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Postharvest Hardness and Color Evolution of White Button Mushrooms (*Agaricus bisporus*)

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Abstract:

The quality evaluation of mushrooms was studied by storing fresh white button mushroom (*Agaricus bisporus*) for 6-8 days, at various controlled temperature conditions (3.5 -15°C) and measuring the instrumental textural hardness and color of the mushroom cap for different product batches. A non linear mixed effect weibull model was used to describe mushroom cap texture and color kinetics during storage considering the batch variability into account. Storage temperature was found to play a significant role in controlling texture and colour degradation. On lowering storage temperature i) the extent of the final browning extent in the mushroom after storage was reduced; and ii) the rate textural hardness losses was slowed down. A linear dependence of the final browning index with temperature was found. An Arrhenius type relationship was found to exist between the temperature of storage and storage time with respect to textural hardness. The average batch energy of activation was calculated to be 207±42 kJ/mol in a temperature range of 3.5-20°C.

Practical application

This article evaluates how temperature abuse affects mushroom texture and colour, applying methods that allow for the consideration of the natural product variability that is inherent in mushrooms. Its result apply to mushroom producers, retail distribution and supermarkets for effective storage management.

Introduction:

Mushroom marketers often face difficulties in choosing a safe storage conditions on receiving different batches of mushrooms. Mushrooms may vary in their harvesting date and time, cultivated mushroom variety, harvest batches, storage conditions adopted and cold chain regime followed (Hertog and others 2007a; Aguirre and others 2008). Post-harvest, mushrooms immediately start to soften and begin to brown in color due to enzymatic breakdown of plant cells and loss of moisture through respiration (Burton and others 1987, Jolivet and others 1998, Brennan and others 2000; Zivanovic and others 2003; Zivanovic and others 2004; Lespinard and others 2009). This results in reduced product acceptability, as consumer's preference and demand is for white, unblemished and hard textured mushrooms. Additionally, bruising and storage at elevated temperatures enhances the degradation process and reduces mushroom shelf-life (Burton, 1986). Consequently, monitoring cold-chain storage conditions that will preserve the quality of mushrooms is both critical and challenging (Aguirre and others, 2009)

Quality control during postharvest requires precise methodologies to estimate the acceptability of fresh produce of varying batches, growers, cultivation practices and post harvest treatments. In an ideal situation, all products should arrive with the same homogeneity as if it was from an experimental station unit, however, food retailers face an input of produce arising from different growers, possibly harvested on different dates and locations and using very different cultural practices. Taken together, this has a significant effect on the homogeneity of the product and its' time to reach the limit of marketability (Hertog and others 2007b; Schouten and others 2004). Moreover, there is biological variation contributed by micro nutrients, growing conditions, etc. for each batch of produce. Different units of an individual batch may behave differently, even when stored under similar storage conditions (Brennan and others 2000; Hertog and others 2007a).

Modeling the quality kinetics of fresh products attempts to better understand the fate of quality during storage, taking not only the primary modeling variable (time) into account, but more importantly, the secondary variables that may be controlled during storage to optimally maintain the quality attributes of the product. Such information would be helpful to both producers and sellers in enabling them to optimize product storage conditions and in identifying the significant factors affecting product shelf-life. Modeling may also reveal the ways in which variability affects the quality during operating storage conditions, which may in turn be used to define limits beyond which the quality of product may be compromised within a certain tolerance (Lavelli and others 2006).

An assessment of fresh produce shelf-life requires proper understanding of the two phenomena affecting the process i) biological metabolism, and ii) underlying variability. Model building is employed to assess the shelf-life, normally based on experimental data that is generated through repetitive quality measurements, either by destructive or non–destructive methods carried out in real-situation or laboratory conditions. The repetitive measurements form a longitudinal data structure which is well correlated with the subject within a batch, but are independent of the intra batch variability (Lammertyn and others 2003). Least squares regression is commonly used to analyze the data by averaging repeated measurements. Although this statistical method is robust to build models within normal food experiments, it accumulates all the variation in one error term and does not allow for the estimation of the different possible sources of variation. While this is sufficient for use with many experiments, it may be more desirable to estimate other and different sources of variability. In particular, postharvest technology is a field where this approach might prove to be interesting from a number of different perspectives, such as; i) to be able to estimate the weight of different variability sources (within batch, between batches, between producers), which will help to make clearer purchasing decisions ii) to identify if variability can be reduced at any particular storage condition and iii) to evaluate through a scenario analysis if making an hypothetical optimization in the cold chain, this optimisation will actually result in an appreciable improvement of the shelf life taking account of product variability. Mixed-effects models may be useful for those cases where one has to deal with within-subject, as well as between-subject variability, especially when having to deal with a biological commodity. A mixed effects model has two components i) fixed effect term, which deals with the trend components and ii) random effect term, which deals with subject specific intercepts and variance (Pinheiro and Bates, 2000). Moreover, it allows for the presence of missing data and can allow for time-varying or unbalanced designs with unequal numbers of subjects across experimental groups (Pinheiro and Bates 2000; Lammertyn and others 2003). Several studies have been undertaken to predict the quality kinetics of fresh produce using mixed effect models (Lammertyn and others 2003; Piagentini and others 2005; Latreille and others 2006; Schouten and others 2007; Aguirre et al. 2009). A mixed effect model that addresses a hierarchical level of variation has been employed by various researchers (Fonseca and others 2002; Montanez and others 2002; Ketelaere and others 2006). Mushrooms are known to have a very short shelf- life and susceptible to browning and moisture loss due to the enzymatic activity and lack of cell wall. The quality deterioration is even faster at higher storage temperature conditions, due to enhanced metabolic activity. Therefore modeling the quality deterioration with respect to storage conditions provides ample opportunity for the mushroom growers and marketers to modify the storage and handling conditions in order to have higher shelf-life, thus reducing the economic loss. In this study, attempts were made to model product instrumental texture and color characteristics in order to predict mushroom shelf-life under different temperature storage conditions, taking batch variation into consideration, using a non-linear mixed effect model.

2.0 Materials and methods:

Closed cup *Agaricus Bisporus* button mushrooms (white, close, uniform, clear, fresh, L value= 90±5, a=0.3±0.8, b=10±2), sourced from the Ranairee mushroom farm (Macroom, Ireland) and commonly destined for retail supermarket sales, were delivered to the laboratory using a temperature monitored distribution chain (6 ± 2°C, 80 ± 15% RH) in 7 kg crates without any individual packaging. Bruised and damaged samples were discarded and samples for analysis were taken at random from each batch of crates. Half of the mushrooms from the same batch were stored in temperature controlled cold rooms at different temperatures (5, 10, 15 ± 0.6°C) and the corresponding relative humidity was monitored (86 ± 7%). The other half of the sample was kept in a domestic refrigerator that reproduced the ideal storage temperature during retail and distribution of 3-4°C (3.5 ± 1.5°C, RH 92 ± 5%) and served as the control sample to observe differences between ideal storage and the temperature used for each individual batch tested. The temperature range of 3.5-15°C was chosen considering the practical temperature distribution chain of mushrooms i.e. during post-harvest handling, transportation and storage. Texture and color measurement were performed after the mushrooms reached equilibrium temperature and every 24 hr thereafter, until the end of the storage experiment, which varied between 6-8 days, depending on storage temperature, taking random samples from the lot. A total of 14 batches of experiments were performed, covering a period of 1 year of production.

2.1 Instrumental texture measurement:

Texture measurement is a complex measurement, especially in a highly variable and anisotropic solid as mushrooms (McGarry and Burton 1994). Stored mushrooms were removed from storage and held at room temperature for 0.5 hr before performing textural assays. All such experiments were carried out using a texture profile analyser (Texture Expert

Exceed, Stable Microsystems, UK), with a 5 kg load cell following a modification of the method proposed by Gonzalez-Fandos and others (2000). The crosshead speed of the spindle for the pre-test, post-test and test speed were kept at 1 mm/min. Only the mushroom caps were used for texture hardness measurements. In order to obtain a sample with the same tissue orientation and dimensions, a cylindrical sample of 10 mm diameter was bored out from the mushroom cap using a steel borer and cut to 10 mm length using a sharp knife and was then compressed to 50% of the original height using a 35 mm aluminium cylindrical probe so as to achieve compression of the mushroom sample. Product hardness was the variable analyzed for each sample. Tests were performed on 5 replicate mushroom samples, from each storage condition, on each storage day, during the whole course of the trial period, accounting for over 700 measurements.

2.2 Color measurement:

The color of the mushroom cap was measured using a Minolta Chroma Meter (Model CR-331, Minolta Camera Co., Osaka, Japan), using the Hunter Lab Color Scale. The color was measured at three equidistant points on each mushroom cap using an aperture diameter of 4mm. Five mushrooms were randomly selected from each batch per day for the color measurement, accounting for over 2800 measurements of color. Mushroom color has been commonly measured using the L value of the Hunter scale (Brennan and others 2000; Jolivet, 1998; Cliffe-Byrnes and O'Beirne 2007), however some studies have pointed to changes in other parameters of the hunter scale (a* and b*) related to browning (Aguirre and others 2008; Vizhanyo and Felföldi, 2000; Burton, 1998). In order to capture this variation in a single index that would be related to a turn towards brown colour, the Browning index (BI) was calculated using the following expression (Maskan 2001; Bozkurt and Bayram 2006):

$BI = 100 \times \left(\frac{X - 0.31}{0.17} \right)$, where $X = \frac{(a^* + 1.75L)}{(5.645L + a^* - 3.012b^*)}$, L, a*, b* values represent the lightness, redness and greenness of the sample.

1.0 Mathematical modeling

The mathematical model to predict mushroom shelf-life was carried out using the data generated from measurement of the textural hardness and color (as indicated by the browning index).

Model building was performed using the following procedure:

1. An ANOVA analysis of the quality parameters clearly showed that they were all affected by temperature and storage time ($p < 0.05$). The primary modeling of the data was then performed using suitable mathematical models for individual temperatures and batch experiments. After a graphical, the first order model, the biexponential model, the logistic model and the weibull model were used as candidate models to describe the kinetics of texture and browning. The most appropriate model which gave maximum determination coefficient R^2, a low standard error, lower Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) was chosen. The AIC and BIC are model discrimination criteria used for selection nonlinear models, which consider the goodness of fit of the model and the number of parameters employed. The smaller the value of the AIC and BIC the better a model performs (Pinheiro and Bates, 2000).
2. The secondary modeling of the data considered two components: i) dependence of the texture and browning primary model parameters was described following the equations proposed in section 3.3 below ii) batch variation would be expected to follow the hypothesis of Hertog and others (2007a) that each individual product and batch has perturbation at the initial state at which it is processed. Extra random effects were

introduced following this and its addition tested using a log-likelihood ratio test. A likelihood-ratio test is a statistical test for making a decision between two models where the hypothesis is based on the value of the log-likelihood ratio of the two models following a chi-square distribution (Bates and Watts, 1988). The log-likelihood ratio test is a conservative test that will check for statistical significance of adding further nested random effects to a model (Pinheiro and Bates, 2000). The test requires that the two models must be nested, this is, that if one of the models can be transformed into the other by fixing one parameter.

3. Finally prediction plots using the Best Linear Unbiased Prediction (BLUP), which depict the model prediction of each individual experiment considering the random effects assigned to it in the model (Pinheiro and Bates, 2000), were made to confirm the suitability of the candidate models.
4. An iterative procedure was used to find the best candidate secondary model that could describe, with a minimum set of parameters, that data that resulted from the experimentation.

3.1 Modeling texture

The best candidate primary model to describe the texture and browning kinetics, in a similar way as with Kong and others (2007).

The textural hardness of the mushrooms was described by the weibull model as follows:

$$H = B_H + (A_H - B_H)e^{-e^{lk_H} \times t^{\beta_H}} \qquad (2)$$

Where, H is the textural hardness of the mushroom cap, A_H, and B_H are the initial and final hardness of mushroom cap during storage, t is the time of storage (day), lk_H is the natural logarithm of the rate constant of the reaction and β_H is the dimensionless shape parameter. The shape parameter accounts for upward concavity of the curve ($\beta_H < 1$), a linear curve ($\beta_H = 1$) as in case of first order kinetics, and downward concavity ($\beta_H > 1$) (Pinheiro and Bates, 2000).

3.2 Modeling color

The browning index of the mushroom caps was analyzed using a modified weibull model, to force the rate constant parameter to be positive:

$$BI = A_{BI} + (B_{BI} - A_{BI})e^{-e^{lk_{BI}} \times t^{\beta_{BI}}} \qquad (3)$$

Where, *BI* is the browning index, A_{BI} is the upper asymptotic value of the weibull curve, B_{BI}, is the initial value of the browning index, *t* is the time of storage is days, lk_{BI} is the log rate constant of the reaction, and β_{BI} is the shape factor for browning index.

3.3 Temperature dependence

The temperature dependence of the rate constant was modeled following an Arrhenius relationship

$$k = k_{ref} e^{-\frac{Ea}{R}\left(\frac{1}{T} - \frac{1}{T_r}\right)} \qquad (4)$$

Where k_{ref} is the rate constant at the reference temperature T_{ref} (5°C), E_a is the energy of activation of the process and R is the universal gas constant (8.314 kJ Mol^{-1} K^{-1}). In this way k_{ref} and E_a are easy to interpret parameters and allow for comparison of the temperature dependence of this process with other quality factors (chemical or not).

The temperature dependence of the *A*, *B* and β parameter followed a polynomial relation:

$$y = a + b \times T + c \times T^2 \qquad (5)$$

Where *y* is the parameter *A*, *B* or β and *a* and *b* and c are the intercept, linear and quadratic dependence of the parameter with temperature, respectively. Parameters statistically non-significant (p>0.05) were dropped from the model building.

3.5 Statistical analysis

On the basis of the primary models generated, the secondary models were developed by including the random effect terms that addressed batch and individual variance effects on quality evolution. The non-linear mixed modeling was performed using the nlme library (Pinheiro and Bates, 2000) from the R 2.9.1 software (R Development Core Team 2007), for textural hardness and browning index.

4.0 Results and discussion

4.1 Textural hardness

The textural hardness kinetics of button mushrooms stored at different temperatures is shown (Figure 1). It was evident that the while cap hardness could be maintained with storage at 3.5°C, higher temperatures produced a decline in textural hardness that was more pronounced with the increase in storage temperature. If storage temperature was changed to 10 °C, after 4 days the mushrooms would have a texture different ($p<0.05$) from the control at 3.5 °C and if changed at 15°C after the 2nd day of storage.

The estimated fixed and random effect parameters of the final model are outlined in table 1 with 95% confidence intervals, all parameters being significant ($p<0.05$). Initial models were built considering within-lot and within-batch variability similar to Mohapatra and others 2008. When performing individual fits in each batch, it was observed that the standard deviation of the estimated power terms was very low compared to the average (2.2±0.2). In this way, the random effect associated to the β term was removed from the model.

As indicated in Figure 1, the kinetics, and therefore the rate constant, of texture decay was found to be dependent on the storage temperature. In order to study this, an Ahrrenius plot with the random effects associated to the k parameter of a model without temperature dependence was built (see Figure 2) which confirmed this dependence. From the slope of the linear regression of Figure 2, energy of activation of 190±40 kJ/mol could be estimated. This value was used as an initial estimate for the one-step estimation of the model parameters.

The activation energies at the 95% confidence level and the estimates of the initial and final values of hardness and the power term for the final model are shown (Table 1). The activation energy for the loss of mushroom hardness (207±42 kJmol^{-1}) value was well within the range of other quality characteristics for other reported forms of stored vegetables (Giannakourou and Taoukis 2003; Piagentini and others 2005). The estimated power term ($2.2 > 1$) suggested that the kinetics had a downward concavity feature that made texture kinetics depart from conventional first order kinetics. The best fitted values for mushroom textural hardness when stored under different temperature-time for different batches of mushrooms are shown (Figure 3). It can be seen that the model describes the kinetics and the differences between abuse storage temperature and control. Despite the natural variability, mushrooms abused suffer a decrease in hardness that is apportioned to the temperature abuse and that the model built in the present study is able to reproduce.

The random effect terms in Table 1 suggest that the final value of the mushroom hardness at the end of storage (σ_{BH}) did not vary much among batches, compared to the variation in initial textural hardness ($\sigma_{A\text{-}BH}$), which is 5 times higher. The structure of the best model fit and the estimated parameters point to the interesting hypothesis that as a result of storage, the variation between batches of mushrooms will decrease. The variation of the reaction rate constant between batches showed a coefficient of variation of over the 30%, (Table 1). This is characteristic of the high variability associated to fresh produce for retail in general and in particular of mushrooms (Aguirre and others 2009)

4.2 Browning index

The kinetics of the average browning index for different temperatures of storage is shown in (Figure 4). From a graphical inspection similar conclusions can be drawn as with the texture in respect to the effect of temperature abuse during the storage of mushrooms can be concluded, with time and temperature having a significant effect ($p<0.05$). Since the loss of hardness and browning of mushrooms are governed by enzymatic activities, low temperature storage would inactivate the enzymes thus slowing down the metabolic activities and other biochemical process. Storage at 5°C after 5 days produces a browning index different from control conditions and after 4 days at 10°C. From comparing Figure 1 and Figure 4 variation in color of mushrooms seems to be less pronounced than that of texture. This is in agreement with previous results found for enzymatic activity responsible of browning (Mohapatra and others 2008).

The best fit model to the data is presented in Figure 5. There was an increasing trend in the browning index with respect to storage days and storage temperature. The pattern does not seem to follow first order kinetics, although many researchers have proposed a logistic function, or a zero order function, to describe this color change in fruits and vegetables during storage (Giannakourou and Taoukis 2002; Lukasse and Polderdijk 2003; Muskovics and others 2006; Hertog and others 2007b). In this study, a steady increase in the color pattern was evident as storage time progressed. When the mushrooms were initially received/purchased, their color was predominantly white, but as the storage days progressed the discoloration on the cap intensified due to both enzymatic reactions (Jolivet and others 1998; Mohapatra and others 2008). The enzymes responsible for browning react with the substrate and the evolution of brown pigmentation occurs. When there is no more substrate available over a longer storage time, the enzymatic reaction slows down and the formation of browning pigments stops (Jolivet and others 1998). As no decline or reversal in browning pigments occurs once formed, the weibull model is most suitable in describing browning index kinetics or color kinetics in mushrooms. There was a difference in the kinetics of browning index at higher temperatures. The estimates of both fixed and random parameters are listed (Table 2). The final candidate model indicates that when storage temperatures are very low, there will be no change in the BI with time, however, as temperature increases the final value of the BI at long storage times will be higher. From the structure of the model it can be inferred that no significant increase of browning index would be found theoretically at 0^{o}C (through extrapolation). Therefore the best policy would be to employ the lowest refrigeration temperature possible, where the least color variation would be found. This points to the need of ensuring cold chains in mushrooms that ensure the lowest level of browning by maintaining the lowest temperature (Aguirre and others 2009). In terms of slowing down browning as no significant dependence of the rate constant (lk_{BI}) or the shape parameter (β_H) with temperature browning kinetics will proceed in the same way independently of the temperature. This seems to be in disagreement with previous results found for frozen mushrooms (Giannakourou and Taoukis, 2002). This is possibly due to the biological processes associated to fresh products where possibly an enzyme expression process is taking place due to the natural senescence of the mushroom (Mohapatra, 2008), instead of the slower temperature controlled processes in frozen foods. However the significant temperature effect found in the parameter $\boldsymbol{B_{BI}}$-$\boldsymbol{A_{BI}}$ indicates that the higher the temperature the higher the final browning stage of the mushrooms will be. Previous studies (Mohapatra and others 2008) have pointed to an earlier over expression of browning related enzymes associated with temperature abuse, which would be in agreement with this result. While the initial stages of browning might be controlled by the integrity of the mushroom tissues, the integrated effect of an earlier induction of high activity of browning enzymes by temperature abuse would create higher color formation over time. The random effect components of the models represent the effect that the product variability have on the uncertainty of both quality index. As such, the $\boldsymbol{B_{BI}}$-$\boldsymbol{A_{BI}}$ associated to browning is the parameter with a bigger variability (70% CV at 3.5°C) followed by the initial value of the BI $\boldsymbol{A_{BI}}$ (30%), whereas for the texture the $\boldsymbol{lk_H}$ is the parameter most affected by product variability (30% CV). This means that the biggest uncertainty resides in controlling the final browning stage of the mushrooms, and then the rate of hardness losses will present the biggest variability. Because of this under the present temperature range, the optimization of texture through temperature control might appear more manageable than the control of browning. However, the policy for controlling browning is clear despite of variability, the lower the temperature the lower the extent of the browning.

5.0 Conclusion

This study has demonstrated the ability to predict the quality of fresh mushrooms stored under isothermal conditions, using models that take into account not only the instrumental error as a source of variance, but also components of variability arising from product variability. The temperature dependence of these qualities gives further insight into the ability to choose proper time-temperature management during storage. Storage under low temperature would delay the biological decay process associated to texture and would extend the shelf-life of the product. In the same way, lower temperature will produce lower levels of browning. The models built can be useful in predicting the quality attributes of fresh mushrooms under a temperature range of 3.5-15°C, which is adopted by most conventional distribution chains and more specifically, during the commercial storage of mushrooms. Browning seems to be the quality index most influenced by product variability, especially in the final value at long storage times. However a strategy of minimising storage temperature warrants a minimum browning appearance.

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List of abbreviations

σ	Standard deviation
σ_{A-BH}	Variation in the hardness value at the initial stage, N
σ_{ABI}	Variation in the browning index value at the final stage
$\sigma_{ABI-ABI}$	Variation in the browning index value at the final stage
σ_{BH}	Variation in the hardness value at the final stage, N
β_{BI}	Dimensionless Shape factor for browning index.
β_{H}	Dimensionless shape parameter for hardness
σ_{lkBI}	Variation in the log rate constant of the weibull curve for browning index
σ_{lkH}	Variation in the log rate constant of the weibull curve for hardness
a,b,c	Constants of polynomial equation
A_{BI}	Upper asymptotic value of the weibull curve
A_{H}	Initial hardness of mushroom cap, N
AIC	Akaike's Information Criterion
B_{BI}	Initial value of the browning index
B_{H}	Final hardness of mushroom cap, N
BI	Browning Index
BIC	Bayesian Information Criterion
BLUP	Best linear unbiased prediction
CV	Coefficient of Variation
E_a	Activation Energy of the process, $kJmol^{-1}$
H	Textural hardness, N
k	Rate constant for weibull distribution
k_{ref}	Rate constant at the reference temperature
lk_{BI}	Log rate constant of the browning reaction

lk_H	The rate constant of texture decay at the reference temperature
p	Probability
R	Universal gas constant, 8.314 kJ Mol^{-1} K^{-1}
R^2	Coefficient of determination
REML	Restricted maximum likelihood
t	Storage duration (day)
T_{ref}	Reference temperature (278K)

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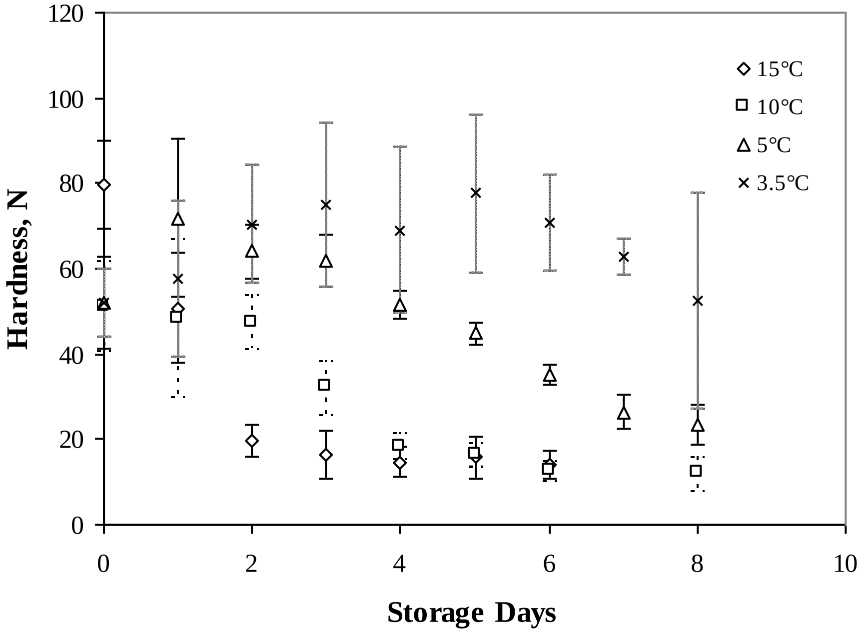
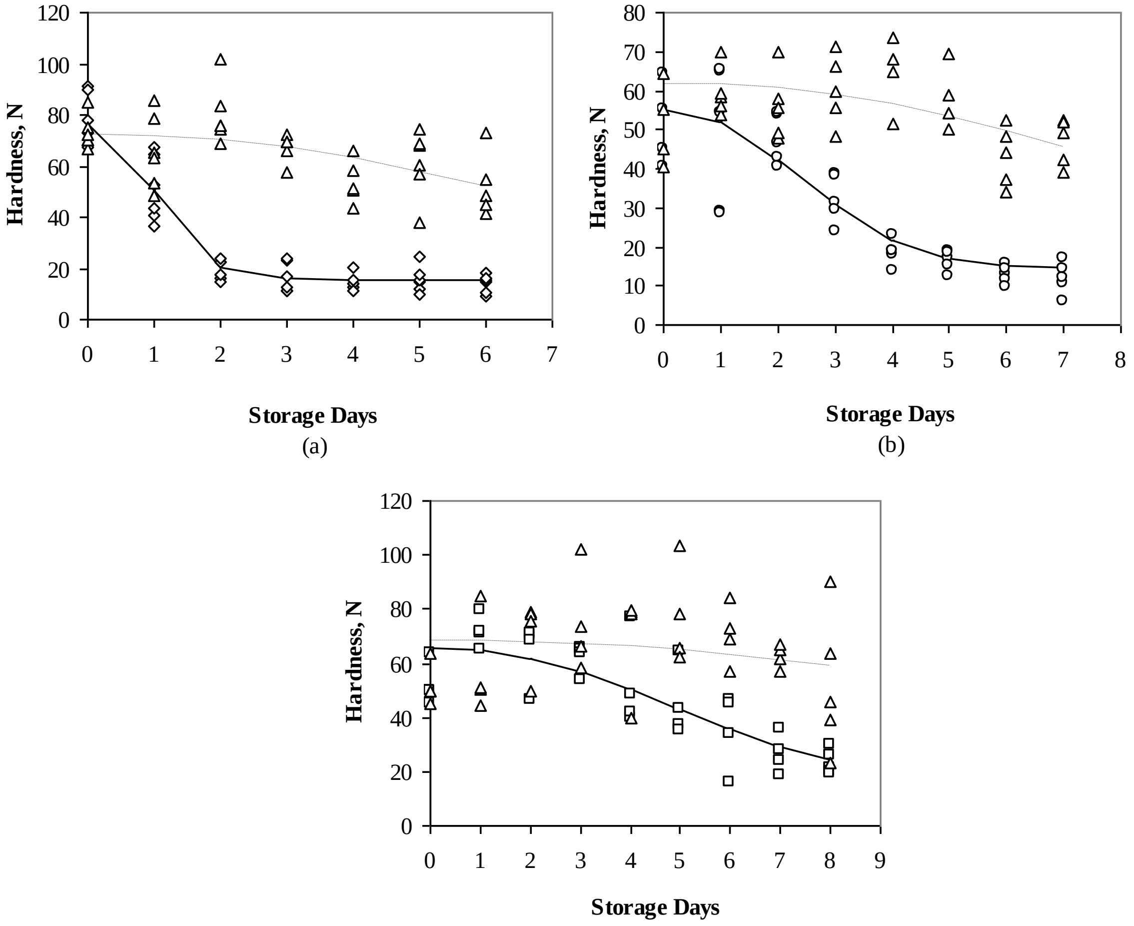


Figure 1 Typical textural hardness kinetics of mushrooms at different storage temperatures ◊ 15°C, o 10°C, Δ 5°C, × 3.5°C (control)



(a)

(b)

(c)

Figure 2 Typical textural hardness kinetics of mushrooms at different storage temperatures fitted to weibull model (a) ◊ 15°C (observed), - 15°C(predicted),(b)o 10°C (observed), - 10°C (predicted), (c) □ 5°C (observed), - 5°C (predicted), Δ 3.5°C(observed), --- 3.5°C (predicted)

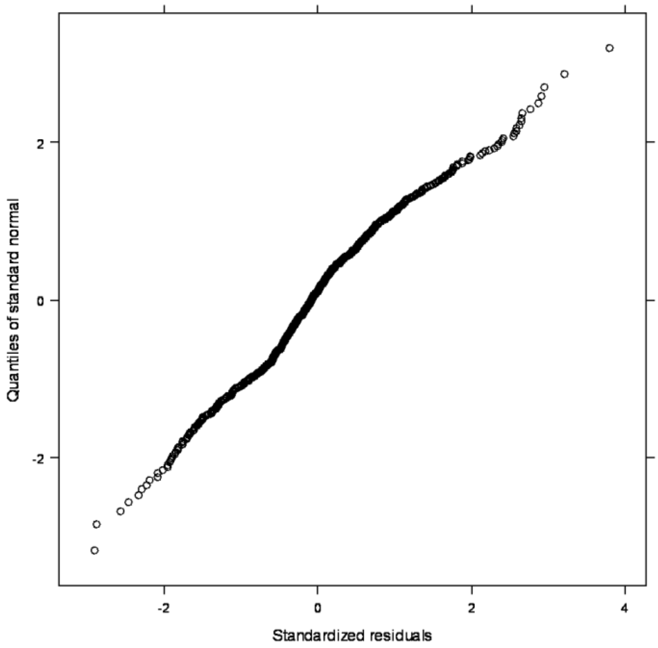


Figure 3 Normal distribution plot for the proposed weibull model fitted to the textural hardness data of mushrooms stored under controlled conditions of temperature considering the batch variability

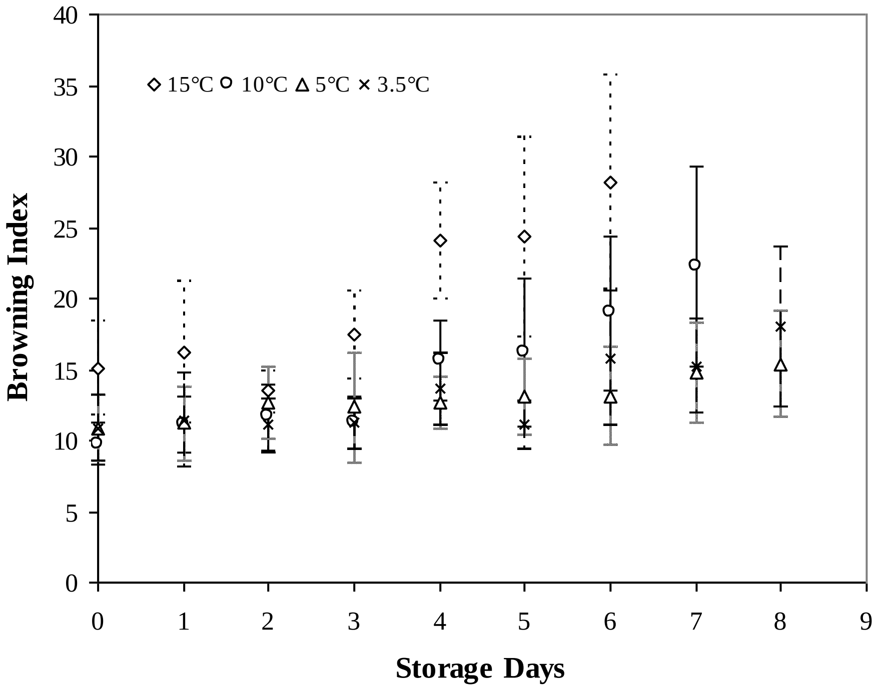
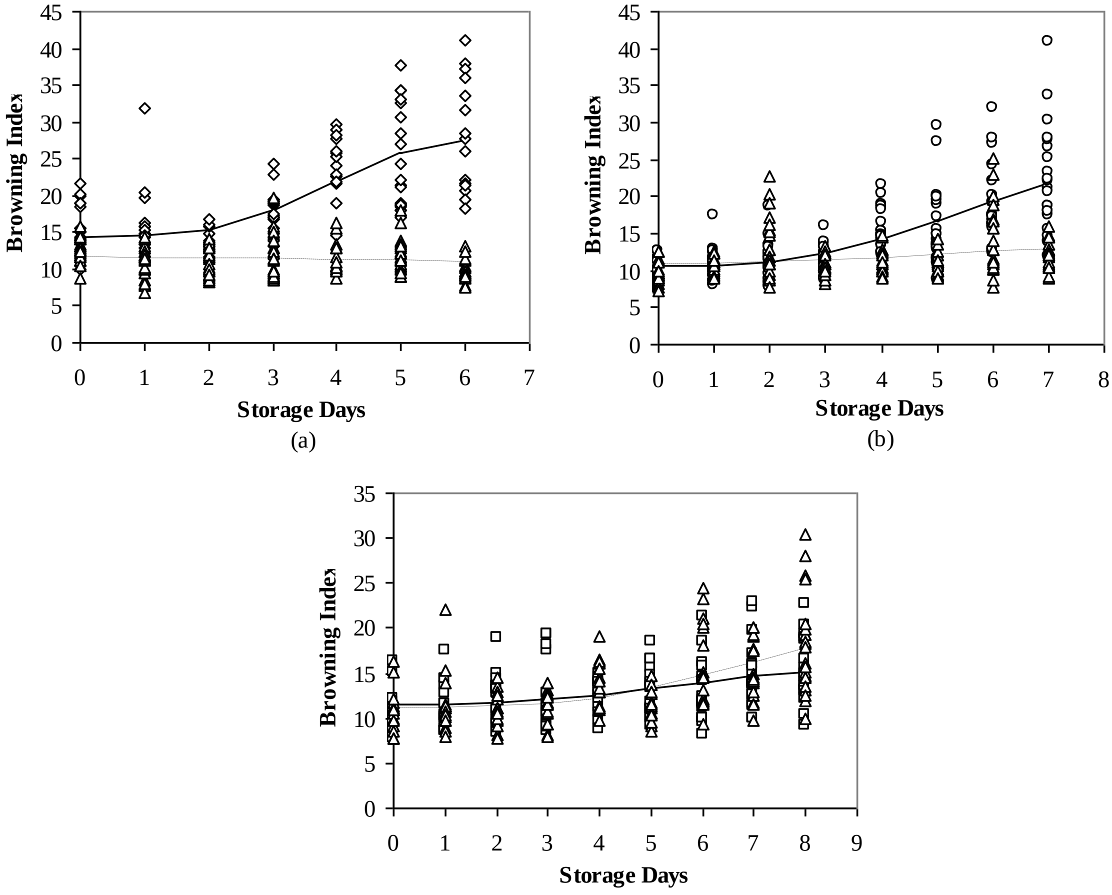


Figure 4 Typical browning index kinetics of mushrooms at different storage temperatures ◊ 15°C, o 10°C, Δ 5°C, × 3.5°C (control)



(a) (b) (c)

Figure 5 Typical browning index kinetics of mushrooms at different storage temperatures fitted to weibull model (a) ◊ 15°C (observed), - 15°C(predicted),(b)o 10°C (observed), - 10°C (predicted), (c) □ 5°C (observed), - 5°C (predicted), Δ 3.5°C(observed), --- 3.5°C (predicted)

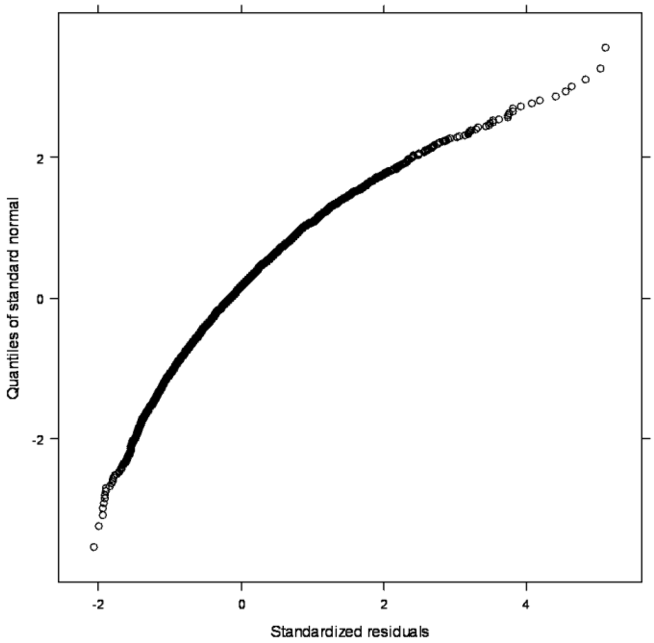


Figure 6 Normal distribution plot for the proposed weibull model fitted to the browning index of mushrooms stored under controlled conditions of temperature considering the batch variability

Table 1 Parameter estimates of the Weibull model for predicting the textural hardness of mushroom

Fixed Parameters

Parameter	Low 95% CI	Estimate	Up95%CI
A	13.241	15.726	18.211
A-B	-55.322	-49.876	-44.429
n	1.840	2.234	2.628
τ.*(Intercept)*	-1.443	-0.263	0.917
τ. *[1/Temperature]*	-179252.8	-127525.4	-75798.1

Random parameters

Parameter	Low 95% CI	Estimate	Up95%CI
σ*(A)*	0.444	1.913	8.252
σ*(A-B)*	6.945	10.250	15.126
σ*(*τ*[Intercept])*	0.830	1.207	1.755

* shows the direct temperature effect on the rate constant of the hardness

Table 2 Parameter estimates of the Weibull model for predicting the browning index of mushroom

Fixed Parameters

Parameter	Low 95% CI	Estimate	Up95%CI
Asymp	17.542	21.470	25.397
$\mathit{Initial}$	11.462	12.184	12.905
$I\tau$	1.307	1.540	1.772
β	2.212	3.005	3.799

Random parameters

Parameter	Low 95% CI	Estimate	Up95%CI
$\sigma(\mathit{Asymp})$	5.588	8.135	11.842
$\sigma(\mathit{Initial})$	1.082	1.540	2.192
$\sigma(I\tau)$	0.250	0.392	0.615
β	0.668	0.936	1.312