

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.







Productivity and Efficiency Analysis for Livestock Grazing under Grazing Pressure using Directional Distance Function

Wei Huang¹, Bernhard Bruemmer¹

1. Department of agricultural economics and rural development, University of Goettingen, Goettingen, Germany, D37073

Abstract

With the use of first hand field survey data from 193 yak grazing households combined with remote sensing Net Primary Productivity data on the Qinghai-Tibetan Plateau, a directional output-orientation distance function is developed with four inputs, grassland area, labor, capital and initial livestock stocking, and two outputs, good output of livestock grazing revenue and undesirable output of grazing pressure. The average technical efficiency is estimated to be 0.82, and shadow price of grazing pressure to livestock revenue is estimated to be -1.8. According to Morishima elasticity of substitution between inputs, there is significant complementary relationship between grassland area, labor and capital. Elasticity of substitution between grassland and initial livestock stocking is estimated to be 0.50. Treating grazing pressure as an undesirable output of livestock grazing in the directional distance function is a new step in the general direction of better accounting for natural resource depletion in efficiency and production analysis.

Keywords: directional distance function, grazing pressure, technical efficiency, shadow price, Morishima elasticity of substitution



1. Introduction

The concerns about environmental problems caused by economic development in developing countries have received a lot of attention in recent years. Grassland is one of the main land use types on earth and is essential for livestock grazing and grassland ecosystem service supply; the method of finding a balance between environment and livestock grazing has been a major focus in research (De Haan *et al.*, 1997; White, *et al.*, 2000; McDowell, 2008). However, demand for livestock products is being accelerated by population growth, economic growth and expanding urbanization, especially in developing countries or regions. High demand for livestock products has resulted in increasing grazing pressure, which is associated with overgrazing.

Overgrazing appears when the stocking rate exceeds the proper grassland carrying capacity, and is accompanied with increasing grazing pressure, which threatening both economically and ecologically the sustainable use of grassland, e.g. to result in grassland degradation. Three quarters of the world's grazing lands are so degraded that they have lost more than 25% of their capacity to support animals (White, et al., 2000; UNEP, 2005), as well as that on The Qinghai-Tibetan Plateau is a perfect example of a region heavily affected by advancing grassland degradation over wide areas and overgrazing is assumed to be one of the main courses (Akiyama, et al., 2006; Zhou, et al., 2006; Zhang, 2008; Harris, 2010).

Grassland in the Qinghai Province of China, one of the largest grasslands in China, was found to have a high overgrazing status by comparing actual and proper livestock carrying capacity (Fan *et al.*, 2011; Zhang *et al.*, 2014). Fan *et al.* (2011) studied the temporal-spatial dynamics of grazing pressure during the period from 1988 to 2005. Over grazing was considered as one of the main factors resulting in grassland ecosystem degradation, although the grazing pressure was steadily reduced. In recent research on the overgrazing status in the Sanjiangyuan region, overgrazing still remained a problem in 2010 (Zhang, Zhang and Liu *et al.*, 2014). Combining the data from the field survey, the overgrazing ratio is more than 300% in sample counties (Table 1), overgrazing remains a serious problem and the overgrazing status is highly correlated with grazing pressure. The strong effect of the overgrazing status on grassland degradation makes us interested in researching the performance of livestock grazing under the control of grazing pressure, by adopting the grazing pressure as an undesirable output from livestock grazing using the directional distance function.

The directional distance function was probably first proposed by Chung *et al.* (1997) and Chambers *et al.* (1998) with a similar introduction previously from the Luenberger index. It has surged in popularity over the last 10 years (Färe, *et al.*, 2013; Feng and Serletis, 2014). Rather advantageously, the directional distance function loses the assumption that radial changes of inputs or outputs take place simultaneously. In reality, the pursuit of more undesirable outputs ("bad outputs") is not encouraged proportional in producing good outputs. It prevails to use directional distance analysis for polluting technology, which produces pollution as a byproduct, such as electric utilities producing electricity and air pollution (Atkinson and Dorfman, 2005; Färe *et al.*, 2005; Cuesta *et al.*, 2009; Coelli *et al.*, 2013; Wang *et al.*, 2013; Yao *et al.*, 2015) and dairy farming (Reinhard 1999; Reinhard et al. 2000; Fernández *et al.*, 2002; Reinhard 2002; Sauer and Latacz-Lohmann, 2014; Njuki and Bravo-Ureta, 2015).

Before the development of the directional distance function, the productivity of the decision making unit when some outputs are undesirable has been studied. Pittman was perhaps the first to develop an index of productivity change which takes environmental effects into account. He modeled pollution as an input in the production function because of the relation between an environmentally detrimental variable and output (Pittman 1981; Pittman 1983). Undesirable outputs in pulp mills industry sector have been heavily researched; such topics have included the environmental effects of undesirable outputs in the Finnish pulp and paper industry (Hetemäki, 1996), Swedish pulp and paper industry (Brannlund et al. 1998) and the paper recycling industry in Vietnam (Van Ha *et al.*, 2008). Färe *et al.* (1986; 1989; 1993) modeled environmental effects as undesirable outputs with U.S. electricity generation data by using econometric models. The directional distance function was then applied later by other researchers (Cropper and Oates, 1992; Yaisawarng and Klein, 1994).

To evaluate the environmental goods - sometimes called nonmarket goods - such as air pollution emissions, soil pollution or ecological diversity loss from human economic activity, relative shadow prices of nonmarket goods are derived based on the distance function as well as elasticities of complementary or substitutionary relationships among inputs or outputs (Blackorby and Russel, 1989; Färe *et al.*,1993; 2005; Morrison Paul *et al.*, 2000; 2005; Hailu, 2000; Cuesta, 2009; Rahman, 2010; Serra *et al.*, 2011). In this paper, we incorporate grazing pressure as an undesirable output from livestock grazing to determine the environmental-grazing relationship.

We extend the contribution of the directional distance function by incorporating the grazing pressure as an undesirable output and deriving the shadow prices of grazing pressure to grazing revenue, elasticity of directional distance with respective to inputs and outputs, and elasticity of complementary or substitutionary relationships among inputs. The directional distance function with MLE estimation procedure is developed by using 193 households' level data on livestock grazing. We would like to stress a deeper understanding of the performance of extensive livestock grazing on the Qinghai-Tibetan Plateau by taking into account the grazing pressure.

The structure of the paper is as follows. Section 2 presents the theoretical framework, methodology. Section 3 presents the empirical model specification and data description. The empirical analysis results are presented in section 4, followed by section 5 which concludes with discussion.

2. Theoretical framework and methodology

A multi-input multi-output directional distance function incorporating grazing pressure as the bad output is developed in order to measure the production performance of grassland grazing under the framework of environmental efficiency. As grassland grazing on the Tibetan Plateau still adopts the traditional half-nomadic pastoral system (Davies and Hatfield, 2007; Harris, 2010), this might be advantageous for the distance function, not considering the exact price of inputs and outputs. We adopt the distance function approach instead of the deterministic approach because of the advantage of the stochastic approach to separate the random noise from the technical inefficiency term.

2.1 Conceptual framework

The directional distance function is applied to all properties of the distance function introduced by Shephard (1970) with defining inputs $x = (x_1, \dots, x_K) \in \Re^{K+}$, outputs $y = (y_1, \dots, y_M) \in \Re^{M+}$, and the output possibility set $P(x) = \{y : x \text{ can produce } y\}$, which is assumed to satisfy the set of axioms depicted in Färe *et al.* (2000). The directional distance function measures the distance from the production unit to the efficiency boundary along with a directional vector, given the directional vector $g = (-g_x, g_y)$ with $g_x \in R_+^N$ and $g_y \in R_+^M$, determined by which of the inputs would be contracted and which outputs would be expanded, as described in Figure 1, when firms adjust the production behavior along the vector from producing point A. Then, the directional distance function is given by

$$\vec{D}(x, y; g_x, g_y) = \sup\{\vartheta: (x - \vartheta g_x, y + \vartheta g_y) \in P\}$$
 (1)

where $\overrightarrow{D}(x,y;g_x,g_y) \geq 0$, $\vartheta \in R$, which inherits all properties of the directional distance function described in Chambers *et al.* (1998) and Färe *et al.* (2005). The directional distance function can take the quadratic form as:

$$\vec{D}(x, y; g_x, g_y) = \sum_{k=1}^{N} \alpha_k x_k + \sum_{j=1}^{M} \beta_j y_j + \sum_{k=1}^{N} \sum_{l=1}^{N} \alpha_{kl} x_k x_l + \sum_{j=1}^{M} \sum_{h=1}^{M} \beta_{jh} y_j y_h + \sum_{k=1}^{N} \sum_{j=1}^{M} \gamma_{kj} x_k y_j$$
(2)

The translation property of the directional distance function allows for an empirical use:

$$\vec{D}(x - \vartheta g_x, y + \vartheta g_y; g_x, g_y) = \vec{D}(x, y; g_x, g_y) - \vartheta$$
(3)

This property indicates the producer decreases the distance to efficiency boundary by scalar ϑ , while output is improved by ϑg_y and input is reduced by ϑg_x simultaneously, given the technology is available. It is a radial input distance function if $g_y = 0$, as the firm close to the efficient frontier from point A to point B; and it is a radial output distance function if $g_x = 0$, when the firm is moving the producing point from point A to point C, therefore, the radial distance function is – in special cases - the directional distance function (Färe and Grosskopf, 2000). Based on the directional distance function framework, the output oriented directional distance function and the input oriented directional distance function can be derived. We use the output oriented directional distance function for grassland grazing in this paper.

[Figure 1. Directional distance function]

Specifically, the producer is efficient in the director $(-g_x, g_y)$ if

$$0 = \vec{D}(x, y; g_x, g_y) + \varepsilon_i \tag{4}$$

where $\varepsilon_i = v_i - u_i$, $v_i \sim \text{i.i.d.}\ N(0, \sigma_v^2)$ and $u_i \sim N(\mu_i, \sigma_u^2)^+$, $i=1,2,\cdots,N$.

Hence, by substituting (4-4) into (4-3), we get

$$-\vartheta_i = \vec{D}(x - \vartheta g_x, y + \vartheta g_y; g_x, g_y) + v_i - u_i$$
 (5)

The translation property given above requires the restrictions as discussed in Färe *et al.* (2005), which will be explained in more detail in next section. The mean μ_i is defined for technical inefficiency u_i , where the technical inefficiency model is written in equation (6).

$$\mu_i = \sum_{c=1}^C \tau_c * Z_{ci} \tag{6}$$

where Z_{ci} is a vector of household characteristic variables associated with the technical inefficiency effects and τ_i is a vector of unknown parameters to be estimated (Battese and Coelli, 1988, 1995, 1997; Coelli and Battese, 1996). Maximum Likelihood Estimation (MLE) could be used to estimate the parameters (Aigner, Lovell and Schmidt, 1977).

Given the production frontier specified as

$$Y_i = f(X_i, \beta). \exp(v_i - u_i)$$
(7)

Technical efficiency (TE) is defined as the ratio of the observed output to the corresponding potential output, which is written as

$$TE_i = \frac{f(X_i, \beta) \cdot \exp(v_i - u_i)}{f(X_i, \beta) \cdot \exp(v_i)} = \exp(-u_i)$$
(8)

2.2 Relative shadow prices and Morishima elasticity of substitution

Thanks to the duality theory between the distance function and cost function or revenue function (input distance function for cost minimization function, output distance function for revenue maximization function), shadow prices for non-market goods can be derived (Shephard, 1970; Färe and Primont, 1996). Assuming that the directional input (output) distance function and the cost (revenue) functions are differentiable, application of Shepherd's dual lemma would lead to the shadow price formulas:

$$\nabla_x \vec{D}(x, y) = r^*(x, y) \tag{9}$$

where $r^*(x, y)$ is the cost minimizing inputs prices vector.

Because the input prices are not available and optimal cost of production cannot be accurately estimated in this paper, then relative shadow prices can be derived from the following formula:

$$R_{kl} = \frac{r_k^*}{r_l^*} = \frac{\partial \vec{D}(x, y)/\partial x_k}{\partial \vec{D}(x, y)/\partial x_l}$$
(10)

where r_k^* and r_l^* are the shadow prices of the inputs x_k and x_l , respectively. This ratio is the relative shadow price of input x_k with respect to input x_l . These shadow prices reflect the trade-off between different inputs (Färe *et al.*, 1993; Hailu and Veeman, 2000).

Because of the duality between the input distance function and the cost function, the degree of substitutability along the surface frontier, such as frontier curvature, can be calculated. The indirect Morishima elasticity of substitution (MES) from a directional input distance function can be computed as formula (11) (Blackorby and Russell, 1989).

$$MES_{kl} = -\frac{\partial (\overrightarrow{D}_k / \overrightarrow{D}_l)}{\partial (\overrightarrow{X}_k / \overrightarrow{X}_l)}$$
(11)

where the subscripts on the distance functions refer to partial derivatives with respect to inputs. This represents the change in relative marginal products and input prices required to affect substitution under cost minimization. High values reflect low substitutability and low values reflect relative ease of substitution between the inputs (Morrison-Paul *et al.*, 2000). The MES can be simplified as follows:

$$MES_{kl} = \varepsilon_{kl} - \varepsilon_{kk} \tag{12}$$

where ε_{kl} and ε_{kk} are the constant output cross and own elasticity of shadow prices with respect to input quantities. The first term provides information on whether pairs of inputs are net substitutes or net complements, and the second term is the own price elasticity of demand for the inputs. It should be noted that these elasticities are indirectelasticities. Therefore, for $\varepsilon_{kl} > 0$ net complements are indicated, and for $\varepsilon_{kl} < 0$ net substitutes are indicated.

The shadow price elasticities with respect to input quantities are given by:

$$\varepsilon_{kl} = (\alpha_{kl} + S_k S_l) / S_k \text{ if } k \neq l$$
 (13)

$$\varepsilon_{kk} = [\alpha_{kk} + S_k(S_k - 1)]/S_k \text{ if } k = l$$
(14)

where S_k is the first order derivatives of the distance function with respect to input x_k , that is

$$S_k = \partial \vec{D} / \partial x_k \tag{15}$$

3. Empirical model specification and data descriptive statistics

3.1 Empirical model specification and estimation measurement

Following Chambers *et al.* (1998, 2002) and Färe *et al.* (2005), we first build the output oriented directional distance function in equation (16). The advantage of the output oriented directional distance function is thhat it allows us to expand the good output while contracting the bad output while leaving inputs unchanged, as showed in Figure 2. Assuming point A is the production point of a household, then the household improves the production along the directional vector $g = (g_y, -g_b)$, that is to add ϑg_y to good output y while subtracting ϑg_b from the bad output b.

[Figure 2. Output orientation directional distance function]

$$\overrightarrow{D_o}(x, y, b; g_y, -g_b) = \sup\{\vartheta: (y + \vartheta g_y, b - \vartheta g_b) \in P\}$$
(16)

While satisfying the translation property, equation (16) can be denoted as equation (17),

$$\overrightarrow{D_o}(x, y + \vartheta g_v, b - \vartheta g_b; g_v, -g_b) = \overrightarrow{D_o}(x, y, b; g_v, -g_b) - \vartheta \tag{17}$$

We parametrically estimate the directional distance using stochastic estimation methods following Kumbhakar and Lovell (2000), then the empirical stochastic specification form is written in equation (18).

$$-\vartheta_i = \overrightarrow{D_o}(x, y + \vartheta g_y, b - \vartheta g_b; g_y, -g_b) + v_i - u_i$$
(18)

Assuming $g = (g_y, -g_b) = (1, -1)$, the quadratic form for our case, 4 inputs and 2 outputs (1 good output y and 1 bad output b), is denoted by equation (19).

$$\overrightarrow{D_o}(x, y, b; 1, -1)$$

$$= \alpha_0 + \sum_{k=1}^{4} \alpha_k x_k + \beta_1 y + \beta_2 b + \frac{1}{2} \sum_{k=1}^{4} \sum_{l=1}^{4} \alpha_{kl} x_k x_l + \frac{1}{2} \beta_{11}(y)^2$$

$$+ \frac{1}{2} \beta_{22}(b)^2 + \sum_{k=1}^{4} \gamma_{k1} x_k y + \sum_{k=1}^{4} \gamma_{k2} x_k b + \delta y b$$

$$(19)$$

To hold the translation property, the required restrictions are

$$\beta_1 - \beta_2 = -1$$
, $\beta_{11} = \beta_{22} = \delta$, $\gamma_{k1} = \gamma_{k2}$, k=1,2,3,4.

Additional, symmetry conditions require: $\alpha_{kl} = \alpha_{lk}$, k = l = 1,2,3,4.

In our case, we choose $\vartheta = b$, then the quadratic form of the empirical specification for grassland grazing is

$$-\vartheta_{i} = \overrightarrow{D_{o}}(x, y + b, 0) + v_{i} - u_{i}$$

$$= \sum_{k=1}^{4} \alpha_{k} x_{k} + \beta_{1} y^{*} + \frac{1}{2} \sum_{k=1}^{4} \alpha_{kk} (x_{k})^{2} + \frac{1}{2} \beta_{11} (y^{*})^{2}$$

$$+ \sum_{k=1}^{4} \sum_{l=1, k \neq l}^{4} \alpha_{kl} x_{k} x_{l} + \sum_{k=1}^{4} \gamma_{k1} x_{k} y^{*} + v_{i} - u_{i}$$

$$(20)$$

where $y^* = y + b$. y describes the good output of grassland grazing, denoted by the revenue of livestock meat and milk produced in the year; b denotes the bad output, grazing pressure, defined as ratio of livestock live weight divided by grassland forage biomass. X is the vector of inputs with x_1 = grassland area size, x_2 = labor, x_3 = household productive capital and x_4 = initial yak stock. v_i is a random error term, intended to capture events beyond the control of the herdsman and u_i is a non-negative random error term, intended to capture technical inefficiency in production. In order to compare different effects of the directional vector, we use $g = (g_y, -g_b) = (1, -1)$ and $g = (g_y, -g_b) = (1, 0)$ in empirical analysis, the setting with g = (1, 0) means ignoring the bad output in the production process.

The technical inefficiency model referred to equation (6) in this chapter is written as

$$\mu_i = \tau_0 + \sum_{c=1}^8 \tau_c * Z_{ci} \tag{21}$$

where Z is a vector of explanatory variables associated with the technical inefficiency effects including total NPP change of each household (z_1) , household size (z_2) , distance from fixed home to summer pasture (z_3) , grazing experience (z_4) , summer pasture area (z_5) and winter pasture area size (z_6) , dummy variable of pasture plot (z_7) and dummy variable of whether there is leased-in grassland from other households (z_8) .

3.2 Data and descriptive statistics

The social-economic data used in this paper was drawn from field survey data in the Sanjiangyuan region in Qinghai province conducted by the Center for Chinese Agricultural Policy (CCAP) of the Chinese Academy of Sciences in August and October, 2012. The Net Primary Production data is from the MODIS GPP/NPP Project. The Sanjiangyuan region in

China, known as the Three-River Headwaters in English, is located in the northeast of the Qinghai-Tibetan Plateau, where more than 90% of the local people are of Tibetan Ethnic Minority. The average elevation of the Sanjiangyuan region is between 3500 and 4800 m. Like other parts of the Tibetan plateau, a cold season from approximately November to the following May and a warm season from June to October can be identified. The annual mean temperature is about 1 to 2 degrees Celsius, and the annual precipitation ranges from 600 mm to 800 mm. The stratified random sampling method was used to select observations and 144 of them are available for this paper.

Classic inputs are aggregated into four categories (grassland area, labor, capital and initial yak) and outputs are aggregated into two categories (y as good output of revenue from grassland grazing and bad output b, grazing pressure). There are two kinds of pastures on the Qinghai-Tibetan Plateau: Summer/autumn pasture and winter/spring pasture, where grassland area (x_1) is the sum of summer pasture area and winter pasture area for each household. Labor (x_2) consists of family labor, measured by person. Capital (x_3) consists of productive machinery (irrigation machine, transportation machine and so on). It is calculated by sum aggregation of each item obtained from the questionnaires. Initial yak stock (x_4) means the initial yak input at the beginning of the year and is calculated by multiplying the average weight of a yak by the yak number per household. Good output y denotes the revenue of yak meat produced in the year and revenue of the other outputs, including the revenue from Tibetan sheep meat, output of milk, yak hide, Tibetan sheep wool and so on. Bad output y denotes the grazing pressure of livestock grazing on the Qinghai-Tibetan Plateau; detailed information of bad output y0, grazing pressure, is given in the next paragraph.

The important variable that we are focusing on is the bad output, grazing pressure. Grazing pressure is international terminology which forms the relationship between animal live weight and forage mass per unit of grassland on the grazed land given a specific time (Allen *et al.*, 2011). Grazing pressure is highly positively correlated to the over grazing ratio: The more the livestock stocking rate surpasses the proper carrying capacity, the higher the grazing pressure. As grazing pressure is the relationship of animal-to-forage ratio, we calculate grazing pressure as the ratio between livestock live weight and total grassland Net Primary Productivity (NPP), where total grassland NPP is used as representative of grassland biomass. Grassland total NPP is computed with unit NPP multiplying the total grassland area, while unit NPP is computed with daily MODIS land cover, FPAR/LAI and global GMAO surface meteorology at 1km for the global vegetated land surface (Zhao and Running, 2010). These variables provide the

initial calculation for growing season and carbon cycle analysis, and are used for agriculture, range and forest production estimates. After matching the rough boundary of summer pasture and winter pasture to the 1km NPP raster data file, and getting samples of NPP for each pasture according to the pasture area, we summarize the NPP of pastures for each grazing household.

For the technical inefficiency model, operational and farm-specific variables were considered including the total NPP change of each household's pasture (z_1) , household size (z_2) , distance from fixed home to summer pasture (z_3) , grazing experience (z_4) , summer pasture area (z_5) and winter pasture area size (z_6) , dummy variable of pasture plot (z_7) and dummy variable of whether there is leased-in grassland from other households (z_8). Total NPP change of each household (z_1) is calculated by total NPP in the year 2012 subtracted by total NPP in the year 2011. Household size (z_2) is the population in one family. Distance from fixed home to summer pasture (z_3) measures the geographic distance from the fixed home to the summer pasture. Grazing experience (z₄) denotes how many years of grazing experience each household head has. Summer pasture area (z_5) and winter pasture area (z_6) are pasture area size in summer and winter respectively, while dummy variable of pasture plot (z_7) means whether the summer pasture and winter pasture are located in the same plot or adjacent plots. Dummy variable of lease-in grassland (z_8) measures whether there is leased-in grassland from other households, which equals 1 if the household grazes on leased-in grassland, and 0 for otherwise. A statistic description of variables in the directional distance function and technical inefficiency model is shown in Table 2.

[Table 2. Statistic descriptive of variables]

4. Results

Before presenting the performance of inputs and outputs in the directional distance function, we compared the directional distance functions with different assumptions of directional vectors $g = (g_y, -g_b) = (1, -1)$ and $g = (g_y, -g_b) = (1, 0)$ (Table 3). We assigned model 1 with directional vector g = (1, -1), which means to expand good output while subtracting bad output of the grazing pressure. In model 2, g = (1, 0) is assumed, denoting the expansion of good output without subtracting the bad output grazing pressure. A Hausman test is used to compare the two models with a null hypothesis that there are no systematic differences between the two. From the Hausman test below Table 3, we can see the null hypothesis is strongly rejected, indicating that there are systematic differences between the estimates of the

two models. Taking into account the distributional signals and monotonicity conditions, model 1 with directional vector g = (1, -1) is preferred. Hereafter, all analysis and estimates will be based on the directional vector of $g = (g_y, -g_b) = (1, -1)$ in model 1. The δ_u is estimated to be 0.586, which means relatively unignorably inefficiency term u_i , which supports us in setting the directional distance function combined with technical inefficiency model, as showed Table 3, where the likelihood value is -3.554 with degree of freedom 31. The likelihood value of model 1 is -36.824 with degree of freedom of 23. According to the likelihood ratio test, LR $Chi^2(8) = 66.54$, which is significantly larger than the criteria value of $x_{0.005}^8(8) = 21.955$; this implies that the setting of the technical inefficiency model would definitely improve the model specification. We took likelihood ratio tests for the technical inefficiency model setting (Appendix Table 1). According to all the likelihood ratio tests and one-sided inefficiency random components, we choose the final model setting in Table 4, and consequently calculate the first order conditions, shadow price and Morishima elasticity of substitutions between inputs.

[Table 3. Directional distance function with different directional vector]
[Table 4. Estimates of directional distance function and technical inefficiency model]

4.1 Parameter estimates of directional distance functions

The one-step approach for both the directional distance function and technical inefficiency model using maximum likelihood is presented in Table 4, with all variables divided by mean. Most coefficients are estimated to be significant; especially the first order coefficient and second order coefficient of good output y, and cross interacting terms between input and good output The output distance function is concave outputs, thus, $\partial^2(\overrightarrow{D_o}(x,y,b;1,-1))/\partial y\partial y=\beta_{11}\leq 0\ ,\ \ \text{and}\ \ \text{according}\ \ \text{to}\ \ \text{the}\ \ \text{translation}\ \ \text{property},$ $\partial^2(\overrightarrow{D_o}(x,y,b;1,-1))/\partial b\partial b = \partial^2(\overrightarrow{D_o}(x,y,b;1,-1))/\partial y\partial b = \beta_{11}, \beta_{11}$ is estimated to be -0.263, significant at the 1% statistical level.

Based on the estimates from the directional distance function, the elasticities of the directional distance function with respect to inputs and outputs are calculated to get a full understanding of the performance of inputs and outputs in the grassland grazing process, elasticities of the sample mean are presented (Table 5). A T Test is used to test whether the elasticities are different from zero at the 10% statistical level. The monotonicity conditions of the directional distance function require $\partial^2(\overrightarrow{D_o}(x,y,b;1,-1))/\partial x \geq 0$. With the exception of input x_4 , the

initial yak at the beginning of the year, elasticity of distance with respect to inputs grassland area size, labor and capital have expected positive signs, implying that increasing the input of any of these inputs will increase production potential substantially. The largest elasticity of the directional distance with respect to inputs comes from the grassland area, which is estimated to be 0.64, implying a 1% increase of grassland area would enhance production potential by 0.64%. The monotonicity conditions of the directional distance function for outputs require $\partial(\overrightarrow{D_o}(x,y,b;1,-1))/\partial y \leq 0$ and $\partial^2(\overrightarrow{D_o}(x,y,b;1,-1))/\partial b \geq 0$. The elasticity of distance with respect to good output ϵ_v is -0.36 and elasticity of bad output grazing pressure ϵ_b is estimated to be 0.64; both are significant at the 1% statistical level. A 1% increase in good output would reduce the distance by 0.35%, while a 1% increase in bad output, grazing pressure, would expand the distance by 0.64%.

[Table 5. Elasticity of distance with respective to inputs and outputs]

4.2 Shadow price of grazing pressure

As grazing pressure cannot be traded in the market directly, the relative shadow prices of grazing pressure to revenue of livestock grazing are calculated for a better understanding of their relationship with each other. The relative shadow price of grazing pressure is estimated to be -1.8 at the sample mean, which means the "price" coming from grazing pressure is higher than production of one unit of good output. As there is no reason to interpret shadow price for the observations that violate the monotonicity conditions (Färe et al., 2005), we summarize the relative shadow price for a partial sample which meets the monotonicity conditions in the third column of Table 6. Thus, we can see that the relative shadow price of grazing pressure is -3.99, which means that the higher cost household should pay for one unit production of good output, again confirming that grazing pressure is a bad output from livestock grazing. In previous literature on environmental efficiency analysis, most of the studies on shadow prices of environmental outputs were assumed to be negative (Reinhard, 1999; Färe et al., 1993, 2005; Hailu and Veeman, 2000), which mean that these environmental outputs are "bad outputs". The value of M_{bv} is estimated to be -0.55 for all samples, and -0.73 for partial samples which meet the monotonicity condition. A more negative M_{bv} indicates a greater change of relative shadow price of grazing pressure to good output livestock revenue, thus resulting in a greater cost to reduce the grazing pressure.

[Table 6. Relative shadow price of outputs and elasticity of transformation]

4.3 Morishima elasticity of substitution between inputs

Morishima elasticity of substitution (MES) can be used to measure changes in relative output and input quantities as a consequence of changes in relative prices (Färe et al., 2005; Sauer et al., 2012). Using equations (11) to (15), we calculate MES for substitution or complementarity relations among inputs based on estimates of the directional output distance function (Table 7). A positive MES indicates a complementary relationship between two inputs and negative MES indicates a substitutionary relationship between inputs; in terms of absolute value of MES, high values reflect a low degree of complementarity or substitutability and low values reflect a high degree of complementarity or substitution between the inputs (Blackorby and Russell 1989; Morrison-Paul et al., 2000; Rahman, 2010). Most of the elasticities are positive and are significantly different from zero by the T-test. An exception is the substitution elasticity between the grassland area size and the initial livestock stock which is equal to 0.50; there are further complementary relationships among other combinations.

[Table 7. Morishima elasticity of substitution between inputs]

4.4 Estimates for technical inefficiency model and technical efficiency

The general-to-specific modeling method (Hendry, 2000) was used in variable selection for deciding on the technical inefficiency model specifications. We first estimate a model including all control variables (Appendix Table 2), and then we drop the least significant variables according to a likelihood ratio test and estimate the model again. This procedure is repeated until only variables that are significant enough to pass the likelihood ratio test at the 10% level remain. The final determinants for the variation of a grazing households' technical inefficiency are estimated in the technical inefficiency model (right part of Table 3). Because technical inefficiency is the dependent variable in the technical inefficiency model, a negative parameter coefficient for the variables indicates a negative effect on technical inefficiency and conversely, meaing a positive effect on technical efficiency.

Total grassland NPP change (z_I) is estimated to be negative in relation to the technical inefficiency, -0.265 significant at the 1% statistical level. This indicates that the more the total NPP on grassland changes, the greater the efficiency of the household will be. However, as the total NPP change might be assumed to be consumed by livestock, which would let us be aware of the more the total NPP change, the higher trend to be overgrazed. Household size (z_2) is estimated to be positively related to technical inefficiency, which can be explained as larger household sizes would distract the household head's attention away from grazing, thus

resulting in higher inefficiency. There is no significant effect of distance from the fixed home to the summer pasture (z_3) on inefficiency, but it is suggested that this variable be kept in the model by a general-to-specific process. More grazing experience would increase the technical efficiency, which was obtained from estimates of grazing experience (z_4) , -1.058. We treat summer pasture area (z_5) , winter pasture area size (z_6) and the dummy variable of pasture plot (z_7) as a variable block, and we can see winter pasture area size is positively related to technical inefficiency, with 1.033 significance at the 1% statistical level. The dummy variable of lease-in grassland (z_8) has a highly positive affect on technical inefficiency, which means to lease in grassland from other households would increase the technical efficiency.

We calculate each household's technical efficiency after estimation of the stochastic distance function and technical inefficiency model. The average estimated technical efficiency is 0.82 (Table 8), which indicates that on average, grazing households can improve technical efficiency by 18% in terms of expanding livestock revenue and reducing grazing pressure given unchanged inputs. The distribution of technical efficiencies seems satisfactory from the histogram graph (Figure 3), and we can see that about 13% of the households have a technical efficiency smaller than 0.70, whereas 12% of households have efficiency greater than or equal to 0.70 and less than 0.80; 39% of households have efficiency greater than or equal to 0.80 and less than 0.90, and 35% households operate with a technical efficiency larger than 0.90 (Table 8).

[Figure 3. Histogram graph of technical efficiency]

[Table 8. Summary of technical efficiency]

5. Conclusion and discussion

Incorporating grazing pressure as the undesirable output from livestock grazing using the directional distance function is a new step toward environmental efficiency analysis under the field of productivity and efficiency analysis. The environmental variable, grazing pressure, as the undesirable output from livestock grazing, plays a significant role in the directional distance function and technical inefficiency model. The average technical efficiency is estimated to be 0.82, implying that the grassland production potential can be increased by 18% with directional adjustment of reduction of the grazing pressure.

With reference to Figure 4, there is a reverse U-shape relationship between cumulative grazing pressure and livestock production per unit area grassland. The livestock production per unit area increases according to cumulative grazing pressure until point A, and then

begins to decline at the critical cumulative grazing pressure. However, the ecological risk is monotonously positively increasing as cumulative grazing pressure increasing, which is strongly associated with the overgrazing status. The higher probability of ecological risk would result in a higher probability of grassland degradation (McDowell, 2008). As from the findings of our study, livestock grazing is probably operating on the line from point A to point B, according to estimates of the directional distance function, which means we would be better to leave constant or increase the production potential of livestock grazing in the Sanjiangyuan region without increasing the grazing pressure given the amount grassland size, labor, and capital.

Livestock grazing can have negative impacts on the environment if it is not controlled within acceptable limits. An efficiency livestock grazing monitor approach is suggested to ensure a proper livestock stocking rate. The tradeoff between traditional livestock grazing production and ecological and environmental protection of grassland calls for more scientific research on how to improve production potential under the sustainable grassland use. Findings of how environmental variables and grazing pressure affect the production potential and technical inefficiency of livestock grazing in this study would be helpful for the development of scientific strategies and programs for local economic development and environmental protection, as well as for the effectiveness of ecological protection projects.

There are a few limitations in this paper, for example, there is an assumption that the quality of livestock meat is homogenous for different livestock age groups. In terms of the approximate pasture boundary matching from a long time schedule and large scale level of remote sensing data to minor scale household level data, there is inevitable measurement error to some extent. For the grazing pressure measurement, we have not considered the grazing pressure from wild stock (Fisher, 2004). The consideration of the impact of both domestic stock and wild stock for analysis of sustainable livestock grazing could be considered in future work when wild stock data is available.

Reference

- Allen, V. G., Batello, C., Berretta, E. J., Hodgson, M. et al., (2011). An international terminology for grazing lands and grazing animals. *Grass and forage science*, 66(1), 2-28.
- Aigner, D., Lovell, C. A. K., Schmidt, P. (1977). Formulation and estimation of stochastic fromtier production function models. *Journal of Econometrics* 6: 21-37.
- Akiyama, T., Kawamura, K. (2007). Grassland degradation in China: Methods of monitoring, management and restoration. *Japanese Society of Grassland Science* 53: 1-17.
- Asante, B. O., Wiredu, A. N., Martey, E., *et al.* (2014). NERICA Adoption and Impacts on Technical Efficiency of Rice Producing Households in Ghana: Implications for Research and Development. *American Journal of Experimental Agriculture* 4: 244-262.
- Atkinson, S. E. and J. H. Dorfman (2005). "Bayesian measurement of productivity and efficiency in the presence of undesirable outputs: crediting electric utilities for reducing air pollution." Journal of Econometrics 126(2): 445-468.
- Battese, G. E., Coelli, T. J. (1988). Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data. *Journal of Econometrics* 38: 387-399.
- Battese, G. E., Coelli, T. J. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics* 20: 325\(\mathbb{B}\)332.
- Battese, G. E., Coelli, T. J. (1997). Special issue: Papers presented at the New England Conference on Efficiency and Productivity Guest Editors' introduction. *Journal of Productivity Analysis* 8: 323-324.
- Blackorby, C.,Russell, R. R. (2014). Will the Real Elasticity of Substitution Please Stand Up? (A Comparison of the Allen / Uzawa and Morishima Elasticities). 79: 882-888.
- Bozoglu, M., Ceyhan, V. (2007). Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun province, Turkey. *Agricultural Systems* 94: 649-656.
- Brannlund, R., Y. H. Chung, et al. (1998). "Emissions trading and profitability: The Swedish pulp and paper industry." Environmental & Resource Economics 12(3): 345-356.
- Brümmer, B. (2001). Estimating confidence intervals for technical efficiency: the case of private farms in Slovenia. *European Review of Agricultural Economics* 28: 285-306.
- Chambers, R. G. (2002). Exact nonradial input, output, and productivity measurement. *Economic Theory*, 20(4), 751–765.
- Chambers, R. G., Chung, Y., Färe, R. (1998). Profit, Directional Distance Functions, *Journal of Optimization and Application* 98: 351-364.
- Chen, Z., Huffman, W. E., Rozelle, S. (2009). Farm technology and technical efficiency: Evidence from four regions in China. *China Economic Review* 20: 153-161.
- Chung, Y. H., Faere, R., Grosskopf, S. (1997). Productivity and Undesirable Outputs: A Directional Distance Function Approach. *Journal of Environmental Management* 51: 229-240.

- Coelli, T.,Battese, G. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural Economics* 40: 103-128.
- Coelli, T. J., Gautier, A., Perelman, S., & Saplacan-Pop, R. (2013). Estimating the cost of improving quality in electricity distribution: A parametric distance function approach. *Energy Policy*, 53, 287–297.
- Cropper, M. L. and W. E. Oates (1992). "Environmental Economics a Survey." Journal of Economic Literature 30(2): 675-740.
- Cuesta, R. a., Lovell, C. A. K. A. K., Zofío, J. L., *et al.* (2009). Environmental efficiency measurement with translog distance functions: A parametric approach. *Ecological Economics* 68: 2232-2242.
- Davies, J., Hatfield, R. (2007). The Economics of Mobile Pastoralism: A Global Summary. *Nomadic Peoples* 11: 91-116.
- De Haan, C., Steinfeld, H., & Blackburn, H. (1997). Livestock & the environment: Finding a balance (p. 115). Rome,, Italy: European Commission Directorate-General for Development, Development Policy Sustainable Development and Natural Resources.
- Fan, J W, Shao, Q Q, Wang, J B et al., 2011. An analysis of temporal spatial dynamics of grazing pressure on grass- land in Three Rivers Headwater Region. Chinese Journal of Grassland, 33(3): 64–72. (in Chinese)
- Färe, R., S. Grosskopf, et al. (1986). "Effects on Relative Efficiency in Electric-Power Generation Due to Environmental Controls." Resources and Energy 8(2): 167-184.
- Färe, R., Grosskopf, S., Pasurka, C. (1989). The Effect of Environmental-Regulations on the Efficiency of Electric Utilities 1969 Versus 1975. *Applied Economics* 21: 225-235.
- Färe, R., Grosskopf, S., Lovell, C. A. K., *et al.* (1993). Derivation of Shadow Prices for Undesirable Outputs a Distance Function-Approach. *Review of Economics and Statistics* 75: 374-380.
- Färe, R., Primont, D. (1996). The opportunity cost of duality. *Journal of Productivity Analysis* 7: 213-224.
- Färe, R., Grosskopf, S. (2000). Theory and Application of Directional Distance Functions. *Journal of Productivity Analysis* 13: 93-103.
- Färe, R., Grosskopf, S., Noh, D.-W., *et al.* (2005). Characteristics of a polluting technology: theory and practice. *Journal of Econometrics*. 469-492.
- Färe, R., Martins-Filho, C., Vardanyan, M. (2009). On functional form representation of multi-output production technologies. *Journal of Productivity Analysis* 33: 81-96.
- Färe, R., Grosskopf, S., Whittaker, G. (2013). Directional output distance functions: endogenous directions based on exogenous normalization constraints. *Journal of Productivity Analysis* 40: 267-269.
- Färe, R., Karagiannis, G. (2013). Radial and directional measures of the rate of technical change. *Journal of Economics* 112: 183-199.
- Fernandez, C., G. Koop, et al. (2002). "Multiple-output production with undesirable outputs: An application to nitrogen surplus in agriculture." Journal of the American Statistical Association 97(458): 432-442.

- Feng, G., and Serletis, A. (2014). Undesirable outputs and a primal Divisia productivity index based on the directional output distance function. Journal of Econometrics, 183(1), 135–146.
- Fisher, A., 2004. Review of total grazing pressure management issues and priorities for biodiversity conservation in rangelands: a resource to aid NRM planning. Desert Knowledge CRC.
- Galdeano-Gómez, E., Céspedes-Lorente, J. (2008). Environmental spillover effects on firm productivity and efficiency: An analysis of agri-food business in Southeast Spain. *Ecological Economics* 67: 131-139.
- Glauben, T., Thijssen, G., Brümmer, B. (2002). Decomposition of Productivity Growth Using Distance Functions: The Case of Dairy Farms in Three European Countries. *American Journal of Agricultural Economics* 84: 628-644.
- Harris, R. B. (2010). Rangeland degradation on the Qinghai-Tibetan plateau: A review of the evidence of its magnitude and causes. *Journal of Arid Environments* 74: 1-12.
- Hailu, A., Veeman, T. S. (2000). Environmentally Sensitive Productivity Analysis of the Canadian Pulp and Paper Industry, 1959 . 1994: *Journal of Environmental Economics and Management*: 251-274.
- Hendry, David F., 2000. Econometrics: alchemy or science?: essays in econometric methodology. OUP Catalogue.
- Hetemäki, L. (1996). Essays on the impact of pollution control on a firm: a distance function approach. Helsinki Research Centre.
- Hoang, V.-n., Alauddin, M. (2012). Input-Orientated Data Envelopment Analysis Framework for Measuring and Decomposing Economic, Environmental and Ecological Efficiency: An Application to OECD Agriculture. *Environmental Resource Economics* 51: 431-452.
- Huppes, G., Ishikawa, M. (2005). Eco-efficiency and Its Terminology. *Journal of Industrial Ecology* 9: 43-46.
- Khanna, M., Kumar, S. (2011). Corporate Environmental Management and Environmental Efficiency. *Environmental and Resource Economics* 50: 227-242.
- Kumbhakar, S., Lovell, C. A. K. (2000). Stochastic frontier analysis. Cambridge University Press. Cambridge, UK.
- Lansink, A. O., Pietola, K., Backman, S. (2002). Efficiency and productivity of conventional and organic farms in Finland 1994-1997. *European Review of Agricultural Economics* 29: 51-65.
- Latruffe, L., Nauges, C. (2013). Technical efficiency and conversion to organic farming: the case of France. *European Review of Agricultural Economics* 41: 227-253.
- Li, M., Wu, J., Deng, X. (2013). Identifying Drivers of Land Use Change in China: A Spatial Multinomial Logit Model Analysis. *Land Economics* 89: 632-654.
- Marchand, S. (2012). The relationship between technical efficiency in agriculture and deforestation in the Brazilian Amazon. *Ecological Economics* 77: 166-175.
- McDowell, R. W. (Ed.). (2008). Environmental impacts of pasture-based farming. CABI.
- Morrison, C. J., Johnston, W. E., Frengley, G. A. G., *et al.* (2000). Efficiency in new zealand sheep and beef farming: the impacts of regulatory reform. *The review of economics and statistics* 82: 325-337.

- Morrison Paul, C. J., Nehring, R. (2005). Product diversification, production systems, and economic performance in U.S. agricultural production. *Journal of Econometrics* 126: 525-548.
- Njuki, E., Bravo-Ureta, B. E. (2015). The Economic Costs of Environmental Regulation in U.S. Dairy Farming: A Directional Distance Function Approach. *American Journal of Agricultural Economics*, 1–20.
- Otieno, D. J., Hubbard, L., Ruto, E. (2014). Assessment of technical efficiency and its determinants in beef cattle production in Kenya. *Journal of Development and Agricultural Economics* 6: 267-278.
- Pascual, U. (2005). Land use intensification potential in slash-and-burn farming through improvements in technical efficiency. *Ecological Economics* 52: 497-511.
- Picazo-Tadeo, A. J., Castillo-Giménez, J., Beltrán-Esteve, M. (2014). An intertemporal approach to measuring environmental performance with directional distance functions: Greenhouse gas emissions in the European Union. *Ecological Economics* 100: 173-182.
- Pittman, R. W. (1981). Issue in Pollution Control: Interplant Cost Differences and Economies of Scale. *Land Economics* 57: 1-17.
- Rahman, S. (2010). Women's Labour Contribution to Productivity and Efficiency in Agriculture: Empirical Evidence From Bangladesh. *Journal of Agricultural Economics* 61: 318-342.
- Rao, E. J. O., Brümmer, B., Qaim, M. (2012). Farmer Participation in Supermarket Channels, Production Technology, and Efficiency: The Case of Vegetables in Kenya.
- Reinhard, S., Lovell, C. A. K., Thijssen, G. (1999). Econometric estimation of technical and environmental efficiency: An application to Dutch dairy farms. *American Journal of Agricultural Economics* 81: 44-60.
- Reinhard, S., Lovell, C. A. K., Thijssen, G. J. (2000). Environmental efficiency with multiple environmentally detrimental variables; estimated with SFA and DEA. *European Journal of Operational Research* 121: 287-303.
- Reinhard, S., Lovell, C. A. K., Thijssen, G. (2002). Analysis of environmental efficiency variation. *American Journal of Agricultural Economics* 84: 1054-1065.
- Sauer, J., Latacz-Lohmann, U. (2014). Investment, technical change and efficiency: empirical evidence from German dairy production. *European Review of Agricultural Economics*: 1-25.
- Serra, T., Lansink, a. O., Stefanou, S. E. (2011). Measurement of Dynamic Efficiency: A Directional Distance Function Parametric Approach. *American Journal of Agricultural Economics* 93: 756-767.
- Shephard, R. W. (1970). Theory of cost and production functions. Princeton: University Press.
- Pittman, R. W. (1981). "Issue in Pollution-Control Interplant Cost Differences and Economies of Scale." Land Economics 57(1): 1-17.
- Pittman, R. W. (1983). "Multilateral Productivity Comparisons with Undesirable Outputs." Economic Journal 93(372): 883-891.
- UNEP (2005). One Planet Many People: Atlas of Our Changing Environment. *Division of Early Warning and Assessment*.

- Van Ha, N., Kant, S., Madaren, V. (2008). Shadow prices of environmental outputs and production efficiency of household-level paper recycling units in Vietnam. *Ecological Economics* 65: 98-110.
- Wang, H., Zhou, P., Zhou, D. Q. (2013). Scenario-based energy efficiency and productivity in China: A non-radial directional distance function analysis. *Energy Economics*, 40, 795–803.
- White, R., Murray, S., Rohweder, M. (2000). Pilot analysis of global ecosystems: Grassland ecosystem. Washington, D.C.: World Resources Institue.
- Wollni, M.,Brummer, B. (2012). Productive efficiency of specialty and conventional coffee farmers in Costa Rica: Accounting for technological heterogeneity and self-selection. *Food Policy* 37: 67-76.
- Yaisawarng, S. and J. D. Klein (1994). "The Effects of Sulfur-Dioxide Controls on Productivity Change in the United-States Electric-Power Industry." Review of Economics and Statistics 76(3): 447-460.
- Yao, X., Zhou, H., Zhang, A., Li, A. (2015). Regional energy efficiency, carbon emission performance and technology gaps in China: A meta-frontier non-radial directional distance function analysis. *Energy Policy*, 84, 142–154.
- Zhang, Y. J., Wang, X. B., Glauben, T., et al. (2011). The impact of land reallocation on technical efficiency: evidence from China. *Agricultural Economics* 42: 495-507.
- Zhou, H. K., Zhou, L., Zhao, X. Q., et al. (2006). Stability of alpine meadow ecosystem on the Qinghai-Tibetan Plateau. *Chinese Science Bulletin* 51: 320-327.
- Zhao, M., Running, S. W. (2010). Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. Science (New York, N.Y.) 329: 940-943.
- Zhang, J. (2008). Ecological Current Situation of Grassland and Its Countermeasures in the Three Rivers District of Qinghai. *Pruataculture & Animal Husbandry* 1: 30-3fA2.
- Zhang, J., Zhang, L., Liu, W., Qi, Y., & Wo, X. (2014). Livestock-carrying capacity and overgrazing status of alpine grassland in the Three-River Headwaters region, China. Journal of Geographical Sciences, 24(2), 303–312.

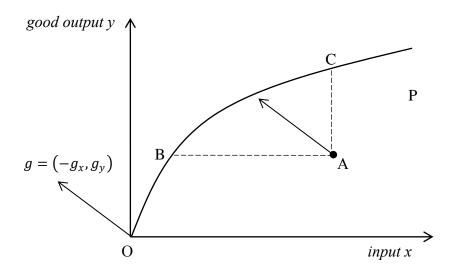


Figure 1. Directional distance function

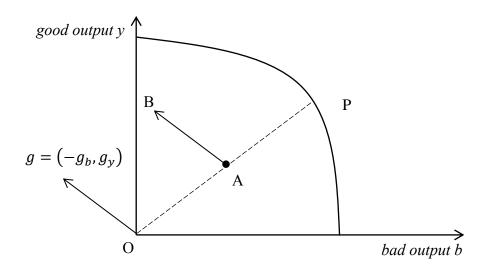


Figure 2. Output orientation directional distance function

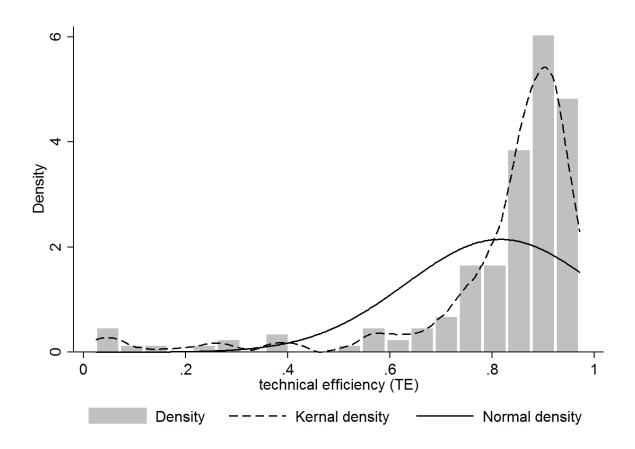


Figure 3. Histogram graph of technical efficiency

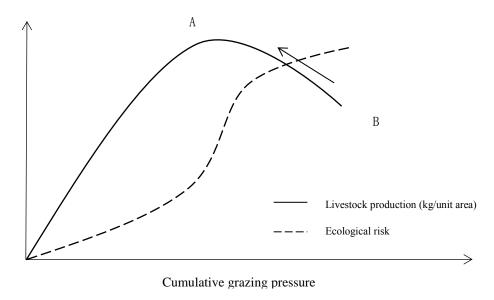


Figure source: McDowell, 2008, P.136.

Figure 4. Relationship between cumulative grazing pressure, ecological risk and livestock production

Table 1. Overgrazing status in the sample counties

Charing status valeta vanishla	County			
Grazing status relate variable	Tongde	Zeku	Maqin	
Proper carrying capacity (SU/km²) (Zhang, Zhang, Liu et al., 2014)	127.07	90.58	81.34	
Overgrazing ratio of 2010 (%) (Zhang, Zhang, Liu et al., 2014)	112.25	323.5	47.6	
Overgrazing ratio from 1988 to 2005 (%) (Fan et al., 2010)	600	500	300	
Overgrazing ratio from our field survey (%)	347	490	568	

Note: The proper carry capacity is referred to Zhang, Zhang, Liu et al., 2014

Table 2. Statistic descriptive of variables

Variable Description	Symbol	Measurement Unit	Mean	Std. Dev.
Inputs variables				
Grassland area size	x_1	mu	937.38	1413.14
Labor	x_2	person	2.31	1.27
Productive capital	x_3	1000yuan	129.21	186.87
Initial yak at the beginning of 2011	x_4	1000kg	7.17	8.15
Outputs variables				
Good output: revenue from livestock grazing	у	1000yuan	105.26	112.02
Bad output: grazing pressure	b	-	0.21	0.28
Household characteristics variables				
Total NPP change in 2011	z_1	1000kgC	4.94	13.57
Household size	z_2	head	4.72	1.67
Distance from fixed home to summer pasture	<i>Z</i> ₃	km	15.24	19.68
Grazing experience	Z ₄	year	29.87	11.97
Summer pasture area	Z ₅	1000mu	542.98	911.04
Winter pasture area	z_6	1000mu	395.65	649.29
		No. of $dummy = 1$	No. of	dummy = 0
Dummy variable pasture plot (1 = the winter pasture and summer pasture are different plots; $0 = other$)	Z ₇	44	149	
Dummy variable of whether there is leased-in grassland (1=yes; $0 = no$)	Z8	43	150	

Table 3. Directional distance function with different directional vector

Variables	Coef.	Std. Err.	Coef.	Std. Err.
dep. var.: - θ	Model1: Direction	onal vector $g = (1,-1)$	al vector $g = (1,-1)$ Model2: Direction	
Constant	0.050	0.125	-0.165**	0.074
x_I	0.350**	0.143	0.251***	0.044
x_2	-0.464***	0.173	0.097	0.079
x_3	0.172***	0.065	-0.048	0.032
x_4	-0.232	0.170	0.361***	0.066
<i>y</i> *	-0.263***	0.074	-0.678***	0.034
$0.5 \cdot x_1^2$	-0.029**	0.014	-0.031***	0.006
$0.5 \cdot x_2^2$	0.555***	0.178	-0.027	0.065
$0.5 \cdot x_3^2$	0.027	0.031	0.014	0.012
$0.5 \cdot x_4^2$	0.087	0.067	-0.121***	0.035
$0.5 \cdot y^{*2}$	-0.125***	0.023	0.011	0.02
$0.5 \cdot b^2$	a		-0.11**	0.045
$x_I \cdot y$	0.310***	0.029	0.056**	0.028
$x_2 \cdot y$	-0.166***	0.056	0.271***	0.035
$x_3 \cdot y$	-0.003	0.018	0.017	0.012
$x_4 \cdot y$	0.057*	0.030	0.074***	0.019
$x_1 \cdot b$			-0.129***	0.031
$x_2 \cdot b$			-0.365***	0.041
$x_3 \cdot b$			0.007	0.013
$x_4 \cdot b$			-0.077***	0.022
$x_1 \cdot x_2$	-0.200**	0.085	-0.073**	0.032
$x_1 \cdot x_3$	0.067***	0.013	-0.001	0.006
$x_1 \cdot x_4$	-0.393***	0.038	-0.039	0.03
$x_2 \cdot x_3$	-0.112**	0.056	0.008	0.021
$x_2 \cdot x_4$	0.439***	0.120	-0.202***	0.042
$x_3 \cdot x_4$	-0.065	0.041	-0.014	0.013
$y \cdot b$			0.017	0.031
lnsig2v				
Constant	-20.355*	10.815	-4.360***	0.102
lnsig2u				
Constant	-1.070***	0.102	-12.967	92.348
δ_v	0.000	0.000	0.113	0.006
δ_u	0.586	0.030	0.002	0.071
δ^2	0.343	0.035	0.013	0.001
Log likelihood	-3	6.824		146.841

Hausman test:

$$Chi^{2}(20)$$
 = (b-B)'[(V_b-V_B)^(-1)](b-B)
 = 698.38
 $Prob>chi^{2} = 0.0000$

Notes:1. a, according to restrictions, they can be calculated. 2. Coefficient of parameter b in Model1 can be calculated according to restrictions, and parameter b is transformed to left side variable in Model2. 3. *Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05), ***Significant at 1% level (P < 0.01).

Table 4. Estimates of directional distance function and technical inefficiency model

Variables	Coef.	Std. Err.	Variables	Coef.	Std. Err.
Stoc.	frontier normal/half	-normal model	Tech	nnical inefficiency m	nodel
Dependent va	riable: - ϑ		Dependent variable: lnsig2u		
Constant	0.084	0.098	Constant	-4.358***	1.662
x_1	0.197**	0.096	z_1	-0.265***	0.081
x_2	-0.300**	0.135	z_2	1.176**	0.548
x_3	0.097	0.059	<i>Z</i> ₃	-0.348	0.212
x_4	-0.063	0.113	Z4	-1.058*	0.595
<i>y</i> *	-0.639***	0.059	Z ₅	-0.016	0.174
$0.5 \cdot x_1^2$	-0.069***	0.016	<i>Z</i> ₆	1.033***	0.208
$0.5 \cdot x_2^2$	0.263**	0.110	<i>Z</i> ₇	1.781	1.258
$0.5 \cdot x_3^2$	-0.105***	0.020	Z8	-1.947***	0.543
$0.5 \cdot x_4^2$	-0.152***	0.049			
$0.5 \cdot y^{*2}$	-0.071***	0.013			
$x_1 \cdot y$	0.485***	0.031			
$x_2 \cdot y$	-0.076**	0.036			
$x_3 \cdot y$	-0.092***	0.014			
$x_4 \cdot y$	0.105***	0.020			
$x_1 \cdot x_2$	-0.075	0.069			
$x_1 \cdot x_3$	0.023	0.022			
$x_1 \cdot x_4$	-0.409***	0.058		Log lik	elihood=-3.554
$x_2 \cdot x_3$	0.134***	0.041		Number of ob	servation =193
$x_2 \cdot x_4$	0.214***	0.071		Wald Chi ² (20) = 5807.730
$x_3 \cdot x_4$	0.157***	0.025		Pro	ob.>Chi ² =0.000
lnsig2v					
Constant	-3.681***	0.231			

 $Notes: *Significant \ at \ 10\% \ level \ (P < 0.10), \ **Significant \ at \ 5\% \ level \ (P < 0.05), \ ***Significant \ at \ 1\% \ level \ (P < 0.01).$

Table 5. Elasticity of distance with respective to inputs and outputs

Elasticity	Mean	Std. Dev.	Min	Max
Inputs elasticity				
$\epsilon_{\mathrm{x}1}$	0.64***	0.68	-0.73	3.93
ϵ_{x2}	0.08***	0.33	-1.02	1.67
ϵ_{x3}	0.12***	0.18	-0.71	0.57
ϵ_{x4}	-0.04	0.64	-6.08	1.64
Outputs elasticity				
$\epsilon_{ m y}$	-0.36***	0.73	-1.51	6.58
ϵ_{b}	0.64***	0.73	-0.51	7.58

Notes: T-Test for elasticity different from 0, *Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05), ***Significant at 1% level (P < 0.01).

Table 6. Relative shadow price of outputs and elasticity of transformation

Variable	Full sample (Obs. = 193)	Partial sample (Obs. = 173)
Relative shadow price: $\frac{\partial \vec{D}(x,y,b)/\partial y}{\partial \vec{D}(x,y,b)/\partial b}$	-1.80	-3.99
M_{by} : Morishima elasticity substitution of b to y	-0.55	-0.73

Table 7. Morishima elasticity of substitution between inputs

	MES(row, column)	x_1	x_2	x_3	x_4
		grassland area	labor	capital	initial yaks
x_{I}	grassland area	-	0.43***	0.71***	-0.50***
x_2	labor	0.75	-	0.73***	0.75***
x_3	capital	2.07***	1.99**	-	1.96**
χ_4	initial yaks	1.02	2.07	1.96	-

Notes: T-Test for elasticity different from 0, *Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05), ***Significant at 1% level (P < 0.01).

Table 8. Summary of technical efficiency

Variable	Obs.	Percentage	Mean	Std. Dev.	Min.	Max.
TE < 0.70	25	13%	0.42	0.24	0.02	0.70
$0.70 \le TE < 0.80$	24	12%	0.76	0.03	0.70	0.80
$0.80 \le TE < 0.90$	76	39%	0.86	0.03	0.80	0.90
$TE \ge 0.90$	68	35%	0.93	0.02	0.90	0.97
Technical efficiency (TE)	193	100%	0.82	0.19	0.02	0.97

Appendix

Appendix Table 1. Hypothesis test for model selection

Model	Description	Likelihood value	Degree of freedom
H_0	Final model presented in paper	-3.554	31
H_1	directional distance function without setting technical inefficiency mode: $\tau_0 = \tau_1 = \tau_2 = \tau_3 = \tau_4 = \tau_5 = \tau_6 = \tau_7 = \tau_8 = 0$	-36.823	23
H_2	Full model seeting	-1.985	35
H_3	$\tau_1 = 0$	-8.678	30
H_4	$\tau_2 = 0$	-6.888	30
H_5	$\tau_3 = 0$	-5.016	30
H_6	$ au_4 = 0$	-5.964	30
H_7	$\tau_5 = \tau_6 = \tau_7 = 0$	-18.008	27
H_8	$ au_8 = 0$	-11.782	30

Appendix Table 2. Model setting with all reasonable variables in technical inefficiency model

Variables	Coef.	Std. Err.	Variables	Coef.	Std. Err.
Stoc. fron	tier normal/half-n	ormal model	Tech	nical inefficiency	model
Dependent var	riable: - θ		Dependent varia	able: lnsig2u	
Constant	0.074	0.095	Constant	-5.404***	2.014
x_{I}	0.202**	0.094	z_1	-0.246***	0.079
x_2	-0.292**	0.133	z_2	1.131**	0.54
x_3	0.097	0.059	<i>Z</i> ₃	-0.234	0.173
χ_4	-0.053	0.112	Z.4	-1.031*	0.566
<i>y</i> *	-0.631***	0.064	Z_5	-0.015	0.18
$0.5 \cdot x_I^2$	-0.068***	0.015	<i>Z</i> ₆	0.959***	0.202
$0.5 \cdot x_2^2$	0.267**	0.111	z_7	1.764	1.295
$0.5 \cdot x_3^2$	-0.107***	0.02	<i>Z</i> ₈	-1.662***	0.513
$0.5 \cdot x_4^2$	-0.139***	0.049	<i>Z</i> 9	-0.049	0.077
$0.5 \cdot y^{*2}$	-0.071***	0.013	Z ₁₀	0.587	0.663
$x_1 \cdot y$	0.483***	0.031	z_{11}	0.559	0.421
$x_2 \cdot y$	-0.080**	0.038	z_{12}	-0.082	0.398
$x_3 \cdot y$	-0.090***	0.014			
$x_4 \cdot y$	0.100***	0.02			
$x_1 \cdot x_2$	-0.087	0.07			
$x_1 \cdot x_3$	0.025	0.022		Log lik	xelihood = -1.985
$x_1 \cdot x_4$	-0.411***	0.057		Number of	observation =193
$x_2 \cdot x_3$	0.140***	0.042		Wald chi	2(20) = 5530.070
$x_2 \cdot x_4$	0.214***	0.073]	Prob>chi2=0.000
$x_3 \cdot x_4$	0.154***	0.026			
lnsig2v					
Constant	-3.742***	0.26			

 $Notes: *Significant \ at \ 10\% \ level \ (P < 0.10), \ **Significant \ at \ 5\% \ level \ (P < 0.05), \ ***Significant \ at \ 1\% \ level \ (P < 0.01).$

Appdendix Table 3. Descriptive statistics for additional variables in appendix table 4.3

Variable Description	Symbol	Unit	Mean	Std. Dev.
Continuous variables				
Total direct subsidy from government	Z 9	1000yuan	9.52	21.40
grazed month of summer pasture	z_{10}	month	5.52	1.38
duration of getting the use right of pasture	z ₁₁	year	19.56	7.59
Dummy variables		No. of dum	nmy = 1	No. of $dummy = 0$
Dummy variable of education (1=has been education; 0 = no education)	z_{12}	58		135