverse effects of precipitation (early ripening/harvesting)

Table 3 Input and weather effects for relative variability in apple output in J&K, 1990-2015

	1. Final Specification	2. Drop inputs
Intercept	0.272 (0.0116)***	0.0543 (0.0258)***
Inputs		
Capital	0.073 (0.0492)	
Labor	- 0.514 (0.193)	
Energy	0.123 (0.0982)	
Material inputs	0.091 (.0305)***	
Seedling	-0.1223 (0.0645)***	
Manure	-59.540 (8.946)	
Land apple	-0.173 (0.612)*	
Capital squared	0.532 (0.0028)***	
Labor squared	0.264 (.0243)*	
Energy squared	-0.0082 (0.043)***	
Material inputs squared	-0.0151 (.0042)***	
Seedling squared	0.0149 (0.011)***	
Capital*labour	-0.0375 (0.0016)**	
Capital*seed-ling	-0.0089 (0.0032)**	
Labor*energy	0.0632 (0.0024)***	
Seedling*ma-nure	7.281 (0.1897)*	
Weather		
Prec. Stage 1	0.05 (0.142)***	0.032 (0.021)*
Prec. Stage 2* north	-0.187 (0.214)***	-0.261 (0.0861)**
Prec. Stage 1 squared*north	-0.87 (0.432)**	-0.65 (0.344)***
Pot. evapotrans-piration stage 1	0.443 (0.154)***	0.312 (0.098)**
Growing degree days stage 2	0.164 (0.327)**	0.212 (0.074)*
Solar radiation stage 2	-0.041 (0.002)***	-0.562 (0.073)**
Solar radiation stage 2 squared	0.541 (0.141)**	0.254 (0.312)***
Prec. Stage 2	-0.019 (0.007)***	0.014 (0.009)*
Killing degree days stage 3	-0.183 (0.032)***	-0.0128 (.003)**
Prec. Stage 4	-0.039 (0.034)**	-0.431 (0.042)***
Prec. Stage 4*north	0.823 (0.621)**	0.0972 (0.0615)***

Continue...

Prec. Stage 4 squared*north	0.424 (0.78)***	0.621 (0.101)**
Controls		
Year 2002	-0.833 (0.001)**	-0.754 (0.004)***
Flood 2014	-0.089 (0.011)***	-0.417 (0.014)*
R^2	0.83	0.74
Adj. R^2	0.77	0.69

Note: Dependent variable: first logged apple yield disparities. Logs are weather, levels are input. Coefficients/ standard deviations multiplied by 100 for inputs. First differentiated explanatory variables; mean focused on weather/inputs. Robust standard errors in spatial and serial correlation ( ) Point: potential; prec.: rainfall.
*p < 0.1
**p < 0.05.
***p < 0.01.

are predicted to result in additional water shortages in later ripening crops. Since early maturation is part of the fourth cycle, in which the water shortage is very likely to increase yields in north Kashmir relative to other areas.

We find negative effects of precipitation and positive effects for GDD for the second stage. In other words, lower temperatures have a positive impact on apple growth and therefore on output. Solar radiation has a positive non-linear effect due to improved photosynthesis (Roberts *et al.,* 2013). However, a growing supply of water in this developmental stage is hindering progress, as the negative coefficient suggests. This finding shows that average water supply is almost optimal. In the third stage (heading/early maturation), we see major temperature impacts: DDK has a detrimental influence on production in compliance with current studies (Roberts *et al.,* 2013). However, these results remain limited: from the mean sample, an improvement in KDD by one standard deviation will result in a 1.8 percent yield loss. Despite taking into account regional KDD, the heat wave for the Jammu region has another important impact. Our findings show the significance of spatial-temporal distribution and its reliance on soil conditions, along with the various effects of precipitation in North and South Kashmir during two phenologic phases.

In short, all weather consequences can be derived and are consistent with earlier agronomic-theoretical explanations. The sophistication of yield formation reflects our component collection and phenological data aggregation.

Decomposing apple yield volatility

In order to answer the problem of the shift across areas and over time and to determine its causes, we dissect the standard deviation of the apple growth rates.

The inputs clarify about 49% of the overall real apple yield fluctuations, over time and regions; while weather accounts for 43%. The volatility of apple yield rises as real volatilities are compared over time for sub-periods. The north portion of Kashmir is at risk in terms of temperature and inputs.

We use state-level provincial aggregated returns. Spatially uncorrelated risks are unlike company-level statistics, which mean that unusual 'self-diversifying' shocks, although there are more structural variations in their overall range (Woodard and Garcia, 2008; Marra and Schurle, 1994) Therefore, State-level weather driven uncertainty can be seen in terms of structural weather risk measurement in horticultural development (Xu *et al.,* 2010). The instability caused by weather varies marginally by area in the north part with increased volatility. In comparison with the volatility generated by input modifications, we see higher input-induced volatility in comparison to the volatility traced to weather shift in the entire north area and in some south sections. Over time, the real uncertainty is rising, on average. This can only be due to mutual temperature and input increases in some areas. Whilst increases in fluctuations caused by temperature and feedback in other regions display opposite signals. Nevertheless, the rise in real fluctuations cannot be attributed solely to changes in weather and input. For the first time in comparison with the second cycle, we see an increased share of explained real fluctuations. However, it is clarified that nearly 76 percent of the real variance was 25 percent between 2002 and 2014. Input and weather from 1996-2002 accounted for 72% of real fluctuations in all continents. This finding will be partially accountable by the inclusion of time stupid variables in regression models, segregated from volatility input and meteorology, but of particular importance to the second cycle. We therefore possibly underestimate the weather influence, as ordinary time dummy variables grab typical weather shocks. We also explored whether the multiple geographical areas in the districts impact the findings in order to ensure robustness, but we do not. At state level, weather induced variance remains very low as the shifts due to weather conditions are assumed to be higher. In other words, we believe that our model cannot only trace systematic danger to weather (regional temperature, solar radiation, precipitation and evapotranspiration) also macro level typical shocks are important. The above involve severe weather conditions, but also improvements in policies and price, as well as input modifications for several farms. The substantial yearly dumb variables after 2002 capture macroeconomic and policy shifts precisely. But above all, in contrast to the entire model, the unexplained component is bigger. Therefore, the explanation of the traditional shocks would be too much attention. This will overestimate the systemic macro danger. However, input adaptations, which are just fair adaptations by producers, are not at the same time addressed at all as future effects of cost and policy shocks.

CONCLUSION

We see all inputs and weather shifts in relative yields in line with output economy. The instability of the decomposition of apple returns exposes weather-induced instabilities at regional levels. If the study is divided into two sub-periods, there is actual uncertainty over time when macro level disruptions such as serious weather lead. In other places, however, only those rises are attributed to the weather-induced part and the part impacted by changes in the input mix. In many locations, weather variance decreases with time as well.

The seasonal forecasting of weather-related likely crop shortages could increase given the phenological weakness of yield at the regional level. Better understanding of the likelihood of returns will also allow growers to change their orchard management to better deal with the risk of downturns.

Apple-yield susceptibility may also be of benefit to the design of insurance and model of weather conditions risk at the area phenological level. When our methodology breaks down climate and input effects on apple productivity and averages dense shocks, it may be helpful for insurers to boost the assessment of insurance claims. For insurance, only weather induced damages can be compensated. In addition, a more economical accounting of weather losses will increase the systemic risk of insurance undertakings. The insurer and the insured will benefit from this.

Appendix

A.1. Weather Variable Choices

The selection of weather variables, summation levels of weather data and the functional form expressing the input-output and the weather-yield connections are three decisions crucial for adding weather into the production function.

The bulk of the weather variables use temperature and precipitation, however slightly, as well as radiation and evapotranspiration. Soil moisture capture variables are not often used since this often needs spatially precise data (Bakker *et al.,* 2005). Recent research highlight VPD as a significant yield-determining variable (Lobell *et al.,* 2014; Roberts *et al.,* 2013). However, VPD does not cover the water holding capacity of the soil and, in circumstances when water supply is sufficient, might thus imply dry conditions. In the literature we examined its minor difference across time and space, but it was not possible to quantify the effects of atmospheric CO_2 concentration in econometric models (Finger and Schmid, 2008) except with rare exceptions (Blanc, 2012).

As aggregate data at multiple phenological phases indicate, agronomic knowledge increases evidence of weater impacts on yield/variability, albeit data needs are considerable (Dixon *et al.,* 1994). In order to study adaptation opportunities on farms, for example, (Butler and Huybers, 2015) or (Ortiz-Bobea and Just, 2013) incorporates phenological phases while examining the influence of the weather on the maize output.

While these studies emphasize temporal aggregation, spatial aggregation has been analyzed in greater detail by (Garcia *et al.,* 1987).

A continuous study area, in particular in production literature, is to find the correct functional form representing the input/output connection (Coelli *et al.,* 2005, Griffin *et al.,* 1987). A proper functional form is in fact vital, because faults because of the malformation of the functional form are of the same magnitude as the neglected variable faults. Usually used functional forms are Cobb-Douglas, linear or quadratic with linear weather additives. Other forms are rarely taken into consideration, especially those which account for non-linear weather influences; (Odening *et al.,* 2007; Schlenker and Roberts, 2009; Lobell *et al.,* 2014).

A.2. Explanation Of Terms

Days without precipitation (DWP)

$$DWP_p = \sum_{d=1}^{D} dwp_d = \begin{cases} 1, if\ PREC_d = 1 \\ 0, if\ PREC_d > 0 \end{cases}$$

with PRECd denoting the daily precipitation level and subscript d denoting a day within a phenological period p as defined in the paper.

Growing degree days (GDD)

$$GDD_p = \Sigma_{d=1}^{D} gdd_d = \begin{cases} Temp_{opt} - Temp_{min}\ if\ Temp_{avg'd} > Temp_{opt} \\ Temp_{avg'd} - Temp_{min}\ if\ Temp_{min} < Temp_{avg'd} \leq Temp_{opt} \text{with Temp}_{opt} = 20\_C \text{ and} \\ 0, if\ Temp_{avg'd} \leq Temp_{min} \end{cases}$$

$Temp_{min} = 4^0C$. All temperatures refer to the daily average temperature ($Temp_{avg;d}$).

Killing degree days (KDD)

$$KDD_p = \Sigma_{d=1}^{D} kdd_d = \begin{cases} Temp_{avg'd} - Temp_{opt}\ if\ Temp_{avg'd} > Temp_{opt} \\ 0\ if\ Temp_{avg'd} \leq Temp_{opt} \end{cases}$$

The Haude potential evapotranspiration (ETPH) was computed using the vapour pressure deficit product (VPD) and the Haude factor fH, the empirical correction factor (Haude, 1955). For the fH, we utilised the wheat factors (Schrodter, 1985). VPD_d was calculated using the Magnus formula (Sonntag, 1990) with the maximum ($Temp_{max,d}$) and the minimum temperature ($Temp_{min,d}$) instead of the dew point temperature (Castellvi *et al.,* 1996; 1997).

Temperature normalized solar radiation: Similar as

Gornott and Wechsung (2016, p. 92).

$$SRT_p = \sum_{d=1}^{D} \frac{SR_d}{Temp_{avg,d} + 20}$$

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