Where honesty and hard work is the only stable strategy: Design, evolution and pilot implementation of a support cum reward game in developmental economics.

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Abstract: We describe here the design, evolution and experimental implementation of a real life, game theory based system for supporting farmers suffering heavy crop damage by wild herbivores near protected areas. The system is community operated in which farmers self-report their produce, which is endorsed by neighbouring farmers. The average deficit in the productivity is compensated by an automated "support cum reward (SuR)" computation, which is directly proportional to the average productivity deficit of the group but also directly proportional to the individual farmer's produce. As a result, farmers are assured a 'support' against the average damage but at the same time a 'reward' for individual's productivity. The design of the game is such that only honest reporting gives maximum returns. An under-reporting farmer receives reduced benefit since the SuR amount is directly proportionate to his self-reported produce. If a farmer over-reports, other farmers of the community suffer a loss since the average deficit reduces. Therefore the endorsing farmers, for their own selfish interest, prevent over-reporting. The system involves multiple game situations, the combined result of which is expected to be a stable honest and hard worker strategy. A trial implementation with a group of 71 farmers over 6 cropping seasons showed that, after a few initial attempts to cheat, honesty prevailed in the entire group; the average crop productivity increased up to 2.5 fold, in spite of the risk of damage, owing to spontaneous increase in inputs by farmers. Apart from wildlife conflict resolution the model offers a promising alternative to crop insurance and a potential behavioural green revolution.

Crop damage by wild herbivores is a major human wildlife conflict issue in the Indian subcontinent where a high human density and agricultural economy coexists with many wildlife reserves teaming with herbivore populations. Compared to carnivore conflict, herbivore conflict is less appreciated but its economic and social impact is orders of magnitude more serious than the carnivore conflict (Fungo 2011, Karanth et al 2013, Manral et al 2016, Bayani et al 2016). In our study area, namely the western boundary of the Tadoba Andhari Tiger Reserve, Maharashtra, India, earlier studies (Bayani et al 2016) have shown that farmers lose on an average 50 % of the crop to wild herbivores in spite of active guarding day and night. In India, law enables compensation to the affected farmers but many studies reveal that the procedure for implementing the law is highly inefficient (karanth et al 2018, Johnson MF et al 2018) and therefore has failed to mitigate the problem. Our prior study revealed that faced with the risk of damage, farmers are reluctant to spend more money towards crop intensification (Watve et al 2016a, b). This loss of productivity owing to partial disinvestment is greater than the actual damage inflicted by animals. Such indirect losses are also not covered by the current compensation law and there is a need for a better alternative to support farmers along the forest-agriculture interface.

The existing compensation law requires verification of damage claim by every individual farmer by a set of government officials, assessment of damage by visual inspection and then payment of compensation after a set of bureaucratic procedures. In contrast, we describe here an alternative to compensation which arose through a combination of design and evolution, in the form of a community operated system for data collection, reliable assessment of average damage and providing assurance to farmers along with a reward for higher productivity in spite of the risk of damage. The entire system is operated by the farmer community with little, if any requirement of government personnel. The farmers collect their own data, determine the average damage, upload the data in an automated system and get the due payment. However, the system is designed in such a way that only honest collection of data gives maximum benefits to farmers. The system can be described in the form of an *N* person game, in which honesty turns out to be the only stable strategy. We describe here the theoretical solutions of the game as well as observed behaviour of farmers in a pilot scale implementation over three years. The experiment shows that honesty along with hard work is the only stable strategy for farmers to usurp maximum benefits from the game.

The evolution and stability of cooperation, when there is a possible benefit to cheating, is a long standing conundrum. A variety of strategies to arrest cheating or defection have been suggested including direct and indirect reciprocity (Trivers 1971, Axelrod and Hamilton 1981, Nowak and Sigmond 1998, Gintis 2000, Panchanathan and Boyd 2003, Panchanathan and Boyd 2004, Bowles and Gintis 2002, 2006), policing and punishment (Boyd and Richerson 1992, Henrich and Boyd 2001, Fehr and Gachter 2002, Fehr et al 2002, Boyd et al 2003, Gardner and West 2004, Fowler 2005, Henrich et al 2006, Nakamaru and Iwasa 2006, Hauert et al 2007), rewards for punishing (Kendal et al 2006), reputation (Milinski et al 2002), gossiping and blackmailing (Watve et al 2011) and counterproductive refinement of cheating strategies (Eldakar et al 2007, 2008, Dahanukar and Watve 2009) which work with context specific outcomes. Most of these models use prisoner's dilemma (PD) as the paradigm. However, there are many other games of interest. Relatively little attention has been given to the question whether the game itself might evolve or be designed to make it immune to cheating. Real life social systems are likely to be more complex than the assumptions of a game and it is like that a combination of games or game like situations are simultaneously at work. The ultimate success of game theory would be in designing stable and robust cooperative systems for real life use. Game theory has been used for addressing problems in business (Remeikiene 2017) or politics (Wolitzky 2013), but attempts to design institutional or community governance structures based on game theoretical principles (Young 1998, Jiang et al 2020) are yet to reach their full potential.

Community managed institutions of social interest should be such that there is nil or minimum conflict between individual behavioural optimum and the collective common goal. If the payoff of a cooperative act in the context of the system is greater than what would have been of an otherwise selfish act, cooperation would be stable without an added provision for reciprocity, policing or punishment. This approach can be particularly important in addressing problems in developmental economics using theoretical as well as experimental behavioural science. Experimental approach has gained substantial importance in economics (Banerjee and Duflo 2009) and a combination of developmental and behavioural thinking is likely to result in better design of developmental schemes and systems (Banerjee et al 2009). People have an evolved intuitive economic behaviour and their economic decisions are likely to follow their intuitive models (Watve and Ojas 2020) which mainstream economists need to understand in order to increase the success of economic upliftment interventions.

The support cum reward (SuR) system that we describe here originated from a modification of a theoretical model by Watve et al (2016b). The modification evolved through several rounds of collective thinking with the farmer community, social workers, wildlife ecologists and park management. The main modification brought about by the collective thinking process during this study was that the objective was transformed from “compensation of damage” to “assurance and incentivisation for increasing crop productivity in spite of the damage risk”.

In the SuR system the crop damage by wild animals is assessed not for individual farms but for an agricultural belt covering a group of farmers with comparable risk of damage. Farmers sharing a crop and similar risk level form a voluntary group. At the end of a cropping season the farmers self-report their produce which is endorsed by other farmers of the group. Based on these data, the average deficit in productivity is used to calculate the support cum reward amount (SuRA) payable to farmers in terms of percentage. Each farmer of the group is rewarded this percentage on his own produce. In other words, the farmers are paid SuRA proportionate to the average loss of productivity but also directly proportional to the individual farmer’s produce. The entire estimate is based on farmers’ self-reporting and therefore ensuring honesty is critical for serving the purpose of the system.

It can be easily seen that underreporting the produce is against the interest of individual farmers and therefore out of selfish interest they are unlikely to under-report. On the other hand, over-reporting the produce can increase the relative benefit of an individual farmer but reduces the average deficit thereby reducing the percentage payoff of the entire group. Therefore the farmers endorsing the self-reporting are unlikely to allow over-reporting. Thus honesty can be ensured out of selfish interest of every player in the *N* person game. Further, there is a dual reason for increased productivity. On the one hand, since an assurance against average damage is given, farmers need not hesitate to invest in intensifying agriculture, and on the other since the reward is proportionate to the individual farmer’s produce, there is an incentive for increased productivity. In this study we examined the predictions regarding honesty and productivity using a combination of theoretical and experimental approaches.

Although the SuR model was developed in the context of relief to farmers suffering from crop damage by wild animals, the model has a potential to provide a behaviourally sound platform to boost agriculture in the developing world. It can substitute crop insurance as well as provide incentive to facilitate improved agricultural technologies, new varieties, crop diversity and better agricultural practices.

Results

1. The evolution of detailed implementation protocol:

Prior to the present study, the research group has been working in the study area since 2008. Therefore communication with a group of farmers was already established. In addition an open declaration and appeal was made to farmers of two villages namely Vadala-Tukum (20°18'12.5"N 79°15'08.4"E) and Viloda (20°15'27.9"N 79°14'39.1"E) on the western buffer area of Tadoba Andhari Tiger Reserve in Maharashtra State in India. The appeal was to participate voluntarily in a self-study by a farmers' group to better understand the problem of farmer-wildlife conflict and develop a possible solution. No promises of any direct monetary benefits were made, apart from indicating a possibility of it. In reality the research group was able to raise sufficient money to pay the SuRA to farmers for two out of the three years, but this was not a promise to begin the experiment. After obtaining informed consent and ensuring voluntary participation, the group was explained the earlier published model by Watve et al (2016b) and was asked to understand, discuss and work out an implementation plan. Collective thinking and modifications were allowed if made by consensus. The research group did not make any attempt to ensure honesty, but obtained productivity data independent of farmers' self-reporting from the threshing machine operators and buyers of the produce. Three main modifications of the Watve et al (2016b) model evolved out of farmers' and researchers' collective thinking. One was that we changed the objective from paying compensation for the damage to encouraging productivity in spite of the risk of damage. The other was that the farmer group intrinsically worked out the procedure for validation of self-reports, locally called "panchanama". The formal procedure for panchanama was an optimization between the objective to be fulfilled and the practical constraints faced on the field. The consensus procedure was that two to three farmers will coordinate the validation activity for the entire group and ensure that at least three other farmers from the group were present when the crop from any given farm was being harvested, threshed and packaged. Farmers either volunteered to be validators, or at times requested by the coordinating group to do the duty. There was no formal randomization procedure followed as per the original model. The number of validators required was decided to be three. As explained later, increasing this number can increase the chances of honest reporting. It was thought that if we have difficulty in ensuring honesty of reporting, we can increase the number of validators, but no need was felt throughout the pilot implementation to increase the number. After collecting all self-report and validation data, it was shown to the entire group and the need for this transparency was emphasized and appreciated by the entire group. In one case, there was an error in computer entry of the data and it was pointed out and corrected when the data were made open to the entire group. The principle of computing SuRA (Watve et al 2016) was unchanged and was as follows

SuRA for a i^{th} farmer $= y_i . \frac{S-R}{R}$ Equation 1.

Where *S* is the expected productivity per unit area, *R* the mean productivity per unit area of the farmer group in the study area and y_i = the productivity of i^{th} farmer expressed in terms of money by the current market rate. However, unlike in the original model (Watve et al 2016b) we did not maintain fully protected control plots to get a working estimate of *S*. Instead, the average productivity of agricultural lands away from the forest in that season was decided to be taken as *S* of the model.

The data collection and computation procedure followed was as in the original model and is described in the methods section.

2. Honesty- Empirical results:

In the first monsoon season of crop, 38 farmers participated out of which 31 self-reports matched exactly with other independent sources of data, 6 appeared to attempt manipulation with 5 over-reporting and 1 under-reporting and their endorsers did not carefully verify their honesty. The research group did not interfere or expose the dishonest reporting but farmers themselves realized the consequences and corrected themselves or each other before finalizing the data for calculations. In the second season there was only one over-reporting attempt to which other farmers objected. The over-reporting farmer apologised and corrected himself. In the following 4 seasons no incident of dishonesty was reported. This real life experiment is compatible with earlier imaginary game trials (Watve et al 2016) where players tried to manipulate initially and then realizing that any departure from honesty leads to loss, continued to play honestly in the subsequent iterations of the game.

3. Honesty – game theory and other analytical considerations:

Following the assumptions of classical game theory, we modelled SuR as a game. In the baseline model the payoffs of honest, under-reporting and over-reporting farmers was considered at a constant efficiency of validation μ, i.e. the probability at which an over-reported can be detected and prevented from over-reporting. Using the replicator dynamics approach, we get a dynamics in which the Nash equilibrium is crucially dependent upon μ (see supplementary material S1). At no condition under-reporting is stable since it can be invaded by honest as well as over-reporter. Over-reporter, on the other hand has a short term advantage over under-reporter as well as honest individuals. However, this depends upon the existing value of μ. If an attempt to over-report is exposed, the over-reporter suffers embarrassment and thereby pays a social cost *c*. According to the range of μ, there are five possible patterns of dynamics (figure 1). For $\mu > \mu_2$ honest reporting is the only Nash equilibrium. For $\mu_1 < \mu < \mu_2$ a mixed strategy equilibrium exists in which honest and over-reporters can coexist. Only when $\mu < \mu_1$ over-reporting can be stable.

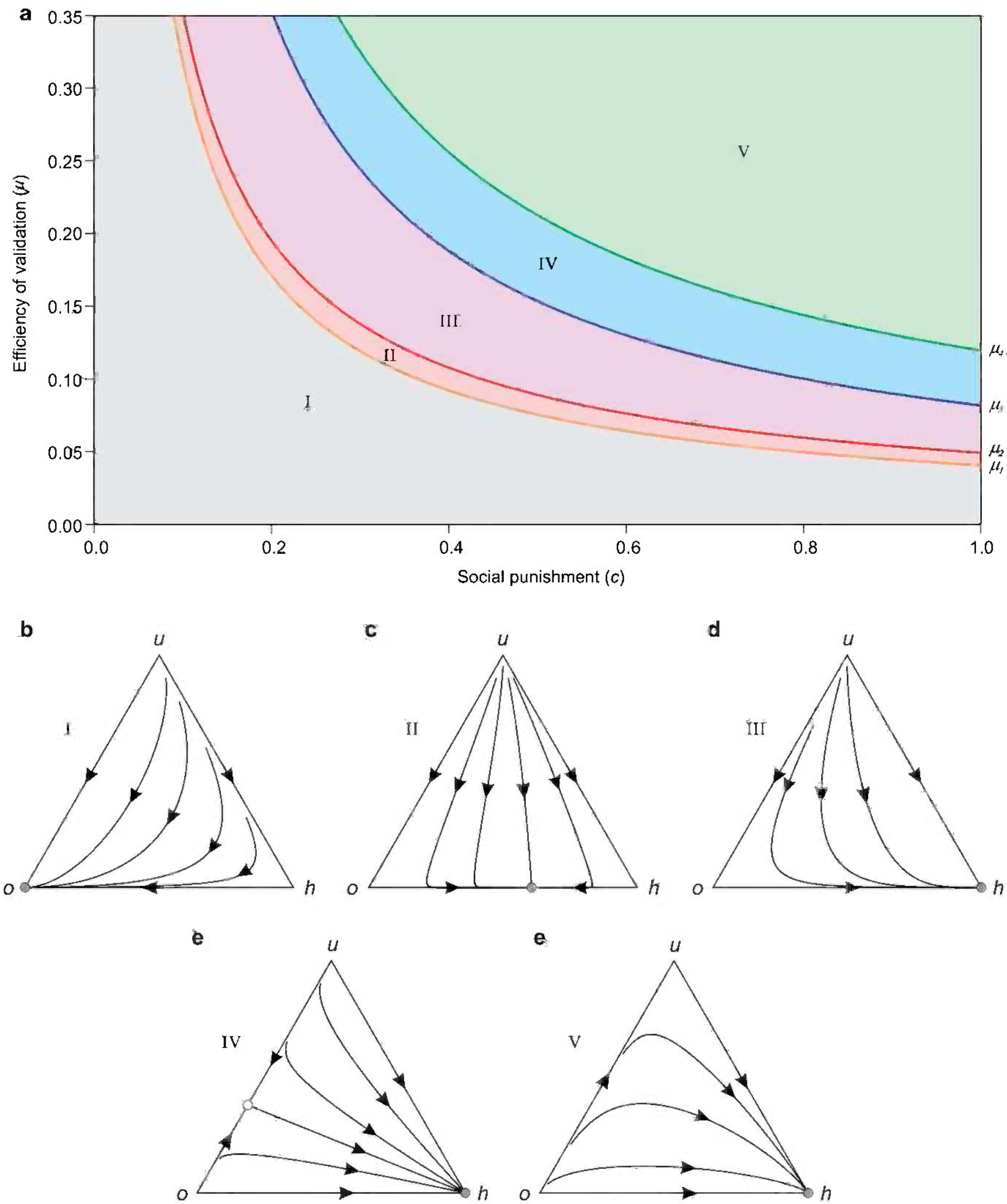

Figure 1: Evolutionary dynamics of SuR game at different efficiency of validation and social punishment. u, o and h stand for under-reporter, over-reporter and honest reporter respectively. (a) Parametric space demarcating different evolutionary dynamics of the game. (b-f) Simplexes of evolutionary dynamics under different efficiency of validation and social punishment. Grey circles indicates stable Nash Equilibriums and white circle indicates unstable Nash Equilibrium of the game. Curves μ_1 to μ_4 refers to eq. (8) to (11) respectively of the supplementary material. The cut-offs μ_1 to μ_4 are dependent upon the social cost of

exposing over-reporting and the extent of over-reporting ε. Other simulation conditions: S = 1, y = 0.5, ε = 0.05.

What decides μ? The validator dynamics:

The critical parameter μ of the dynamics above, i.e. the probability of catching and detecting over-reporting is not a constant but a function of the proportion of honest validators in the population. Since over-reporting reduces the pay-offs of the entire group, preventing over-reporting is a common interest. However, it is possible that the over-reporter can bribe validators to approve the over-reporting. Validators can be corrupt or honest. We assume that by the protocol v number of validators are required for every panchanama procedure. Even one honest validator among the v is sufficient to prevent over-reporting. Bribing the validator is comparable to the ultimatum game in which a 'fair' distribution of the benefit is the most acceptable outcome (Debove et al 2016). Therefore we assume that the over-reporter has to distribute the benefit among himself and v number of validators. With increasing number of over-reporters and larger ε, R becomes large and the benefit of over-reporting reduces according to equation 1. In addition, if over-reporting is exposed, the corrupt validators also lose their reputation and respect among the group, thereby paying a social cost c'. Thus the cost-benefits of a validator strategy depend upon the frequency of over-reporters and the stability of over-reporters is decided by μ which is a function of the number of honest validators. This results into a dynamic relationship between r of the above model and a, the frequency of honest validators (see supplementary information S2). This is captured by adaptive dynamics which shows that in the absence of social punishment to corrupt validators, over-reporting and corrupt validation is the only stable Nash equilibrium. But in presence of a social punishment, above a threshold a^*, honest reporting is stable with a large basin of attraction (Fig. 2b). Thus validation by one or more individuals and social punishment for an exposed over-reporting are essential components for the stability of honesty.

The SuR model has many additional features not captured by the game theory model. These features can stabilize honest reporting and validation by multiple synergistic ways.

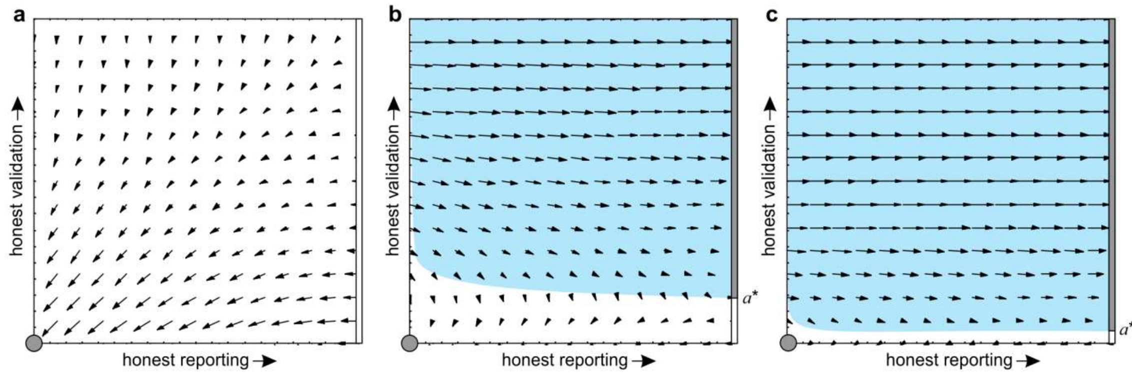

Figure 2: Adaptive dynamics between reporters and validators. (a) c = 0.0, v = 2, (b) c = 0.05, v = 2, (c) c = 0.05, v = 5. Grey circles and bars are stable Nash Equilibriums. White bar is unstable Nash Equilibrium. Honest reporting is stable in the blue region. Other simulation conditions: S = 1, y = 0.5, ε = 0.05.

Additional factors (AF) stabilizing honesty:

AF1: Game theory solutions work under a set of simplistic assumptions and human behaviour is likely to be more complex than the outcomes of a simple model. Therefore we consider more alternative model considerations and their solutions that might affect the outcome. Typical game theory dynamics considers the relative benefits of different strategies and assumes that the one with a better pay-off replicates or increases in frequency in the population.

However, we have a situation in the SuR dynamics where one has to choose between absolute versus relative pay-offs. When the proportion of over-reporters increases, *R* increases and thereby the SuR amount decreases according to equation 1. By preventing this decline in SuRA an honest validator gains a benefit along with everyone in the population. On the other hand the bribe that a corrupt validator gets from an over-reporter decreases with increasing *r*. The rise in SuRA by preventing over-reporting can be greater than the bribe one can possibly get by approving over-report when

$$r > \frac{S-y}{S.(v+1)+\varepsilon} \qquad \text{Equation 2.}$$

Therefore if validators are rational, flexible and take a decision to maximize their absolute pay-offs, they will all become honest above a critical r (See S3 AF1 of supplementary information). This means that at large r, μ will tend to 1 and thereby encourage honest reporters. So if farmers take decision based on their absolute pay-offs, the 'over-reporter-corrupt validator' Nash equilibrium of Fig. 2a is impossible. This critical r above which μ tends to one can be small if y, v or ε are large. This can be achieved by increasing the number of validators required for validating every self-report. On the other hand, ε will evolve to be larger on its own since a larger ε always gives an advantage to an over-reporter over a smaller ε. Note that this additional factor stabilizing honesty can operate independent of the cost c' to the corrupt validator.

AF2: The consequences of variance in productivity:

In the model, so far we have assumed for simplicity that everyone gets the same yield *y.* In reality there is a substantial variance across farmers. This variance is another natural means that is likely to keep dishonesty in control by known behavioural principles. Since the game is a non-zero-sum game, coalition for underreporting can bring higher payoff to everyone. However, how to show lower yields is a complex question. In a group, if everyone contributes to a lie in order to get a benefit, everyone would expect the same gains. If everyone decides to show his/her produce as $y_i - \alpha$, the due SuRA will increase by a constant percentage, but the ones with lower y_i can complain of getting disproportionately lower benefit of the dishonesty. If on the other hand they report $\frac{y_i}{\beta}$, where $\beta > 1$, the ones with lower yields can still complain about lower absolute benefit of dishonesty. Cooperation for dishonesty is unlikely to be stable unless everyone gets the same benefit of dishonesty and has a feeling of fairness. Rejection and refusal to cooperate on seeing an unfair outcome is shown to be a trait in humans as well as non-human primates (Brosnan and de Wall 2014, Debove et al 2016) owing to which underreporting with a wide variance around *y* is unlikely to be stable. If, on the other hand, the group decides to forget about actual yields and only cooks up numbers for claiming equal benefit, the cooked up data will have distributions and other statistical patterns so widely different from real life patterns that it will not be difficult to expose the dishonesty.

AF3: The consequences of variability in behavioural responses and social relations:

Unlike the assumptions of the game theory model, there is considerable individual variability in rationality, in complying with the assumptions of the model and in the speed at which a behavioural change is adopted. Individual responses are also shaped by subtle factors in relationships between individuals. Therefore apart from rational economic gains, strategies of players are also affected by subtle rivalries and friendships. Since volunteering for panchanama is permitted, it is likely that individuals will actively come forward to prevent their rivals from taking advantage of over-reporting. Owing to such sources of behavioural variance, and intra-individual dynamics it is likely that some validators keen to prevent over-reporting will always be present. Above a threshold v it is very likely that μ becomes sufficiently large to prevent over-reporting.

AF4: Incomplete information at the time of panchanama and credibility of promise:
When the farmer's self-report is to be validated, the group's average productivity is not yet calculated. Therefore, the possible benefits of over-reporting are yet unknown. Bribing the validators at this stage is therefore not practicable although the game theory model considers this possibility. Making exact promises is also not possible with incomplete information. Even if a promise is made, it's credibility is questionable. The validator cannot take up an open fight if the over-reporter defects, since exposing the deal will invite punishment to over-reporter as well as corrupt validator. Therefore although we have considered the possibility of bribing the validators and getting an over-report approved, it does not seem to be possible in real life. Even with the possibility of bribing, the model has a restricted parameter space in which dishonesty can be stable. With the additional difficulty of ensuring fair division of the over-reporting benefit, stability of dishonesty at any parameter space is questionable.
AF5: Openness of data and the "cues of being watched": The entire farming operation is a open act and farmers have a good judgment of each other's success. The harvesting, threshing and packaging is done in the open, it's a prolonged operation and there is substantial time gap between packaging and transport. Therefore there is plenty of opportunity for other farmers to know any farmer's net produce. Also farmers and their family members help each other and work as manual labour on each other's farms. It is not possible to do the harvesting act secretively. Therefore over-reporting one's yield without the knowledge of other farmers is difficult. The 'cues of being watched' has been shown to induce honesty (Bateson et al 2006) even in situations where secretive cheating is possible. For operations under the open sky, one is unlikely to dare cheat the system when others are aware that it is against their interest.

AF4: Government as a player can easily destabilize underreporting coalition:

The government, which is expected to provide the support cum reward to farmers, is an important player in the game that we haven't considered so far. The interest of this player is to provide a realistic solution to affected farmers and keep them satisfied with minimum cost incurred. It is easy to visualize that when the farmers behave honestly, the government need not intervene, except making the SuR money available. If the farmers tend to over-report on an average, they cannot blame the government for the smaller than realistic benefit obtained. However, the government needs to worry about a coalition of the entire group of farmers to under-report. The game theory model has shown that such a coalition is unlikely to be stable. However, the government can decide to be more cautious and can achieve this by an official attending only one or a few harvesting and validation operations from a group. If everyone is underreporting, the one whose validation is independently checked and therefore honest, will get disproportionately large pay-off thereby resulting into unfair outcomes destabilizing cooperation.

Collectively It can be seen that by known principles of game theory and human behaviour, honesty is reinforced by multiple factors acting synergistically. Therefore the empirical finding that after a few initial attempts to cheat, absolute honesty prevailed for all further iterations, is not surprising.

4. Honesty – Farmers' perception about the factors contributing to honesty:

In contrast to theoretical considerations, let us look at the ground realities in farmer behaviour observed during the experimental implementation. As the initial attempts by a few individuals to manipulate the system for selfish interests failed and all farmers started reporting honestly, we encouraged a group discussion on which factors, in their perception, were important in ensuring honesty. Three factors were perceived to be the strongest, one being that a farmer who attempted to over-report but was caught in the act suffered a loss of respect and reputation by the rest of the group. The embarrassment brought by this is perceived to be a high cost that nobody could afford. The other was transparency of the entire data to everyone. Any error or effort to manipulate could be corrected when the entire group met to look at the data collectively. This was the time when questions about suspicious data could be raised. The third was that they perceived the absolute benefit coming from the system as more important than the relative benefit of alternative behavioural decisions. This implies that solution AF1 in our analysis above may be an important factor at work in stabilizing honesty. These three factors emerged as consensus factors in preventing dishonesty, although many other reasons including ethical considerations and spiritual beliefs figured in the group discussions.

5: Productivity: In a prior study, the self-reported produce by farmers in the study area, (but not the same group of farmers in the present study) was recorded between 2010 to 2015 (Bayani 2016). Our experiment started in 2017. From the baseline of average between 2010 to 2015, during the study period there was a monotonic rise in productivity of all the crops and the maximum rise was over 4 fold for wheat and gram and about 2.5 fold for rice (figure 3a). This dramatic rise was at least partially contributed by good rainfall received in 2018 and 2019 monsoon. But the 2017 monsoon was bad and we still observed a rise in productivity over the previous years' average.

Since annual variation in rainfall is shared by the entire district more or less equally, we compared the productivity of our group with the district average data obtained from the Maharashtra government official online data portal (http://krishi.maharashtra.gov.in/1250/Taluka-Level). In the indices relative to the district average there was a similar monotonic increasing trend (figure 3b), indicating that the rise was much more than what can be explained by the monsoon. The expectation of the model that implementation of it would assure and incentivise farmers and thereby increase average productivity appears to be fulfilled beyond our expectation.

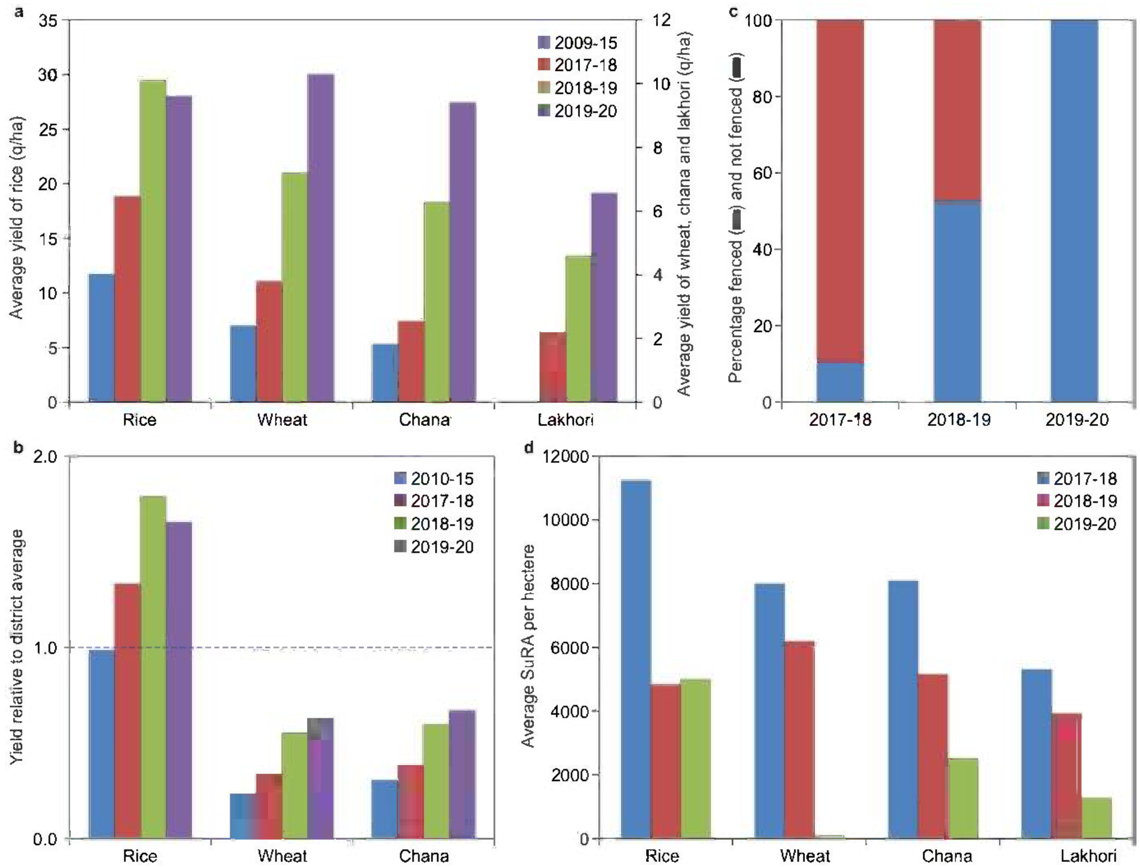

Fig 3: Empirical data of productivity. (a) Trends in absolute productivity in rice, wheat, gram and lakhori and (b) relative to district average of that year (district average not available for lakhori). Note the monotonic and impressive increase in both absolute and relative measures. (c) The proportion of farmers using solar fences for crop protection. (d) The SuRA per hectare computed for three consecutive years: Note that owing to increasing productivity, the required support showed a decreasing trend.

Rice in the study area is a monsoon crop and the other three are post monsoon crops. The problem of wild animal damage is more intensive in the post monsoon season. Also since the area is particularly good for rice, it can be seen that rice productivity in the study area was not lower than the district average, but it rose by 60 to 80 % over the three years of intervention. The post monsoon crops were substantially lost to wildlife which is reflected in the very low relative baseline yields. However, during the intervention years it increased from about 20-30% of the district average to 60-70% of it. Animal activity did not stop during the intervention years but farmers took greater efforts to grow as well as protect the crops and that is the most likely factor reflecting in the increased productivity. It is notable further that the required SuRA per hectare decreased substantially as the productivity increased (figure 3D). The productivity of the SuR model is indicated further by the inputs to productivity ratio. When SuRA of Rs. 1.14 million was paid to the farmers, and subsidy on solar fences worth Rs 0.5 million was made available during the intervention period, by prevalent market value their productivity increased by Rs. 6.96 million. This demonstrates that apart from being a relief to farmers affected by wildlife damage, SuR actually works as an effective investment in improving agricultural productivity in spite of the damage.

6. Inputs and efforts: An expectation of the SuR model was that farmers' inputs in agriculture will increase. Such an increase was observed by at least two indicators. Solar powered fences are a potential measure to prevent animals from entering the farms. In the study area solar fences offer significant, though not complete protection from wild herbivores. Prior to our intervention, the forest department and eco-development committees had offered farmers solar equipment either free of cost or at high subsidies but only 15 % farmers in the group were using them. During the three years of implementation, the percentage of farmers using solar fences in the intervention group increased to 100% whereas it did not cross 30% in non-participant farmers from the same area. Prior study in this area by Bayani et al (2016) had shown that farmers close to forest boundary are reluctant to spend on fertilizers owing to the risk of damage. We did not collect quantitative data on fertilizer use but qualitatively the diversity of fertilizers used by the participant group increased during the intervention period. In the year 2019-20, from our group 21 farmers decided to use bacterial inoculants for the first time. The two examples demonstrate that farmer's inputs in agriculture increased qualitatively as well as quantitatively during the intervention period.

7. Responses of the lesser beneficiaries: Since the benefits of the scheme were proportional to individual farmer's productivity, the benefits differed substantially among individual farmers. We suspected that the lesser beneficiaries may feel disappointed and may drop out from the scheme, or may express their resentment. However, to our surprise this did not happen. In the group meetings the causes of lower productivity of some of the farmers were discussed and there was a spirit to improve on it rather than complain about the provisions in the scheme.

8. Causes of variability within the group: Although the principle of the scheme specified that farmers with comparable risk should form a group, there was always substantial variance in productivity across different farmers. If the assumption of comparable risk is not complied with, those with higher risk are at a disadvantage and those with lower risk get an undue share of the benefit. Therefore it was important to know the causes of the variability in productivity. In a prior study in the area (Bayani et al 2016), the risk of damage was shown to reduce approximately linearly with distance from forest over a span of 5 km. Our farmer group were at distances between zero to slightly over one km. Therefore we looked at correlation with distance from the forest (See supplementary material S4 (i)). In 2017-18, there were positive trends between distance from the forest and productivity for the four crops, two of which were statistically significant. The variance explained was small (8.3%) for rice but high (72 %) for lakhori. However, in all the subsequent seasons the trend with distance vanished completely for all crops. This indicates that difference in wildlife damage was not a predominant cause of the variance. A possible reason for the vanishing trend was the acquirement of solar fences by all farmers, following which the risk of damage was not different among the farmers. This was reassuring since it validates the assumption of comparable risk across the group.

The variance in productivity was discussed in the farmers' meetings and they agreed that animal damage was not appreciably different among the group, particularly after everyone acquired solar equipment. Their interpretation was that irrigation facility, individual farmer's wisdom and efforts were mainly responsible for the variance. The wisdom and efforts were not quantifiable but we could classify the irrigation available into good, medium and poor and this classification could explain between 7 to 50% variance along the crop year matrix for post monsoon crops (see supplementary information S4(ii)). For the monsoon grown rice there was no correlation with irrigation facility as expected. Farmers' own interpretation that the difference in wisdom and inputs was responsible for the productivity difference is likely to have been a big motivating factor since there was increased awareness and readiness to learn about techno-improvisations and new agricultural technologies among the group. In the year 2019-20 a group of 21 farmers used bacterial inoculants for the first time on a trial basis. In short, the expectation of the model that rewards for productivity would provide an effective incentive appears to have come true.

The frequency distribution of productivity (see supplementary material S3 (iii)) shows that the increase in average productivity was not solely due to some outliers achieving very high productivity. The entire distribution shifted to the right indicating that there was improvement in the low productivity farms as well.

9. Reducing the role of the researcher group: Although farmers were self-reporting and validating themselves, for ensuring the accuracy of data, the research group needed to keep a close check on the process of documentation. However, the intention was to make the farmer group self-organized and self-sufficient. From the third season onwards farmers were ready to get trained and shoulder various responsibilities, including handling GPS recorder, collect field data, maintain *panchanama* reports etc. Although some monitoring by the research group was needed as a quality assurance backup, most of the operation of the scheme could be driven by the farmer community by the end of the 6^{th} season.

10. Perception of wild life: owing to the background belief systems and cultural practices, Indian forest dwellers and farmers are generally tolerant to wild life. However, it is difficult to sustain heavy losses of crops and other livelihood options and this creates resentment. Earlier studies had shown that in this area the average crop loss was over 50 %. This is equally evident in the relative productivity data given above. Group meetings and individual interactions revealed that given the support cum reward assurance, people lost hostility towards wild animals almost entirely. During the study period there were documented instances in which injured wild herbivores were found stranded or strayed into human habitations and people, instead of killing, troubling or hurting them further, helped rescue operations by the wildlife management.

Discussion:

The experimental implementation of the *N* person game based community operated support cum reward scheme for farmers affected by wild herbivore damage complied with its predictions that (i) honesty was the only prevalent and stable strategy (ii) with the feeling of support as well as incentivisation, there was remarkable increase in productivity. (iii) group discussion and individual interactions revealed substantial relaxation of feeling of conflict with wildlife and resentment against the wildlife management.

The SuR system is a complex game and a single game theory model does not capture the entire dynamics of the system. We see that multiple game like situations are involved including prisoner's dilemma, volunteer's dilemma, ultimatum game involving behavioural principles including punishment, reputation, rejection of unfair outcomes and cues of being watched, all promoting and reinforcing honesty in mutually compatible or synergistic ways. Particularly remarkable is the spectacular increase in productivity in the absence of any detectable change in the reported animal density of the park. There are three possible reasons for the trend. Earlier studies in the area have shown that facing the risk of damage, farmers tend to reduce the inputs in agricultural practices. Since there is a chance of losing the entire crop with some probability, they cannot afford to take the risk of investing more. Therefore the general tendency was to try to get some crop with minimum investment. When an assurance against total loss was obtained, their investment and inputs showed a detectable increase. Simultaneously there was an incentive for higher productivity. The third important factor was that they came together and discussed a variety of issues during which they exchanged information on the one hand and developed a competitive spirit on the other. The uniqueness of this experiment was that there was no technological or biological intervention. No new seed, variety, fertilizer or agricultural practice was introduced by the researchers. Only a behavioural economics intervention was responsible for the over two fold increase observed in productivity.

The small scale experiment has a good potential to be scaled up for the following features. The system is behaviourally sound and robust. If everyone behaves selfishly, honesty and smooth conduct is expected to ensue. Therefore the entire system can be operated by the farmer community themselves and convenient mobile based app and software can be developed through which they can upload the data collected by them, based on which the money transactions can be automatically processed. Since there is no middleman required, there is no scope for corruption in the system. Since selfishness itself ensures honesty, realistic data about agricultural produce can be automatically generated year after year with little centralized efforts. This will put minimum pressure on government agencies for implementation on a wider scale. Substantial relaxation of a major human wildlife conflict issue can make coexistence and conservation easier. But the potential of SuR model goes beyond human-wildlife conflict can give a promising alternative to crop insurance and boost agricultural productivity particularly of small farmers in the developing world.

Methods:

Study area: The field experiments were carried out in two villages along the western boundary of the Tadoba-Andhari Tiger Reserve (TATR, 19° 59'–20° 29' N and 79° 11'–79° 40' E), in Chandrapur district of Maharashtra, India. The Tiger Reserve extends over 1727 sq. km out of which 625.5 sq. km is the core zone. TATR is a Teak (*Tectona grandis*) dominated mixed deciduous forest supporting good faunal diversity. Along the western boundary buffer through most of the length, the transition between forest cover and agriculture lands creates a sharp ecotone. Therefore the distance from the forest edge is well correlated to the frequency of crop raiding by wild herbivores (Bayani et al 2016). Crops are cultivated in two seasons, viz. kharif (south west monsoon crops) and rabi (winter crops). Rice (Oryza sativa) is the primary kharif crop whereas wheat (*Triticum aestivum*) and chickpea, locally called chana (*Cicer arietinum*) and a locally popular pulse Indian pea or lakhori (*Lathyrus sativus*) are primary rabi crops. The area also commonly grows cotton *(Gossypium arboreum*). The mammalian fauna of the western periphery of TATR is dominated by herbivore species including nilgai (*Boselaphus tragocamelus*), chital or spotted deer (*Axis. axis*), wild pig (*Sus scrofa*) and carnivore species including tiger (*Panthera tigris*), leopard (Panthera pardus), dhole (*Cuon alpinus*) and sloth bear (*Melursus ursinus*).

Prior and preparatory work: Area - Vadala-Tukum (20°18'12.5"N 79°15'08.4"E) and Viloda (20°15'27.9"N 79°14'39.1"E) The behavioural experiment has a background of prior ecological work in close association with some of the farmers in the group over eight years. This preparatory phase mainly helped in identifying the qualitative as well as quantitative aspects of the problem of crop damage by wild animals (Bayani et al 2016, Watve et al 2016a). In the following phase an association with the farmer group was established using individual interactions, group meetings, focussed discussions and preliminary socioeconomic documentation. Having secured some level of mutual trust, the vision of the game as a possible long term solution to the problem was introduced and voluntary participation with informed consent was sought. In the designing phase, the voluntary group discussed and worked out the details of the action planning and modus operandi, except one operation (see below) which the research group did not share with the participant farmer group.

The promised outcome for the participant group was that we will devise a method by which we can maintain our own record of how much damage farmers in this area have been suffering. However, direct monetary benefits were not assured since the project funding at that time did not provide for any payment for farmers. At a later stage, we were able to raise sufficient money through philanthropic agencies so that we could pay the farmers the calculated SuRA for the first two years. But since the amount was not promised in the beginning, farmers who were interested in seeking and trying out alternative solutions participated voluntarily.

In the first monsoon or kharif season, 57 farmers participated voluntarily. However owing to unfavourable rainfall, only 38 could grow rice crops. So the first season participation was only 38 farmers which grew to 71 in the two consecutive seasons. Although an increasing number of farmers were willing to participate in the following seasons, we stopped accommodating more farmers owing to our limited capacity and funding. The rate of attrition was very small and only 3 farmers dropped out during the subsequent seasons.

<u>Structure and working protocol of Support cum Reward (SuR)</u>:

The inclusion criteria for participation were that the farmer belongs to the study area, has a farm not more than 1 km away from the forest edge and thereby comes in the high damage risk zone, grows at least one out of the four types of crops being covered under the scheme. Four crops which were being traditionally and commonly being grown there and which experienced substantial damage by wild animals were covered. These included rice which was the predominant Kharif or monsoon season crop; wheat, chickpea or chana and lakhori, a locally grown pulse crop were the post monsoon or rabi season crops. For each of the four crops covered, an expected productivity standard was decided based on prior knowledge, average yield for the district and experience for the agroclimatic zone. At harvest, the total yield of each farm and the area under crop was self-reported by each farmer and verified by 3 other neighbouring farmers from the group. The verification record locally called 'panchanama' was signed by the farmer and the verifiers. The protocol for organization of the panchanama was that two or three volunteers from the group shouldered the responsibility to coordinate the panchanamas. Every farmers communicated to the coordinators the proposed date of harvest of his/her farm. All farmers of the group were free to volunteer as validators for any farmer's harvest. Wherever volunteers were not there the coordinators requested some members of the group to be the validators for a given farm. At the time of threshing and packaging the total yield was recorded as number of standard sized bags filled. This was later converted to weight by a common formula unique to every crop. At the time of validation if there was any dispute, any of the validators was given the freedom to all the rest of the group to confirm. In practice the need to do so was not felt any time.

All the data collected were transparent and accessible to all farmers on request any time, but collectively a meeting of all farmers of the group was called to have a look at the data together. After addressing issues with the data, if any, it was made available for calculation of SuR amount. Thus SuR was not calculated and paid until all the productivity data was approved by everyone. The SuR amount was calculated as described by (Watve et al 2016b). The intuitive meaning of the formula is that the damage is not estimated for an individual farm but calculated by the average loss in productivity. Further the SuR payable to a farmer is paid as percentage of the total produce of that farmer.

<u>Evaluation of the outcome</u>: Honesty of self reporting, integrity of the mutual validation process, farmers' inputs in productivity, the actual productivity outcome in absolute as well as comparative terms and the smoothness and ease of operation were the important evaluation criteria.

1) Monitoring honesty: All the self-reports and mutual validation data were kept open to all and any objections or accusations of under or over-reporting were welcome. Objections, whenever raised, were discussed openly during all participant meetings.

At a second level, the research group had a second source of data. The prevalent practice in the study area is that at harvest threshing machines are hired for the required time by each farmer. The machine owners are paid according to the amount of harvest processed. We obtained individual outputs of every farm from a confidential arrangement with the machine operators. This arrangement was not disclosed to farmers. It is possible that in later seasons farmers may have come to know about it, but by that time honesty was well established and transparency to everyone was unanimously perceived as a reliable means of ensuring honesty.

2) Monitoring productivity: The self-reported and mutually validated records of total produce were used for the productivity analysis. The area under cultivation for each of the crops was precisely measured using GPS Garmin etrex 30x and overlaid on ArcGIS. Productivity in terms of grain yield in Quintal per hectare calculated collectively as well as separately for each farm were used for analysis. Since in the study area monsoon is the main limiting factor in crop productivity which is highly variable year to year, the absolute productivity pattern is expected to be dominated mainly by the monsoon. Therefore we expressed productivity relative to the district average obtained from online data sources of the Government agencies (http://krishi.maharashtra.gov.in/1250/Taluka-Level). Since yearly monsoon variation is shared more or less equally by the entire district, relative productivity is interpreted as reflecting the farmers' inputs and efforts in intensifying productivity.

3) Indices of farmers' inputs: Quantifying farmers' efforts in agricultural operations and use of fertilizers etc was found difficult to quantify reliably. However, a clear trend in the use of solar fences for protecting the crops was apparent and we use it as an index of farmers' tendency to invest in growing and protecting the crops. Qualitatively we observed a trend of experimenting with novel technologies and practices.

4) Farmers' observations, impressions and interpretations: During growing and harvesting seasons discussion meetings of all participant farmers were conducted with an average frequency of one per month. Farmers noted and shared their observations, experiences, and interpretations. Objections if any, were also discussed in these meetings aimed towards consensus solution as far as possible. The observation of the researchers such as

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Supplementary information

Where honesty and hard work is the only stable strategy: Design, evolution and pilot implementation of a support cum reward game in developmental economics.

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This supplementary information file contains

S1. Basic model

The model addresses the problem of whether honest reporting can be ensured in the support cum reward system. Since the operation of the system is based on self-reporting agricultural produce by every farmer, which is validated by other farmers in the group, there is a chance of manipulation of the system to extract maximum benefit.

We will consider the compensation model proposed by Watve et al. (2016). Compensation for the i^{th} farmer will be,

$$E = \frac{S-R}{R} y_i \qquad (1)$$

Where, S is the standard yield constant, R is the average yield of the population and y_i is the yield reported by the i^{th} farmer. We consider a population with three types of farmers, namely the honest reporters (h), the under-reporters (u) and over-reporters (o). Frequency of each type of reporter is p, q and r, respectively, such that $p + q + r = 1$. For simplicity we assume all farmers have the same yield y. Honest farmers report the yield y while the under-reporters and over-reporters report the yields y-ε and y+ε respectively. If a farmer under-reports, that individual suffers from reduced compensation, as compensation (eq. 1) is directly proportional to the yield reported by the farmer. Further, if a farmer under-reports this reduces the average yield for the entire population and other farmers are benefitted. As a result, an underreporting farmer need not be scrutinized by the population. However, if a farmer over-reports, such a farmer will increase his individual gains while reducing the gains of the population by increasing the average yield. Thus, there is a need to validate the claims made by such a farmer. We assume that each reported yield is validated by some fraction v of the population. Let μ be the probability that the over reported claim is rejected by validators so that the over-reporters are made to report honest yield. We will treat μ as the efficiency of validation, so with (1-μ) the over-reported claims are accepted. Although we consider μ as a constant in the basic model we will relax this assumption later. The more the validatorsneeded for validating one report, the higher will be the efficiency of validation or the probability that higher claims will be rejected. We also consider that if the over-reporter is caught, he pays a social punishment c, where $c > 0$. Because social punishment can be in the form of embracement, we assume that there is little cost of executing such a punishment to the populaiton.

The average reported yield for the population, will be,

$$R = py + q(y - \varepsilon) + r[(1 - \mu)(y + \varepsilon) + \mu y] \quad (2)$$

Let S be the standard yield value. Then the payoff of the three types of reporters are,

$$E_h = \frac{S-R}{R} y \tag{3}$$

$$E_u = \frac{S-R}{R} (y - \varepsilon) \tag{4}$$

$$E_o = (1-\mu)\frac{S-R}{R}(y+\varepsilon) + \mu\left(\frac{S-R}{R} y - c\right) \tag{5}$$

Average payoff of the population is,

$$\bar{E} = pE_h + qE_u + rE_o \tag{6}$$

We can use replicator dynamics to understand the evolutionary dynamics of the population (Maynard Smith 1982; Hofbauer & Sigmund 1998),

$$\dot{f}_i = f_i(E_i - \bar{E}) \tag{7}$$

Where, E_i (where, $i = h, u, o$) is the payoff or fitness of the individual using strategy i and f_i ($= p, q, r$) are the frequencies of each type of farmer. The replicator equation describes deterministic but frequency-dependent selection dynamics. The replicator dynamics ensures that even if the population starts from any initial frequency of individuals adapting different strategies, it will eventually change and will converge to a Nash Equilibrium (Hofbauer & Sigmund 1998). Once the population converges to a Nash Equilibrium it will stay at the Equilibrium forever.

Analysis of basic model

Under different efficiencies of validation (μ) and social punishment (c), there are five different game dynamics (main text, Fig. 1), which are demarcated by four threshold values of μ.

$$\mu_1 = \frac{c\varepsilon - 2\varepsilon^2 + \varepsilon S + cy - \varepsilon y - \sqrt{4(c-\varepsilon)\varepsilon^2(\varepsilon - S + y) + \left(\varepsilon(S - 2\varepsilon - y) + c(\varepsilon + y)\right)^2}}{2\varepsilon(c-\varepsilon)} \tag{8}$$

$$\mu_2 = \frac{\varepsilon(S-y)}{S\varepsilon + yc - y\varepsilon} \tag{9}$$

$$\mu_3 = \frac{c\varepsilon - 3\varepsilon^2 + \varepsilon S + cy - \varepsilon y - \sqrt{8(c-\varepsilon)\varepsilon^2(\varepsilon - S + y) + \left(\varepsilon(S - 3\varepsilon - y) + c(\varepsilon + y)\right)^2}}{2\varepsilon(c-\varepsilon)} \quad (10)$$

$$\mu_4 = \frac{2\varepsilon(S+\varepsilon-y)}{S\varepsilon + yc + \varepsilon^2 - y\varepsilon - c} \quad (11)$$

If there is no validation or the efficiency of validation is low, such that $0 = \mu = \mu_1$ then over-reporting individual always gets better than the under-reporters and honest individuals. As a result, over-reporting is the only stable Nash Equilibrium of the game (main text, Fig. 1a, b). At this equilibrium, all individuals suffer a net loss of 'ε' and the average payoff of the population lowers to 'y- ε' instead of 'y' if all had cooperated and reported honest yield. The dynamics of the game between over-reporters and honest individuals follows Prisoner's Dilemma, where the over-reporting equilibrium is not Pareto efficient. Under-reporting is dominated by both, the honest and over-reporting strategies.

If the efficiency of validation exceeds the threshold μ_1, then honest individuals can invade population of over-reporters, even when rare. This invasion dynamics follows four different dynamics (main text, Fig. 1a, c-f). In the interval $\mu_1 < \mu < \mu_2$, both honest individuals and over-reporting individuals can invade when rare. Because, under-reporters are dominated by both honest and over-reporters , there is a single a mixed strategy equilibrium $(p^*, r^*) = \left(1 - \frac{S}{\mu c + \varepsilon(1-\mu)} + \frac{y}{\varepsilon(1-\mu)}, \frac{S}{\mu c + \varepsilon(1-\mu)} - \frac{y}{\varepsilon(1-\mu)}\right)$, which is the only stable Nash equilibrium of the game (main text, Fig. 1c). At this equilibrium both over-reporters and honest individuals co-exist and the equilibrium frequency of the over-reporters decreases rapidly with increase in efficiency of validation μ and social punishment c (Fig. S1a).

In the interval $\mu_2 < \mu < \mu_3$, honest individuals are the only stable Nash Equilibrium of the game (main text, Fig. 1d). Although under-reporters are dominated by both over-reporters and honest individuals, honest individuals dominate over over-reporters and form the stable equilibrium of the game.

Above the threshold μ_3, under reporters invade the population of over-reporters when they are rare. In the interval, $\mu_3 < \mu < \mu_4$, both over-reporters and under-reporters can invade each other's pure populations when rare. This leads to a mixed strategy Nash Equilibrium $(q^*, r^*) = \left(1 - \frac{s}{\mu c + \varepsilon(2-\mu)} + \frac{y-\varepsilon}{\varepsilon(2-\mu)}, \frac{s}{\mu c + \varepsilon(2-\mu)} - \frac{y-\varepsilon}{\varepsilon(2-\mu)}\right)$, in the absence of honest individuals. However, because honest individuals dominate over both under-reporters and over-reporters, the mixed strategy Nash Equilibrium is unstable and honest individuals form the only stable Nash Equilibrium of the game (main text, Fig. 1e). The equilibrium frequency of over-reporters at the unstable mixed strategy Nash Equilibrium decreases rapidly with the increase in efficiency of validation and social punishment (Fig. S1b).

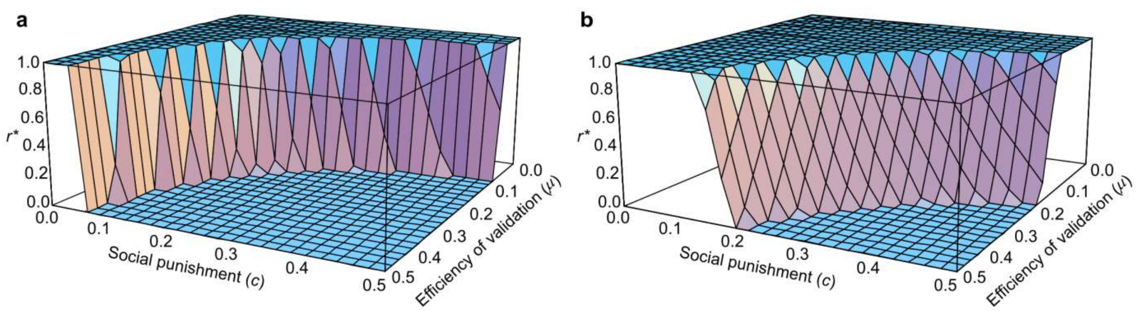

Fig. S1: *Equilibrium values of over-reporters at different efficiency of validation and social punishment. Equilibrium r* in mixed strategy Nash Equilibrium in (a) main text, Fig. 1c and (b) main text, Fig. 1e.*

At higher values of efficiency of validation, $\mu \geq \mu_4$, under-reporters dominate over-reporters. However, since honest individuals dominate over both under and over-reporters, honesty is the only evolutionary stable Nash Equilibrium of the game (main text, Fig. 1f).

Can coalitions among under-reporters beat the system?

In all the simulations of the basic model, we can see that under-reporting is a dominated strategy by honest individuals under all circumstances and by over-reporters when efficiency of validation and social punishment is low (main text, Fig. 1). Since under-reporting is always dominated by honest individuals we will only focus on this sub-game for further arguments. Since the compensation is directly proportional to the individual yield, an honest individual will always outperform under-reporter as long as $S > R$. Since under-reporting reduces the average yield of the population, which in turn increases gains for the other individuals, validators will not be inclined to reject any under-reported claims.

However, what if all the farmers decide to under report. If all the farmers under report, average payoff of the population will be $S\text{-}y+\varepsilon$, which is higher than $S\text{-}y$ that everyone will get if all the farmers report honestly. As a result, if all the farmers form a coalition and under report, then all will be better off. However, in this system a farmer who will fail to form coalition and reports honestly will always gain better. This is because the average yield of the population of under-reporters and honest farmers will be $R = y\text{-}q\varepsilon$ and honest farmers will always gain better than under-reporters $E_h > E_u$ as long as $S > y\text{-}q\varepsilon$, which is always true since $S > R$. As a result, pure coalition of under-reporting is not possible as it will always be dominated by honesty and a rare honest farmer will invade and disrupt coalition among under-reporters.

S2. Over-reporters and corrupt validators

Based on pervious arguments, we will consider a sub-game between honest and over-reporting farmers. We can ignore under-reporting farmers as it is an all time unstable strategy. In the basic model we assumed that the efficiency of validation μ to be constant. However, this value will be decided by the validators in the system and how they validate the claims. Since an over-reporter gets direct benefits from over-reporting and wants to avoid being exposed, he can bribe validators. However, since the validation needs agreement between all validators, if at least one validator is honest then over-reporter will be caught and face social punishment.

We will consider that each farmer is characterized by doublet of probabilities $(p,a)\in[0,1]^2$, where p is the probability that the farmer will report honestly (which means, he will over-report with probability $1-p$) and a is the probability he will validate honestly (which means with probability $1-a$ he will accept a bribe and validate over-claims). Let us assume that there are v number of validators. If at least one of the validators is honest the over-reporter will be caught, will have to report honestly and will also pay the social punishment. However, if all the validators are dishonest, which will happen with the probability $(1-a)^v$, then over-reporters can get away with the over-reporting given that they bribe the validators. As suggested by Watve et al. (2016), the bribe will follow ultimatum game dynamics (Nowak et al. 2000) and at equilibrium the bribe should be an equal share of the over-reporter's benefit of over reporting, $\left(\frac{S-R}{R}\right)\varepsilon$, among $(1+v)$ individuals including over-reporter and all the validators.

Average yield reported by the population, employing strategy (p, a) will be,

$$R = py + (1-p)[(1-(1-a)^v)y + (1-a)^v(y+\varepsilon)] \quad (12)$$

Then the payoff of a rare mutant strategy (p',a') in the population playing (p,a) will be,

$E(\acute{p}, \acute{a}|p, a) = \frac{S-R}{R}\left(\acute{p}y + (1-\acute{p})\big((1-(1-a)^v)y + (1-a)^v(y+\varepsilon)\big)\right) + (1 - \acute{p})(1-a)^v\left(-\frac{\varepsilon(S-R)v}{R(f+1)}\right) + (1-\acute{a})(1-a)^{v-1}(1-p)\left(\frac{\varepsilon(S-R)}{R(v+1)}\right) + (1-\acute{p})(1-(1-a)^v)(-c)$ (13)

We will use adaptive dynamics, which can be formulated as a differential equation in the space of all strategies (Page & Nowak 2000). The system of differential equations can be given as,

$$\dot{p} = \frac{(1-(1-a)^v)c(1+v)(y-(1-a)^v(p-1)\varepsilon)-(1-a)^v\varepsilon\left(S-y+(1-a)^{fv}(p-1)\varepsilon\right)}{(1+v)(y-(1-a)^v(p-1)\varepsilon)} \quad (14)$$

$$\dot{a} = \frac{(1-a)^{v-1}(p-1)\varepsilon(S-y+(1-a)^v(p-1)\varepsilon)}{(1+v)(y-(1-a)^v(p-1)\varepsilon)} \quad (15)$$

Evolutionary dynamics of eq. (14) and (15) suggests is shown in Fig. 3. When there is no social punishment (c = 0), over-reporters and dishonest validators (0, 0) is the only stable Nash Equilibrium of the game (main test, Fig. 2a). The entire edge (1,1)–(1,0) has the same payoff because honest reporters do not bribe or give extra benefit to dishonest validators. Although this entire edge is in Nash Equilibrium, it is unstable as over-reporters in the presence of honest or dishonest validators can invade when rare (main test, Fig. 2a).

In the presence of social punishment to the over reporter and frequency of honest validators above the threshold a^*, honest reporting is stable under high basin of attraction (main test, Fig. 2b). The threshold value of a^* can be given as,

$$a^* = 1 - \sqrt[v]{\frac{c(1+v)y}{c(1+v)y+(S-y)\varepsilon}} \quad (16)$$

The value of a^* decreases exponentially with the social punishment and number of validators v (Fig. S2). However, social punishment plays a more significant role than the number of validators (Fig. S2). If the social punishment is sufficiently large, a rare honest validator can ensure that the entire population stays at honest reporting equilibrium.

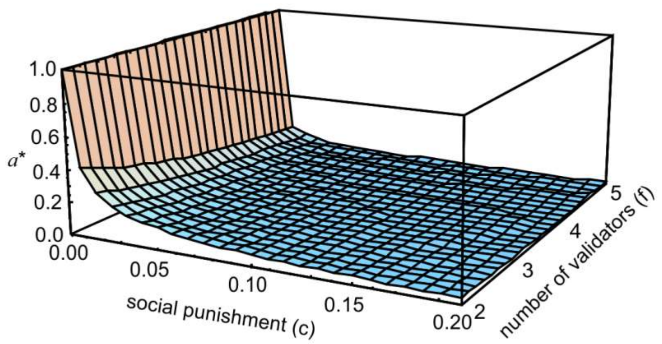

Fig. S2: *Threshold value of honest validators above which honest reporting is stable as a function of social punishment (c) and number of validators (v).*

S3. Other additional factors (AF) that can affect the dynamics

AF1: Effect of ε on the dynamics

Although we considered the value of ε to be constant, for over reporters, one with a larger ε gives greater benefit than one with a smaller ε. Therefore, ε can monotonically evolve to be large. However, this does not drastically change the dynamics of the game. The threshold value of honest validators a^* required to evolve and stabilize honest reporting will be marginally affected by the value of ε (Fig. 5). A slightly larger value of social punishment will still insure that rare honest validator can evolve and stabilize honest reporting. Since social punishment can be in the form of embracement, in small and viscous populations such punishment will anyway be high.

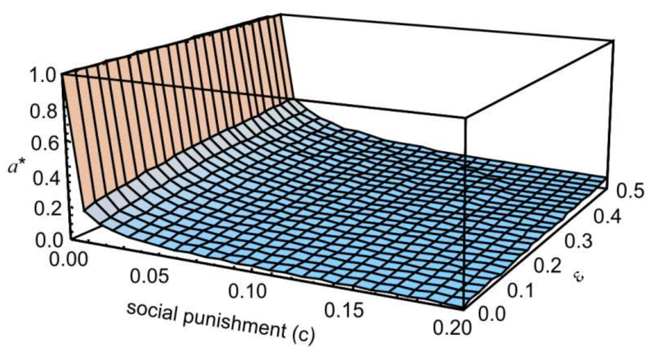

Fig. S3: *Threshold value of honest validators above which honest reporting is stable as a function of social punishment (c) and ε.*

A large ε, on the other hand, is more useful in increasing the absolute payoff of honest validation as described in AF2.

AF2: If validators are rational, flexible and take decision by absolute than by relative pay-offs.

When r is 0, $R = y$. Therefore SuRA = S-y.

When r persons over-report, R increases by r.ε Therefore by preventing over-reporting one gets

$$(S-y)-y.\frac{S-(y+r.\varepsilon)}{(y+r.\varepsilon)}$$

$$=\frac{S.r.\varepsilon}{y+r\varepsilon}$$

On the other hand if v number of validators and one over-reporter share the benefit of over-reporting equally they get $\frac{\varepsilon.(S-R)}{(v+1).R}$.

Preventing over-reporting is more beneficial to the validator in terms of absolute payoff when

$$\frac{S.r.\varepsilon}{y+r\varepsilon}>\frac{\varepsilon.(S-R)}{(v+1).R}$$

Substituting R,

$$\frac{S.r.\varepsilon}{y+r\varepsilon}>\frac{\varepsilon.(S-y-r.\varepsilon)}{(v+1).(y+r.\varepsilon)}$$

This condition is satisfied when

$$r>\frac{S-y}{S.(v+1)+\varepsilon}$$

Thus when r exceeds this threshold, honest validation is more beneficial than accepting a bribe. Therefore if all validators are rational and flexible in their strategy, above the threshold r, everyone will reject over-reporting. As ε becomes large, for reasons discussed in AF1, this condition will be satisfied for smaller and smaller r. Also if v is kept sufficiently large in the system operation, honesty in validation will give a larger absolute payoff than the possible bribe for approving over-reporting. This ensures a sudden rise in μ at a small rise in r which effectively undermines the advantage of over-reporting.

However, the benefit of honest validating is not uniquely availed by the validator but shared by the entire group. This makes it similar to a snowdrift or volunteer dilemma game (Diekmann 1985). But owing to the requirement of v number of validators, even one of them being honest serves the purpose. This increases the benefit to what Diekmann (1985) calls superrationality.

S4. Supplementary field data

(i) Correlations with distance from forest:

From our earlier study in this area, (Bayani 2016), animal damage decreases monotonically with distance. In the first year of the intervention, there was a positive trend in productivity per unit area (Quintals/Hectare) which was significant for rice and lakhori. The trend vanished in the following years possibly owing to better crop protection measures employed by all farmers. The lack of correlation is compatible with the assumption that all farmers share comparable risk of damage by wild herbivores.

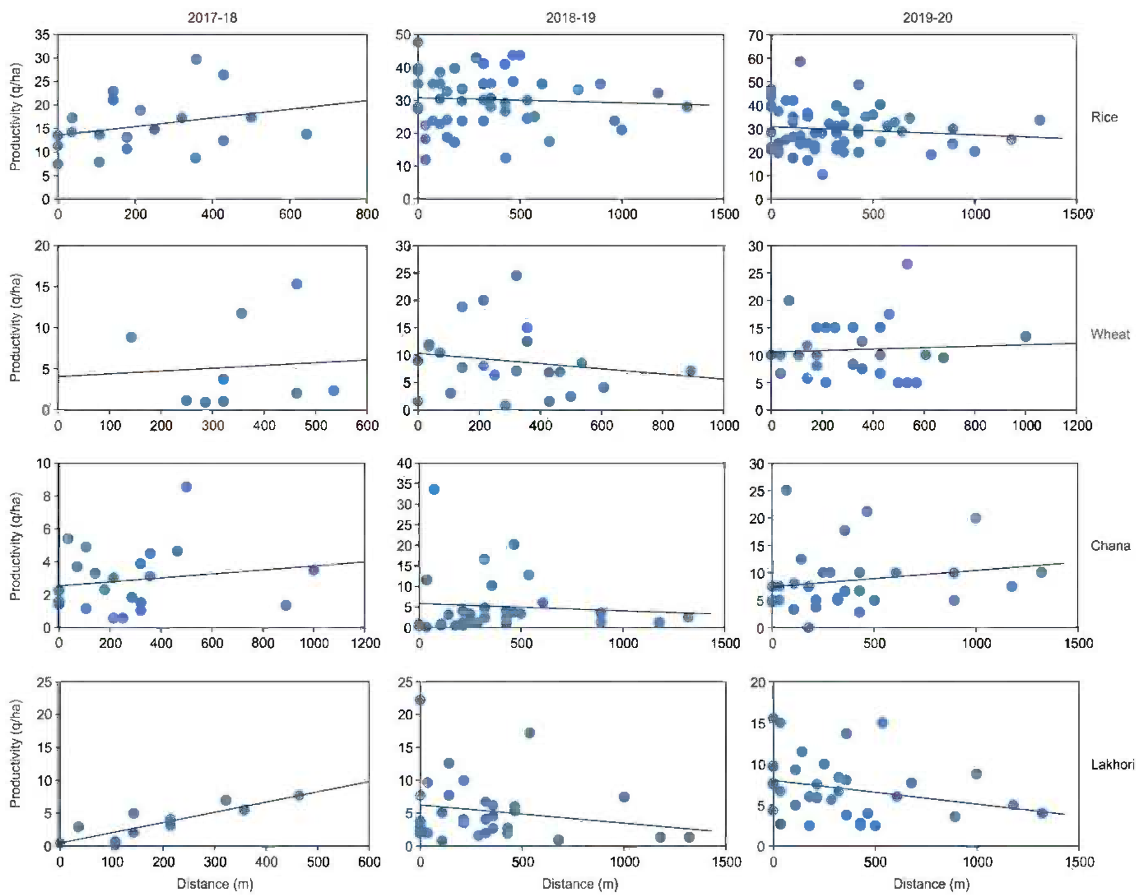

Fig. S4: Correlation between distance from the forest and productivity.

(ii) Correlation with irrigation facility: One of the causes of variability in productivity within the group was perceived to be difference in irrigation facility. Since the irrigation facility was difficult to quantify, we categorized it in three levels, 1 representing minimum and 3 representing adequate, the categorization being based on months of water availability in a year and ease of lifting and irrigating. The perception seems to be true from the correlation with productivity of the three post monsoon crops which depend upon irrigation. Rice, being a monsoon crop, is least dependent on irrigation, and shows no significant correlation.

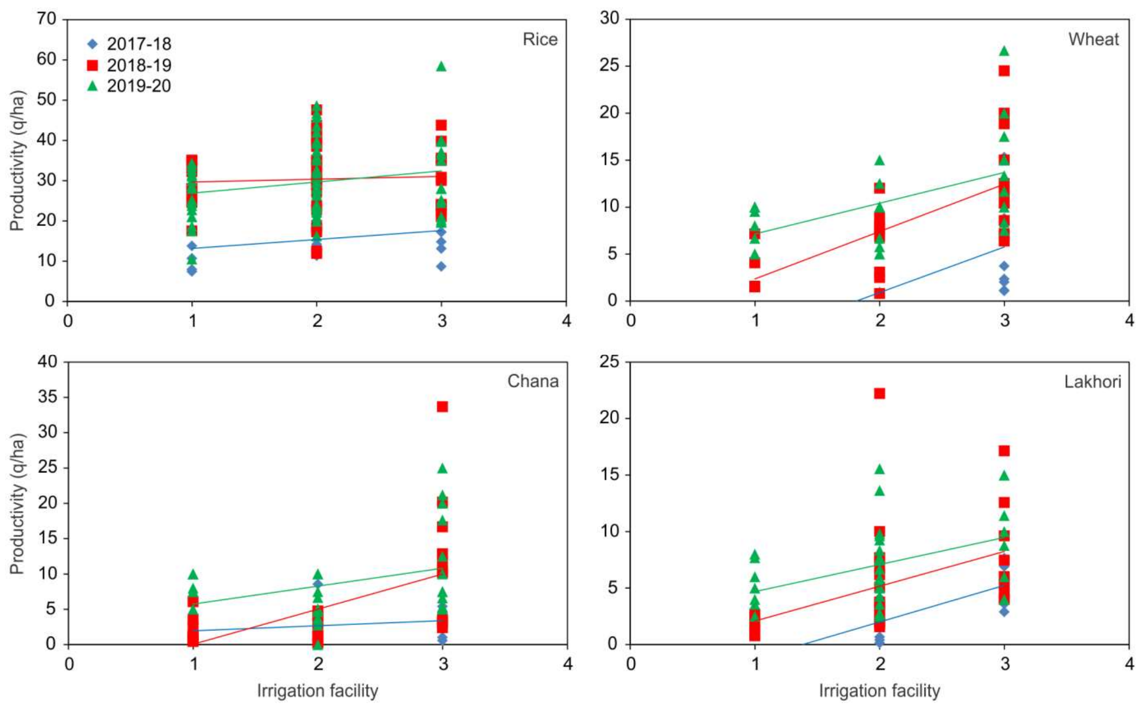

Fig. S5: Correlation between irrigation facility and productivity.

The rise in productivity in successive years was independent of the irrigation availability as seen by the more or less parallel upliftment of the regression lines. Irrigation facility is also an indicator of the resourcefulness of the farmer, since richer farmers have their own traditional or bore wells. Thus, the benefits of support cum reward model were well distributed amongst the poorer as well as better off farmers.

(iii) The frequency distribution of productivity:

As the mean productivity increased, the entire distribution can be seen to have shifted right, indicating that the raised average was not a result of some outlier achievers but almost every farmer benefited from the SuR model. The model therefore is likely to work well for the upliftment of the poor.

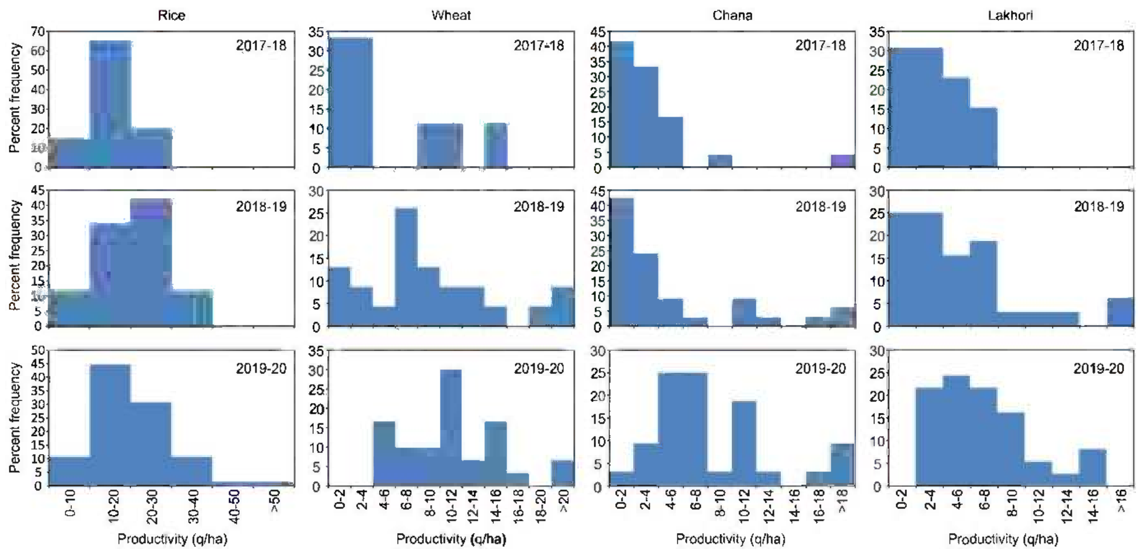

Fig. S6: *Frequency distribution of productivity of four crops for three consecutive years .*

S5. References

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